An Investigation into the cognitive and behavioural mechanisms that impede recycling behaviours.

by

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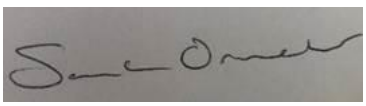
Signature of Candidate 

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Abstract

This thesis investigates the cognitive mechanisms that impede environmentally responsible behaviour, focussing specifically on the Negative Footprint Illusion (NFI) - a systematic judgement error in which the addition of environmentally friendly items to conventional ones paradoxically reduces perceived environmental impact. Across five experiments, this research examined the robustness and boundary conditions of the NFI in the context of recycling. Experiment 1 demonstrated that item type (e.g., bottles vs. houses) did not moderate the illusion, while Experiment 2 showed that the effect persists across both same-category and cross-category pairings. Experiments 3 and 4 tested individual differences, revealing that neither working memory capacity nor actively open-minded thinking predicted the magnitude of the illusion. Experiment 5 explored temporal framing and the potential for corrective nudges, finding that judgments were guided by averaging rather than summation, even when participants were prompted to consider total impact. Taken together, the findings suggest that the NFI arises from an averaging bias applied during intuitive vice–virtue categorisation, rather than from limitations in cognitive capacity or domain knowledge. This work contributes to our understanding of how cognitive biases distort environmental judgment and has important implications for the design of interventions aimed at promoting sustainable behaviour.

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Chapter 1

Introduction: Cognitive Mechanisms and Environmental Decision-Making

The consensus on climate change is overwhelming (e.g., UK climate change risk assessment 2017. 2017; IPCC, 1995, 2008, 2016; USGCRP, 2017), with both individual researchers (e.g., Cooke et al., 2013; Doran & Zimmerman, 2009; Oreskes, 2005) and intergovernmental organisations (European Commission, 2023; IPCC, 2015; NATO, 2024), presenting scientific evidence that humans are the primary drivers of its rapid development. For example, Cooke et al. (2013) report that 97% of climate scientists agree that the trends observed in climate-warming over the past century were very likely due to the activity of humans. Harmonious with this finding, Doran and Zimmerman (2009) surveyed climate scientists and reported that 97% agreed that changing mean global temperatures were significantly influenced by human activities. Similarly, the Intergovernmental Panel on Climate Change (IPCC) stated in their 2015 report that they are 95-100% confident that humans are the main cause of global warming.

A major contributor to climate change is carbon dioxide (CO_2) emissions that arise from human activities such as the burning of fossil fuels and deforestation (IPCC, 2014). Carbon dioxide emissions have reached unprecedented levels, being 150 times greater now than in 1850 pre-industrial times (IPCC, 2015; World Resources Institute, 2014), which correlates strongly with the onset of industrial activities utilising fossil fuel burning. CO_2 and other so-called “greenhouse gases” trap heat in the Earth’s atmosphere, leading to the “greenhouse effect”: a warming of the planet. Although a natural process, human activities have increased the concentration of greenhouse gases, thereby magnifying the effect and producing global warming.

The negative consequences of global warming are manifold and include extreme weather events (e.g., hurricanes, typhoons, droughts, heavy rainfall, and heatwaves), ocean

acidification, rising sea levels, and biodiversity loss (Doney et al., 2009; Nicholls et al., 2021; Weiskopf et al., 2024). These will impact on agriculture and fisheries, thereby undermining food security and global food supply (Doney et al., 2009; Nicholls et al., 2021; Weiskopf et al., 2024). This will convey a significant economic burden that will also be impacted through damage to infrastructure, increasing requirement for insurance, reduced tourism and addressing increased health risks that higher temperatures bring (e.g., heat-related illnesses, the spread of vector-borne diseases) (Calleja-Agius et al., 2021). Due to the strong consensus and extensive evidence for climate change, several warnings have been issued. For example, the World Health Organization (2017) has identified global warming as the greatest threat to global health in the 21st century, and the World Economic Forum (2016) regards it as a greater risk than weapons of mass destruction.

Tackling Climate Change

Psychologists and researchers from various fields (Conservation physiology, Cooke et al., 2013; marine science, Doney et al 2009; cognitive psychology, Threadgold et al, 2022), recognise the importance of addressing climate change (American Psychological Association, 2008), and it has been acknowledged as one of the major challenges of the 21st century (Sörqvist, 2016). Technological solutions to mitigate climate change effects already exist (e.g., Smith & Stirling, 2010). However, a significant portion of anthropogenic climate change is attributed to everyday behaviours such as transportation (Köhler, 2006), food consumption (de Vries & de Boer, 2010), energy use (Bin & Dowlatabadi, 2005) and recycling (EPA, 2020).

Recycling refers to the process of collecting, sorting, and processing materials that would otherwise be considered waste, the key goal being to turn typically used materials (e.g., paper, glass, metal, and plastics) into raw materials that can be used to manufacture new products (Defra, 2011). While recycling is perhaps more commonly thought of as addressing sustainability issues (e.g., resource conservation, waste reduction, energy

efficiency, and the circular economy), it also plays a key role in reducing CO_2 emissions (*Carbon WARM report, n.d*). Recycling conserves finite natural resources. Further, recycling reduces landfill waste which contributes to the production of the potent greenhouse gas, methane (European Commission, 2022). Climate change[1] and sustainability are interconnected concepts, and recycling relates to both. For this reason, the term "environmental impact" is used in the current thesis to cover decisions that affect both the climate and sustainability.

If it is accepted that a notable proportion of human-produced climate change stems from daily activities (Bin & Dowlatabadi, 2005; de Vries & de Boer, 2010; Köhler, 2006), and such activities are not curtailed despite widely dispersed knowledge of the damage they produce to the environment, then it follows that psychological factors may be a route cause of numerous obstacles that impact climate change (Gifford, 2011; Sörqvist, 2016). Indeed, cognitive factors (e.g. negative spillover effects, compensatory green beliefs, or attribute substitution) may influence individuals' propensity to engage in climate-friendly actions. Previous research suggests that an individual's decisions and behaviours can be influenced by their past actions (Sorrell et al., 2020), habitual patterns (Marien et al., 2019), irrelevant cues (Guéguen, 2012) and cognitive shortcuts and biases. These factors can lead to behaviours that contribute to detrimental environmental impacts. This thesis seeks to understand how cognition underpins interactions between human behaviour (e.g., failing to undertake climate change mitigating actions) and the environment.

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[1] [1] *In relation to climate change, it is estimated that recycling could reduce carbon dioxide emissions by approximately 700 million tonnes per year, and by 10.4–11.2 Gt between 2020 and 2050—equivalent to the annual CO_2 emissions of Japan* (European Commission, 2022). *Additionally, recycling reduces landfill waste, which is a major source of methane, a greenhouse gas with a global warming potential over 25 times greater than CO_2 over a 100-year period (IPCC, 2014).*

Cognitions and Behaviours that Adversely Affect the Environment

There are various cognitive biases involved in decision-making related to anthropogenic climate change. For example, research has found that engaging in one pro-environmental behaviour can increase the likelihood of engaging in additional pro-environmental behaviours, via positive spillover effects (Thøgersen & Ölander, 2003). Negative spillover effects can also occur, leading to further detrimental environmental impacts. These negative spillover effects have been extensively studied in psychological and economic research (Truelove et al., 2014). In an environmental context, negative spillover effects occur when the adoption of one environmentally friendly behaviour inadvertently reduces the likelihood of engaging in additional pro-environmental behaviours (Truelove et al., 2014; for reviews of environmental spillover effects, see Geiger et al., 2021; Maki et al., 2019; Nilson & Tuvlind, 2020). For example, suppose a person installs energy-efficient LED light bulbs throughout their house to reduce electricity consumption. In this case, they may feel justified in leaving the lights on for longer periods and engaging in increased usage of other electronic devices, such as the television, because they perceive their overall energy use as more efficient. A rebound effect then occurs because the increased usage offsets some or all of the energy savings that had been achieved through switching to the use of LED bulbs. Thus, the energy savings are less than the individual expects.

In their review of the negative spillover effect, Ehrhardt-Martinez and Laitner (2010) indicate that rebound effects negate approximately one-third of energy efficiency gains, ultimately resulting in a negative environmental impact. In this vein, Jacobsen et al. (2012) report that participation in a green energy program has been linked to higher household energy consumption, and Hirst et al. (1985) report that making a home more resistant to the effects of the weather can lead to increased thermostat settings during winter. It is therefore important to consider the overall net effect in the context of rebound effects because the behaviours may still result in improved energy efficiency (Jacobsen et al., 2012).

Cognitive Bias in Recycling: Negative Spillover Effects

In relation to recycling behaviour, an example of negative spillover and subsequent rebound effects can occur when an individual increases their purchase of bottled drinks because they believe they can recycle the plastic bottles afterwards and that the act of recycling mitigates the negative environmental impact. In reality, the increased consumption of single-use plastics can lead to more plastic production and an increase in the overall generation of waste. Additionally, suppose not all bottles are properly recycled (e.g., not cleaned prior to recycling). In that case, the environmental benefits intended are diminished (Catlin et al., 2021). In general, negative spillover or rebound effects in recycling behaviour can occur when an individual or household increases their consumption of packaged goods under the assumption that recycling offsets the environmental impact of the packaging itself. Another example is a household that becomes diligent about recycling paper and cardboard. Individuals in the household may purchase more products with excessive packaging because of a belief that their recycling behaviour effectively manages the waste. Here, the rebound effect arises due to (mis)placed confidence in the recycling infrastructure, resulting in behaviour that gives rise to greater environmental impact caused by the production and transportation of packaged goods and the recycling process itself.

Moral licensing

Moral licensing effects (e.g., Merrit et al., 2010), another type of negative spillover effect, occur when individuals permit themselves to act immorally after having established their moral credentials (e.g., Gholamzadehmir et al., 2019; Mazar & Zhong, 2010). Because pro-environmental behaviour is often viewed as moral behaviour (e.g., Steg et al., 2005; Stern, 2000), moral licensing effects have frequently been observed in the environmental domain. For instance, Sachdeva et al. (2009) found that recalling past moral behaviour made individuals less likely to support anti-pollution measures. Similarly, Klöckner et al. (2013) found that electric car owners felt less compelled to engage in moral behaviour

compared to those owning conventional cars. Likewise, Mazar and Zhong (2010) found that people were more likely to cheat and steal after being exposed to eco-friendly products than those exposed to conventional products. In the experiment, participants were asked to make purchases from either a conventional store that stocked nine conventional and three green products or a green store that stocked nine green and three conventional products. Then, they engaged in a seemingly unrelated visual perception task in which a box divided by a diagonal line was displayed on a computer screen (Mazar & Ariely, 2009). Participants were informed that on each trial, they would see a pattern of 20 dots scattered within the box. The pattern would stay on the screen for 1 s, and the task was to press a key to indicate whether there were more dots on the left or right side of the diagonal line for a monetary sum. Participants reported more dots than presented to earn more money and took more money than they 'earned' at the end when they had made purchases from a 'green' store as opposed to a conventional store. In a real-world context, this might involve individuals using the redistribution of food to prevent food waste or to prevent excess food from being deposited in landfills, and to take more than they require. This may inadvertently prevent those who could benefit from the resource from being able to access sufficient food.

In the context of recycling, moral licensing may occur in a situation wherein an individual who recycles regularly feels justified in wasting water because they believe their positive recycling behaviour offsets the negative water-wasting behaviour. However, it should be noted that some attempts to replicate moral licensing effects have not been successful (Urban et al., 2019), and some researchers have questioned whether the evidence for moral licensing effects has been inflated by a publication bias (Kuper & Bott, 2019).

A similar phenomenon to moral licensing is moral cleansing, which refers to behaviours aimed at regaining moral balance after immoral actions (Fanghella & Thøgersen, 2022; Sachdeva et al., 2009; Stikvoort et al., 2016). On this view, an initial environmentally harmful behaviour (e.g., flying abroad) increases the likelihood of producing pro-

environmental behaviour (e.g., taking a bicycle instead of a car to work). An example of moral cleansing was identified by Tang and Hinsch (2018), who found that materialistic individuals engaged in indirect pro-environmental behaviour to compensate for their materialism. Pro-environmental behaviour was measured by measuring the willingness to pay (WTP) for pro-environmental items, using the three-item scale from Laroche, Bergeron, and Barbaro-Forleo (2001) that asks whether the subject would pay 10% more food purchases that are packaged in an environmentally friendly way, 10% more in taxes that would fund an environmental cleaning, and five dollars a week to purchase more environmentally friendly products. The items were measured on a 7-point Likert scale before presentation of the scenario, and again after presentation and thinking about the purchase (luxury vehicle, luxury wardrobe, or modest house). Higher WTP is indicated by higher WTP scores. Materialism was measured using Inglehart's (1971) post materialistic values scale. with questions relating to maintaining a high rate of economic growth, fighting rising prices, a non-materialist would choose to move toward a society where ideas count more than money or friendlier and less impersonal society (Tang & Hinsch, 2018). In a real-world context, people may be willing to pay more for environmentally positive products, such as recycled items, rather than single-use products. Therefore, the higher price paid by the consumer goes towards the environment. The product purchase indirectly benefits the environment. Hence, the idea of morality in decisions about mitigating our seemingly pro-environmental actions may be a convenient fiction.

This thesis is primarily concerned with heuristics and biases underpinning environmental decision-making (see the forthcoming section). It is important to note that explanations grounded in mental processing (i.e., cognition) and social processing that do not necessarily involve heuristics and biases can also explain some behaviours that are detrimental to the environment. The theory of self-control (e.g., Baumeister et al., 2007) and the idea of goal-balancing (Inzlicht et. al, 2014) would both predict that after exerting self-

control or completing a *have to* goal, maintaining a healthy diet by resisting consumption of unhealthy food may make it more difficult to immediately engage in other arduous or have to behaviours such as recycling.

Behavioural Consistency

Another theory that might explain engagement in behaviours negative for the environment is behavioural consistency theory (e.g., Bem, 1972, as cited in Berkowitz, 1972). With this approach, individuals strive to maintain consistency in their actions. Thus, engaging in one negative behaviour increases the likelihood of engaging in additional negative behaviours to maintain consistency. In relation to consistency, identity and social norms may also play a role. In relation to identity, individuals often act in ways that align with their social identities and the norms of the groups to which they belong (Turner & Tajfel, 1979). Negative behaviour can spill over if it aligns with the perceived norms and values of their social group. For example, suppose a workplace culture tolerates minor recycling violations (e.g., putting a non-reusable coffee cup into recyclable waste). In that case, the employees may be more likely to engage in additional negative behaviours (e.g., wasting water). Several studies have shown that spillover effects in relation to environmental actions are influenced by environmental identity (Carrico, 2021; Ha & Kwon, 2016).

Normative influence also plays a role in recycling behaviour (Perry et al., 2009; Linder et al., 2023; Nilsson et al., 2017). Normative influence involves conforming to the behaviour of others to fit in or be accepted. For example, in contexts where recycling is highly visible and socially encouraged, individuals may focus on this pro-environmental behaviour to gain social approval but at the same time may neglect less visible but equally important behaviours such as reducing energy consumption.

Goal Dilution

Another contributor to negative spillover effects may be goal dilution (cf. Fishbach & Choi, 2012). This occurs when the presence of multiple goals reduces the perceived

importance or impact of any one goal. For example, if individuals adopt one pro-environmental behaviour, such as recycling. In that case, it can dilute the perceived importance of other pro-environmental actions, leading them to neglect further environmentally-friendly practices. Goal dilution affects an individual's pro-environmental behaviour but can also impact organisational planning. For example, a primary goal of a municipal recycling program may be to collect and process recyclable materials to reduce the city's overall waste footprint. However, secondary issues such as contamination, economic pressure, logistical challenges, and public perception may dilute the primary goal of environmental conservatism by detracting from the core objective of the recycling program. This can lead to negative spillover effects where the intended positive impact (reducing landfill waste and environmental conservation) is compromised or even reversed.

Cognitive Dissonance

Two other theories, cognitive dissonance (Festinger, 1957; Thøgersen, 2004) and mental accounting (Thaler & Sunstein, 2008), may shed light on an understanding of the spillover of negative behaviours. The theory of cognitive dissonance holds that individuals experience psychological discomfort when they engage in behaviours that are inconsistent with their values or beliefs. This discomfort can be reduced by changing their attitudes in line with their behaviours. However, this sometimes leads to a spillover of negative behaviours if individuals rationalise their actions to align with negative behaviours. To illustrate, suppose an individual who strongly values environmental conservation and who makes a conscious effort to regularly recycle excessively uses single-use plastics. Here, there is a clash between the initial behaviour of recycling consistently that aligns with their environmental conservation values and the conflicting behaviour of frequently using single-use plastics. This is because the excessive use of single-use plastics contradicts the individual's environmental conservation values. This inconsistency between the values held by the individual (environmental conservatism) and their behaviour (using single-use plastics)

creates a cognitive dissonance that results in psychological discomfort. The dissonance created can be reduced through the individual justifying their use of single-use plastics through convincing themselves that the recycling efforts that they do make sufficiently offset the negative impact of their frequent use of single-use plastics. A false sense of balance is created through this rationalisation process. This justification process may lead the individual to abandon other environmentally friendly practices, such as conserving household energy because they feel that their effort in recycling gives them a "license" to behave with less diligence in other areas. Thus, moral licensing may be tied to cognitive dissonance.

Mental Accounting

The theory of mental accounting (e.g., Thalar, 1985, 1999) generally proposes that individuals categorise, evaluate, and keep track of their activities by mentally separating them into different accounts and is offered as an explanation for negative behavioural spillover and moral licensing (Jordan et al., 2011). Individuals mentally segregate their behaviours into "good" and "bad" deeds. In the environmental context, recycling regularly might be mentally accounted as a "good" deed in an environmental account. In this view, performing positive actions (e.g., recycling) can create a surplus in the "good" account. This surplus within the good account, or "moral credit," can lead individuals to feel justified in engaging in a negative behaviour (e.g., use of single-use plastics), thinking the positive action(s) compensates for the negative one(s). In this approach, individuals engage in a process of balance-seeking whereby as long as they feel their "good" account is balanced or surplus, "bad" actions are permissible. This balancing of actions within different accounts can lead to negative spillover, where one good deed can be followed by one or more negative behaviours (Mazar & Zhong, 2010; Thaler & Sunstein, 2008). That is, depositing one pro-environmental action (e.g., recycling) within the mental ledger can result in a feeling of entitlement to "withdraw" by engaging in less eco-friendly behaviour in the belief that their overall balance remains in the positive. Since moral behaviour can be costly for an individual

(Eisenberg & Shell, 1986), people seem to use moral licensing in this way to return to a more comfortable state, thereby regaining moral balance after immoral actions (Sachdeva et al., 2009). Several studies suggest that people try to balance their good and bad deeds, or their “moral currency,” in this manner (Sachdeva et al., 2009).

Moral cleansing is similarly explained as the result of individuals keeping a moral account and balancing good and bad deeds (e.g., Jordan et al., 2011; Thaler, 1999). In this case, individuals engage in a pro-environmental action following an environmentally damaging behaviour because they have the desire to remove an inner tension of having done something morally questionable. That is, individuals want to restore a balance between good and bad deeds such that the former is in surplus.

Compensatory Green Beliefs

Negative spillover appears to be related to another concept called compensatory green beliefs (CGB; Gromet et al., 2013; Radtke et al., 2014). This is the belief that environmentally good deeds compensate for environmentally bad deeds. For example, engaging in a positive environmental action, such as recycling, might lead individuals to believe they have earned the right to perform a negative action, such as using more water or energy, under the assumption that the good action compensates for the bad. Compensatory green beliefs (CGBs) can take different forms (Penker & Seebauer, 2023), including normative CGB (the idea that one should compensate), efficient CGB (the idea that one can compensate), and general CGB (compensation makes it permissible to continue with environmental wrongdoings).

Other accounts that ascribe a key role to cognition in spillover effects include the notion that learning the outcomes of one behaviour influences learning about the consequence of other behaviours (e.g., the action-based learning approach; Thøgersen & Noblet, 2012) and the role of context. Littleford et al. (2014) discovered that the transfer of behaviours between the workplace and home environments hinges on how similar these

contexts are. This observation echoes the concept of context-dependent memory, where recalling information is facilitated when undertaken in the same environment where the information was initially learned (Smith & Vela, 2001). Recent studies have explored various cognitive aspects related to behavioural spillover. Sintov et al. (2019) found that cognitive accessibility, which refers to how easily information comes to mind, plays a role in mediating the relationship between an initial behaviour and its spillover effect on subsequent behaviours. Additionally, Fanghella and Thøgersen (2022) observed that recalling instances of immoral behaviour increases the likelihood of donating money, possibly to resolve cognitive dissonance caused by recalling moral transgressions.

The next sections will consider how environmental behaviours are linked to heuristics and biases. Prior to this, however, an appropriate overview of the meaning of heuristics and biases will be given.

The Role of Cognition, Heuristics and Biases in Decision-Making.

Researchers claim that there are two cognitive mechanisms that underpin decision-making (e.g., Gilbert et al, 1999). Dual process theory describes two systems, System 1, and System 2 (e.g., Evans & Stanovich, 2013a, b). System 1 has the correlated features of being rapid, automatic, and intuitive, whereas System 2 has correlated features of being slow, controlled, and reflective (Evans & Stanovich, 2013a). The defining feature of System 1 is that it does not require working memory whereas the defining feature of System 2 is it does require working memory (Evans & Stanovich, 2013a). Some evidence suggests that the intuitive System 1 is largely responsible for biased responses and intuitive decision-making (e.g., De Neys, 2006) but that these responses are monitored by System 2 and can, in some cases, be overridden (Newell et al., 2016). Consider this classical problem known as the "ball and the bat 4 problem": "If a ball and a bat cost £1.10 in total and the bat costs 1 pound more than the ball, how much does the ball cost?". Most people answer that the ball costs 10 pence (Kahneman & Frederick, 2002), which is wrong. The ball, in fact, costs 5 pence. In

this classical problem, System 1 is thought of as proposing an intuitive answer (i.e., 10 pence), which is monitored by System 2. System 2 can then either accept or reject the response. Neurological (McClure et al., 2004), experimental (De Neys, 2006) and correlational evidence (Toplak et al., 2011) exist for the involvement of these two types of processing in decision-making. However, it is important to note that System 1 can lead to correct answers, and System 2 can be incorrect in some cases.

It is likely that fast responses, given by System 1, were necessary for survival and success in our ancestral past and during evolution (Haselton & Gildersleeve, 2016). Throughout evolution, the human brain has been shaped to help people make fast and frugal decisions that require little effort. This is because using sophisticated strategies for each decision in one's everyday life is hardly advantageous in the long run. For example, using complex algorithms for each decision takes time and requires more attentional resources compared to simpler alternatives. The additional effort needed to employ a more sophisticated strategy often surpasses the potential benefits of improved accuracy (Arkes, 1991). To help make these fast and frugal decisions, people use heuristics (characterised by System 1), which can be described as a rule of thumb or a mental shortcut toward making a decision (Haselton et al., 2015). More specifically, people disregard parts of the information when making a decision. Instead of finding the best solution (i.e., optimising a decision), they aim to find a solution that is "good enough" (Gigerenzer, 2008).

Despite several misconceptions about heuristics (e.g., specifically, that they may produce suboptimal results), heuristics often work well in decision-making (Gigerenzer, 2008). This can be observed in the context of the N/1-heuristic. This heuristic is used when making decisions regarding investment behaviour (allocating money across funds) and implores individuals to allocate their money equally to each of N funds (Gigerenzer, 2008). There is, indeed, empirical evidence that suggests this heuristic is better in terms of

monetary return compared to various portfolio models designed to optimise the choice of allocating one's money (DeMiguel et al., 2009).

Heuristics also have an impact on moral behaviour. For example, consider the vast gap between organ donors in the U.S. (28%) and France (99.9%). At first glance, one might think that individuals in France are more moral than Americans. However, this gap is a consequence of the default heuristic, which posits that if a default is an option, then do nothing. More specifically, in France, every person is a potential organ donor since being a donor is the default option. French individuals must choose not to donate by opting out. The opposite is true for Americans (Johnson & Goldstein, 2003). These two examples are instances in which heuristics can help people make – justifiably – good decisions. However, heuristics can, on the other hand, lead to systematic biases, which can harm our decisions when used in inappropriate contexts.

Perhaps the two most common examples of heuristics that can impair our decisions in some contexts are the availability and representativeness heuristic. The representative heuristic was first coined and demonstrated by Tversky and Kahneman (1983). They asked participants to estimate the likelihood of a fictional character named Linda having different occupations. The participants first read a description of Linda, written in such a way that it was representative of a feminist. Next, they were requested to make likelihood estimates as to her occupation. Participants in the study estimated that it was more likely that Linda was a (1) feminist, and a bank teller compared to (2) a bank teller alone. As the first alternative includes the second alternative, it must have a lower probability compared to the second according to the conjunction rule, $P(A) > P(A+B)$. The authors coined this erroneous way of reasoning the conjunction fallacy, and to their surprise, over 80 % fell prey to the fallacy. The authors suggested the representativeness heuristic as the underpinning mechanism for the fallacy (people answered the degree to which Linda resembled a feminist rather than the likelihood of having different occupations). As the above examples reveal, even though a

heuristic can lead to correct estimates and judgements, when they are adapted to use in information-processing tasks, they can lead to systematic biases when used in inappropriate contexts (e.g., Tversky & Kahneman, 1983). Biases (or cognitive biases) can be considered a deviation from rational (or correct) responses. Biases are hence associated with reasoning mistakes; they are arguably the result of intuitive System 1 processing and occur even though all necessary information for a correct response is available and understood.

One reason for biased responses might be “attribute substitution” (Kahneman & Frederick, 2002), which states that individuals faced with a challenging question will often respond to an easier one instead, typically without realising they have made the substitution. Attribute substitution may be one reason why, for example, people overestimate the energy demand of large appliances and vice versa (i.e., a size heuristic; Cowen & Gatersleben, 2017). More specifically, when individuals are asked how much energy an appliance demands (i.e., the target attribute), they (according to the attribute substitution) might have answered an easier question instead: how large the appliances were (i.e., the heuristic attribute). Similarly, in the case of the “Linda problem” explained above, individuals may answer the degree to which Linda resembled a feminist (i.e., the heuristic attribute) instead of how likely it was that Linda was a feminist and a bank teller (i.e., the target attribute). As target attributes and heuristic attributes often are considerably different, attribute substitution can inevitably lead to systematic biases (Gilovich et al., 2002).

Heuristics and Biases in the Environmental Domain

Ideally, beliefs about climate change and sustainability would be based solely on scientific and concrete evidence without being swayed by irrelevant factors. However, extensive psychological research shows that this is not the case. For instance, beliefs about climate change can be affected by outdoor temperature (Zaval et al., 2014), priming (Joireman et al., 2010), indoor plants (Guéguen, 2012), the type of temperature scale used (Fahrenheit versus Celsius; Chan, 2018), and framing (Schuldt et al., 2011).

Decisions and behaviours affecting climate change, like beliefs, are influenced by seemingly irrelevant factors such as prior actions (e.g., Sorrell et al., 2020). For example, prior action may be the choice to ride a bicycle instead of taking the car to work. This may give the cyclist a sense of achievement for their environmental behaviour earning moral credit resulting in a moral spillover (i.e., excusing future, emission-intensive goods and activities).

Several mechanisms underlie human behaviours, including those related to negative spillover effects. For instance, compensatory green beliefs (e.g., “I recycle, so I am able to drive to work”) may be precursors to rebound effects (Kaklamanou et al., 2015). Another precursor is the single action bias, which suggests that people sometimes believe that a specific risk (e.g., flooding) is mitigated by one ameliorative action (Weber, 1997), potentially overlooking more effective climate change interventions. The likelihood of a decision leading to negative spillover also seems to depend on the context of the initial decision. Specific contexts that evoke positive or negative emotions can unintentionally influence subsequent decisions. For example, decisions made in contexts eliciting fear, guilt, or risk may drive people to engage in behaviours aimed at alleviating such negative emotions. Since negative emotions are often aversive, a single action is usually sufficient to reduce the negative mood (Weber, 1997). Thus, one can argue that misusing the affect heuristic (i.e., making decisions based on the overall affect elicited by a stimulus) results in single-action bias. Conversely, research indicates that negative spillover effects related to moral licensing (and cleansing) can be driven by a desire to balance good and bad deeds (e.g., Sachdeva et al., 2009; Wang et al., 2009; see mental accounting, e.g., Thapar, 1999). These moral licensing effects may stem from misusing an evolutionary old balancing heuristic aimed at restoring balance in interpersonal relationships (Sörqvist & Langeborg, 2019).

The misuse of heuristics can lead to systematic biases. Numerous heuristics and biases exist that can influence the environmental domain. Some of these biases will be introduced before focusing on those central to the current thesis. In what follows, numerous

biases and heuristics will be introduced to illustrate first, how they can negatively affect environmental decision-making generally and second, how they relate specifically to suboptimal decisions that inevitably perpetuate environmental damage in the case of recycling. It is important to note that the heuristics and biases included are not exhaustive.

Availability Heuristic

This cognitive bias occurs when individuals judge the likelihood or frequency of an event based on how easily examples of that event come to mind (Tversky & Kahneman, 1973). For example, individuals typically think that words ending with “ing” are more frequent in the English language compared to words ending with “_n_,” even though the first is included in the second (Tversky & Kahneman, 1973). This is because words ending with “ing” are more accessible – making generating examples easier. Thus, the availability heuristic can lead to judgement inaccuracies because easily recalled events may not accurately represent the actual probability or frequency. Since memory accessibility plays a role in the availability heuristic, the vividness (Nisbett & Ross, 1980), recency (Tversky & Kahneman, 1973), and affective valence (Slovic et al., 2007) of information may disproportionally affect perceptions and increase the bias. In relation to the environment, individuals may overestimate the frequency and severity of natural disasters due to their significant and extensive media attention; such exposure may lead individuals to believe that events like these are becoming more common and pose a greater risk than the statistical data for their occurrence suggests (Slovic, 1987). Bias can influence public opinion and policy decisions, leading to prioritisation for extreme weather events such as hurricanes at the expense of formulating long-term climate change strategies that may even be more pressing.

In relation to recycling, the availability heuristic may manifest when individuals perceive recycling to be more widely practised and effective than it is due to frequent exposure to campaigns about recycling and the visibility of recycling efforts within the

community (Schultz, 1999). Exposure to promotional advertisements concerning recycling, its appearance in media (e.g., articles or news programs about its success), and watching neighbours recycle might lead to overestimating the overall recycling rate in the community and the impact of an individual's recycling efforts. The upshot of this might be behavioural complacency: individuals consider their environmental impact is sufficiently mitigated by their own recycling habits, thereby neglecting other sustainable practices, including waste reduction, reuse of items, or the support of systematic changes targeting greater environmental impact.

Optimism bias

Optimism bias refers to the tendency for individuals to underestimate the probability that they themselves will experience a negative event while overestimating their likelihood of experiencing a positive event. An example of optimism bias in environmental reasoning is when individuals (or policymakers) underestimate the potential negative impacts of climate change or overestimate the effectiveness of future technological solutions to address environmental issues in time to prevent catastrophic outcomes. Therefore, the individual or group may perceive that no significant changes to current behaviour or policies will be required. Optimism bias can hinder efforts to reduce carbon emissions and adapt to climate change thereby exacerbating the very issues that it has set out to resolve.

In relation to environmental degradation, Hatfield and Job (2001) found that participants believed that their own area was less likely to be affected by environmental issues (e.g., air pollution) compared to the average local area of their peers. They also perceived themselves to be more knowledgeable about behaviours which can diminish problems posed by environmental hazards. Optimism bias may be influenced by dispositional optimism, a psychological trait characterised by general expectations that good things will happen in the future coupled with a tendency to interpret events and outcomes in a positive light. Further, optimism bias may affect an individual's attention to different aspects

of climate-related information. For example, in an eye-tracking study wherein individuals read an article containing arguments in favour or against climate change, optimists demonstrated significantly shorter fixation durations in arguments favouring climate change than in arguments against it (Beattie et al., 2017). Non-optimists did not show this pattern. Further, individuals with higher levels of dispositional optimism spent less overall time focusing on the content of the climate change articles, regardless of the argument being presented (supportive or opposing). When asked to summarise what they had just read, non-optimists described the content as arguments supporting climate change, while optimists framed their summaries as a debate between conflicting viewpoints. In a follow-up study with different participants, non-optimists were twice as likely as optimists to believe climate change would affect them personally.

Self-serving Bias

Another bias that can affect decision-making and behaviour within the environmental context is self-serving bias (Babcock & Loewenstein, 1997). This manifests when individuals or organisations attribute their efforts to their positive traits while they blame external factors for their failures. A prominent example of self-serving bias in the environmental domain is the Volkswagen emissions scandal, in which the company marketed their diesel engine vehicles as being environmentally friendly with low emissions. While tests initially found evidence to support the low emissions as claimed by the company, it transpired that the vehicles had been fitted with devices to cheat the emissions test. Volkswagen demonstrated self-serving bias by focusing on its perceived positive actions toward the environment (e.g., commitment to, and pledges toward, sustainability) in its public relations efforts and deflecting attention from its significant negative environmental impact.

In the context of recycling, self-serving bias occurs when an individual believes that they are an environmentally responsible person even though they do not recycle consistently. When they do not recycle, they might justify their failure by blaming the situation

(no available bins) rather than blaming themselves for their behaviour. This bias can undermine genuine pro-environmental efforts and overestimate an individual's positive environmental impact.

Anchoring Bias

Anchoring bias (e.g., Wansink & van Ittersum, 2003) occurs when an individual makes judgements or decisions that rely too heavily on initially encountered information (the anchor). Applied to the environmental context, this could mean that individuals' judgements or decisions rely on outdated or incorrect information about the state of ecosystems or the effectiveness of environmental policies. Applied to recycling, an individual may learn that a particular city has a 30% recycling rate, and they may use this percentage as a benchmark for their own recycling efforts regardless of the actual rate of recycling in their city (or community). Even when arbitrary, the initial figure encountered by the individual influences their perception and behaviour and persists even in the face of new information that becomes available later.

Confirmation Bias

Confirmation bias occurs when individuals seek out information that confirms their pre-existing beliefs or hypotheses (Nickerson, 1998). Individuals exhibiting this bias tend to prefer or search actively for information or data that supports their view, interpret ambiguous or neutral information as supporting their beliefs, and remember information that aligns with their beliefs more easily than recalling information that contradicts them. In relation to the environment, an individual who believes that climate change is not real may overly weigh the occasional cold weather event or isolated studies that downplay climate change severity while at the same time ignoring the overwhelming scientific consensus and extensive data that supports global warming and its impacts. The effects of confirmation bias may also hinder effective action on environmental issues. For example, if those individuals capable of making a difference (e.g., policymakers) are influenced by confirmation bias, comprehensive

climate change models and risk assessments might be disregarded in favour of selective data that align with their economic or political interests. The knock-on effect of such a scenario is the passing of inadequate and misinformed environmental policies. In relation to recycling, confirmation bias can occur if individuals believe that recycling plastic is highly effective and beneficial – this could lead them to focus on reports and scientific papers that highlight the success of plastic recycling programs while dismissing or ignoring studies that focus on the inefficiencies and environmental costs that are associated with plastic recycling (for a review, see Schultz, 2002).

Status Quo Bias

Status quo bias (e.g., Samuelson & Zeckhauser, 1988) leads individuals to prefer things to remain the same or to choose an option that would lead to the perpetuation of a current situation. Thus, individuals who exhibit this bias prefer the current state of affairs, possibly an aversion to change, and will select default options when presented with choices. This bias can cause individuals to be resistant to change and adhere to established behaviours (habits, practices, or decisions) due to perceived comfort or lower risk, even when alternatives might offer or lead to better outcomes. In relation to the environment, status quo bias is observed when individuals or organisations prefer to maintain their existing environmental policies and practices even in the face of clear evidence demonstrating that change is required to address the degradation of the environment or climate change. The bias may lead to resistance against adopting novel, more sustainable practices, or technologies simply because individuals find the status quo more comfortable or familiar. For example, a city might continue to rely on fossil fuel-based energy resources rather than investing in renewable energy alternatives (e.g., solar panels and wind turbines). Despite the long-term benefits and reduced environmental impact that renewable energy offers, the decision makers and residents might prefer to keep the current system because changing it could involve perceived risks, initial costs, or disruptions.

Another example of status quo bias in recycling may be single-use plastics. Consumers and businesses might continue to use and provide single-use plastic products such as straws, bags, and containers simply because they perceive it to be the norm, ignoring the strong evidence for environmental harm caused by plastic pollution. Therefore, efforts to ban or reduce single-use plastics may face opposition because individuals have become accustomed to their convenience and are resistant to altering their habits and routines.

In the same vein, individuals may continue to dispose of their waste in the same manner despite the city introducing new, more efficient recycling programs such as curbside recycling that requires residents to sort their recyclables into specific categories. Individuals may resist recycling and continue to throw all their waste into a single bin because this has been their routine for years. Further, this can occur despite the individual knowing that the new program is better for the environment and more effective. In these two examples, status quo bias can hinder the transition to more sustainable practices and technologies and delay necessary actions that would mitigate environmental issues.

Overconfidence Bias

This bias occurs when individuals believe their own abilities or performance to be better than they are. Individuals manifesting this bias are excessively certain that their beliefs or predictions are accurate and that they have superior skills or are better at tasks than others. This can result in underestimating risks, implementing insufficient risk mitigation strategies, and overestimating an individual's capabilities, resulting in poor performance due to inadequate preparation (for a review, see Moore & Healy, 2008). Overconfidence bias may arise in the environment when individuals or policymakers overestimate their ability to manage or mitigate environmental risks. This can lead to a failure to undertake sufficient precautionary measures and thereby entail consequences of high severity. For example, the government might be overly confident in its flood protection systems through its existing

control infrastructure (e.g., dams or levees). Through this overconfidence, the government might fail to heed warnings from climate scientists about the increased frequency of floods and storms due to climatic change. As a result, the existing infrastructure may fail, resulting in catastrophic flooding and extensive damage to ecosystems and the community.

In the context of recycling, overconfidence bias may occur when individuals believe they are more knowledgeable about recycling rules and practices than they are (McKenzie-Mohr, 2000). For example, an individual may confidently place a greasy cardboard food container or certain type of plastic into a recycling bin under the false belief that they are recyclable. As a result of this overconfidence, recycling streams are contaminated, reducing the efficiency, and increasing the expense of the recycling process. Generally, overconfidence bias can lead to an underestimation of environmental risk and failure to take appropriate and/or timely actions that would protect the environment, thereby worsening environmental issues.

Sunk Cost Fallacy

This refers to a situation wherein individuals or organisations continually neglect future benefits to invest in a project or decision based on the cumulative prior investment which may be in the form of money, resources, or time (Arkes & Blumer, 1985). The fallacy can be summed up with the commonly used expression “throwing good money after bad,” meaning that individuals or organisations do not want to “waste” those resources they have already spent. In the case of environmental reasoning, individuals or organisations may continue with their investment and/or support of projects or technologies that are environmentally harmful because they consider that they have already invested a significant amount of resources in them. Further, such reasoning may persist regardless of evidence that changing or abandoning the projects would be of future (e.g., long-term) benefit. For example, a city may have invested considerable resources in building a coal-fired power plant. During construction, new information comes to light about technological advances

concerning solar and wind that would be less costly and friendlier to the environment in the longer term. Instead of switching to cleaner alternatives, decision-makers might feel compelled to finalise the project and operate the plant because they have already poured significant financial resources into the coal plant. The focus is on the money already spent (the sunk costs) even though the product (the coal plant) has longer-term costs and leads to greater environmental damage.

As an example, in the context of recycling, a city may have invested high-level resources in a recycling program that uses outdated technology that is less efficient and cost-effective than current-market alternatives. Despite the availability of newer, more efficient alternative recycling technologies, the city perseveres with its investment and use of the outdated system due to the significant past spending. Decision-makers are thus unwilling to write off the initial expenditure and switch to a new technology that would benefit recycling across the city in the long run (for further discussion, see Arkes & Blumer, 1985). Opportunities to adopt sustainable solutions are thus prevented, and an irrational persistence with ineffective or harmful practices increases the promulgation of environmentally harmful activities.

Groupthink

Suboptimal decision-making can result from groupthink (Janis, 1972). Perhaps the most famous example of groupthink can be observed in the decision-making processes that led to the 1986 Challenger Space Shuttle disaster (Vaughan, 1996). In this context NASA Engineers and the contractors responsible were aware that seals used in the booster rockets could stiffen and fail to seal joints in the rocket booster at low temperatures. Groupthink, however, led to the downplaying of these concerns in favour of keeping the shuttle launch on schedule. In this context, groupthink influenced the decision-making process by increasing the pressure to conform: the concerned Engineers bowed to the pressure exerted by the group’s consensus to initiate the launch. In doing so, some team members also suppressed

dissent (i.e., their doubts and objections) to maintain harmony and avoid conflict within the group. Groupthink also led to the perception of invulnerability – that contrary to evidence, the launch decision would not result in such a catastrophic failure, and group rationalisation of warnings and negative feedback that convinced members of an acceptable level of risk (for further discussion, see Vaughan, 1996).

Groupthink may also occur in the context of reasoning with consequences for the environment (Funabashi & Kitazawa, 2012). For example, groupthink may occur when a group of decision-makers within a government agency collectively rationalise and support an environmentally unsustainable policy because they avoid critical evaluation of its potential environmental impacts due to a desire for consensus and cohesion. This can be observed by considering the example of a government committee that is responsible for urban development. Perhaps the group has a few influential members who dominate the group and who prioritise economic growth versus environmental sustainability. To preserve group harmony, other group members may suppress legitimate concerns over the long-term impact of the proposed developments for the environment. This can result in the committee approving projects that create environmental damage through, for example, increased carbon emissions, increased deforestation, and decreased biodiversity, despite group members being well aware of such consequences.

In the context of recycling, suppose again that a municipal government is introducing a new recycling program. Further, suppose that the waste management department within the city launches a recycling program where recyclables are collected together and unsorted (a so-called “single-stream” recycling program). The decision-making process underpinning the single-stream recycling program may demonstrate indicators of groupthink if, for example, the group believes their single-stream recycling program is foolproof and will significantly increase recycling rates at the same time ignoring the potential contamination between items and the limited effectiveness of such a program. Further, when presented

with empirical data concerning the limited effectiveness of single-stream recycling and the abundant risk of contamination, the group may rationalise these warnings as manageable minor issues. Rather than voice their doubts or concerns over a single-stream recycling program, members of the waste management department might keep silent due to pressure to maintain group harmony and conform to the dominant opinion within the department. This yields an illusion of unanimity of support for the single-stream recycling program and reinforces the belief that it comprises the optimal solution. The implementation of a single-stream recycling program in this scenario results in an ineffectual system that, over time, gives rise to high rates of contamination. This, in turn, will lead to the inability to recycle much waste, with a lot of waste winding up in landfills. Thus, groupthink can lead to decision-making that can directly undermine the goals of the city to reduce and control waste.

Green Halo Effect

This refers to a cognitive bias in which people perceive products, companies, or practices as more environmentally sustainable than they truly are, often based on a single, superficial “green” attribute. For instance, a company promoting the use of recyclable packaging may be viewed as highly eco-conscious despite engaging in other environmentally harmful practices (e.g., high carbon emissions). This perception is frequently the result of positive environmental branding or “greenwashing,” where minimal eco-friendly elements are exaggerated to project a more sustainable image. The focus on one green attribute (like recyclability) can overshadow and distort people’s overall evaluation of the environmental impact.

In the context of recycling, the green halo effect may arise when a company advertises its product packaging as 100% recyclable. Consumers might then view the entire product and brand as environmentally friendly simply because of the recyclable packaging, overlooking other harmful aspects of the product’s lifecycle. For example, a bottled water company might highlight that its bottles are made from recyclable plastic, leading consumers

to believe that purchasing the product is an eco-friendly choice. However, they may ignore the significant environmental costs involved in producing, transporting, and recycling the plastic or the fact that much of it may not even get recycled. This green halo effect causes consumers to overestimate the environmental benefits of such products, disregarding the larger negative impact of single-use plastics (Luchs et al., 2010).

Averaging Bias

Averaging bias (e.g., Chernev & Gal, 2010) occurs when individuals fail to give appropriate weight to different pieces of information during their decision-making, even when some of that information should be given more or less weight depending on its relevance, accuracy, or importance for the decision in question. Averaging bias can lead to decisions that do not consider that different data points vary in significance. For example, decision-makers in a company may assign equal weight to a comprehensive peer-reviewed study that provides a very detailed report of the environmental impact rather than to a brief non-expert opinion from a blog post that entails a less accurate overview of the environmental impact of the company. Thus, the estimated environmental impact of the company will be an average of expert and non-expert reports, which may yield a misguided understanding of the company's actual environmental impact. For example, the company may conclude that its processes generate a moderate environmental impact based on averaging the information. However, the two reports may go in different directions – the expert report suggests that work needs to be done to decrease environmental impact. At the same time, due to a lack of expertise and depth of knowledge, the non-expert opinion might underestimate the severity of the environmental impact. Thus, averaging bias can give rise to poor strategic decisions.

It is easy to see how averaging bias in the context of recycling can occur by supposing that the two sources of information (expert and non-expert reports) reflect reliable and less reliable sources' evaluations of a recycling program – the first being a detailed analysis of a recycling program's performance from an environmental consulting firm, and

the second being feedback from a community survey proving resident's opinions and perceptions concerning the recycling program. If the waste management department gives equal weighting to the two reports concerning the success of the program, they are exhibiting an averaging bias. They are potentially inaccurately assessing the true effectiveness of the recycling program which should give greater weight to the expert report provided by the consultancy firm than the arguably less accurate subjective survey reports. To illustrate, imagine that the expert report finds 40% of the collected recyclables are contaminated, while the community survey shows that residents believe only 10% of the recyclables are contaminated. If an individual or organisation averages the two figures (30% + 10%), they will conclude that 20% of recyclables are contaminated. This is potentially misleading, and for a more accurate judgement, the data from the expert report (consulting firm) should be given more weight in the decision-making process.

Averaging bias is pervasive within the reasoning and decision-making literature and has been observed in multiple domains. When highly favourable information about a product is accompanied by additional, moderately favourable information, people make less favourable evaluations of the product compared to when only the highly favourable information is presented (Weaver & Lewis, 2012). Kunz et al. (2017), correspondingly, found that investors' perceived risk of a risky stock decreases when a safe stock is added, even though the risk strictly increases. Further similar effects include adding less favourable arguments to highly persuasive arguments, thereby decreasing the persuasiveness of the overall message (Weaver et al., 2016); strong evidence of fraud is perceived as weaker when combined with weaker evidence (Lambert & Peytcheva, 2020); and adding a healthy side dish (e.g., a salad) to a whole meal makes people believe that the calorie content of the whole meal decreases when it, in fact, increases, termed the negative calorie illusion (Chernev & Gal, 2010).

The Negative Footprint Illusion is a phenomenon thought to be underpinned by the averaging bias. Gorissen and Weijters (2016) demonstrated that people mistakenly believe that the carbon footprint of a whole meal *decreased* when an eco-friendly side dish was added, which is necessarily incorrect as eco-friendly products also contribute to a carbon footprint. From an averaging perspective, the idea is that people categorise items or actions as good or bad (i.e., health vs. unhealthy, eco-friendly vs. conventional) and then base their decision on the average rather than on the aggregated sum of the items (Chernev & Gal, 2010). Thus, individuals consider that adding positive environmental actions (e.g., planting new trees or recycling) can offset or nullify the negative actions they are responsible for (e.g., driving a petrol car, intensive electricity use)

Environmental Decision Making: The Negative Footprint Illusion (NFI).

This introduction to cognitive biases and heuristics demonstrates that errors in reasoning can influence environmental decision-making. This thesis focuses on the negative footprint illusion and the leading explanation of the effect: the averaging bias (Chernev & Gal, 2010). The justifications for focusing on the negative footprint illusion and averaging bias are manifold. First, much decision-making is done fast and intuitively (Kahneman, 2011), which is, in part, the reason why the averaging bias occurs. The Negative Footprint Illusion (NFI) emerges when individuals intuitively evaluate a situation in terms of vices and virtues. When individuals weigh a product's economic and environmental cost and averages it against the benefits, this results in a reduction of the cost (i.e., an increase in the benefits) through the averaging process (Holmgren, Andersson et al., 2018). Second, the NFI is robust across expertise (Holmgren et al., 2018b) and contexts (Gorissen and Weijters., 2016; Kim and Schuldt., 2018). Third, while the vices and virtues of items are accepted as the rationale for the averaging bias (Chernev & Gal, 2010), research is needed to understand the cognitive processing underlying this bias. Could the averaging bias still impact the negative footprint illusion if items were seen as more closely connected on the

spectrum of vice and virtue? Understanding the ideals of vice and virtue and how they manifest is crucial. Does the dichotomisation of good versus bad or right versus wrong allude to a stronger NFI? If this direct contrast clarifies the vice-virtue, then it follows that If mediocre sat in between good and bad, the contrast might be reduced. Fourth, an understanding of the bias may aid improvements in environmental decision-making. Specifically, explaining the erroneous tendency to average may provide a subtle intervention strategy (i.e., nudge) to promote less detrimental decision-making to the environment. A better understanding of our decision-making related to the environment is crucial in the human contribution to the climate change crisis.

In the NFI, the introduction of a perceived lower environmental impact item (Ateş, 2020; Gorissen & Weijters, 2016), a low carbon footprint item (Holmgren et al., 2018a; Holmgren et al., 2018b; Holmgren et al., 2019) or an organic item (Threadgold et al., 2022) aids in the reduction of the overall estimate. However, when these labels such as “organic” are removed, the NFI remains (Holmgren et al., 2019; Kusch & Fiebelkorn, 2019). This result begs the questions are all practices that are conventional bad or perceived as a vice and are anything that is labelled “green” or environmentally certified automatically good or virtuous? Further, is it only when comparisons are drawn from polar opposites that erroneous negative assessments occur? Does the word “recyclable” illicit a more positive environmental assessment than “non-recyclable”? Furthermore, when considering choosing between a bottle or can of fizzy drink it might be the material used (i.e., plastic) that impacts judgements rather than the words “bottle” and “can” or the other way around. Therefore, an aim of this thesis is to identify factors that influence the NFI via the wording or phrases identifying the recyclability of an item and its environmental impact.

Chapter 2

Theoretical Framework: Heuristics, Biases and the Negative Footprint Illusion

As outlined in Chapter 1, the NFI occurs when people underestimate the total environmental impact of a set of items that includes an environmentally friendly product, incorrectly assuming it reduces the overall footprint (Andersson et al., 2024; Ateş, 2020; Gorissen & Weijters, 2016; Gorissen et al., 2024; Holmgren et al., 2018a, 2018b, 2019, 2021; Kusch & Fiebelkorn, 2019; MacCutcheon et al., 2020; Sörqvist & Holmgren, 2022; Sörqvist et al., 2022; Sörqvist & Marsh, 2024; Threadgold et al., 2022). The first study to demonstrate this effect was by Gorissen and Weijters (2016) who developed an experimental paradigm using food products. Participants were first introduced to the environmental impact of food production and transport. They were then given a standardised explanation of the footprint metric: '*Each footprint represents 2.1 kg of* CO_2*—equivalent to a 10 km car journey*'.

To ensure participants understood the rating scale, they were shown an example meal (potatoes, vegetables, and meat) and its associated carbon footprint. This anchored their judgements by providing a reference point at the centre of the rating scale, allowing them to compare subsequent meals against this benchmark.

They were then randomly assigned to one of three conditions: a basic meal (potatoes, steak, and mushrooms), the same meal plus an organic side (organically labelled salad), and the same meal plus a non-organic side (e.g., packaged sauce). Participants judged the total environmental impact of the meal in each condition. The key finding was that participants incorrectly rated the meal with the organic side as having a lower footprint than the basic meal alone—despite the addition of an extra food item. This suggests that they treated the organic food as having negative emissions, leading to a misjudgement of total impact ($A + B < A$).

Following Gorissen and Weijters' (2016) initial demonstration of the NFI, subsequent studies have replicated the effect across various domains, including housing, transportation, and consumer goods (Andersson et al., 2024; Ateş, 2020; Gorissen & Weijters, 2016; Gorissen et al., 2024; Holmgren et al., 2018a; Holmgren et al., 2018b; Holmgren et al., 2019; Holmgren et al., 2021; Kim & Schuldt, 2018; Kusch & Fiebelkorn, 2019; MacCutcheon et al., 2020; Sörqvist & Holmgren, 2022; Sörqvist et al., 2022; Sörqvist & Marsh, 2024; Threadgold et al., 2022). The paradigm has been extended beyond food products, demonstrating that the NFI occurs when estimating the environmental impact of eco-friendly versus conventional houses and hybrid versus petrol cars (Ateş, 2020; Kusch & Fiebelkorn, 2019; Gorissen & Weijters, 2016; Holmgren et al., 2018b).

The illusion also persists across different time scales—for instance, when participants estimate carbon emissions over 5 versus ten years (Holmgren et al., 2019). Researchers have also explored different methods of measuring the NFI. Some studies have used compensatory judgements, such as estimating how many trees would need to be planted to offset emissions from household energy consumption (Holmgren et al., 2018). Others have relied on Likert-type rating scales (Holmgren et al., 2019; Kim & Schuldt, 2018; Holmgren et al., 2018; Holmgren et al., 2021), with some incorporating midpoints of zero—which allow participants to assign negative values to environmental impact (Kim & Schuldt, 2018; Holmgren et al., 2019).

However, the framing of these scales significantly influences the strength of the NFI. Studies suggest that green-framed scales (assessing how environmentally friendly an item is) tend to increase the illusion, as participants focus on the perceived virtue of eco-friendly items. In contrast, grey-framed scales (assessing environmental harm) can weaken or even eliminate the effect, as they direct attention toward the total impact rather than the presence of "green" options (Gorissen et al., 2024). However, Sörqvist and Marsh (2024) challenge the notion that framing alone modulates the NFI, arguing that while response format may alter

how judgements are expressed, it does not eliminate the underlying bias. Even when objective CO_2 estimation measures are used or participants are explicitly encouraged to engage in summation rather than heuristic averaging (e.g., Holmgren et al., 2021), the illusion persists or fails to reverse. This suggests that the NFI is not merely an artifact of response format but reflects a deeply ingrained cognitive bias that cannot be easily mitigated by simple task manipulations.

Notably, empirical evidence suggests that the NFI is highly robust and does not diminish with expertise—even individuals with advanced knowledge of energy systems (e.g., engineers, sustainability specialists) exhibit the effect (Holmgren et al., 2018b). This underscores the cognitive complexity of the NFI, suggesting it is not merely a result of environmental ignorance but rather a deeply ingrained heuristic bias.

Theoretical Accounts of the NFI

The seminal work of Gorissen & Weijters (2016) was pivotal in identifying the cognitive bias underlying the NFI. They argued that the NFI arises when individuals compare the carbon emissions of a set that includes both environmentally friendly and conventional items, leading to a systematic underestimation of the total footprint. Specifically, participants incorrectly assume that adding a “green” item (e.g., an organic side dish) reduces the overall environmental impact of the entire set—when in reality, the total emissions should be higher due to the addition of another item.

A closely related cognitive illusion has been documented in the domain of calorie estimation. Chernev & Gal, (2010) and later Chernev (2011), demonstrated a similar effect in nutritional judgements—the so-called Negative Calorie Illusion. In their studies, participants estimated the caloric content of a high-calorie item (e.g., a cheeseburger) either alone or paired with a small, healthy side dish (e.g., three celery sticks). Paradoxically, the addition of the healthy food led participants to estimate a lower overall calorie count for the combined meal compared to the cheeseburger alone—mirroring the NFI in the environmental domain.

These parallel illusions suggest that human judgement is systematically biased when evaluating bundles of “good” and “bad” items, whether in terms of environmental impact (NFI) or calorie content (Negative Calorie Illusion). The presence of a virtuous element appears to distort perception, leading individuals to incorrectly assume that the “good” offsets or reduces the “bad.”

The NFI and the Negative Calorie Illusion (Chernev, 2011) both stem from a systematic misjudgement when evaluating combined sets of items with opposing attributes (virtues and vices). In Chernev’s work, participants underestimated the total calorie content of a high-calorie food (e.g., a hamburger) when paired with a low-calorie food (e.g., carrots), mistakenly assuming that the presence of a “healthy” option offset the unhealthier choice.

This illusory reduction in both calorie and environmental impact suggests a shared mechanism: instead of summing the environmental impact of all items, individuals tend to average them. As a result, adding an eco-friendly item (e.g., an organic salad) to a conventional set creates the illusion of a lower total footprint—even when the actual impact is greater. This averaging bias distorts judgements across multiple domains, leading to systematic underestimations of both caloric and environmental costs.

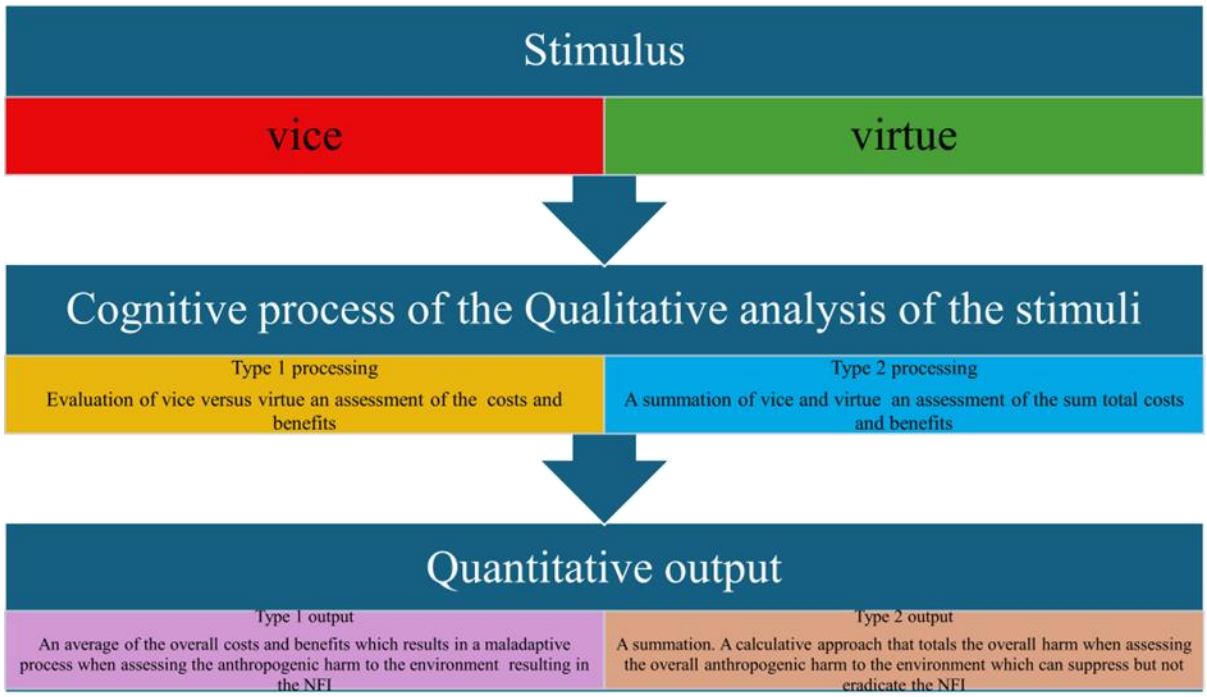
Averaging Bias

The NFI arises from a vice-virtue categorisation of items, where people classify products as either environmentally harmful (“vices”) or environmentally friendly (“virtues”) (Chernev & Gal, 2010). Rather than summing the carbon footprints of all items in a set, individuals average their impact leading to a distorted judgement. This occurs because the cognitive system relies on heuristic shortcuts, recycling complex numerical estimations to binary evaluations (e.g., “good” vs “bad” or “harmful” vs “eco-friendly”).

During this averaging process, an environmentally friendly item reduces the perceived environmental cost of an entire bundle, even though logically, adding any item—regardless of its eco-label—should increase the total environmental impact. For example, when

participants judge the carbon footprint of different meals, a basic meal alone (potatoes, steak, mushrooms) receives a higher carbon footprint estimate than the same meal with an organic yoghurt added—despite the additional food item increasing overall emissions. This systematic bias extends beyond food choices: individuals who purchase energy-efficient appliances may increase their overall energy consumption, e.g., automatically switching on energy efficient light bulbs when entering a room and leaving them on for longer when not in us believing they are reducing their environmental footprint with an eco-friendlier item. The averaging bias is an adaptive cognitive short-cut, enabling quick decision-making while minimising cognitive effort. However, in the context of environmental judgements, it introduces systematic errors that can lead to maladaptive behaviours—such as underestimating the true impact of consumption choices. This thesis considers that there is more than one way to average. There are two ways to assess averaging, one being quantitative and one being qualitative. A quantitative assessment involves a numerical evaluation of the costs and benefits where a positive or a virtue (good) is an addition and a negative or a vice (bad) is a deduction permitting a mathematical equation and a summative mindset. In contrast, a qualitative assessment is evaluative, whereby it permits an overview that each element may have more than one vice or virtue that may also be influenced by surrounding vices and virtues. This evaluation involves more than a singular item, but the qualities or characteristics associated with it are an aggregate valued judgement. Utilising an evaluative mindset. A diagram illustrating the averaging process can be seen in Figure 1.

Figure 1: ***An illustration of the Averaging process***



Boundary Conditions

The NFI remains robust, (Holmgren et al., 2018b), suggesting it is not merely a consequence of environmental ignorance but a deeply ingrained cognitive bias. However, research has identified several key factors that modulate its strength.

One critical factor is the spatial distribution of items. When high- and low-carbon footprint items are grouped together, the illusion is weaker, but when the same items are scattered irregularly, the NFI is accentuated (Sörqvist et al., 2022). This suggests that visual organization influences how people track environmental impact, with scattered arrangements making numerical comparisons more difficult.

The number of “green” items in a set also plays a role. Increasing the absolute quantity of eco-friendly items magnifies the NFI, even when the ratio of green to conventional items remains constant. For example, adding 150 green houses to 30 conventional ones produces a stronger illusion than adding 10 green houses to 30 conventional ones (Andersson et al., 2024, Experiment 1). Similarly, in larger sets (e.g., 40

conventional houses + 10 green houses vs. 400 conventional houses + 100 green houses), the NFI is more pronounced (Andersson et al., 2024, Experiment 3). However, when only a small number of green items is introduced (e.g., 4 conventional houses + 1 green house), the NFI disappears, producing a zero-footprint illusion, where participants perceive no overall environmental change.

Another boundary condition is overall numerosity. Larger stimulus sets produce a stronger NFI than smaller ones, even when the ratio of green to conventional items remains unchanged (Holmgren et al., 2018a, 2018b; Sörqvist et al., 2024). For example, people are more likely to misjudge impact when evaluating a large set of buildings (Andersson et al., 2024; Holmgren et al., 2018a) than when assessing a single meal (Gorissen & Weijters, 2016). This suggests that when dealing with larger quantities, people default to heuristic-based reasoning rather than engaging in explicit summation.

These findings challenge a strict averaging bias account. If the NFI were solely driven by mathematical averaging, its magnitude should remain the same when the proportion of green to conventional items is constant. However, the total number of items affects the NFI, suggesting that other cognitive biases—such as perceived numerosity or categorical distortions—may also contribute (Sörqvist et al., 2024). Additionally, factors like task framing, visual presentation, and whether participants judge items sequentially or simultaneously can further influence the strength of the NFI (Holmgren et al., 2021).

Overall, while the heuristic averaging bias remains a dominant explanation, the NFI appears to be influenced by multiple interacting cognitive mechanisms—including numerical estimation errors, perceptual organisation, and categorical reasoning. Understanding these boundary conditions is crucial for designing interventions that mitigate the illusion and improve environmental decision-making.

Category Type

The type of item also seems to matter to some extent. When an organic apple (a low carbon footprint item) is added to a burger (a high carbon footprint item), and people are asked to estimate the carbon footprint of the full meal comprising both items, the NFI arises (Gorissen & Weijters, 2016). The same effect is observed when representations of green buildings (low carbon footprint items) are combined with conventional buildings (high carbon footprint items) into a common set (Andersson et al., 2024; Holmgren et al., 2018a; Holmgren et al., 2018b; Sörqvist et al., 2022; Sörqvist & Holmgren, 2022; Threadgold et al., 2022). Similarly, the NFI appears when hybrid cars are combined with petrol cars (Holmgren et al., 2021; Threadgold et al., 2022). However, the effect does not consistently emerge when organic apples are combined with regular apples (Threadgold et al., 2022).

Interestingly, buildings tend to exhibit a stronger NFI effect than food. This may be because buildings are often judged in a more abstract way than other items. Unlike food, which people frequently purchase and consume, buildings involve considerations of energy efficiency, insulation, and long-term environmental costs—which may make individuals more prone to misjudging their impact through heuristic averaging rather than precise estimation (Andersson et al., 2024). This distinction suggests that the NFI may be more pronounced for highly abstract, less immediately consumable goods, where intuitive reasoning dominates over direct numerical assessment.

On this line of reasoning, the stimuli set (apple and burger) deployed by Gorissen et al. (2024) does not lend itself easily to quantitative reasoning because it involves just one apple and one burger, without explicit quantities, apart from the apple's organic label. This difficulty in comparing dissimilar items may encourage participants to adopt a qualitative evaluation strategy (e.g., "one is good, one is bad") rather than a quantitative one (e.g., summing up carbon footprints). This aligns with prior research suggesting that people tend to process categorical differences (e.g., organic vs conventional) differently from numerical

variations (e.g., one apple vs two apples; Chernev, 2011; Kim & Schuldt, 2018). Thus, a key consideration for future research is whether the comparability of stimuli—how easily they can be numerically or categorically assessed—modulates the cognitive processes responsible for computing environmental impact.

Priming

The robustness of the NFI suggests that it is a deeply ingrained cognitive bias, but researchers have explored whether it can be mitigated through priming—the process of activating a particular cognitive framework before making judgements. Priming manipulations can encourage participants to adopt either an evaluative (qualitative) mindset or a summative (quantitative) mindset with important consequences for their environmental judgements.

At a basic level, the boundary conditions of the NFI can be summarised as people incorrectly estimating that a combined set of conventional and environmentally friendly items has a lower environmental impact than the conventional items alone (e.g., A + B < A). However, parameters become more dynamic under priming conditions. Summation priming, for example, prompts participants to process information with an additive mindset requiring them to assess items individually before estimating the total impact (Holmgren et al., 2021). This method has been shown to reduce the magnitude of the NFI, as participants are forced to engage in explicit summation rather than implicit averaging. However, it does not eliminate the bias entirely—rather, it sometimes leads to a zero-footprint illusion, in which participants rate the combined set and the conventional set as having identical environmental impact (Holmgren et al., 2021). This finding highlights the difficulty of overriding the NFI. Even when participants are explicitly encouraged to adopt an additive mindset, their judgements do not always align with objective reality (A + B = AB). This suggests that priming alone is not sufficient to fully correct the bias, but it provides valuable insight into the cognitive mechanisms underpinning the environmental impact judgements.

Beyond priming, several contextual factors modulate the NFI's strength. Studies suggest that time pressure increases reliance on heuristic processing, leading to a stronger NFI when individuals make quick, intuitive judgements rather than engaging in deliberate reflection (Sörqvist & Holmgren, 2022). Furthermore, individuals with high environmental concern tend to exhibit a stronger NFI, potentially because they are more motivated to recognise eco-friendly attributes while overlooking the total footprint of a mixed set (Gorissen et al., 2024). These findings highlight that virtue-based heuristic processing is not only an automatic cognitive bias but also influenced by external pressures, individual motivations, and task constraints.

A methodological factor that can influence the strength of the NFI is whether a study uses a between-subjects or within-subjects design. Some studies suggest that within-subjects designs—where participants directly compare multiple conditions—may attenuate the NFI, as explicit comparisons can encourage deliberative summation over heuristic-based averaging (Gorissen & Weijters, 2016, Study 4). However, the effect is still observed in many within-subject designs, suggesting that direct comparisons do not necessarily override the bias (e.g., Holmgren et al., 2018b; Threadgold et al., 2022). In contrast, between-subjects designs, where participants assess only one condition at a time, often yield stronger NFI effects, likely because individuals lack a direct reference point for comparison. This methodological insight suggests that while the NFI is a robust cognitive bias, its magnitude can be modulated by experimental structure and task demands rather than being entirely fixed.

Priming and the NFI

Priming influences the cognitive framework participants use when making judgements. Specifically, an evaluative mindset leads participants to assess items based on affective or qualitative dimensions (e.g., “good” vs “bad”), whereas a summative mindset encourages explicit numerical calculations (Woltz & Was, 2006). Research suggests that

different types of priming can influence the magnitude of the NFI. For example, Gorissen et al. (2024) found that when participants used a green-coloured rating scale, they were more likely to adopt an evaluative mindset, leading to stronger NFI effects. By contrast, when they used a neutral-coloured scale (e.g., grey), the NFI was weaker, suggesting that the absence of a “green” cue reduced participants’ reliance on virtue-based averaging. A related finding concerns summation priming, which encourages participants to engage in explicit numerical reasoning rather than holistic evaluations, shifting their cognitive processing toward summation rather than averaging. Holmgren et al. (2021) examined this by inducing a summative mindset in participants, encouraging them to focus on the total environmental impact rather than an average.

In Experiment 1, participants were divided into two groups: one assessed the carbon footprint of blue cars, while the other was primed with electric cars to determine whether the presence of a "green" alternative would alter their environmental judgements. Experiment 2 aimed to refine the method by removing ambiguities found in the first experiment. Experiment 3 clarified that participants were working with numerical values, though still in a narrative format. Finally, in Experiment 4, participants engaged in both summation and averaging tasks, actively prompting them to shift their reasoning style away from heuristics. A control group was included, in which participants completed colour-based priming tasks rather than explicit numerical reasoning tasks.

The findings showed that inducing a summative mindset reduced the NFI but did not completely reverse it —again, it sometimes led to the zero-footprint illusion (where A + B is judged as equal to A rather than greater than A). Participants were more likely to engage in quantitative rather than qualitative reasoning when primed, yet their estimates still reflected some degree of bias. This suggests that heuristic processing remains robust, even when participants are encouraged to adopt a more systematic approach to evaluating environmental impact.

A key implication of these findings is that cognitive biases underpinning the NFI may be deeply ingrained and resistant to intervention. Even when explicitly prompted to engage in summation rather than averaging, participants continued to exhibit a bias to some extent. This raises important questions about how individuals process and comprehend recycling and environmental impact, particularly in real-world contexts where judgements are often made quickly and intuitively.

Findings from hemispheric studies provide further insight into the underlying mechanisms of these biases. Research suggests that summative processing is more dependent on right-hemisphere activity, which is associated with cognitive flexibility and divergent thinking (Faust & Kahana, 2002). In contrast, the left hemisphere, typically associated with linguistic processing, is less able to integrate incongruent semantic information. This could explain why virtue-based averaging dominates environmental judgements—participants may default to a left-hemisphere processing style that prioritises categorical labels (“green” vs “not green”) over numerical summation.

Overall, while priming can modulate the NFI, it does not fully eliminate bias. This suggests that deep-seated cognitive heuristics, such as averaging and categorical processing, play a key role in environmental decision-making.

Individual differences

Not all individuals are equally susceptible to the NFI. Research suggests that cognitive styles, beliefs, and reasoning abilities influence the extent to which people exhibit the bias. However, expertise does not necessarily protect against the NFI. Holmgren et al. (2018b) demonstrated that engineers, sustainability experts, and energy specialists—who have direct experience with environmental impact assessments—still exhibit the illusion. This underscores the robustness of heuristic-based reasoning, even among those with high domain-specific knowledge. One possible explanation is that experts, despite their technical expertise, may still rely on categorical labels (e.g., “green” vs. “conventional”) rather than

engaging in explicit numerical summation when making rapid judgements. This finding aligns with broader research suggesting that cognitive biases persist even among highly educated populations, reinforcing the need for interventions that actively promote summative reasoning over heuristic processing.

While expertise alone does not appear to provide immunity against the NFI, individual cognitive tendencies may play a role. One key individual difference measure is Actively Open-Minded Thinking (AOT) which reflects a person's tendency to engage in analytical, reflective reasoning rather than relying on heuristics and intuitive judgements (Stanovich & Toplak, 2023). Threadgold et al. (2022) found that individuals with higher AOT scores were less prone to the NFI, particularly when making environmental judgements about buildings and cars. However, the effect was not observed when participants made judgements about apples, suggesting that the influence of cognitive style may be domain-specific. The failure to observe an NFI also occurred in Gorrisen and Weijters' (2016) Experiment 4 when they included an organic lettuce. These results may be due to the perception of apples and lettuce being naturally low in carbon. It might be the case that naming an item that is known to be low in carbon as environmentally certified creates a cognitive dissonance that, in turn, triggers a System 2 thinking style.

Another important factor is Compensatory Green Beliefs (CGB)—the idea that engaging in one pro-environmental behaviour (e.g., cycling to work) can "compensate" for environmentally harmful behaviours (e.g., flying abroad for a holiday) (Kaklamanou et al., 2015). MacCutcheon et al. (2020) found that individuals who strongly endorse compensatory green beliefs were more likely to exhibit the NFI. This suggests that some participants may not perceive environmental impact in strict numerical terms, but rather as a moral balance—believing that green behaviours "offset" environmentally damaging ones. This moral aspect of decision-making also ties into the concept of moral spillover—the tendency for people to seek psychological balance by engaging in compensatory ethical behaviours (Rees et al.,

2014). For example, Sörqvist et al. (2022) found that individuals who engaged in carbon offsetting (e.g., tree planting) often did so in response to engaging in environmentally harmful actions. This further supports the idea that perceived moral valence can shape environmental judgements, potentially exacerbating the NFI.

Overall, these findings suggest that both cognitive style and environmental beliefs influence the NFI. Individuals who engage in analytical reasoning (high AOT) are less prone to the bias, whereas those who rely on moral or compensatory reasoning (high CGB) are more susceptible. This highlights the complexity of the NFI and suggests that interventions to reduce the bias may need to be tailored to different cognitive and belief profiles.

Actively open-minded thinking (AOT)

Actively open-minded thinking (AOT) refers to an individual's tendency to seek out, evaluate, and integrate new information, even when it challenges their pre-existing beliefs (Stanovich & West, 1997). People high in AOT are more likely to engage in reflective, analytical thinking, while those low in AOT tend to rely on intuitive, heuristic-based reasonings—which can make them more susceptible to cognitive biases such as the NFI. To measure AOT, Stanovich and West (1997) developed a scale incorporating elements of flexible thinking, openness to new ideas, and resistance to dogmatic or categorical thinking. Later refinements of the scale, such as the AOT-7 and AOT-17 (Svedholm-Häkkinen & Lindeman, 2018), improved its reliability while preserving its core dimensions. The AOT-17 includes four subfactors: Dogmatism (rigid adherence to beliefs), Fact Resistance (rejection of empirical evidence), Liberalism (openness to different viewpoints) and Belief Personification (emotional attachment to beliefs).

Threadgold et al. (2022) explored the relationship between AOT and the NFI in a series of experiments. They found that people who scored highly on AOT-7 were less susceptible to the NFI when evaluating buildings (Experiment 1). They also found that participants with higher AOT-17 scores showed reduced susceptibility to the NFI for both

buildings and cars (Experiment 2). However, AOT did not influence susceptibility to the NFI when participants judged apples (Experiments 1 and 2). Further analysis showed that the subfactors of AOT differentially predicted NFI susceptibility depending on the object being judged: for buildings, lower Dogmatism and lower Fact Resistance were associated with reduced NFI, whereas for cars, lower Dogmatism and lower Belief Personification predicted reduced NFI susceptibility. One possible explanation is that assessing environmental impact for buildings often requires engaging with quantitative data, such as energy efficiency ratings or carbon emissions, which may be easier to integrate for individuals who are more accepting of empirical evidence (i.e., lower Fact Resistance). In contrast, judgements about cars may be more susceptible to identity-driven reasoning, as cars can carry symbolic or ideological significance. Individuals with lower Belief Personification—who are less likely to emotionally attach themselves to their beliefs—may therefore be better able to override intuitive heuristics when evaluating environmental impact in this domain.

These findings suggest that AOT may serve as a protective factor against the NFI, but its effectiveness depends on the type of object being evaluated. One possible explanation is that evaluating environmental impact for buildings and cars requires more analytical reasoning (e.g., understanding energy efficiency or carbon emissions), whereas evaluating food items may rely more on intuitive, value-based judgements (e.g., organic = good). Interestingly, this aligns with research suggesting that AOT is more effective at reducing biases in situations that require deliberate, quantitative reasoning (Pennycook et al., 2015). In contrast, when moral or affective considerations dominate, even high AOT individuals may rely on heuristics rather than engaging in detailed calculations.

The findings on AOT and the NFI suggest that encouraging analytical thinking (e.g., asking people to justify their estimates numerically) may help reduce the NFI. Further, interventions that promote AOT could improve environmental decision-making by reducing heuristic-based errors. The role of AOT in different domains (e.g., cars vs food) also

highlights the need to tailor interventions based on cognitive demands. Overall AOT appears to moderate the NFI in some contexts but not others, emphasising the complexity of cognitive biases in environmental judgements.

Additional Cognitive Correlates of the NFI

Threadgold et al. (2022) also examined other cognitive measures that were not directly related to the NFI but were of broader relevance to individual differences in reasoning. They included the Cognitive Reflection Test (CRT) as a measure of reflective reasoning ability. The CRT is designed to assess the extent to which individuals engage in intuitive versus deliberate thinking, with higher scores reflecting greater cognitive reflection. Although CRT performance did not strongly predict susceptibility to the NFI, borderline significant correlations were found in their Experiment 2, suggesting that the ability to override intuitive responses may play a minor role in reducing the illusion.

Additionally, other measures were administered such as impulsivity, which has been implicated in various decision-making biases. However, non-significant association was found between impulsivity and susceptibility to the NFI. This suggests that while some cognitive biases may be related to impulsive decision-making, the NFI does not appear to be driven by impulsivity.

Beyond these general cognitive measures, Threadgold et al. (2022) also included explanatory measures such as conjunction fallacy tasks in their Experiment 1 to determine whether biases in probabilistic reasoning were related to susceptibility to the NFI. However, no clear relationship emerged between conjunction fallacy performance and the illusion, leading to the exclusion of this measure from their Experiment 2.

These findings collectively suggest that while some general cognitive abilities such as AOT, may offer limited protection against the NFI, other cognitive traits such as impulsivity and probabilistic reasoning biases do not appear to contribute significantly. Future research

could further explore the cognitive mechanisms underlying the illusion by incorporating additional measures of executive functioning and decision-making strategies.

Compensatory Green Beliefs (CGB)

Compensatory Green Beliefs (CGBs) refer to the perception that environmentally harmful behaviours (e.g., flying for leisure) can be justified if they are counterbalanced by environmentally friendly actions (e.g., cycling to work) (Kaklamanou et al., 2015). These beliefs allow individuals to rationalise environmentally negative choices by offsetting them with eco-friendly behaviours, even when the net environmental impact remains high. For example, an individual might believe that using energy-efficient appliances negates the impact of consuming imported food with a high carbon footprint.

To measure CGBs, Kaklamanou et al. (2015) developed a 16-item scale containing statements such as:

> “Not driving a car compensates for flying on holiday.”
>
> “You do not need to worry about what country your food comes from if you use energy-efficient appliances in the home.”

Participants rate their agreement with these statements on a Likert scale, assessing whether they truly believe compensation occurs between different environmental actions. The CGB scale is particularly relevant in understanding how people justify environmentally harmful behaviours through correction-based reasoning—where a negative behaviour is deemed permissible because a positive behaviour was enacted as a direct response to it.

Using this scale, MacCutcheon et al. (2020) found that individuals who scored highly on CGBs were more prone to the NFI, suggesting that belief in compensatory logic may drive misperceptions of environmental impact. Specifically, participants with strong CGBs were more likely to mentally “average” the environmental impact of mixed eco-friendly and non-eco-friendly choices, rather than sum them, leading to underestimation of total impact.

This aligns with previous research indicating that individuals often fail to recognise the absolute costs of environmentally harmful behaviours when they believe they can be offset (Sörqvist et al., 2016).

However, Threadgold et al. (2022) failed to replicate the relationship between CGBs and the NFI, raising questions about the robustness of the original findings. Their study, which used a similar methodology but a larger and more diverse sample, found no significant correlation between CGB scores and participants' tendency to underestimate the environmental impact of combined eco-friendly and non-eco-friendly behaviours. This suggests that while CGBs may be conceptually related to compensatory reasoning, their specific role in driving the NFI is less clear than initially proposed. One possible explanation for this discrepancy is that the effect may be contingent on contextual factors, such as how the environmental choices are framed or the specific domains in which compensatory reasoning is applied.

A related psychological mechanism is moral spillover, where individuals experiencing guilt from a negative behaviour (e.g., flying) seek to restore moral balance by engaging in a corrective action (Rees et al., 2014). Sörqvist et al. (2022) demonstrated this by showing that individuals who took environmentally costly trips were more likely to endorse tree planting as a compensatory action, suggesting that moral judgement plays a key role in environmental decision-making. Given this, it is plausible that some instances of the NFI may be driven by moral spillover, particularly in contexts where individuals feel personal responsibility for environmental harm. This could mean that NFI susceptibility varies based on how personally relevant an environmental decision is—a factor that future research could explore.

Together, these findings highlight the role of CGBs and moral spillover in shaping environmental reasoning. Understanding these mechanisms is crucial for designing interventions that discourage compensatory thinking and instead promote an additive model

of environmental impact, where individuals accurately assess the total costs of their choices rather than assuming harmful actions can be neutralised by separate positive ones.

Perceived Numerosity and the NFI

Perceived numerosity refers to the way individuals estimate the number of objects in a given set, which can be influenced by grouping cues based on object co-occurrences and spatial arrangement. For instance, a set of sixteen circles may be interpreted as sixteen individual circles, eight pairs of circles, or a structured arrangement of grouped elements, depending on how they are perceived (Zhao & Yu, 2016). The way in which these objects are grouped or dispersed affects numerical estimation: items that share a high degree of contextual coherence (e.g., grouped by shape, colour, or spatial proximity) tend to be perceived as more numerous, whereas irregularly arranged items often lead to greater accuracy in perceived numerosity (Qu et al., 2024). This suggests that perceptual organisation influences numerical judgements, sometimes leading to systematic biases.

Perceived numerosity is relevant to the NFI, as evidence by research on spatial distribution. In environmental judgement. Sörqvist et al. (2022) investigated how the arrangement of environmentally certified buildings influenced perceived impact. They found that when these buildings were irregularly distributed rather than neatly grouped together, the magnitude of the NFI was stronger. This implies that regular spatial patterns may reduce perceived numerosity, leading individuals to perceive fewer buildings in total and therefore underestimate their collective environmental impact.

This phenomenon aligns with the broader principle that structured arrangements (e.g., grid-like formations or grouped colour patterns) can create an illusion of lower numerosity (Zhao & Yu, 2016). At the same time, higher overall numerosity tends to be underestimated, meaning that as the total number of elements increases, the likelihood of perceptual distortion in environmental judgements also rises. It is also important to consider that spatial distribution is just one aspect of perceived numerosity—adding grouping cues,

such as colour similarities or categorical distinctions, could further influence perceived impact. In the case of the Sörqvist et al. (2022) study, the effect could have been amplified if additional cues (e.g., distinguishing between sustainable vs. non-sustainable buildings) had been present.

Overall, the interaction between perceived numerosity and the NFI highlights how cognitive biases in numerical estimation may contribute to errors in environmental reasoning. Future research could examine whether deliberately manipulating grouping cues—such as presenting eco-friendly and non-eco-friendly choices separately rather than mixed together—reduces susceptibility to the illusion. By understanding how perceptual organisation affects environmental judgements interventions could be designed to help individuals recognise the cumulative impact of their choices more accurately.

Quantity insensitivity and the NFI

Quantity insensitivity refers to a cognitive bias in which individuals fail to properly account for numerical magnitude in their judgements, often leading to distortions in decision-making. Baron and Greene (1996) describe this bias as manifesting in several ways, particularly in relation to willingness to pay (WTP). One such manifestation is the embedding effect, where an item's perceived value is diminished when it is presented as part of a larger set rather than as a standalone entity. Another form of quantity insensitivity involves disregarding numerical quantity altogether and instead relying on monetary cost as a proxy for value, leading to the substitution of one judgement criterion for another. A further form of this bias is seen when individuals fail to properly sum the values of multiple items, such that the perceived worth of two items together is judged to be less than the sum of their individual values.

This insensitivity to numerical magnitude extends beyond financial decisions and has direct relevance to how people assess environmental impact. Kim and Schuldt (2018) explored quantity insensitivity in the context of green versus conventional consumption,

drawing implicit parallels to the NFI. Although their study did not explicitly frame the effect as the NFI, their findings align closely with its underlying principles. In their study, participants were asked to judge the environmental impact of families who owned either one or two vehicles, which were either petrol or hybrid cars. The results showed that participants were highly sensitive to the number of petrol cars, judging a family with two petrol cars as having a substantially larger carbon footprint than one with a single petrol car. However, when evaluating hybrid cars, participants exhibited clear quantity insensitivity. A family with two hybrid cars was not judged as significantly worse than a family with just one, suggesting that the presence of a second hybrid vehicle was not viewed as meaningfully adding to the total environmental impact.

This tendency to ignore absolute numerical differences aligns with the averaging bias, a mechanism thought to underpin the NFI. If participants were engaging in additive reasoning, they would recognise that two hybrid cars, while less polluting than two petrol cars, still produce more total emissions than just one hybrid car. However, if participants were using an averaging strategy, they would effectively treat the impact of two hybrid cars as no worse than that of one, as though hybrid status itself neutralised emissions rather than merely reducing them. This is similar to classic demonstrations of the NFI, in which the addition of eco-friendly items to a set of conventional ones reduces the perceived environmental harm rather than increasing it, as would be expected under an additive framework (Sörqvist et al., 2016).

One possible explanation for quantity insensitivity in environmental judgements is heuristic reasoning. Rather than engaging in careful calculations of total environmental impact, individuals may rely on simple mental shortcuts, such as the assumption that hybrid cars are categorically “eco-friendly,” leading them to downplay their actual contribution to emissions. Another potential explanation is moral licensing, whereby the presence of an environmentally friendly choice psychologically offsets a less sustainable one, making

people feel justified in disregarding the total impact. Additionally, numeracy limitations may play a role, as individuals with lower numerical competence might struggle to engage in summative reasoning, instead relying on proportional rather than absolute comparisons when making environmental judgements (Peters et al., 2006).

The findings of Kim and Schuldt (2018) suggest that quantity insensitivity is a key driver of the NFI and may shape how people mentally represent environmental impact across a range of domains. Future research could explore ways to counteract this tendency, such as providing explicit prompts that encourage additive reasoning by presenting total emissions rather than qualitative descriptions. Understanding whether numeracy influences susceptibility to the NFI could also be valuable, as it may reveal whether those with stronger numerical skills are better able to recognise cumulative environmental costs. Beyond this, investigating whether quantity insensitivity extends beyond vehicle emissions to other areas, such as food consumption, energy use, and waste management, could provide further insights into how people conceptualise environmental impact. Ultimately, addressing this bias is crucial for designing interventions that help individuals make more accurate environmental assessments, moving away from misleading compensatory reasoning and toward a clearer recognition of total environmental costs.

Attribute Substitution and the NFI

Attribute substitution occurs when individuals replace a complex environmental calculation with a simpler heuristic—such as categorising products as “green” or “harmful.” Rather than summing the true impact, they substitute the judgement with an intuitive average, leading to the NFI. This cognitive shortcut has been proposed as a potential mechanism underpinning the averaging bias in environmental judgements. According to Sörqvist and Marsh (2024), neither averaging bias nor attribute substitution alone fully explains why the NFI occurs. Instead, they suggest that in some cases, individuals may lack a clear conceptual understanding of carbon footprint or carbon emissions and, as a result,

attempt to answer as best they can based on more familiar environmental heuristics. However, they also acknowledge that attribute substitution cannot account for instances where the NFI arises from manipulations involving size, ratio (Andersson et al., 2022), or spatial distribution (Sörqvist et al., 2002), indicating that other factors must be at play.

Further evidence for attribute substitution comes from studies on quantity insensitivity, such as the research conducted by Kusch and Fiebelkorn (2019). In their investigation, participants judged the environmental impact of meat, vegetarian, and insect-based burgers, with the latter being a relatively novel and unfamiliar food option at the time. Since insect burgers lacked a well-established mental representation, participants likely relied on attribute substitution, using sustainability heuristics from more familiar food categories to make their judgements. This highlights how individuals, when faced with uncertainty, default to simplified reasoning processes, which may also be influencing NFI-related judgements.

A key reason why attribute substitution is relevant to the NFI is its potential connection to the averaging bias (Holmgren et al., 2018). When individuals assess the carbon footprint of a mixed set of high- and low-carbon footprint items, they may substitute the task of estimating total impact with a more intuitive evaluation of how "environmentally bad" the set is overall. As a result, rather than summing the impacts of all items, they assign a judgement closer to the average of the items in the set. This leads to the characteristic NFI pattern, where adding eco-friendly options to an environmentally harmful set paradoxically reduces the perceived total impact. If participants interpret the task in this way, their response could even be considered normatively accurate—not in terms of carbon footprint estimation, but in terms of perceived environmental friendliness (Toplak, 2021). This alternative interpretation could explain why people misjudge the total impact of hybrid versus petrol cars (Kim & Schuldt, 2018) or green versus conventional buildings (Sörqvist et al., 2022), as their responses align with heuristic reasoning rather than summative processing.

However, despite its explanatory power, attribute substitution alone does not fully account for all aspects of the NFI. One key limitation is its failure to explain why stimulus distribution across the visual field affects the illusion's magnitude (Sörqvist et al., 2022). When low-carbon footprint items are presented in an irregular spatial arrangement, they tend to be judged as more environmentally friendly, increasing the NFI effect. However, if attribute substitution were the sole explanation, then the same irregular distribution of high-carbon footprint items should increase their perceived environmental harm—yet this does not appear to be the case. Similarly, attribute substitution cannot fully explain why larger sets consistently receive smaller carbon footprint estimates than smaller sets, even when the proportion of high- to low-carbon footprint items remains the same (Andersson et al., 2024). If individuals were purely substituting a complex numerical task with a simpler heuristic, it remains unclear why an increase in both eco-friendly and non-eco-friendly items does not cancel out the perceived reduction in environmental harm.

One possible explanation is that a positivity bias is at play, where individuals place greater weight on environmentally friendly items than on their environmentally harmful counterparts when forming judgements. If an irregular spatial distribution increases the perceived numerosity of the set or if the number of eco-friendly objects increases, this could interact with a positivity bias to amplify the NFI. This suggests that the illusion may not only result from averaging or substitution mechanisms but also from an inherent tendency to prioritise positive environmental cues over negative ones. Future research could explore this possibility, examining whether interventions that explicitly highlight the absolute impact of harmful items could mitigate the bias.

Together, these findings suggest that attribute substitution plays a role in the NFI, particularly when individuals lack clear environmental knowledge or struggle with numerical reasoning. However, its inability to account for distributional and set-size effects indicates that additional cognitive mechanisms—such as positivity biases and numerosity distortions—

may also contribute to the illusion. Understanding these underlying mechanisms is critical for improving environmental communication strategies, ensuring that individuals base their decisions on accurate, additive reasoning rather than misleading heuristics.

Investigating the NFI

Although the NFI is not necessarily amplified by the use of symbolic phrasing (Holmgren et al., 2019), it may still be influenced by the perception of environmental positivity. If an item is semantically or heuristically associated with environmental benefits, individuals may unconsciously overestimate its positive impact, reinforcing the NFI. Understanding these cognitive distortions is crucial, as they shape environmental decision-making and influence behaviours intended to reduce ecological harm.

There are numerous instances where well-intended behaviours result in unintended environmental consequences. For example, an individual may believe that not driving a car compensates for flying on holiday (Kaklamanou et al., 2015), or that improperly disposing of an item is acceptable simply because it was made from recycled material. Such compensatory green beliefs (CGBs) may stem from the same cognitive mechanisms underlying the NFI, leading individuals to misjudge the true environmental impact of their actions. While some materials, such as aluminium cans, have infinite recyclability (Recycling Facts, 2022), improper waste disposal can still undermine their sustainability potential.

Addressing these cognitive biases is essential for improving environmental policies and interventions. If individuals systematically miscalculate the impact of household waste disposal (WFH) in a manner similar to the NFI, it suggests that the same erroneous cognitive processes drive misperceptions in waste management and carbon footprint estimation. By investigating these biases in Experiment 1, this thesis aims to determine whether recyclable items are subject to the same systematic errors in environmental evaluations that give rise to the NFI. If so, this research could provide valuable insights into how to restructure environmental messaging and education to promote additive reasoning rather than

misleading compensatory logic. Ultimately, these findings could help reduce environmentally harmful behaviours and contribute to a more sustainable future.

Chapter 3

Experiment 1: The Role of Item Type in Negative Footprint Judgements

Addressing faulty recycling behaviour is a global and national priority, as effective recycling plays a crucial role in mitigating environmental damage. In the UK, the government has set a target to recycle 50% of household waste (Howard et al., 2019), yet the most recent statistics show a recycling rate of only 44.7% (Plan for England, 2021). While landfill waste per capita decreased by 7% in 2022, this trend is overshadowed by an 8.6% decline in overall recycling rates (DEFRA, 2024). These figures suggest that despite reductions in waste, individuals may not be engaging in productive recycling practices, potentially due to misperceptions about their environmental impact.

The decline in waste production could reflect greater environment awareness, as individuals may be making conscious choices to reuse items or purchase products with reduced packaging. However, it is also possible that economic constraints play a significant role. The UK's ongoing cost of living crisis may be leading individuals to purchase fewer goods, inadvertently reducing waste generation (Beth, 2024). While this reduction is positive, it remains unclear whether it reflects a genuine shift toward sustainable behaviour or a temporary response to financial pressures.

Despite growing awareness of waste reduction, significant challenges remain. Many individuals continue to dispose of waste incorrectly, leading to cross-contamination in recycling streams (Avery, 2022). Furthermore, the extraction of raw materials continues at unsustainable levels (Bremer, 2018), undermining the benefits of recycling. Even when individuals recognise the importance of proper recycling, this awareness does not always translate into action—80% of people fail to recycle electronic waste correctly (Arain et al., 2020). This gap between intention and behaviour highlights the cognitive biases that may underlie environmental decision-making (Ran & Zhang, 2023).

Research suggests that failures in recycling behaviour may stem from cognitive biases that distort environmental estimations, leading individuals to rely on heuristics rather than objective calculations (Holmgren et al., 2018a, 2018b; Kusch & Fiebelkorn, 2019; Gorissen & Weijters, 2016; MacCutcheon et al., 2020; Holmgren et al., 2021; Ateş, 2020).

One such bias is myside bias, which refers to the tendency to evaluate evidence in a way that supports one's pre-existing beliefs (Stanovich et al., 2007). A related phenomenon is confirmation bias, which involves selectively recalling or interpreting evidence that aligns with one's existing views (Nickerson, 1998). In the context of recycling, individuals who strongly associate "recyclable" with "environmentally friendly" may overestimate the benefits of recycling, leading to systematic errors in judgement. Similarly, those who view certain materials as intrinsically harmful may fail to recognise nuances in sustainability, leading to overgeneralised environmental estimations. Another key bias is the tendency to average environmental costs and benefits rather than assessing the total impact of an item, which can lead to systematic distortions in recycling behaviour (Gorissen & Weijters, 2016). This process, which involves weighting a product's "vices" (negative environmental aspects) against its "virtues" (eco-friendly attributes), can lead to distorted judgements. Because individuals may rely on outdated or incomplete information when forming these estimates, their recycling behaviours may not align with actual environmental impact. Understanding these biases is crucial for designing interventions that promote more effective recycling.

Improving recycling behaviours could have a significant positive impact on carbon emissions. Recycling allows materials to be repurposed rather than sent to landfills, where decomposition releases harmful greenhouses gases into the atmosphere (Michel Devadoss et al., 2021). Additionally, recycling reduces the demand for raw material extraction which often involves the use of heavy machinery that further contributes to carbon emissions (DEFRA, 2022). By increasing both the quantity and the efficiency of recycling, these environmental harms can be mitigated.

Recycling certain materials, such as aluminium and steel, yields significant environmental benefits. The average household uses approximately 980 food and drink cans each year. Recycling just one tonne of aluminium prevents nine tonnes of CO_2 emissions from entering the atmosphere and saves 95% of the energy required to produce new aluminium from raw materials. To put this into perspective, recycling a single aluminium can generates enough energy to power a television for three hours (Metal recycling facts, 2024). Despite these advantages, recycling rates remain lower than expected, possibly due to cognitive biases that shape environmental decision-making.

Plastic recycling has received significant media attention in recent years, with a strong preference for recyclable plastics over single-use plastics (Nuojua et al., 2022). A systematic review identified several factors that influence plastic waste avoidance, including willingness to pay (WTP) social norms, convenience, environmental concern, and knowledge gaps (Jacobsen et al., 2022). These factors are likely influenced by cognitive biases such as the averaging bias, where individuals weigh environmental benefits against perceived costs. If, for example, “green” values override concerns about convenience, or social norms shape knowledge gaps, targeted interventions could help reduce these biases and improve recycling behaviours. Plastic bottle waste remains a major environmental challenge in the UK. On average each person uses 117 plastic bottles per year, amounting to 7.7 billion bottles annually. One tonne of recyclable plastic can be repurposed into 20,000 new bottles, and recycling a single plastic bottle generates enough energy to power a lightbulb for three hours. Despite these benefits, plastic takes up to 500 years to fully decompose, yet only 45% of plastic waste in the UK is currently recycled (Lancaster.gov, 2023). Understanding why individuals fail to recycle effectively is crucial for developing strategies that promote better waste management.

The NFI describes a cognitive bias in which individuals mistakenly believe that adding environmentally friendly items to a scenario reduces overall environmental impact—

even when total consumption increases (Ateş, 2020; Gorissen & Weijters, 2016; Kusch & Fiebelkorn, 2019). However, individual susceptibility to the NFI may vary depending on cognitive style. Threadgold et al. (2022) found that the NFI for a building scenario was significantly correlated with the fact resistance sub-scale of the AOT-17, while the NFI for a car scenario was associated with both fact resistance and dogmatism. These findings suggest that individuals who are less willing to revise their beliefs in light of new evidence may be more prone to heuristic-based misjudgements in environmental decision-making. Therefore, the present study examines whether the AOT-17 similarly predicts susceptibility to the NFI in the context of recycling.

The NFI has been demonstrated across multiple domains, including food (Kim & Schuldt, 2018), housing (Holmgren et al., 2018b), and transportation (Holmgren et al., 2021). However, it remains unclear whether the NFI operates as a domain-general bias or whether it depends on contextual factors, such as the type of materials being evaluated. If the illusion arises from general cognitive heuristics (e.g., averaging environmental attributes rather than summing them), then it should appear consistently across different product types. Conversely, if category-specific knowledge plays a role, then the effect may vary depending on whether the items being evaluated are perceived as similar or different. The present study explores this issue by investigating whether the NFI extends to recycling decisions—an area where vice-virtue trade-offs are particularly salient.

Ineffective recycling behaviour may also stem from cognitive biases similar to those driving the NFI, including averaging bias, where individuals perceive that an environmentally positive action (e.g., recycling) offsets environmentally harmful behaviour (e.g., increased consumption). However, such misjudgements may also reflect rebound effects, in which people justify increased resource use based on the belief that their prior pro-environmental actions mitigate the damage (Catlin & Wang, 2013). In this case, participants may not have

fallen for the NFI per se but instead engaged in compensatory behaviour—using more paper while maintaining a subjective sense of environmental responsibility.

From a dual-process perspective, these misjudgements may arise from fast, intuitive (Type 1) reasoning, where individuals apply simple heuristics—such as assuming that recycling inherently reduces environmental harm—rather than engaging in effortful calculations. In contrast, engaging in slower, analytic (Type 2) reasoning may sometimes exacerbate moral licensing effects, as individuals feel explicitly justified in engaging in environmentally harmful behaviour after having reasoned about their previous pro-environmental actions (Gholamzadehmir et al., 2019; Mazar & Zhong, 2010). This suggests that while heuristic-based reasoning may facilitate the NFI, more deliberate reflection may strengthen rebound effects and compensatory justifications. Understanding these mechanisms is essential for designing interventions that counteract heuristic-driven misjudgements. One possible approach is to use numerical framing interventions (e.g., Holmgren et al., 2021), where participants are explicitly encouraged to sum rather than average environmental impact when evaluating waste items. Comparative feedback—such as showing real-world CO_2 emissions of different waste compositions—may also help override heuristic biases. Additionally, restructuring recycling choices to emphasise the trade-off between waste reduction and disposal could shift decision-making away from a purely moral evaluation and towards an analytical cost-benefit analysis.

To fully understand rebound effects, Hischier et al. (2020) propose analysing behaviour at three levels: micro (individual product efficiency), meso (improvements in energy efficiency), and macro (economic and social factors influencing supply and demand). However, research on rebound effects remains inconsistent, with financial factors often playing a dominant role. A systematic review by Andrew et al. (2024) found that over 70% of rebound effects stem from financial motivations (e.g., reinvesting savings from energy-efficient choices into further consumption), while only 6% are attributed to psychological

factors. This suggests that while cognitive biases such as the NFI contribute to environmental misjudgements, economic considerations also play a substantial role. Future research should further clarify the psychological mechanisms underlying compensatory environmental behaviours, particularly how Type 1 and Type 2 reasoning interact with moral licensing and cognitive distortions like the NFI.

Another potential explanation is Compensatory Green Beliefs (CGB)—the idea that individuals rationalise environmentally harmful actions by engaging in separate pro-environmental behaviours (MacCutcheon et al., 2020; Kaklamanou et al., 2015). For example, someone may justify excessive paper use by reasoning that they walk to work instead of driving. This form of cognitive miscalculation resembles the NFI, where individuals perceive their total environmental impact as lower simply because they have added a "green" element. Understanding the extent to which CGB contributes to recycling-related misjudgements is crucial for designing effective behavioural interventions. There are other suggestions as to what the mental construals are for the negative footprint illusion; other possible explanations for the negative footprint illusion could be category size bias (Andersson et al., 2024), perceived numerosity (Sörqvist & Holmgren, 2022), and quantity sensitivity (Kim & Schuldt, 2018; Kusch & Fiebelkorn, 2019) and attribute substitution (Kusch & Fiebelkorn, 2019) moral, halo and spillover effects (Kim & Schuldt, 2018; Sörqvist et al., 2022) to name a few (see Chapter 2).

This research seeks to determine whether the NFI extends to recycling, and to identify the cognitive mechanisms influencing environmental impact estimations. Previous research has demonstrated the NFI across various domains, including food (Gorissen & Weijters, 2016), housing (Holmgren et al., 2018a, 2018b; MacCutcheon et al., 2020; Sörqvist et al., 2022; Threadgold et al., 2022), and transportation (Kim & Schuldt, 2018; Threadgold et al., 2022). However, its relevance to recycling decisions remains underexplored. Given that recycling is often perceived as an inherently positive environmental action, it is crucial to

investigate whether individuals misjudge their overall environmental impact when they combine recyclable and non-recyclable materials.

By uncovering the cognitive biases that shape recycling decisions, this research aims to provide a theoretical framework for understanding why individuals may overestimate the effectiveness of their recycling efforts. Additionally, the findings may inform theoretical interventions aimed at improving recycling accuracy and efficiency. In doing so, this study contributes to a broader understanding of how cognitive processes influence pro-environmental behaviour and how these processes may hinder or support sustainable decision-making.

Replication and Adaptation of NFI

Experiment 1 investigates whether the NFI manifests in estimations of environmental impact for recyclable products. Specifically, this study examines whether biases previously documented in judgements about food, houses, and cars also apply to smaller, everyday items such as plastic bottles. If the same cognitive biases underpinning NFI in other domains also drive misjudgements in recycling, it would suggest that the illusion operates at a fundamental level of environmental reasoning, shaping how individuals assess sustainability across different contexts.

It is hypothesised that the NFI observed in judgements of housing and transportation will also be present in the evaluation of recyclable plastics, as individuals may perceive the addition of recyclable materials as reducing overall environmental impact—despite the total volume of waste increasing. By testing this hypothesis, this study will contribute to understanding the cognitive distortions that may contribute to ineffective recycling behaviours.

Method

Design

The design was a 2 (Item Type: houses, bottles) × 2 (Estimate Type: addition, no addition) × 2 (Order: houses then bottles, bottles then houses) mixed design. Item Type and Estimate Type were within participants variables, while Order Type was a between-participant variable. The dependent variable (DV) was participants' estimates of carbon emissions on a 1-100-point scale. Counterbalancing was used to present participants with either houses or bottles first.

Participants

Participants were recruited via Prolific (www.prolific.com). A power analysis using G*Power (Faul et al., 2007) was conducted for a paired-sample t-test comparing estimates in the "no addition" and "addition" conditions. To detect a medium effect size (d = 0.50) with 80% power (α = .05), a minimum of 34 participants was required. To allow for potential exclusions, 64 participants were recruited (M_age = 34.5 years, SD = 7.7, 55% female, all native English speakers). The final sample size could detect a medium effect size (dz = 0.5) with 97.5% power, or a modest effect size of dz = 0.356 with 80% power. All participants self-reported English as their first language. The study took approximately 15 minutes, and participants were compensated £2.25.

Materials and Procedure

The experiment was conducted online via Prolific, with participants redirected to Qualtrics (Provo, UT). Participants first read an information sheet outlining the study and expectations (**Appendix A)** before providing informed consent. They then completed a demographics form (age, gender) before proceeding to the main task, which consisted of environmental impact estimations for houses and plastic bottles.

In the houses condition (**Figures 2 and 3**), participants were instructed to estimate the carbon footprint of houses using a 1-100 scale (higher scores indicate higher carbon emissions). They were given the following definition:

> *Carbon footprint refers to emissions arising from electricity consumption, heating, and other household activities. A higher score indicates greater environmental impact, while a lower score indicates reduced impact.*

To standardise responses, participants were provided with a reference point:

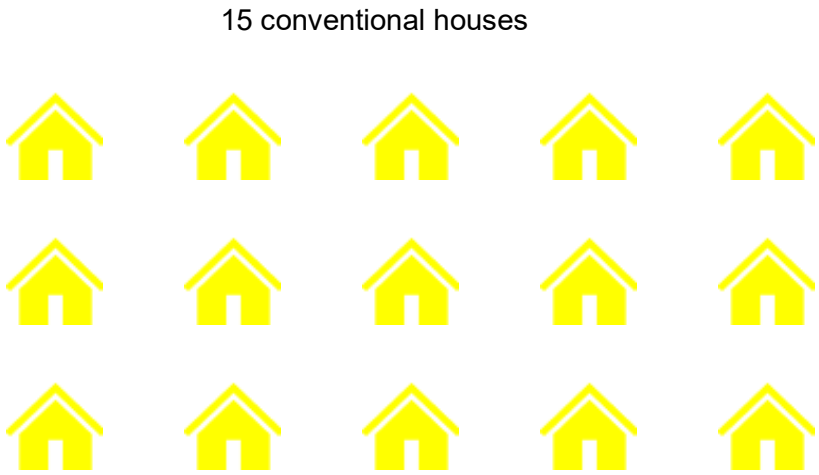
> *A building of 18 apartments would score 50 (midway) on the scale.*

They were then presented with the first condition (15 conventional houses) and estimated the carbon footprint

Figure 2

Non-Addition Condition (Houses):

Illustration of the stimulus used in the non-addition condition for houses. Participants viewed an image of 15 conventional houses, representing standard housing with no environmental certification, and estimated their environmental impact on a 1-100 scale.

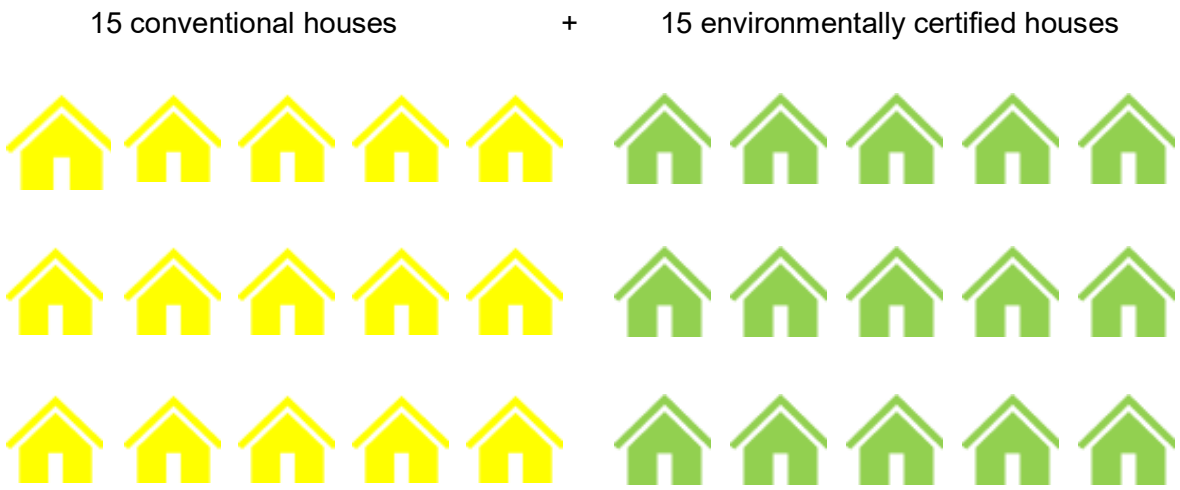


Next, they saw the “addition” condition, where environmentally certified houses were introduced: 15 conventional houses + 15 environmentally certified houses. Participants were informed that environmentally certified houses are built using sustainable materials and energy-efficient technology, reducing their carbon footprint.

Figure 3

Addition Condition (Houses):

Illustration of the stimulus used in the addition condition for houses. Participants viewed an image of 15 conventional houses plus 15 environmentally certified houses, where the latter were designed with sustainable materials and energy-efficient technology. Participants estimated the overall environmental impact.



Participants then made a second carbon footprint estimate using the same 1-100 scale.

For the bottle condition (**Figures 3 and 4**), a similar procedure was followed for plastic bottles. Participants were instructed that carbon footprint estimations referred to the environmental impact of bottle production and disposal. The reference point was:

> *A shelf containing 18 single-use, non-recyclable plastic yoghurt tubs would score 50 (midway) on the scale.*

They were then presented with the first condition: 15 single-use, non-recyclable plastic bottles, and participants estimated the carbon footprint.

Figure 4

Non-Addition Condition (Plastic Bottles):

Illustration of the stimulus used in the non-addition condition for plastic bottles. Participants viewed an image of 15 yellow bottles, representing single-use, non-recyclable plastic bottles, and were asked to estimate their environmental impact on a 1-100 scale.

15 single use non-recyclable plastic bottles

In the “addition” condition, they were informed that recyclable bottles were added: 15 single-use, non-recyclable plastic bottles + 15 environmentally certified plastic bottles (*Environmentally certified bottles are recyclable and made from recycled materials, reducing their carbon impact*).

Figure 5

Addition Condition (Plastic Bottles):

Illustration of the stimulus used in the addition condition for plastic bottles. Participants viewed an image of 15 yellow bottles (single-use, non-recyclable plastic bottles) plus 15 green bottles (recyclable plastic bottles) and estimated the overall environmental impact.

15 single use non-recyclable plastic bottles + 15 environmentally certified plastic bottles

Participants then provided a second estimate on the 1-100 scale.

AOT-17

After the environmental impact estimations for bottles and houses, participants completed the Actively Open-Minded Thinking 17 (AOT-17, Svedholm-Hakkinen & Lindeman., 2018, **Appendix B**) which measures thinking styles across four subscales: Dogmatism (6 items), Fact Resistance (5 items), Liberalism (3 items), and Belief Personification (3 items). Participants rated their agreement with statements (e.g., "*One should disregard evidence that conflicts with your established beliefs*") on a 6-point Likert scale (*1 = strongly agree, 5 = strongly disagree*). Upon completing the survey, participants were debriefed and exited the study (see **Appendix C)**.

Results

Experiment 1

A 2 (Item type: house, bottles) × 2 (Estimate type: no addition, addition) × 2 (Order: houses à bottles, bottles à houses) mixed ANOVA was conducted to test whether environmental impact ratings for plastic bottles would exhibit the NFI similarly to houses. Item Type and Estimate type were within-participant variables while Order Type was a between participants variable. The dependent variable was the estimated environmental impact score.

Main Effects (between subjects)

The main effect of Order was non-significant $F(1, 60) = 0.284$, $MSE = 812.245$, $p = .596$, $\eta^2p = .005$, indicating that whether participants completed the houses or bottles condition first had no effect on environmental impact estimations. Similarly, none of the interactions involving Order reached significance: Order × Item type $F(1, 60) = 0.094$, $MSE = 282.351$, $p = .760$, $\eta^2p = .002$; Order × Estimate type $F(1, 60) = 0.259$, $MSE = 475.489$, $p = .613$, $\eta^2p = .004$; and interaction Order × Item × Estimate type $F(1, 60) = 3.433$, $MSE = 45.061$, $p = .069$, $\eta^2p = .054$. Since Order did not significantly influence estimations, it was excluded from further analysis.

Main Effects (within subjects)

The main effect of Item Type (houses vs bottles) was not significant, $F(1, 61) = 0.021$, $MSE = 278.157$, $p = .879$, $\eta^2p = .000$, indicating that environmental impact estimates did not differ significantly between houses ($M = 60.21$, $SD = 19.69$) and bottles ($M = 59.89$, $SD = 20.02$). In contrast, the main effect of Estimate Type (no addition vs addition) was significant, $F(1, 61) = 10.199$, $MSE = 469.709$, $p = .002$, $\eta^2p = .143$. The estimated environmental impact was significantly lower in the addition condition ($M = 55.64$, $SD = 21.73$) compared to the no addition condition ($M = 64.45$, $SD = 17.99$), despite the total quantity of items increasing. There was no significant interaction between Item Type × Estimate Type, $F(1, 61) = .099$, $MSE = 46.858$, $p = .754$, $\eta^2p = .002$, suggesting that the reduction in estimated environmental impact following the addition of environmentally friendly items was similar for both houses and plastic bottles.

To further investigate the effect of Estimate Type, a paired-sample t-test was conducted, collapsing data across Item Type. Results confirmed a significant decrease in estimated environmental impact when recyclable items were introduced, $t(61) = 3.194$, $p < .001$, $BF_{01} = 0.096$. The effect size was Cohen's $dz = 0.406$, indicating a medium effect. These findings support the presence of the NFI, demonstrating that the addition of environmentally certified items led to a significant underestimation of the total environmental impact.

Actively Openminded Thinking AOT-17

To examine the relationship between Actively Open-Minded Thinking (AOT-17) and susceptibility to the NFI, the magnitude of the NFI was calculated by subtracting the addition condition estimate (second estimate) from the no addition condition estimate (first estimate). Lower scores indicate a stronger NFI effect.

A bivariate correlation analysis was conducted to assess the association between AOT-17 scores and NFI susceptibility for both houses and plastic bottles. The results showed a

strong positive correlation between the NFI for houses and bottles, $r(62) = .819$, $p < .001$, indicating that individuals who showed the NFI for houses were also likely to do so for plastic bottles. The correlations between AOT-17 and NFI magnitude for houses and bottles are presented in Table 1 and Table 2, respectively. AOT-17 fact resistance was the only sub-factor significantly correlated with the NFI for houses ($r = .263$, $p = .039$), whereas no significant correlations were found for bottles. These results partially replicate the findings of Threadgold et al. (2022), who found that the NFI for buildings was significantly correlated with fact resistance ($r = .200$, $p < .001$). In the present study, fact resistance significantly correlated NFI magnitude for houses but not for bottles. Unlike Threadgold et al. (2022), dogmatism did not correlate NFI magnitude in this experiment, suggesting that resistance to belief revision, rather than ideological rigidity, may be the more critical factor in recycling-related judgements.

Table 1

Correlation between AOT-17 and NFI Magnitude (Houses)

AOT-17 and sub factors	*r*	*p*
Dogmatism	.051	.693
Fact Resistance	.263	.039*
Liberalism	.005	.971
Belief personification	.091	.481
AOT-17	.160	.214

*Significant at $p = .05$

Table 2

Correlation Between AOT-17 and NFI Magnitude (Bottles)

AOT-17 and sub factors	*r*	*p*
Dogmatism	-.054	.676
Fact Resistance	.213	.097
Liberalism	-.132	.306
Belief personification	-.019	.883
AOT-17	.032	.804

*Significant at $p = .05$

Regression

To further assess whether AOT-17 scores predicted susceptibility to the NFI, a linear regression analysis was conducted for both houses and bottles.

Houses

The regression model explained 9% of the variance in NFI susceptibility, $R^2 = .093$ (9%), Adjusted $R^2 = .029$ (2.9%), but was not statistically significant, $F(4, 57) = 1.461$, $p = .226$. Among the AOT-17 sub-factors, fact resistance significantly predicted susceptibility to the NFI for houses ($\beta = .352$, $t = 2.276$, $p = .027$). Other sub-factors (dogmatism, liberalism, and belief personification) were not significant predictors ($\beta = -.102$, $t = -.661$, $p = .511$, dogmatism; $\beta = -.124$, $t = -.841$, $p = .404$, liberalism, and $\beta = .068$, $t = .499$, $p = .619$, or belief personification).

Bottles

The model accounted for 12.5% of the variance in NFI susceptibility (R^2 = .125, Adjusted R^2 = .064), but was not statistically significant, $F(4,57) = 2.035$, p = .102. Fact resistance significantly predicted NFI susceptibility for bottles (β = .401, t = 2.638, p = .011), whereas the other sub-factors did not (β = -.170, t = -1.119, p =.268, dogmatism; β = -.231, t = -1.595, p = .116, liberalism; β = -.002, t = -.015, p = .988, belief personification).

Thus, regression analyses showed that fact resistance significantly predicted NFI susceptibility for both houses and bottles. However, the overall models were not statistically significant, indicating that the AOT-17 does not strongly account for variability in NFI susceptibility. These findings suggest that fact resistance may contribute to susceptibility to the NFI, but other unmeasured factors likely play a role in how individuals estimate environmental impact.

Discussion

The NFI was clearly observed in this study, extending previous findings to plastic bottles. Participants systematically underestimated environmental impact when recyclable plastic bottles were added, mirroring the effect previously documents for conventional vs environmentally certified houses. These results suggest that perceived environmental benefits override quantitative considerations of total environmental impact, reinforcing the idea that individuals rely on heuristic-based reasoning when making environmental judgements. This aligns with the averaging bias (Gorissen & Weijters, 2016), where people integrate “green” attributes into their overall estimation rather than considering absolute environmental costs. Some prior studies have even found that removing explicit labels such as “environmentally certified” can result in an NFI effect (Holmgren et al., 2019; Kusch et al., 2019). This suggests that the NFI is not driven solely by symbolic associations and that cognitive biases play a substantial role in the effect. It should also be acknowledged that whereas participants were informed of the construction of environmentally certified houses in

terms of sustainable materials and energy-efficient technology no such description was afforded to conventional houses, which may have created unnecessary ambiguity.

One possible cognitive mechanism underlying the NFI is myside bias—the tendency to favour information that aligns with pre-existing beliefs (Stanovich et al., 2007). Participants who associate “recyclable” with “environmentally friendly” may automatically assume a reduced overall footprint, regardless of the actual environmental cost of the additional items. This confirmation bias could lead to intuitive (Type 1) processing, where pre-existing beliefs override systematic environmental calculations (Evans & Stanovich, 2013). This explanation suggests that interventions should focus on encouraging analytic (Type 2) reasoning by prompting individuals to explicitly calculate environmental costs rather than relying on heuristic-driven judgements.

The variability in participant responses suggests that individual differences in cognitive style play a crucial role in NFI susceptibility. Prior research has shown that while individuals generally agree that pro-environmental behaviour is desirable (Reid, 2021), their environmental estimations may vary based on how they integrate vices and virtues into their judgements. Our finding that fact resistance predicted NFI scores for houses and bottles aligns with previous research suggesting that cognitive rigidity influences environmental misjudgements (Threadgold et al., 2022). Future research should examine whether domain familiarity or perceived environmental impact moderates the relationship between cognitive rigidity and heuristic susceptibility.

Unlike previous studies that found item type effects on NFI (e.g., Gorissen & Weijters, 2016; Threadgold et al., 2022), the current study found no significant difference between houses and bottles, suggesting that the NFI may be driven by fundamental cognitive heuristics rather than product-specific knowledge. It could also be due to the presented images being too abstract and the icons showing little difference. It is possible that whilst the simplistic icons were a replication and extension of a previous study

(Holmgren et al, 2018), the lack of statistical difference is a result of the graphics and not the item type. However, to confirm whether the NFI is truly domain-general, future research must test whether it extends to other item categories with stronger affective associations (e.g., plastic vs glass vs electronic waste) and whether participants use different decision rules when evaluating mixed-material waste.

Averaging bias has been widely proposed as a cognitive mechanism underlying the NFI.

Chernev and Gal (2010) initially demonstrated this effect in the domain of food choices, where individuals judged a meal consisting of both a high-calorie item (a cheeseburger) and a low-calorie item (a salad) as having fewer total calories than the cheeseburger alone. This tendency to mentally integrate vice and virtue attributes rather than sum them has since been extended to environmental judgements (Holmgren et al., 2018). The current findings align with this framework, as participants underestimated the total environmental impact when a recyclable item was added, suggesting that perceived virtues (recyclability) distorted impact estimations. However, unlike Chernev and Gal's (2010) study, where two vices were not averaged, it remains unclear under what conditions individuals may override the averaging heuristic in environmental contexts. Future research should explore whether stronger interventions or cognitive prompts could encourage more quantitative, rather than heuristic-driven, estimations.

The AOT-17 scale was included to examine whether individual differences in cognitive style predicted susceptibility to the NFI. Unlike previous findings (Threadgold et al., 2022), overall AOT scores did not significantly correlate with NFI magnitude. However, fact resistance emerged as a significant predictor for NFI for houses and bottles, suggesting that individuals who resist revising their beliefs considering new evidence may be more prone to heuristic-based environmental misjudgements. This aligns with findings by Svedholm-Hakkinen and Lindeman (2018). Who identified fact resistance as the most robust

component of AOT, and with Stanovich and Toplak (2023) who emphasise belief revision as a critical determinant of rational thinking.

The findings suggest that cognitive mechanisms such as fact resistance and heuristic-based processing play a key role in environmental estimations. While no differences were found between houses and bottles in overall NFI susceptibility, the predictive role of fact resistance for houses suggest that some individuals may struggle to override pre-existing heuristics in complex environmental assessments. This aligns with Stanovich's (2020) cognitive miser framework, which posits that individuals tend to rely on low-effort, intuitive processing rather than engaging in cognitive decoupling—the ability to detach from immediate intuitions and systematically evaluate evidence. This finding is significant because it suggests that environmental interventions should focus not only on providing accurate information but also on promoting cognitive flexibility. The findings also raise the possibility that environmental reasoning is influenced by political and ideological beliefs. Previous research suggests that individuals high in AOT tend to be more sceptical of anthropogenic climate change, particularly when environmental issues become politicised (Kahan & Corbin, 2016). It is possible that participants with strong pre-existing views about sustainability engaged in myside bias, electively interpreting recyclable materials as environmentally positive regardless of their quantitative impact. This highlights the need for further research to examine whether ideological framing influences susceptibility to the NFI and whether interventions should be tailored to different political and cognitive profiles.
The role of myside bias (confirmation bias) in environmental estimations is particularly relevant in this study. Participants may have relied on pre-existing beliefs about recyclability to confirm their assumptions, leading to distorted impact estimations (Nickerson, 1998). For instance, if participants strongly associated "recyclable" with "environmentally friendly," they may have discounted the total waste increase, reinforcing the NFI. However, it is also possible that some participants perceived plastic as inherently harmful, placing it on equal

footing with non-recyclable waste—suggesting that pre-existing attributes, rather than objective assessment, shaped their judgements. This aligns with previous research showing that climate change attitudes do not always correlate with rational environmental decision-making (Stenhouse et al., 2018; Stanovich et al., 2023). Future research should examine whether stronger manipulations—such as altering the framing of recyclability or varying contextual information—can override these biases and encourage more analytical processing.

Further research is essential to fully map out the cognitive mechanisms underlying the NFI and to determine how generalisable the effect is across different item types. While previous research has demonstrated the NFI in cars, food, and houses, this experiment provides the first evidence that it extends to plastic bottles. This raises critical questions: Does the illusion operate consistently across all recyclable materials, or are certain product categories more susceptible than others? If individuals rely on heuristic-based judgements rather than absolute environmental impact calculations, then the NFI may emerge in any context where vice and virtue attributes are combined. However, category-based differences may still play a role—suggesting that future studies should systematically test whether the NFI generalises across multiple product types (e.g., plastic vs glass vs aluminium).

Most research on the NFI has examined comparisons between conventional and environmentally friendly alternatives within a single product category (e.g., conventional vs energy efficient houses). However, real-world recycling decisions rarely involve isolated product types—instead, they often involve mixed materials and multiple items, creating greater cognitive complexity. If individuals rely on heuristic (type 1) processing, they may default to pre-existing assumptions about recyclability, rather than considering the total impact of mixed-material waste streams. This aligns with AOT-17 results, which suggest that fact-resistant individuals may be particularly susceptible to heuristic driven distortions. On the other hand, interventions that induce analytical (Type 2) reasoning may reduce reliance

on myside bias but could also introduce moral licensing effects—where individuals justify environmentally harmful behaviour based on past pro-environmental actions (Gholamzadehmir et al., 2019; Mazar & Zhong, 2010). Future research should explore whether increasing task complexity (e.g., multi-material recycling scenarios) strengthens or weakens the NFI and whether cognitive interventions can mitigate distortions in real-world decision-making.

A key remaining question is whether the NFI operates similarly when environmentally friendly additions come from a different product category. In this experiment, recyclable bottles were added to non-recyclable bottles, maintaining a within-category structure. However, real-world recycling often involves mixed-material waste streams, such as combining plastic with glass or aluminium.

While this study found strong evidence for the NFI in both plastic bottles and houses, it remains unclear whether the effect extends to cross-category comparisons. In real-world recycling, individuals must evaluate waste streams containing multiple materials rather than single-category comparisons. The next chapter examines whether adding an environmentally friendly material from a different category (e.g., recyclable aluminium cans to non-recyclable plastic bottles) produces the same misestimation effects, or whether individuals use different cognitive heuristics when confronted with mixed-material waste streams. Additionally, it explores how variations in item quantity influence the NFI—testing whether individuals' environmental misjudgements scale with increasing amounts of recyclable and non-recyclable materials. These findings will provide crucial insights into how individuals integrate complex environmental information and whether biases extend across material types and larger waste compositions.

Chapter 4

Experiment 2: Valence, Arousal, and Category Membership in Environmental Estimation

Experiment 1 confirmed the NFI in a recycling context with the introduction of recyclable plastic bottles, showing that participants underestimated environmental harm when eco-friendly items were introduced. However, Experiment 2a extends these findings by demonstrating that the NFI persists across different recyclable and non-recyclable item types but is primarily influenced by quantity rather than category-based reasoning. Experiment 2b further reveals that the bias is not driven by affective factors like valence or arousal, suggesting that heuristic averaging—not emotional responses—underlies NFI judgements.

Before considering the role of these additional factors, it is important to first establish the core findings of Experiment 1. Participants demonstrated the same bias when estimating the impact of plastic bottles as they did for houses, with no significant difference between item types. However, a significant difference emerged between the first and second estimations: when a recyclable plastic bottle was added to a single-use plastic bottle, participants judged the overall environmental impact as lower, mirroring the pattern observed when an environmentally certified house was added to a conventional house. The correlation between the magnitude of the NFI in both contexts suggests that this bias is not limited to a single domain but applies broadly to environmental decision-making.

Plastic bottles belong to the broader category of “dry recyclate,” which includes paper, card, glass, waste electrical and electronic equipment (WEEE) and scrap metals (DEFRA, 2024). Dry recyclate constitutes 59.5% of recyclable waste, and reducing landfill waste is crucial for environmental sustainability. Although advancements in landfill management, such as composting, can mitigate greenhouse gas emissions (Lou & Nair, 2009), the most effective strategy remains minimising incorrect disposal. Composting not

only reduces emissions but also improves soil quality, yet some waste inevitably reaches landfill. These findings underscore the importance of addressing cognitive biases like the NFI to improve recycling behaviours and reduce environmental harm.

Improving waste disposal behaviours has been a focus of research, with several studies demonstrating effective interventions. For example, DiGiacomo et al. (2018) found that increasing convenience to waste disposal facilities led to higher rates of correct disposal across various waste categories. However, their study measured waste reduction by weight, which may not fully capture behavioural improvements. Reducing waste volume does not necessarily equate to more effective recycling. This limitation aligns with a broader challenge in waste management: the lowest emission processes do not always correspond to the most sustainable practices (DEFRA, 2022). Moreover, economic, and infrastructural investments in current waste management systems may contribute to inertia in improving disposal practices. The sunk cost fallacy, where prior investments (e.g., waste collection infrastructure, employment, and pricing models) sustain suboptimal systems, may explain why weight-based assessments persist despite their limitations. A more effective approach would focus on preventing waste from reaching landfills altogether, significantly reducing greenhouse gas emissions. Policy initiative suggest that England could improve its recycling rate from 45% to 68% by 2030 (Climate Change Committee, 2020). Understanding how cognitive biases like the NFI shape public perceptions of recyclability could help design interventions to reduce landfill waste and support these targets.

Experiment 1 found no significant difference in environmental impact estimations between houses and plastic bottles. This contrasts with prior findings from Threadgold et al. (2022), where an NFI was observed for houses but not for apples. However, in their study, the number of apples presented was significantly lower than the number of houses or cars, raising the possibility that perceived numerosity rather than object type influenced judgements. One possible explanation for this is that participants grouped houses, and

bottles, based on their shared environmental context rather than their physical properties. This raises the question: Does the NFI depend more on categorical relationships between objects or on their perceived numerical properties? Two cognitive biases—category size bias and perceived numerosity—may contribute to these effects, but they operate in distinct ways.

Category size bias occurs when people rely on broad category groupings rather than evaluating individual items. For example, if participants focus on the general category of "houses" rather than distinguishing between conventional and environmentally certified houses, they might assume that adding an eco-friendly house reduces net environmental harm—even though the total quantity of houses increases. This effect may explain why Threadgold et al. (2022) found no NFI for apples but did for houses. Houses are more likely to be grouped into a meaningful environmental category, whereas apples may not evoke the same kind of categorical thinking. However, Andersson et al. (2024) found that increasing the absolute number of green (eco-friendly) items amplified the NFI, even though the proportion of green to conventional items remained constant. This suggests that judgements were influenced not just by category size bias but also by numerosity effects where people attend to the absolute number of items rather than their relative proportion.

Perceived numerosity, in contrast, refers to how people mentally organise and quantify objects based on their visual or spatial arrangement. This bias can lead people to misperceive quantities, either underestimating or overestimating group sizes depending on contextual cues. For example, a set of 16 circles could be perceived as 16 individual units, 8 pairs, or 4 groups of 4, depending on how they are arranged (Zhao & Yu, 2016). Similarly, when objects share visual properties or spatial proximity, they tend to be perceived as more numerous, while structured arrangements lead to underestimation of quantity (Qu et al., 2024). Applied to the NFI, people may judge the number of recyclable and non-recyclable items differently depending on how they are presented (Zhao & Yu, 2016). When objects

appear similar or are spatially grouped, they tend to be perceived as more numerous, while structured arrangements may lead to underestimation (Qu et al., 2024). In the context of the NFI, this suggests that the way recyclable and non-recyclable items are presented could influence whether participants engage in averaging or summation when making judgements.

Both biases, category size bias and perceived numerosity, may contribute to the NFI in different ways. Category size bias might encourage misclassification, leading participants to assume that adding eco-friendly items reduces environmental harm simply because they belong to the same broad category (e.g., "houses" or "recyclable items"). Perceived numerosity might influence how people mentally cluster recyclable and non-recyclable items. If people see the set as a single environmental category, they may underestimate total waste. Alternatively, if they focus on the "eco-friendly" subset, they may overestimate its contribution, reinforcing the NFI.

These biases may interact, making it difficult for participants to accurately judge environmental impact. Sörqvist et al. (2022) found that the NFI was stronger when stimuli were irregularly distributed, which aligns with research showing that structured layouts reduce perceived numerosity (Zhao & Yu, 2016). However, perceived numerosity alone does not always predict the NFI. Some studies have failed to replicate the illusion under certain conditions (e.g., Gorissen & Weijters, 2016; Threadgold et al., 2022), suggesting that task framing, heuristics, and contextual cues also play a role.

Understanding these biases is crucial for interpreting how people make environmental impact judgements. If individuals rely on category-based heuristics, they may downplay the cumulative effect of waste by focusing on broad labels like "recyclable" rather than actual environmental impact. Conversely, if perceived numerosity drives the effect, participants may be more sensitive to total quantity rather than object categories. This raises an important question: Does the NFI extend across distinct product categories, or is it constrained by category-specific reasoning? The next section addresses this by testing

whether the NFI occurs when recyclable and non-recyclable items come from different product groups. Identifying these overlapping biases can help refine public messaging on recycling and sustainability, potentially improving adherence to proper disposal practices.

However, perceived numerosity alone does not always account for NFI effects. While it plays a role in shaping environmental judgements, its influence may be moderated by other factors such as task framing, decision heuristics, or contextual cues. Some studies have even failed to replicate the illusion under certain conditions, suggesting that additional cognitive biases or methodological choices influence whether the NFI emerges. For example, Gorissen and Weijters (2016) and Threadgold et al. (2022) reported inconsistent findings, suggesting that additional factors, such as task framing or decision heuristics, may influence whether the illusion emerges. Investigating these boundary conditions is crucial for understanding when and why people misjudge environmental impact.

Gorissen and Weijters (2016) initially attributed their failure to replicate the NFI to a methodological change in study design. Their first three experiments used a between-participants design, but the fourth used a within-participants design, which may have influenced participants' response strategies. Three years later, a successful replication reinstated the illusion using both between- and within-participants designs, suggesting that the effect is robust across methodologies (Andersson et al., 2024; Ateş, 2020; Holmgren et al., 2019; Kusch & Fiebelkorn, 2019; MacCutcheon et al., 2020; Threadgold et al., 2022). These findings highlight the importance of study design in shaping how people perceive and estimate environmental impact.

Threadgold et al. (2022) also failed to replicate the NFI for one of three tested items, raising the question of what these experimental designs had in common. In their study, the environmentally positive addition was an organic apple, while in Gorissen and Weijters (2016), it was a side dish that varied between conventional lettuce, organically labelled lettuce, or no lettuce. A possible explanation for these replication failures lies in perceived

numerosity and contextual coherence. Objects with similar low-level visual features (e.g., shape, colour) are more likely to be mentally grouped together, influencing judgements (Qu et al., 2024). In both studies, the additions (apple, lettuce) maintained their original form, meaning they may not have been perceived as introducing a meaningful environmental change. This suggests that subtle perceptual or semantic similarities between items may influence whether the NFI occurs.

This finding is relevant to the current research because factors affecting recycling decisions may be influenced by both semantic associations and physical similarities between items. In Experiment 1 (Chapter 3), item type did not produce a statistically significant effect, potentially because the objects (houses vs plastic bottles) lacked perceptual or categorical similarities. In contrast, a non-recyclable plastic bottle and a recyclable plastic bottle may be perceived as part of the same environmental category as other household recyclables, such as drink or food cans. This increased perceptual and functional similarity may enhance category-based grouping, potentially leading to a stronger item-type effect in future studies.

Rationale for the cross-category manipulation

Previous research has primarily examined the NFI within single-object categories (e.g., houses or cars; Holmgren et al., 2018a, 2018b; Kim & Schuldt, 2018; MacCutcheon et al., 2020; Sörqvist et al., 2022; Threadgold et al., 2022), leaving open the question of whether the effect persists across different categories. Investigating whether the NFI occurs when non-recyclable items (e.g., plastic bottles) are combined with recyclable items from a different category (e.g., aluminium cans) provides critical insights into how people process environmental information. Testing cross-category effects allows us to determine whether the NFI reflects a domain-general cognitive bias or if it depends on category-specific associations. If the NFI persists across categories, this would suggest that the bias is driven by general cognitive mechanisms rather than object-specific heuristics. Conversely, if the

NFI diminishes when items belong to different categories, it would indicate that people rely on category-based reasoning when making environmental judgements.

Different product categories (e.g., bottles vs cans) may evoke distinct environmental associations. For example, bottles are often linked to waste accumulation (Johnston, 2017), while cans are more strongly associated with recycling (The Metal Packager, 2025). If the NFI occurs across such categories, it would suggest that the bias is not dependent on specific category-based associations but instead reflects a broader cognitive tendency. Conversely, if the NFI weakens when people compare different categories, this would indicate that category-specific reasoning plays a role in how environmental impact is judged. Testing the NFI across categories is also important for real-world decision-making, as people frequently evaluate the environmental impact of mixed product categories, such as food packaging and electronic waste. Investigating cross-category effects enhances the ecological validity of the study by mirroring how individuals make environmental choices in everyday contexts. Additionally, testing whether people apply an averaging heuristic across dissimilar products clarifies whether the NFI is driven purely by a tendency to average environmental impact, rather than by perceived similarities between items. Finally, cross-category judgements may accentuate the NFI under certain conditions. If it is the case that people strongly associate items with being eco-friendly (The Metal Packager, 2025), they might disproportionately discount the negative environmental impact of non-recyclable items when non-recyclable and recyclable appear together. In this case, the presence of a highly recyclable item could paradoxically increase the magnitude of the illusion, leading to even greater misjudgement than in same-category comparisons.

From a theoretical perspective, there are arguments both for and against the idea that the NFI extends across categories. First, people often rely on category-based mental models when making judgements (Barsalou, 1983; Smith & Semin, 2004). These mental schemas shape how they process information, which may cause them to evaluate objects

from different categories separately rather than integrating their environmental impact. For instance, people tend to classify foods as either healthy or unhealthy, or as natural versus processed, and they associate different outcomes with each category (Rozin, 2005). A similar effect may apply to recycling: cans may be viewed as environmentally beneficial due to their high recyclability (Benton, 2015), whereas plastic bottles might be linked to pollution and waste (Adyel, 2020). If the NFI relies on the mistaken blending of environmental impact estimates within a single category, then introducing cross-category comparisons could disrupt this effect. In other words, if participants view bottles and cans as fundamentally different in terms of their environmental consequences, they may be less likely to apply an averaging heuristic when estimating their combined impact.

Second, when objects come from different categories (e.g., non-recyclable bottles and recyclable cans), their differences may stand out more, making it harder for participants to blend their environmental impacts. If people view bottles and cans as distinct entities with separate environmental effects, they may judge each on its own terms rather than averaging across them. This would contrast with same-category comparisons, where differences might seem less important, encouraging an averaging effect.

Research supports this idea. Hsee & LeClerc (1998) found that when people evaluate items separately, their unique characteristics become more salient, leading to more precise judgements. However, when evaluated together, people may rely on heuristics that obscure these differences. Applied to the NFI, this suggests that when bottles and cans are considered separately, participants may more accurately assess their individual environmental impact, reducing the likelihood of misjudgement due to averaging.

Additionally, Kahneman & Frederik (2002) propose that when faced with complex decisions, people often substitute a difficult judgement with a simpler one. In the case of environmental impact, rather than integrating the distinct effects of bottles and cans, participants might focus on a more accessible feature—such as whether an item is

recyclable or not. This could explain why the NFI occurs within categories but may be weakened in cross-category comparisons. When recyclable bottles are added to non-recyclable ones, people may simply distinguish between "recyclable vs. non-recyclable" and assume a net benefit. However, when cans are added to bottles, category differences may dominate, making it harder to apply this heuristic, thereby reducing the NFI.

Third, different categories of objects may carry distinct environmental associations that make it harder to blend their impacts. For example, plastic bottles are often linked to waste and pollution, reinforcing negative environmental perceptions. In contrast, cans are frequently associated with sustainability and efficient recycling due to their high recyclability rates (The Metal Packager, 2025). When these opposing cues are present, participants may struggle to reconcile them into a single judgement, making it less likely that they will apply an averaging heuristic. If adding a recyclable can to a non-recyclable bottle creates a cognitive conflict, participants may be more inclined to assess their environmental impacts separately, thereby weakening the NFI.

This aligns with research by Griskevicius et al. (2010), who found that environmental decisions are influenced by social and contextual cues, particularly in the context of “conspicuous conservation”—where people choose eco-friendly options to signal their environmental awareness. If participants associate cans with sustainability, they may be reluctant to merge their impact with bottles, as doing so would undermine the positive status of cans. This could reduce the likelihood of a misleading averaging effect, providing further insight into why the NFI may be less pronounced in cross-category comparisons.

Fourth, variations in people’s knowledge about the environmental impact of different materials may influence their judgements, potentially disrupting the NFI. For example, plastic bottles are widely recognised as a major environmental concern due to extensive media coverage of plastic pollution, whereas knowledge about the recyclability of cans (especially aluminium vs coated cans) may be less consistent. We speculate the knowledge of metals

may influence a strong association with recycling but when two materials are opposed such as plastic and metal this may create an ambiguous understanding leading to confusion in how to recycle. This discrepancy in familiarity may lead people to process these categories separately rather than integrating their environmental impact into a single estimate.

When individuals feel highly confident about the environmental impact of one category but uncertain about the other, they may hesitate to apply an averaging heuristic. Instead, they might engage in more deliberate, category-specific reasoning, assessing the known category with confidence while treating the less familiar category as an unknown variable. This aligns with dual-process theories of judgement (Evans & Stanovich, 2013), which suggest that heuristic reliance tends to decrease when individuals recognise uncertainty and shift toward more analytical processing. Thus, differences in environmental knowledge may create a cognitive asymmetry that weakens the NFI by discouraging automatic averaging across categories (Holmgren et al.,2018b).

Fifth, heuristics such as averaging may operate more effectively within a single category, where objects are perceived as directly comparable, but become less reliable across categories. According to Tversky & Kahneman (1974), heuristic reasoning often depends on perceived similarity between items. If two objects are judged to belong to the same set, people are more likely to apply the same mental shortcut (such as averaging). However, when objects come from different categories (e.g., bottles and cans), the perceived differences may reduce fluency in comparison, making averaging feel less applicable or intuitive.

This aligns with research on comparability effects (Medin et al., 1993) and perceptual fluency (Whittlesea, 1993), which suggest that when people struggle to compare items, they are less likely to engage in heuristic-based judgements. Instead, they may process items separately, reducing the likelihood of the NFI. Thus, if the NFI relies on seamless integration

of information, category differences may disrupt this process by making comparisons feel unnatural or forced.

Sixth, participants may make context-dependent judgements when evaluating items from different categories. Instead of averaging environmental impact across items, they may assess each object based on its typical disposal process. For example, a non-recyclable bottle might evoke concerns about sustainability, whereas a recyclable can might trigger associations of sustainability (De Feo et al., 2022). Because these objects activate distinct mental models of sustainability, participants may struggle to integrate their environmental impacts into a single judgement, potentially weakening the NFI across categories.

This aligns with Smith and Semin's (2004) contextual dependence theory, which suggests that cognition is highly influenced by the immediate environment and shifts depending on the framing of information. In the case of NFI, participants may not treat different waste categories as interchangeable but rather as separate domains requiring independent evaluations. This contextual segregation could prevent the heuristic blending of environmental impact, making the NFI less likely to occur across categories.

In sum, the NFI may fail to emerge across categories because participants mentally separate objects based on distinct schemas and environmental cues. Differences in perceived disposal processes, conflicting environmental associations, and the salience of category distinctions may all discourage heuristic averaging. As a result, participants are less likely to blend environmental impacts across categories, reducing or eliminating the NFI in cross-category comparisons. However, despite these theoretical reasons for category-specific effects, it remains possible that the NFI is a more general cognitive bias that extends beyond individual item types. The following section considers the evidence for this alternative view.

Despite the reasons outlined above, the NFI may still extend across categories if it reflects a general cognitive bias rather than a category-specific effect (Hilbert, 2011). First,

people often simplify complex judgements by relying on heuristic strategies like averaging. This process may operate independently of category boundaries, particularly if participants focus on overall environmental impact rather than distinguishing between specific item types. If both categories (e.g., bottles and cans) are framed as environmentally relevant, participants may perceive them as part of a shared environmental context rather than as distinct entities. This could encourage cross-category averaging, leading to an NFI effect even when the items belong to different groups.

Second, people may focus on a common environmental factor shared across categories—such as carbon footprint or recyclability—rather than the distinct properties of individual items (Schroeder, 2007). When making judgements, participants might prioritise this overarching environmental dimension and mentally group objects that contribute to the same environmental issue. For example, both plastic bottles and aluminium cans may be perceived primarily as more sustainable than other materials (e.g., glass) (De Feo et al., 2022), leading to cross-category averaging. If participants judge environmental harm based on total waste production rather than material differences, this could sustain the NFI across categories.

Third, the NFI may arise from a fundamental misinterpretation of environmental trade-offs (Figge & Hahn, 2012). Specifically, participants might mistakenly believe that adding eco-friendly items inherently reduces total environmental harm, even when non-recyclable items remain. This misconception could lead to averaging across categories, as people assume that the presence of recyclable materials offsets the negative impact of non-recyclable ones—regardless of item type.

Fourth, even when objects come from different categories (e.g., bottles, cans), presenting them in the same context, such as a single scenario about environmental impact-could encourage participants to mentally group the items together. That is, the context of the task (making judgements about environmental harm) might override category boundaries

leading participants to view the object as part of a collective environmental impact. Thus, people might combine the effects of the two categories of objects thereby giving rise to an NFI (Kahneman & Frederik, 2002).

Fifth, individuals may fail to differentiate between the environmental impact of distinct categories, leading them to generalise all waste as equally harmful (Lau, 2019). For example, recyclable cans and non-recyclable bottles may both be perceived simply as “waste,” with their differences overlooked. This failure to process category-specific information could lead participants to apply an averaging heuristic, treating all items similarly and thereby reinforcing the NFI.

Sixth, eco-friendly labels can systematically bias environmental judgements, even when applied to items from different categories (Siraj et al., 2022). When recyclable cans are explicitly labelled as "eco-friendly," participants may extend this positive evaluation beyond the labelled item, leading them to perceive the overall environmental impact of all objects in the scenario as lower. This reflects a Halo Effect (Nisbett & Wilson, 1977), where a single positive attribute (recyclability) influences unrelated evaluations. The NFI may be amplified by this effect, as participants rely on heuristic cues rather than objective environmental impact assessments.

Seventh, when faced with complex environmental judgements, individuals often rely on cognitive simplification strategies (Xie et al., 2024). Instead of analysing distinctions between specific objects (e.g., bottles vs. cans), people may categorise items at a higher level of abstraction (e.g., "recyclable" vs. "non-recyclable"). This tendency aligns with cognitive load theory (Sweller, 1988), which suggests that under high information demands, individuals reduce complexity by applying broad categorical heuristics. In the context of the NFI, this category abstraction may lead participants to erroneously average environmental impact across dissimilar items, reinforcing the illusion that adding eco-friendly products reduces total harm.

Eighth, the framing of the experimental task may unintentionally encourage participants to judge items based on their aggregate environmental impact rather than their individual contributions (Alexander et al., 2009). When objects are presented together as part of a single judgement, participants may assume that they should focus on the total or average environmental effect, rather than considering each category independently. This aligns with normative vs. descriptive decision-making theories (Tversky & Kahneman, 1974), which suggest that people often misinterpret experimental tasks by applying heuristic-based reasoning rather than analytic differentiation. Consequently, the structure of the task may inadvertently promote the NFI, as participants default to averaging rather than making category-specific comparisons.

In sum, the NFI extends across categories because participants rely on broad cognitive heuristics rather than category-specific evaluations. The strongest explanation for this effect is heuristic averaging, wherein individuals blend environmental impacts across dissimilar items instead of evaluating them separately. This tendency may be reinforced by eco-labelling effects, task framing, and perceptual grouping, all of which encourage participants to perceive environmental harm in relative rather than absolute terms. These findings suggest that public messaging on sustainability must counteract heuristic averaging by explicitly prompting individuals to sum, rather than average, environmental impact. One possible intervention is cumulative waste framing, where individuals are shown the total amount of waste generated over time rather than making single-instance comparisons. Additionally, policies could incorporate numerical nudges, such as requiring people to input total waste quantities before making an impact judgement. Future research should investigate whether these techniques can effectively reduce the NFI and improve accuracy in environmental decision-making.

Rationale for Exploring Valence and Arousal

Previous research has shown that individual differences, such as actively open-minded thinking, have no significant relationship with the magnitude of the negative footprint illusion (NFI) or are inconsistently correlated across studies (MacCutcheon et al., 2020; Threadgold et al., 2022; Holmgren et al., 2018; Chapter 3). However, the absence of strong correlations with questionnaire-based measures may stem from the NFI being driven by affect—an observable manifestation of an emotive response such as a gesture or facial expression. Two aspects of affect are valence and arousal (Barrett, 1998). An investigative look at valence and arousal has been linked to the dual-process model (Gomes & Brainerd, 2013). It is a consideration that emotions are effective in learning and the decision-making process, where immediate emotions are experienced at the time of decision-making and are fundamental in reward learning, where valence provides guidance for behaviour and assists the reasoning process, supplying an efficient process of knowledge and logic needed to enable conscious decisions (Ahn & Picard, 2005).

Valence and arousal may influence the NFI by shaping how individuals evaluate immediate versus long-term environmental consequences. This is particularly relevant in the context of recycling, where decision-making often involves a trade-off between short-term convenience and long-term environmental benefits. Research on reward processing suggests that people learn more quickly from immediate rewards than from delayed outcomes (Ahn & Picard, 2005). In single-step decisions, such as throwing a bottle into the bin, the immediate consequence (getting rid of waste) is more tangible than the future environmental impact (reducing carbon emissions). If people assign greater weight to immediate over delayed rewards, they may be less likely to integrate long-term environmental benefits into their judgements. This could contribute to the NFI by making individuals undervalue the cumulative harm of waste production, especially when eco-friendly options are introduced into the scenario.

Secondly, the size of a perceived reward may also influence how people discount future environmental benefits. Larger rewards tend to be more motivating, while smaller rewards are often overlooked—a pattern observed in temporal discounting research (Sohn et al., 2015). In the context of recycling, this suggests that people may underestimate the impact of small-scale waste decisions (e.g., discarding a single plastic bottle) while overestimating the importance of highly visible environmental actions (e.g., large-scale clean-up efforts). This could contribute to the NFI by making individuals less sensitive to incremental environmental harm, particularly when eco-friendly items are introduced into the scenario.

Additionally, heightened emotional arousal can impair cognitive control, leading people to rely more on heuristic-based decision-making (Sohn et al., 2015). When individuals are in a high-arousal state, whether due to time pressure, frustration, or external distractions, they may default to simplified judgements rather than carefully weighing long-term consequences. This could further amplify the NFI by encouraging automatic, rather than deliberate, environmental impact estimations.

Thirdly, heightened arousal can enhance memory performance, which may influence how individuals judge the environmental impact of waste. For example, media coverage of plastic pollution, such as images of ocean waste, can trigger strong emotional responses, leading to greater recall of plastic-related environmental harms (Nuojua et al., 2022). If people associate plastic with high-arousal environmental threats, they may judge plastic waste as more harmful than other materials, even when objective impact is comparable. Conversely, if an item lacks strong emotional associations, individuals may underestimate its environmental cost. This could contribute to the NFI by making people more responsive to the presence of certain waste types (e.g., plastic) while neglecting other pollutants.

Investigating the role of valence and arousal in environmental judgements will help clarify whether emotional responses to different waste materials systematically shape

recycling decisions. Understanding these effects could also inform strategies for improving environmental messaging, ensuring that public perceptions align more closely with actual environmental impact.

Experiment 2a

Experiment 2a builds on Experiment 1 by testing whether the NFI generalises across different categories of recyclable materials. While Experiment 1 found no statistical difference between item types (houses vs. bottles), Experiment 2a examines whether the NFI persists when comparing different types of dry recyclate, such as plastic bottles and tin cans, which vary in physical appearance and recyclability perceptions.

This experiment also expands the scope beyond like-for-like comparisons to determine whether the illusion is driven by category-based biases, quantity effects, or perceived numerosity. If participants average environmental impact rather than summing it, their estimates should reflect a midpoint between the quantities rather than a strict additive increase. However, if category size bias or perceived numerosity influences judgements, then estimates may be distorted based on grouping cues rather than objective quantity. Finally, the study introduces a cross-category manipulation, testing whether the NFI changes when recyclable and non-recyclable items are mixed. This approach will help clarify whether participants base their judgements on item type, environmental context, or more general cognitive heuristics.

Experiment 1 showed that adding environmentally “friendly” items led to lower environmental impact estimations, even when total quantity increased. This suggests that participants may engage in heuristic averaging rather than summation when judging environmental impact. To explore this further, Experiment 2a systematically manipulates the ratio of non-recyclable to recyclable items while keeping the recyclable addition constant at 20 items—ensuring consistency across conditions (cf. Andersson et al., 2024). Three ratio conditions are tested: 1:2 (10 non-recyclable + 20 recyclable items); 1:1 (20 non-recyclable +

20 recyclable items), and 2:1 (40 non-recyclable + 20 recyclable items). This design allows us to determine whether participants' estimates of environmental impact scale proportionally with non-recyclable quantity or if the NFI remains constant across ratios. If heuristic averaging is the primary driver, then even large increases in non-recyclable items may fail to shift overall environmental judgements accordingly, as sometimes part of the available information is ignored (Gigerenzer, 2008).

Experiment 2a tests whether the NFI persists across different categories of recyclable materials, expanding beyond like-for-like comparisons (e.g., houses vs bottles). Specifically, it investigates two key factors. First, category effects: Does the NFI apply equally to within-category comparisons (e.g., non-recyclable bottles + recyclable bottles) and cross-category comparisons (e.g., non-recyclable bottles + recyclable cans)? Second, quantity effects: Does the total number of non-recyclable items moderate the NFI, or does heuristic averaging occur regardless of absolute quantity? The predictions are that the NFI will persist regardless of quantity, meaning that adding recyclable items will reduce perceived environmental impact even when non-recyclable quantity increases. Further, the NFI will be observed in both same-category and cross-category conditions, suggesting that heuristic averaging operates across different item types rather than within a single product group.

Method

Design

The experiment employed a 2 (Item Type: cans, bottles) × 2 (Estimate Type: no addition, addition) × 2 (Category: no cross-category, cross-category) × 3 (Quantity: 10 items, 20 items, 40 items) within participant design. The order of presentation was counterbalanced between participants. The dependent variable (DV) was the estimate of environmental impact given on a 1-100-point scale.

Participants

Participants were recruited via Prolific (www.prolific.com) utilising a UK population with English as a first language. Power analysis was conducted using PANGEA (Westfall 2016), instead of G*Power (Faul et al., 2007) due to the complexity of the experimental design. The analysis indicated that a sample size of 100 participants (N = 100), yielding 2,400 total observations, provided 100% power to detect a medium effect size (*dz* = .45) with *a* = .05 and D = .13. Subsequently, 100 participants were recruited. One participant was giving a default judgement for the second estimate each time and was thus removed and replaced with a new participant. The mean age of the sample was 41.09 years (*SD* = 13.71, 53% male).

The change in power calculation was due to the quantity of independent variables utilising such a large design. Despite the complexity of the design, simplification was avoided to maintain ecological validity. A more streamlined approach would have reduced experimental complexity but failed to capture the cognitive challenges inherent to real-world recycling decisions. Additionally, the financial constraints necessitated a larger design to maximise data collection efficiency.

Materials and Procedures

The methods and procedures followed those of Experiment 1, with the following modifications: The quantity of non-recyclable items was manipulated in the first estimate; In the second estimate, participants evaluated either same-category (e.g., plastic bottle + recyclable plastic bottle) or cross-category (e.g., plastic bottle + recyclable cans) conditions, and the ratio of recyclable to non-recyclable items varied across three levels (see Table 3). The complete list of conditions is in Table 3, and for an example of the cross-category stimuli, see Figure 6 (For other examples of stimuli presentations, see **Appendix D, Figures 7**).

Table 3

The group name, control addition (first estimate) and addition condition (second estimate) for each presentation

Group	Control condition (First estimate)	Addition condition (Second estimate)
Cans 10	10 non-recyclable cans	10 non-recyclable cans + 20 recyclable cans
Cans 20	20 non-recyclable cans	20 non-recyclable cans + 20 recyclable cans
Cans 40	40 non-recyclable cans	40 non-recyclable cans + 20 recyclable cans
Bottles 10	10 non-recyclable plastic bottles	10 non-recyclable plastic bottles + 20 recyclable plastic bottles
Bottles 20	20 non-recyclable plastic bottles	20 non-recyclable plastic bottles + 20 recyclable plastic bottles
Bottles 40	40 non-recyclable plastic bottles	40 non-recyclable plastic bottles + 20 recyclable plastic bottles
Cross-category cans 10	10 non-recyclable cans	10 non-recyclable cans + 20 recyclable bottles
Cross-category cans 20	20 non-recyclable cans	20 non-recyclable cans + 20 recyclable bottles
Cross-category cans 40	40 non-recyclable cans	40 non-recyclable cans + 20 recyclable bottles
Cross-category bottles 10	10 non-recyclable bottles	10 non-recyclable bottles + 20 recyclable cans
Cross-category bottles 20	20 non-recyclable bottles	20 non-recyclable bottles + 20 recyclable cans
Cross-category bottles 40	40 non-recyclable bottles	40 non-recyclable bottles + 20 recyclable cans

Figure 6

Illustration of the stimulus used in the cross-category cans 10 group. Participants viewed 10 non-recyclable cans, followed by 10 non-recyclable cans plus 20 recyclable plastic bottles and estimated their environmental impact on a 1-100 scale.

First estimation

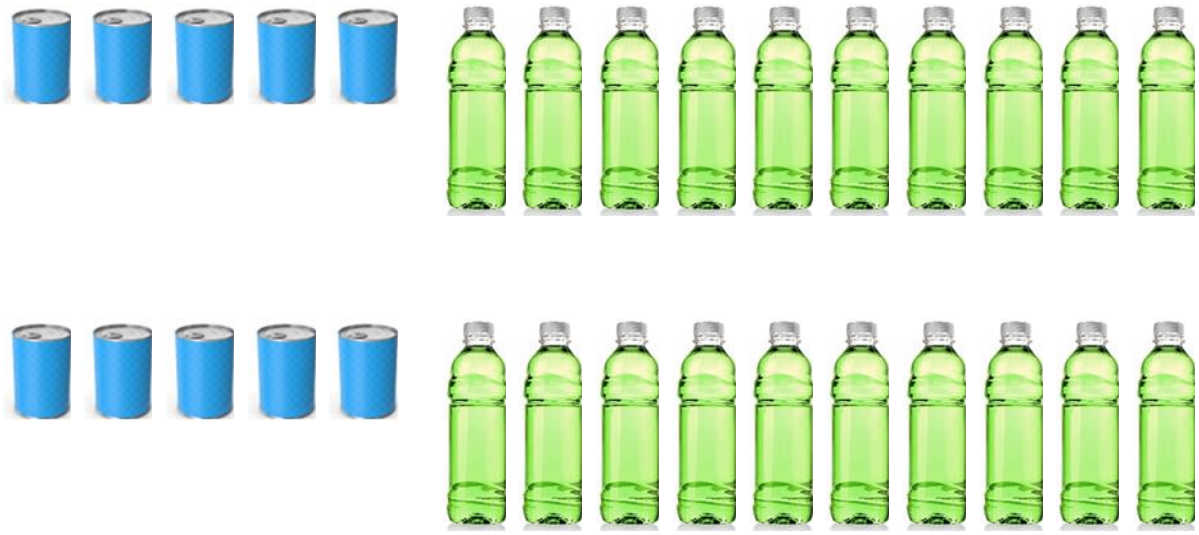
10 Cross-category cans

10 non-recyclable cans

Second estimation

10 Cross-category cans

10 non-recyclable cans **+** **20 recyclable plastic bottles**



Results

Experiment 2a

Experiment 2a examined whether estimations of environmental impact differed between tin cans and plastic bottles, and whether quantity and category type (same vs cross-category) influenced judgements. A 2 (Item type: bottles, tin cans) × 2 (Estimate type: no addition, addition) × 2 (Category Type: same-category, cross-category) × 3 (Quantity: 10, 20, 40) repeated measures ANOVA was conducted, with order randomised across participants to control for sequence effects. Although Experiment 1 found that order had no influence, randomisation was maintained as best practice. The dependent variable was participant's environmental impact estimation score on a 1-100 scale. Means and standard deviations for all independent variables are shown in Tables 4 and 5.

Table 4

The means and standard deviations for Quantities 10, 20, 40, for plastic bottles and cans in the same category and cross category conditions for the non-recyclable (first estimate) and addition recyclable condition (second estimate) for each presentation.

Independent variables	Estimations and quantity											
	Non-recyclable (first estimate)						Recyclable (second estimate)					
	10		20		40		10+20		20+20		40+20	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Same Category Cans	31.23	18.93	42.66	16.81	68.75	20.54	31.50	16.67	45.54	17.63	64.13	21.56
Cross-category Cans	29.83	17.79	44.71	18.10	65.72	21.67	32.47	17.61	44.04	16.95	62.26	22.25
Same Category Bottles	40.76	19.02	58.77	18.15	80.67	19.52	43.06	18.45	56.13	19.45	74.96	20.85
Cross-category Bottles	39.66	18.15	57.04	16.50	79.33	17.21	40.90	17.21	56.15	18.21	73.98	18.48

Table 5 shows all the means and standard deviations for all independent variables.

Table 5

The means and standard deviations for Item type, Category Type, Estimate Type and Quantity Type for groups 10, 20, 40.

	Independent variables								
	Item		Estimate		Category		Quantity		
	can	bottle	First estimate	Second estimate	Same category	Cross category	10	20	40
Mean	46.90	58.45	53.26	52.09	53.18	52.17	36.18	50.63	71.23
SD	1.34	1.20	1.03	1.29	1.10	1.10	1.24	1.11	1.35

Main effects

Item Type significantly affected environmental impact estimates, $F(1, 99) = 57.487$, $MSE = 1391.743$, $p < .001$, $\eta^2p = .367$. Participants rated plastic bottles ($M = 58.45$, $SD = 18.44$) as having a higher environmental impact than tin cans ($M = 46.90$, $SD = 18.87$). Estimate Type did not significantly influence judgements, $F(1, 99) = 1.075$, $MSE = 760.663$, $p = .302$, $\eta^2p = .011$. Participants first estimates ($M = 53.29$, $SD = 18.53$) were not significantly different from their second estimates ($M = 52.09$, $SD = 18.78$), suggesting that adding recyclable items did not systematically alter perceived environmental impact.

Category Type had no significant effect on environmental impact estimations, $F(1, 99) = 1.440$, $MSE = 421.633$, $p = .233$, $\eta^2p = .014$. Judgements were similar whether the recyclable item was from the same category ($M = 53.18$, $SD = 18.96$) or a different category ($M = 52.17$, $SD = 18.34$). Quantity had a strong significant effect, $F(2, 198) = 421.249$, $MSE = 589.194$, $p < .001$, $\eta^2p = .810$. Participants' perceived environmental impact increases as quantity increased ($M = 36.18$, $SD = 17.98$, 10 items; $M = 50.63$, $SD = 17.73$, 20 items; $M = 71.23$, $SD = 20.25$, 40 items). This suggests that larger quantities led to higher perceived environmental harm.

Item × Estimate type, $F(1, 99) = 2.941$, $MSE = 92.738$, $p = .090$, $\eta^2p = .029$, Item × Category type $F(1, 99) = 0.072$, $MSE = 363.260$, $p = .789$, $\eta^2p = .001$, and Category × Estimate type $F(1, 99) = 0.025$, $MSE = 174.016$, $p = .874$, $\eta^2p = .000$, interactions were all non-significant. These results indicate that category type and estimate type did not interact with item type, suggesting that judgements of environmental impact were primarily influenced by item type and quantity, rather than the nature of the recyclable addition.

The interaction between Item × Quantity was not statically significant, $F(2, 198) = 2.897$, $MSE = 161.482$, $p = .058$, $\eta^2p = .028$, suggesting that the effect of item type (bottles vs cans) did not vary depending on quantity. The interaction between Category × Quantity was also non-significant, $F(2, 198) = .709$, $MSE = 163.224$, $p = .493$, $\eta^2p = .007$, indicating that whether items were presented within the same category or across categories had no systematic effect on quantity-based judgements. However, a significant interaction emerged between Estimate Type × Quantity, $F(2, 198) = 25.764$, $MSE = 83.512$, $p < .001$, $\eta^2p = .207$, demonstrating that the quantity of items influenced participants' estimates, and vice versa.

Three-way interactions were not statistically significant, indicating that item type, estimate type, and category type did not interact significantly with quantity (Category × Item × Estimate type, $F(1, 99) = 0.61$, $MSE = 78.443$, $p = .806$, $\eta^2p = .001$; Quantity × Item × Estimate type, $F(2, 198) = 2.183$, $MSE = 58.428$, $p = .115$, $\eta^2p = .022$,; Category × Item × Quantity type, $F(2, 198) = 0.855$, $MSE = 129.193$, $p = .427$, $\eta^2p = .009$, and Quantity × Category × Estimate type, $F(2, 198) = 0.730$, $MSE = 59.224$, $p = .483$, $\eta^2p = .007$). However, a significant four-way interaction emerged, Item × Estimate × Category × Quantity $F(2, 198) = 3.340$, $MSE = 75.071$, $p = .037$, $\eta^2p = .033$. This indicates that the way participants adjusted their estimates depended on a combination of item type, whether an addition was made, whether it was from the same or different category, and the overall quantity. This interaction overrides previous non-significant effects, suggesting that the interplay of these variables modulates environmental impact estimations in a complex manner.

Simple effects

To further investigate the four-way interaction (Item × Estimate × Category × Quantity), simple effects analyses were conducted to examine how environmental impact estimates varied across different item types, estimate types, categories, and quantities. For smaller quantities (10 and 20 items), there were no significant differences in estimated environmental impact (10 items; M = 36.18, SD = 17.98; 20 items, M = 50.63, SD = 17.73). For the largest quantity (40 items), participant's estimates increased significantly (M = 71.23, SD = 20.25), suggesting that larger overall quantities amplify environmental impact judgements. This pattern was consistent regardless of item type (cans: M = 46.90, SD = 18.87; bottles: M = 58.45, SD = 18.43) and category type (same-category: M = 53.18, SD = 18.96; cross-category: M = 52.17, SD = 18.36). As the total quantity increased, so did environmental impact estimates, confirming that quantity influences participant's judgements. The NFI was only observed in the 40-item condition, while smaller quantities (10 and 20) showed no significant illusion. This suggests that the illusion may emerge only when set size exceeds a cognitive threshold. As total quantity increases, individuals likely experience higher cognitive load, making heuristic averaging more attractive as a simplification strategy. Research on numerosity effects (Qu et al., 2024) supports this, showing that perceptual grouping influences judgements of large item sets. This raises an important question for future research: Would interventions such as summation prompts eliminate the NFI at high quantities?

T-test

To further explore the effects of quantity and item type on environmental impact estimations, paired-sample t-tests were conducted. Given that category type did not have a significant main effect, data were collapsed across categories to focus on the significant effects of item type and quantity. When participants added 20 recyclable items to 40 non-recyclable items, environmental impact estimations significantly decreased, $t(99) = 3.591$, p

< .001, Cohen's *dz* = .359, BF_{01} .031. This suggests that adding recyclable items led participants to underestimate the total environmental impact, consistent with the NFI. When participants added 20 recyclable items to 20 non-recyclable items, there was no significant difference, *t*(99) = .263, *p* = .397, Cohen's *dz*= .026, BF_{10} = 12.231. Similarly, when 20 recyclable items were added to 10 non-recyclable items, no significant difference was found, *t*(99) = -1.423, *p* = .079, Cohen's *dz* = .14, BF_{10} = 4.689. The NFI was most pronounced when the total quantity was high (40 non-recyclable items + 20 recyclable items). Smaller quantities (10 or 20 non-recyclable items) did not show a significant NFI effect, suggesting that the bias may only emerge when total quantity is high enough to trigger heuristic averaging. In this case, individuals may estimate or guess the quantity from numerosity when asked to make difficult judgements (Pelham et al., 1994). These findings support the quantity-based sensitivity of the NFI, reinforcing the idea that people rely on an erroneous "averaging" strategy when estimating environmental impact.

Actively Openminded Thinking AOT-17

To examine whether AOT-17 predicts the magnitude of the NFI, a bivariate correlation analysis was conducted. Given that category type did not have a significant main effect, data were collapsed across item type (cans, bottles) and quantity (10, 20, 40 non-recyclable items) to focus on overall trends. There were no significant correlations between AOT-17 scores and the magnitude of the NFI across any condition. AOT-17 scores did not predict environmental impact estimates for bottles or cans, nor did it interact with category type or total quantity (40 items). This suggests that cognitive style, as measured by AOT-17, does not systematically influence NFI magnitude in this study. Table 6 presents the bivariate correlations between AOT-17, its subcomponents, and the NFI magnitude across different item and category conditions.

Table 6

The AOT-17 and sub factors' correlation coefficient and significance scores for its interaction with the magnitude of estimate.

	Dogmatism		**Fact Resistance**		**Liberalism**		**Belief personification**		***AOT-17***	
	r	*p*	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*
Magnitude of estimate	.086	.392	.015	.884	.082	.418	.015	.879	.068	.504
Same Category cans	.162	.108	.156	.122	.070	.490	-.076	.452	.135	.181
Same Category bottles	.153	.129	.031	.760	.011	.912	-.066	.517	.069	.493
Cross category cans	.162	.108	.087	.388	-.052	.607	-.114	.259	.072	.479
Cross category bottles	.032	.754	.014	.888	.048	.636	-.041	.686	.019	.854

*Significant at $p = .05$

Regression

To further examine the relationship between cognitive style and the NFI, a linear regression analysis was conducted to test whether AOT-17 predicts the magnitude of the NFI. AOT-17 did not significantly predict NFI magnitude, $F(1, 98) = .450$, $p = .504$. The model accounted for only 0.5% of the variance in NFI scores, $R^2 = .005$ (0.05%), with a negative adjusted $R^2 = -.006$ (0.06%), indicating no meaningful explanatory power. These results confirm that AOT-17 is not a reliable predictor of NFI magnitude, aligning with the bivariate correlation findings.

The absence of a significant relationship between AOT-17 and NFI susceptibility diverges from previous research (Threadgold et al., 2022), which found that fact resistance significantly predicted NFI susceptibility ($r = 0.200$, $p < 0.001$) and that dogmatism was also predictive in car-related judgements ($r = 0.205$, $p < 0.001$). In contrast, Experiment 1

(Chapter 3) of the current thesis found an association between fact resistance but not dogmatism, while Experiment 2a found no significant correlations with AOT-17. This might suggest that the role of cognitive style in the NFI may be context-dependent, with its predictive power varying by task type (e.g., cars vs recyclables) or participant factors (e.g., domain-specific knowledge, numeracy skills).

The findings from Experiment 2a confirm that the NFI occurs across different recyclable and non-recyclable item types, with quantity effects influencing the illusion. However, the extent to which affective factors contribute to the bias remains unclear. Prior research suggests that valence and arousal influence decision-making (Barrett, 1998) and may play a role in heuristic-based judgements (Gomes & Brainerd, 2013). If individuals mentally categorise non-recyclable items as strongly negative (e.g., single-use plastic bottles as environmentally harmful) and recyclable items as more positive (e.g., recyclable cans as environmentally friendly), they may be more likely to apply an averaging heuristic, assuming that eco-friendly additions offset environmental harm. This idea aligns with the vice-virtue categorisation process (Kim & Schuldt, 2018) and may explain variability in the magnitude of the NFI.

Experiment 2b was designed to test whether individual differences in valence (positive-negative evaluations) and arousal (intensity of response) influence judgements of environmental impact. Specifically, it was examined whether people who perceive non-recyclable items as more negative and recyclable items as more positive show a stronger NFI due to increased reliance on affective averaging heuristics. Experiment 2b thus helps determine whether the NFI is primarily a cognitive bias driven by numerical heuristics or whether it is modulated by emotional responses to environmental information.

Method

Design

Experiment 2b employed a 2 (Item Type: cans, bottles) × 2 (Recyclability: non-recyclable, recyclable) within-participant design. Order of presentation was counterbalanced across participants. The dependent variable (DV) was the individual difference score for valence and arousal, measured on a 1-9 scale.

Participants

Participants were recruited via Prolific (www.prolific.com), selecting a UK-based sample with English as their first language. Power analysis was conducted using PANGEA (Westfall 2016) to determine an optimal sample size. The analysis indicated that 51 participants (total observations = 204) provided 80% power to detect a medium effect size (Cohen's *dz* = .52, *a* = .05, Delta or margin of error = 0.417). The final sample consisted of 51 participants (*M*_age = 40.49 years, *SD* = 13.46, 55% male).

Materials and Procedures

Materials

To investigate the independent variables valence and arousal, participants were shown bottles and cans both either non-recyclable vs recyclable. To control for potential order-effects, the order of presentation for item type was counterbalanced. To measure the dependent variable, we used the measurement scale of 1 (happy) – 9 (sad) for valence **Figure 7** and 1 (high arousal) – 9 (low arousal) for arousal **Figure 8.**

Figure 7

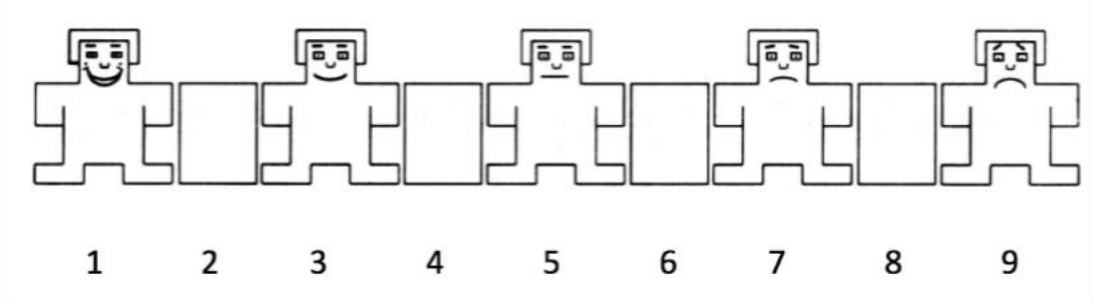
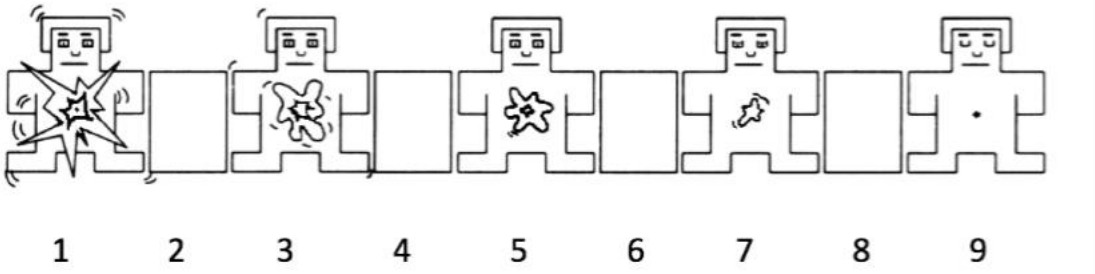


Figure 8



Procedure

To access the survey, participants clicked on the Qualtrics link. They first read a short information sheet outlining the study and relevant expectations. Once participants consented, they answered demographic questions and were then presented with the information that the images depict, a degree happiness and sadness and low arousal and high arousal. Using the scale (Figure 7 or Figure 8) describe how you feel about the item presented. The presented item would be either a non-recyclable can or bottle or a recyclable can or bottle. Then they were asked to mark the number of the figure that corresponds to how they feel about the item, (they were told that they could also use the boxes in between the numbers to make a more fine-grained assessment).

Valence and arousal

Valence ratings

There was no main effect of Recyclability, $F(1, 50) = .146$, $MSE = 14.83$, $p = .704$, $\eta^2p = .003$. Recyclable items ($M = 5.245$, $SE = .305$) did not differ from non-recyclable items ($M = 5.45$, $SE = .468$) in perceived valence. There was a main effect of Item type, $F(1, 50) = 7.789$, $MSE = 17.975$, $p = .007$, $\eta^2p = .135$. Cans were rated more negatively ($M = 4.52$, $SE = .525$) than bottles ($M = 6.176$, $SE = .260$). There was no interaction effect for Recyclability × Item type, $F(1, 50) = .031$, $MSE = 12.907$, $p = .861$, $\eta^2p = .001$. Participants differentiated between bottles and cans in their valence ratings, but recyclability itself did not drive valence perceptions.

Arousal ratings

There was a main effect for Recyclability, $F(1,50) = 5.295$, $MSE = 1.008$, $p = .026$, $\eta^2p = .096$. Recyclable items ($M = 5.814$, $SE = .235$) were rated as more arousing than non-recyclable items ($M = 5.49$, $SE = .269$). There was no main effect of Item type, $F(1, 50) = .429$, $MSE = 7.134$, $p = .515$, $\eta^2p = .009$. Bottles ($M = 5.529$, $SE = .326$) and cans ($M = 5.775$, $SE = .284$) did not differ significantly in arousal ratings. There was no interaction effect for Recyclability × Item type, $F(1, 50) = 1.407$, $MSE = 1.007$, $p = .241$, $\eta^2p = .027$. Participants showed stronger emotional engagement with recyclability, but not with item type itself.

A bivariate correlation analysis was conducted to explore relationships between valence, arousal, recyclability, item type, and NFI magnitude. No significant correlations between valence/arousal and the magnitude of the NFI were found, indicating that affective responses did not directly predict susceptibility to the illusion. Strong positive correlations were found between valence and arousal scores for the same item types, suggesting that participants who felt more positive about an item also tended to rate it as more arousing. A

significant correlation between NFI magnitudes for cans and bottles, $r(51) = .685$, $p < .001$, was found in the 40-item group, indicating a consistent bias across materials.

Summary

Perceived valence was influenced by item type (bottles vs cans), but not recyclability. Bottles were rated more positively than cans, suggesting pre-existing associations about material desirability. Arousal was influenced by recyclability but not item type. Recyclable items were rated as more arousing, indicating that participants may feel a stronger emotional response to “green” items. Neither valence nor arousal predicted NFI magnitude. These findings suggest that the NFI is not primarily driven by affective biases, but rather by cognitive heuristic processes such as averaging. A strong correlation was found between NFI magnitudes for bottles and cans, confirming a consistent error pattern across materials.

The absence of a direct link between valence/arousal and NFI magnitude suggests that the illusion is not simply a result of affective biases but is instead driven by fundamental cognitive heuristics. This contrasts with the vice-virtue framing hypothesis, which predicted that participants who viewed non-recyclable items as more negative and recyclable items as more positive would exhibit a stronger averaging effect.

However, the fact that recyclable items were rated as more arousing suggests that people do engage emotionally with recyclability—just not in a way that systematically distorts environmental impact judgements. This aligns with dual-process theories (Evans & Stanovich, 2013), which suggest that while emotions can influence decision-making, systematic biases like the NFI emerge from cognitive shortcuts rather than affective misjudgements.

Overall, these results reinforce the idea that the NFI is not category-bound, nor is it primarily an affective bias, but rather a domain-general cognitive illusion that persists across different materials and contexts. Future research should investigate alternative cognitive mechanisms, such as numerosity effects or fluency-based heuristics.

Discussion

The results of Experiment 2a revealed significant main effects of item type and quantity, but no main effects for estimate type or category. Participants judged plastic bottles as more environmentally harmful than tin cans, aligning with prior research suggesting that certain materials carry stronger environmental associations. Moreover, as the total quantity of items increased, so did perceived environmental harm—a pattern consistent for both bottles and cans. However, while the NFI was evident for the 40-item condition, participants' estimates in the 10- and 20-item conditions suggested a zero-footprint illusion—the mistaken belief that adding recyclable items results in no net increase in environmental harm. This highlights a cognitive distortion: participants failed to recognise that increasing total waste volume, even with recyclable additions, should logically increase environmental impact rather than maintaining it at the same level.

The finding that plastic bottles were judged as more environmentally harmful than tin cans suggests that participants relied on pre-existing environmental associations rather than purely numerical judgements. This aligns with research indicating that some materials are more readily associated with waste accumulation and pollution than others. However, the lack of a category effect suggests that the NFI is not constrained by domain-specific biases—instead, it operates as a general cognitive heuristic (Hilbert, 2011). The results further support the idea that participants engage in heuristic averaging when estimating environmental impact (Kahneman & Frederick, 2002), treating recyclable and non-recyclable items as functionally interchangeable rather than recognising the additive impact of waste. Additionally, valence, arousal, and cognitive reflectiveness (AOT-17) did not significantly predict susceptibility to the NFI, indicating that affective and dispositional factors were not primary drivers of the illusion in this study.

Unlike Experiment 1, Experiment 2a revealed a significant effect of item type, aligning with findings from Threadgold et al. (2022). This suggests that environmental impact

judgements may be influenced by item-specific associations rather than solely by category-based schemas. The discrepancy between Experiments 1 and 2a raises an important methodological consideration: in Experiment 1, houses and plastic bottles had little contextual coherence, making it unlikely that participants grouped them together in the same mental category. However, in Experiment 2a, plastic bottles and tin cans were more directly comparable, possibly making it easier for participants to apply category-based reasoning. This suggests that the NFI is not driven by information such as, "recyclable" or "environmentally certified", but instead emerges when items share an underlying conceptual link—a distinction that could inform future studies on semantic grouping and heuristic reasoning in environmental judgements.

The findings from Experiment 2a confirm that quantity significantly influences environmental impact estimations, with the NFI emerging most strongly in the 40-item condition. However, in the 10- and 20-item conditions, participants' estimates for the second (recyclable-added) condition remained similar to the first estimate, producing a zero-footprint illusion—the mistaken belief that adding recyclable items offsets the impact of non-recyclable waste rather than increasing total environmental harm. This pattern is consistent with previous findings (e.g., Holmgren et al., 2021), where participants failed to integrate additional quantities into their judgements. The fact that the NFI appears in the 40-item condition but not in lower-quantity conditions suggests a quantity threshold effect: people may only apply heuristic averaging when confronted with larger sets of items. This aligns with previous research on numerical cognition, which suggests that perceptual biases emerge more strongly as set size increases (Qu et al., 2024). While some studies (e.g., Holmgren et al., 2019) have tested interventions such as summation prompts to correct NFI errors, our results suggest that these approaches may only be necessary when the illusion is fully present (i.e., at higher quantities). Future research should examine whether threshold effects

could be mitigated by manipulating numerical presentation formats or explicitly prompting participants to sum rather than average.

Previous research has suggested that the NFI is influenced by cognitive style, particularly the fact resistance and dogmatism subscales of the AOT-17 (Threadgold et al., 2022). In Experiment 1 (Chapter 3) of the present thesis, fact resistance correlated with NFI susceptibility, aligning with prior findings, but dogmatism did not. Moreover, in Experiment 2a, no significant correlations were observed between AOT-17 subscales and NFI magnitude. This discrepancy suggests that the relationship between cognitive style and heuristic biases in environmental judgement may be task-dependent and potentially moderated by the perceived complexity of the judgement task, the framing of environmental decisions, or domain-specific knowledge. Future studies should investigate whether certain environmental contexts amplify the role of cognitive reflection in susceptibility to heuristic biases like the NFI.

The cross-category findings challenge several potential theoretical accounts of the NFI, particularly those that posit a category-specific basis for the effect (cf. Barsalou, 1983; Smith & Semin, 2004). The fact that the NFI persisted when participants judged items from different categories (e.g., plastic bottles vs tin cans) suggests that category-based schemas are not the primary driver of the illusion. According to category-based models, participants typically use distinct mental frameworks to evaluate environmental impact within specific categories (Zhao & Yu, 2016). However, the persistence of the NFI across categories suggests that participants rely on broad heuristics, such as averaging across all presented items, rather than using category-specific cognitive strategies. This aligns with research suggesting that people apply heuristic simplifications when faced with complex environmental judgements, even when object categories vary (Qu et al., 2024). Future research should refine these findings by focusing specifically on the 40-item group, where the NFI was most

pronounced, and testing whether interventions can disrupt heuristic averaging across mixed-category items.

The cross-category persistence of the NFI also undermines theories that suggest heuristic biases operate only within comparable item sets (cf. Tversky & Kahneman, 1974). If averaging heuristics were restricted to within-category comparisons, the NFI should have weakened or disappeared when participants evaluated bottles and cans together. However, the results indicate that participants continued to apply an averaging heuristic, suggesting that they were less sensitive to category differences than expected. This also challenges salience-based accounts of the NFI, which propose that participants should notice and weigh category differences (e.g., the distinct environmental effects of bottles vs. cans) when making judgements. Instead, the data suggest that participants largely ignored these distinctions, supporting the idea that the NFI emerges from a domain-general misapplication of heuristic reasoning rather than a category-bound cognitive bias.

The cross-category persistence of the NFI also challenges contextual dependence theories (Smith & Semin, 2004), which propose that judgements about environmental impact are strongly influenced by the specific context in which objects are evaluated. According to this perspective, the NFI should emerge only when participants perceive items as closely related within a given environmental domain (e.g., energy-efficient vs non-efficient houses). However, the fact that the illusion extended across categories (e.g., bottles vs. cans) suggests that contextual framing was not a necessary condition for the NFI to appear. Instead, participants applied the same heuristic reasoning across distinct product categories, reinforcing the idea that the NFI operates as a domain-general cognitive bias rather than one constrained by environmental context. This has implications for policy and messaging, as it suggests that public misconceptions about environmental impact may not be category-dependent but rather arise from broad cognitive simplifications. Future research should

examine whether framing manipulations (e.g., presenting mixed-category items within distinct environmental narratives) can mitigate or exacerbate the illusion.

Another key implication of the cross-category NFI is that it undermines category-specific accounts of environmental cue processing. Some theories propose that people associate eco-friendly labels with certain product types (e.g., houses vs. cars) and that these associations drive heuristic misjudgements. However, our results indicate that participants applied the same erroneous averaging heuristic across distinct categories, suggesting that category-specific eco-labels were not the primary driver of the NFI. Instead, participants responded to general eco-friendly cues in a way that overrode categorical distinctions. This finding aligns with previous research on heuristic reliance (Hilbert, 2011) and suggests that public misperceptions about sustainability may be less about specific product types and more about how environmental information is cognitively processed. Future research should examine whether eco-labels influence NFI magnitude differently in same-category vs. cross-category contexts—for instance, testing whether an "eco-friendly" label on a recyclable can impacts environmental judgements differently than the same label on a plastic bottle.

Conclusion

Further clarity and replication are necessary to refine our understanding of the cognitive mechanisms underlying the NFI. The key finding that the illusion extends across product categories suggests that it is driven by general cognitive heuristics, such as averaging strategies or reliance on eco-friendly cues, rather than category-specific knowledge. Given that the NFI was most pronounced in the 40-item condition, future studies should focus on replicating and expanding this effect under controlled conditions. Additionally, since valence, arousal, and actively open-minded thinking (AOT-17) did not predict individual differences in NFI susceptibility, alternative cognitive processes should be examined. A promising direction is to test the relationship between working memory capacity and the NFI, using measures such as the SYMSPAN task (spatial working memory) and the

OSPAN task (verbal working memory). If the NFI correlates with working memory limitations, this would suggest that it arises due to capacity constraints in integrating environmental information, rather than from a purely affective or category-based bias. Investigating these mechanisms could provide important insights into cognitive barriers to accurate environmental judgements, with potential implications for educational interventions and sustainability messaging strategies.

Chapter 5

Experiment 3: Working Memory Capacity and the Averaging Bias in the NFI

Reducing carbon emissions can be approached in various ways, including fostering community-led initiatives, granting individuals autonomy over climate action, and promoting social reciprocity in environmental engagement (Huang et al., 2017). A key aspect of this effort is ensuring the proper disposal of waste, preventing recyclable and reuseable items from being unnecessarily discarded into landfills (Lancashire.gov, n.d.; Foster, 2020). When items are disposed of in landfills instead of being recycled, new products must be produced from raw materials, exacerbating environmental harm. For example, recycling 1,000 kilograms of aluminium cans prevent the release of approximately 9,000 kilograms of CO_2 into the atmosphere. This waste crisis has only intensified during the COVID-19 pandemic, as consumption patterns and disposal habits have changed (Ford, 2020; Adyel, 2020). Hence, investigating a fuller catalogue of item types and the consequences for recycling decisions is crucial.

Across this series of experiments, the role of item type in the NFI has produced contradictory results. In Experiment 1, there was no significant difference between item types (houses vs. plastic bottles), with the NFI occurring to the same degree in both cases. This suggests that the bias applies broadly across different categories, including houses, cars, food, and plastic bottles. However, in Experiment 2, differences emerged when both category type and quantity were manipulated, reinforcing the idea that the NFI is driven by generalised cognitive mechanisms—such as averaging heuristics or reliance on eco-friendly labels—rather than by category-specific or contextual factors. This provides some support for the averaging bias hypothesis, which suggests that individuals mentally integrate environmental impact either by weighing quantities or simplistically incorporating a pro-environmental element into their judgement. However, prior research indicates that removing

symbolically significant phrases (e.g., “organic,” “eco-friendly”) does not consistently reduce or enhance the NFI (Holmgren et al., 2019; Kusch & Fiebelkorn, 2019). If the averaging bias was the sole explanatory mechanism, then environmental impact judgements should be straightforwardly calculable and statistically predictable. Yet, Experiment 2 challenges this assumption. Specifically, environmental impact estimates for the 10- and 20-item groups did not follow a predictable pattern. Despite an increase in the number of non-recyclable items, participants' estimates remained largely unchanged, rather than increasing (to reflect the total quantity) or decreasing (to reflect the addition of recyclable elements). This unexpected stagnation in judgements complicates the notion that the NFI is solely a result of an averaging bias and suggests that additional cognitive factors may be at play.

While the ability of the NFI to extend across categories suggests that item type is not a decisive factor in its emergence, it raises the question of why some previous studies failed to elicit the illusion with certain stimuli (Gorissen & Weijters, 2016; Threadgold et al., 2022). A related issue is why plastic is perceived as more environmentally harmful than tin cans. Is this due to pre-existing knowledge, explicit heuristics learned through education, or implicit information absorbed through media exposure? The distinction between recyclable and non-recyclable materials may elicit cognitive responses that were not apparent when comparing houses and plastic bottles.

Although symbolic labels (e.g., “eco-friendly”) do not appear to influence the NFI, and individual differences in factors such as valence, arousal, and actively open-minded thinking (AOT-17) do not correlate with the effect, these factors may still shape broader schemas that contribute to the generalisation of an averaging bias. Andersson et al. (2024) propose that multiple biases may be at play in the NFI, a view supported by the results of Experiment 2. Specifically, in that experiment, groups estimating the environmental impact of 10 conventional + 20 environmentally friendly items and 20 conventional + 20 environmentally

friendly items did not show the NFI. However, when the quantity increased to 40 conventional + 20 environmentally friendly items, the illusion was observed.

This suggests the presence of a threshold effect, where the NFI only emerges under certain conditions. This pattern has been referred to as a "static boundary condition" (Busse et al., 2017), meaning that the illusion does not occur at all levels of quantity but rather at specific points where cognitive biases, such as averaging heuristics, are more likely to be triggered. Importantly, while environmental impact estimates increased as expected between groups (e.g., the 40-item group produced higher estimates than the 10-item group, serving as a manipulation check), the way participants integrated additional recyclable items did not follow a predictable pattern.

The emergence of a threshold effect in the NFI suggests that certain cognitive constraints must be met for the illusion to appear. But what happens when these constraints are not satisfied? Experiment 2 revealed cases where participants' estimates remained unchanged despite an increase in quantity—a pattern identified as the zero-footprint illusion (Andersson et al., 2024; Holmgren et al., 2021; Threadgold et al., 2022). Unlike the NFI, which reflects a miscalculation of environmental impact, the zero-footprint illusion represents a failure to update judgements altogether. Experiment 2 demonstrated that instead of consistently increasing in line with the total number of items added, environmental impact estimates for smaller quantity groups stagnated.

While both illusions distort environmental judgements, they do so in fundamentally different ways. The NFI reflects faulty integration, where individuals mistakenly assume that eco-friendly additions actively reduce overall harm due to an inappropriate averaging heuristic. In contrast, the zero-footprint illusion arises from a failure to update cognitive representations. This distinction hints at different cognitive mechanisms underlying the two illusions. The NFI appears to arise from faulty integration, where individuals apply an inappropriate averaging heuristic instead of summing environmental impact. In contrast, the

zero-footprint illusion may reflect a stagnation in cognitive updating, potentially due to a heuristic simplification that leads participants to disregard the new quantities. For instance, the NFI overestimates the positives in the environmentally friendly additions, resulting in a reduction of the assessment of overall harm. The stagnation of estimates that occurs within a zero footprint happens when estimates of overall harm remain constant despite the increase in quantity. The estimate of overall environmental harm is the same when an increase in quantity does not impact the estimate of environmental harm and the overall assessment remains unchanged. The presence of the zero-footprint illusion in lower-quantity conditions suggests that individuals may unconsciously treat small additions of recyclable materials as negligible, failing to incorporate them into their overall assessments.

The cognitive mechanisms underlying the NFI and zero-footprint illusion suggest that both distortions arise from limitations in information processing, which his raises an important question: Which individual differences determine susceptibility to these biases?

Working Memory Capacity and the NFI

The results of Experiment 2 suggest that the NFI is not simply a function of category type, symbolic labels, or quantity alone. Instead, its emergence appears to depend on specific cognitive constraints, including a potential threshold effect. Given that individuals must integrate multiple pieces of information—both harmful and eco-friendly actions—into a single environmental impact judgement, cognitive processing limitations may play a key role in shaping these biases. If the NFI arises from a heuristic-driven simplification of environmental information, then individual differences in cognitive capacity may help explain why some people are more susceptible to the illusion than others. Previous research has shown that traits such as actively open-minded thinking and compensatory green beliefs are either weakly related to the NFI or inconsistently correlated across studies (MacCutcheon et al., 2020; Threadgold et al., 2022; Holmgren et al., 2018; Chapter 3 and 4). The absence of strong associations with these questionnaire-based measures raises the possibility that the

NFI is instead shaped by cognitive constraints, particularly limitations tied to working memory capacity (WMC). Regardless of general cognitive ability, biases such as myside bias—the tendency to evaluate evidence in a way that favours one's prior beliefs—are still prevalent (Stanovich & West, 2007). WMC refers to an individual's ability to temporarily hold and manipulate information in service of complex cognitive tasks such as reasoning, comprehension, and decision-making. It is a core component of executive function, playing a crucial role in the attention regulation and cognitive control. Because WMC is limited, individuals may struggle when a task requires integrating multiple pieces of competing information. In complex reasoning tasks, such as problem-solving and logical inference, WMC is essential for tracking multiple variables, updating information as it is processed, and suppressing irrelevant distractions (Carpenter et al., 1990). Research suggests that individuals with higher WMC are generally more effective at filtering out irrelevant information and maintaining focus on task-relevant elements, leading to better performance in decision-making tasks (cf. Kane & Engle, 2003).

There are several reasons why WMC may be particularly relevant to the NFI. First, in the NFI paradigm, individuals must evaluate both harmful and eco-friendly actions and integrate them into a single judgement of environmental impact. This requires holding and processing multiple pieces of information simultaneously. Those with lower WMC may struggle to manage both sources of information at once and may default to heuristic thinking, such as assuming that the presence of eco-friendly actions cancels out environmental harm. In contrast, individuals with higher WMC are more likely to process both pieces of information accurately and avoid such simplifications. Supporting this, Stanovich and West (2000) found that individuals with higher WMC are better able to resist cognitive biases in tasks requiring the evaluation of conflicting information.

Second, WMC is closely tied to inhibitory control—the ability to suppress irrelevant or misleading information. In the context of the NFI, individuals with lower WMC may find it

difficult to override the intuitive but incorrect belief that eco-friendly actions automatically offset harmful ones. Conversely, those with higher WMC are more likely to inhibit misleading heuristics, leading to more accurate environmental impact estimates (cf. Conway et al., 2003).

Third, assessing environmental impact requires individuals to reconcile competing data points—harmful actions on one side, eco-friendly actions on the other. Because this type of integration is cognitively demanding, individuals with lower WMC may fail to maintain both types of information in their working memory at the same time. As a results, they may overweight one aspect (e.g., the eco-friendly actions) while underestimating the overall environmental harm. In contrast, those with higher WMC are better able to balance conflicting information, leading to more accurate and less biased judgements. Oberauer et al. (2003) demonstrated that individuals with higher WMC perform better at tasks requiring the integration of multiple sources of information, particularly when those sources conflict.

Fourth, Individuals with higher WMC exhibit greater mental flexibility, allowing them to revise their judgements when confronted with new or conflicting information. In the NFI, individuals with higher WMC may be more likely to reevaluate their assumption that eco-friendly actions cancel out harm, leading to more accurate assessments. De Neys and Schaeken (2007) found that individuals with higher WMC are better able to detect and revise faulty initial judgements, especially in tasks that require weighing conflicting elements.

Although traits such as actively open-minded thinking or compensatory green beliefs offer limited explanatory power for the NFI, WMC provides a cognitive basis for understanding how individuals process and integrate environmental information. If the NFI is partially driven by heuristic simplifications, then individuals with greater cognitive capacity should be less prone to these distortions. Although this is the first study to directly test the link between WMC and the NFI, prior research has suggested that WMC is relevant to environmental reasoning. For example, concept mapping has been used to reduce cognitive

load and improve environmental decision-making (Watson et al., 2023). By directly examining how WMC influences bias susceptibility in environmental impact judgements, this study seeks to clarify the cognitive constraints that underpin the NFI.

While WMC may help explain individual differences in susceptibility to the NFI, it is unlikely to be the sole determinant. Even individuals with higher cognitive capacity may still exhibit biased judgements, suggesting that the underlying distortion is not eliminated but may instead manifest in different ways. If the NFI is primarily driven by averaging bias, then the key distinction may not be whether individuals fall prey to the illusion, but how they engage in averaging. This raises an important question: does WMC influence the specific type of averaging individuals rely on when estimating environmental impact? The following section explores this possibility by considering whether high and low WMC individuals process environmental information differently, leading to qualitatively distinct manifestations of the same bias.

Two Faces of Averaging Bias?

The discussion of WMC suggests that individuals with greater cognitive resources may be better equipped to process conflicting environmental information, reducing their susceptibility to the NFI. However, WMC may not entirely eliminate the bias, and it is possible that individuals with both high and low WMC are susceptible to the same underlying cognitive distortions—albeit through different mechanisms. If the NFI is rooted in averaging bias, then the way individuals engage in averaging may differ depending on their cognitive capacity. This raises the question: Do high and low WMC individuals process environmental impact judgements in fundamentally different ways?

It is plausible that both high and low WMC individuals fall prey to averaging bias, but the key distinction may lie in how they average environmental impact. For example, both higher and lower WMC individuals may be prone to the averaging bias, but a difference may lie in the type of averaging they use. Those with higher WMC may engage in quantitative

averaging, computing and arithmetic mean of harmful and eco-friendly components—despite this being an inappropriate strategy in the context of environmental impact judgements. In contrast, individuals with lower WMC may rely on qualitative heuristics, using less precise mental shortcuts that still lead to distorted judgements. If both high and low WMC participants apply averaging rather than summation to environmental impact estimates, differences in response patterns may emerge. Specifically, if high WMC individuals engage in quantitative averaging, their estimates may show a more systematic arithmetic pattern—albeit still biased. In contrast, low WMC individuals may show more variable heuristic-based responses due to their reliance on qualitative judgements.

If the NFI stems from quantitative averaging, then its magnitude should be systematically related to WMC. Arithmetic mean calculations require key cognitive processes, including: summation (keeping track of and adding multiple values), division (dividing the sum by the number of values), and simultaneous processing (managing several pieces of information, such as the running total and item count). There is substantial evidence that WMC is critical for arithmetic tasks that require handling multiple pieces of information simultaneously, including mean calculations (DeStefano & LeFevre, 2004; Imbo & Vandierendonck, 2007; Raghubar et al., 2010). If quantitative averaging drives the NFI, then a systematic relationship between WMC and the strength of the illusion should be observed, with high WMC individuals showing a more predictable arithmetic pattern.

The Present Experiment

To isolate the cognitive mechanisms underlying the NFI, the current investigation is refined using the findings from Experiments 1 and 2. First, in relation to item type (Experiment 1), initially no significant difference was found between houses and plastic bottles. To further explore item type, Experiment 2 incorporated additional recyclable materials (plastic bottles and cans). However, this manipulation produced a statistical difference, suggesting that certain item types may be judged differently in terms of

environmental impact. Second, regarding category type (Experiment 2), the results indicate that the NFI occurs across item categories, reinforcing the idea that the illusion is driven by general cognitive mechanisms (e.g., averaging heuristics) rather than category-specific or contextual factors. As this is the first study to examine this effect across multiple item categories, this condition was replicated in the current experiment. Third, with respect to quantity manipulation, prior research (Andersson et al., 2024) has examined how the NFI responds to changes in quantity, particularly in housing-related judgements. However, these studies did not hold the environmental factor constant while manipulating conventional quantities. In Andersson et al.'s study, the addition of "green" houses (either large (150) or small (10)) to 30 conventional houses produced an NFI. However, when Experiment 3 maintained a fixed ratio between conventional and green houses (4:1, 40:10, or 400:100), results diverged from expectations based on the averaging bias. Notably, the smallest ratio (4 conventional + 1 green house) produced a zero-footprint illusion where the perceived environmental impact remained unchanged despite an increase in quantity. This suggests that the NFI may be particularly sensitive to the quantity of either conventional items or of environmentally friendly additions, with small increments failing to trigger the illusion as strongly as larger ones. Thus, it was anticipated that Experiment 3 would help clarify whether the NFI weakens when a constant quantity of green items is maintained, rather than when environmental additions vary unpredictably.

The emergence of the zero-footprint illusion in the 10- and 20-item groups of Experiment 2 suggests that environmental impact is not always processed additively. If the addition of recyclable materials fails to influence estimates meaningfully, it may indicate a threshold effect, where individuals only begin to factor in environmental impact at a higher level of accumulation. Given this, the current study will not focus on zero-footprint conditions, as they do not meet the criteria for a true NFI. Instead, it concentrates on the only condition

that produced an NFI: 40 conventional items (initial estimate) vs. 40 conventional + 20 environmentally friendly items (revised estimate).

The NFI is expected to emerge consistently for both cans and bottles, indicating that item type is not a decisive factor. Furthermore, the magnitude of the illusion is predicted to remain stable across same-category and cross-category conditions, reinforcing the notion that general cognitive mechanisms underlie the effect. Additionally, if WMC influences environmental impact judgements, individuals with higher WMC should demonstrate more systematic, arithmetic-based estimates, whereas those with lower WMC are expected to rely on more variable, heuristic-driven responses.

Method

Design

The study employed a 2 (Item: cans, bottles) × 2 (Estimate: non-recyclable, non-recyclable plus recyclable) × 2 (Category: same category, cross-category) within participants design with the order of presentation counterbalanced between participants. The dependent variable (DV) was the estimate of environmental impact given on a 1-100-point scale.

Participants

Participants were recruited via Prolific (www.prolific.com). A UK population with English as a first language was used. Power ANalysis for GEneral Anova designs (PANGEA; Westfall 2016) was used to indicate sample size (N = 137) with total observations of 1096 permits a power of 100% to detect a medium effect size at d = .45 with a = .05 and D = .24. A total of 137 participants (46% male) completed the study. The mean age was 29.06 years (SD = 4.65). As with Experiment 2 PANGEA was used due to the quantity of independent variables, to enable the cognitive complexities faced in real world recycling challenges. The sample size was chosen to accommodate the complexity of the independent variables and to ensure statistical robustness in measuring variability in environmental impact estimations.

Materials and Procedures

The materials and procedures for the environmental impact estimation task were identical to those used in Experiments 1 and 2, except for the following modifications. The study focused exclusively on the statistically significant 40 non-recyclables (first estimate) and 40 non-recyclables + 20 recyclable items (second estimate) conditions. The full list of conditions is presented in Table 7, and Figure 9 illustrates an example of the cross-category stimuli.

Table 7.

The experimental conditions deployed in Experiment 3: Non-recyclable + recyclable estimates.

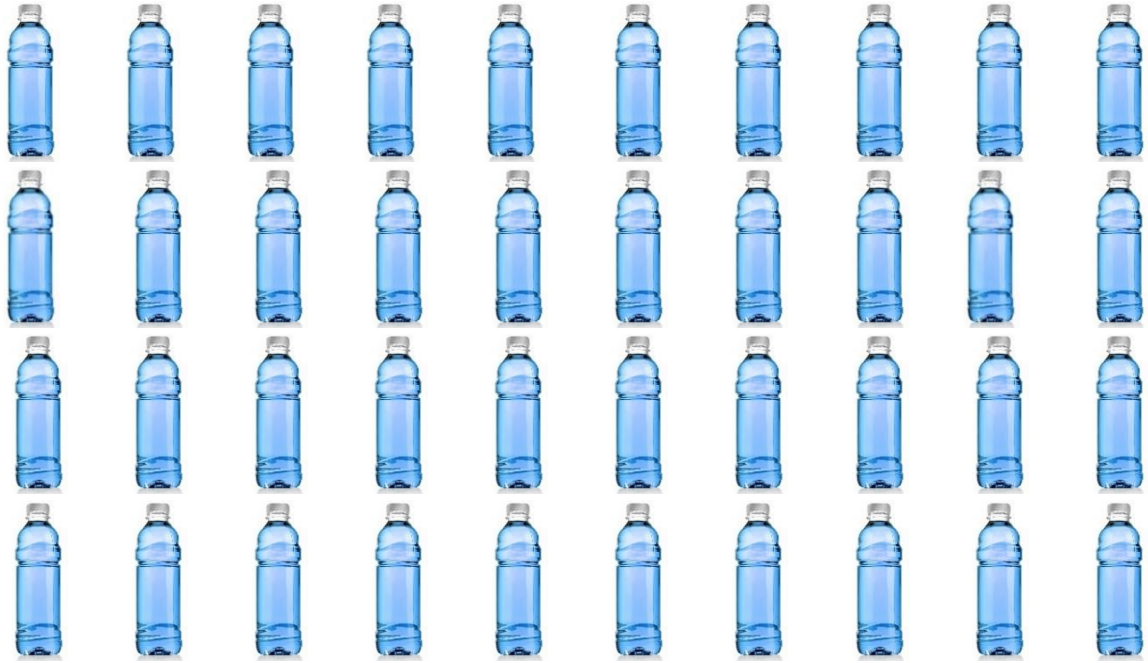
Materials	**Non-recyclable (First estimate)**	**Non-recyclable plus recyclable (Second estimate)**
Same category Cans	40 non-recyclable cans	40 non-recyclable cans + 20 recyclable cans
Same category Bottles	40 non-recyclable plastic bottles	40 non-recyclable plastic bottles + 20 recyclable plastic bottles
Cross-category Cans	40 non-recyclable cans	40 non-recyclable cans + 20 recyclable bottles
Cross-category Bottles	40 non-recyclable bottles	40 non-recyclable bottles + 20 recyclable cans

Figure 9. *An illustration of one of the environmental judgements within Experiment 3 (cross-category).*

40 non-recyclable bottles, 40 non-recyclable bottles +20 recyclable plastic bottles

These non-recyclable bottles--presented in blue--represent 40 bottles on one shelf. All these bottles are made from the same materials and have the same characteristics.

40 non-recyclable bottles



What is the total environmental impact for the 40 items altogether?

Make your estimate on a scale below from 1 (low environmental impact) to 100 (high environmental impact).

As a reference point for your estimations, consider that a shelf with 22 non-recyclable plastic yoghurt tubs would score 50 (midway) on the scale.

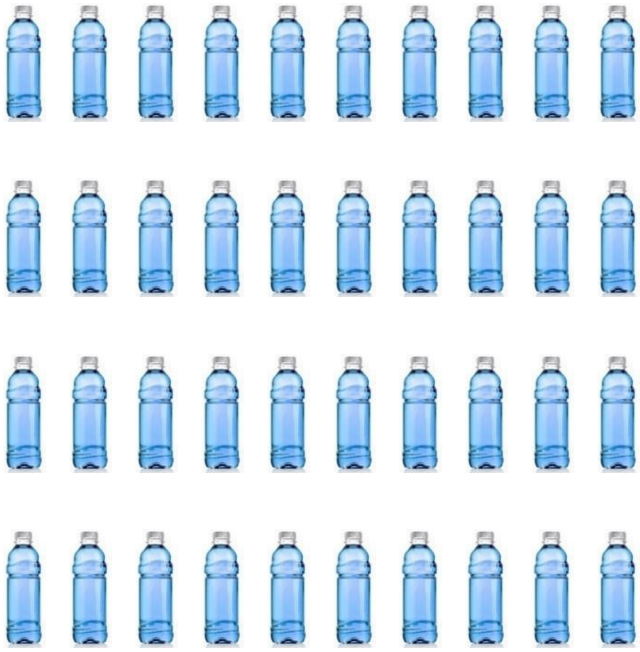
low environmental impact high environmental impact

1 100

Now imagine 20 recyclable bottles—presented in green—have been added to the 40 non-recyclable bottles on the shelf.

Recyclable bottles have a **low** environmental impact

40 non-recyclable bottles



20 recyclable bottles

What is the total environmental impact for all the items together?

Make your estimate on a scale below 1 (low environmental impact) to 100 (high environmental impact).

low environmental impact — high environmental impact

1 — 100

Working Memory Capacity Tasks

Following the environmental impact estimation task, participants completed two standardised online tasks designed to assess WMC, the Symmetry Span (SymSpan) and Operation Span (OSpan) tasks. These were adapted from Foster et al. (2015) and Hicks et al. (2016) and took approximately 30 minutes to complete.

The design followed the protocol established by Unsworth et al. (2005), which incorporates response-time constraints to prevent participants from engaging in excessive rehearsal of to-be-remembered items. Prior to beginning the experimental trials, participants completed practice trials to familiarise themselves with the tasks and establish a baseline response time. During the main trials, they were required to maintain their response time within 2.5 standard deviations of this baseline. This constraint effectively limits the opportunity for rehearsal, ensuring that working memory, rather than short-term memory strategies, is being measured (Foster et al., 2015).

In the SymSpan task, each block comprised trials with three sets of sizes 2 to 5 (e.g., 3 sets of 2, 3 sets of 3…3 sets of 5). Each trial began with the presentation of a 4 × 4 grid, where a single red square was displayed. Participants were required to remember its location. The task then advanced automatically based on the participant's timed response, displaying an 8 × 8 grid with black squares forming a pattern. Participants determined whether the pattern was vertically symmetrical, responding true or false. This sequence continued for 2 to 5 iterations, with each iteration alternating between a memory task (4 × 4 grid) and a symmetry judgement task (8 × 8 grid). After completing the final iteration, a blank 4 × 4 grid was shown, and participants were required to recall and select the previously displayed red square locations in the correct serial order.

The OSpan task followed a similar structure but focused on verbal working memory. Each block comprised trials with three sets of each length from 2-7 (e.g., 3 sets of 2, 3 sets of 3…3 sets of 7). In each trial, participants were first presented with a single letter to

remember. After viewing the letter, they completed an arithmetic verification task where they evaluated a mathematical equation and its proposed answer by selecting either true or false. This letter-memorisation and arithmetic problem-solving sequence repeated for 3 to 7 iterations. After the final iteration, participants were prompted to recall and select the letters they had seen, entering them in the correct serial order.

Throughout both tasks, participants received performance feedback after each trial. The feedback included their memory accuracy for that trial as well as their overall performance on the distractor task, displayed as a percentage of correct responses.

These complex span tasks were chosen over simple span tasks (e.g., digit span) because they offer a more comprehensive measure of individual differences in WMC. Unlike simple span tasks, which primarily assess short-term memory storage, complex span tasks evaluate an individual's ability to engage with a focal task while simultaneously managing competing cognitive demands (Hughes et al., 2013; Kane & Engle, 2003). This feature makes them particularly suitable for studying cognitive functions related to executive control, attentional regulation, and working memory resource allocation.

Actively Open-Minded Thinking (AOT-17)

After completing the WMC tasks, participants completed the Actively Open-Minded Thinking (AOT-17) Scale (Svedholm-Häkkinen & Lindeman, 2018), 2019; see Experiment 1 and 2).

Results

Experiment 3

The results of Experiment 3 provide further insight into how individuals estimate environmental impact when recyclable materials are introduced. A three-way within participants repeated measures ANOVA examined the effects of item type (cans vs bottles), estimate type (non-recyclable vs non-recyclable + recyclable), and category type (same-

category vs cross-category), on participant's environmental impact judgements. The means and standard deviations for all independent variables are shown in table 8.

A significant main effect of item type emerged, indicating that participants judged cans (M = 68.75, SE = 1.38) as having a lower environmental impact than plastic bottles (M = 72.19, SE = 1.30), $F(1, 136) = 9.148$, $MSE = 354.033$, $p = .003$, $\eta^2p = .063$. This aligns with previous research suggesting that certain materials are perceived as more harmful than others, possibly due to pre-existing beliefs about their recyclability and environmental impact. A second key findings was the significant main effect of estimate type, with environmental impact ratings decreasing when a recyclable component was added. Participants rated the non-recyclable-only condition (M =73.55, SE = 1.28), as having a higher environmental impact than the non-recyclable + recyclable condition (M = 67.38, SE = 1.47), $F(1, 136) = 22.996$, $MSE = 453.289$, $p < .001$, $\eta^2p = .145$. This finding is consistent with the NFI, whereby individuals incorrectly assume that adding eco-friendly elements reduces overall environmental harm rather than summing the total impact of all items. Interestingly, no significant main effect of category type was found, $F(1, 136) = 1.131$, MSE = 111.675, $p = .290$, $\eta^2p = .008$, suggesting that whether recyclable items were from the same or a different category did not influence participant's estimates. In other words, the NFI appeared to persist regardless of whether recyclable additions matched the material of the non-recyclable items or were from a different category.

Further analyses explored whether these factors interacted in shaping environmental impact judgements. A significant Item × Estimate interaction was observed, $F(1, 136) = 6.591$, $MSE = 70.180$, $p = .011$, $\eta^2p = .046$, indicating that when recyclable materials were introduced, estimates of environmental impact systematically decreased across both cans and bottles. This finding suggests that the NFI applies similarly to different materials.

The interaction between item type and category type approached significance, $F(1, 136) = 3.333$, $MSE = 149.900$, $p = .070$, $\eta^2p = .024$, with slightly less variability in cross-

category conditions compared to same-category conditions. However, this effect was not statistically robust. A similar trend was seen in the estimate type × category type interaction, which was marginally significant, $F(1, 136) = 3.876$, $MSE = 71.735$, $p = .051$, $\eta^2p = .028$, suggesting that category pairing may influence how individuals perceive the environmental impact of mixed waste streams, though the effect was not strong enough to draw firm conclusions. Finally, the three-way interaction between item type, estimate type, and category type was non-significant, $F(1, 136) = .038$, $MSE = 55.176$, $p = .846$, $\eta^2p = .000$, confirming that the combined influence of all three factors did not create an additional effect beyond the individual and pairwise interactions.

To break down the significant 2-way interaction, pairwise comparisons revealed a significant mean difference ($p < .001$) in environmental impact estimates between the first and second estimates for bottles ($M = 7.47$, $SE = 1.43$), and a significant mean difference ($p < .001$) between the first and second estimates for cans ($M = 4.86$, $SE = 1.33$).

Table 8

The means and standard deviations for plastic bottles and cans in the same category and cross category conditions for the non-recyclable (first estimate) and addition recyclable condition (second estimate) for each presentation.

Descriptive Statistics			
	Mean	Std. Deviation	N
Bottles: 1st estimate same category	75.71	18.905	137
Bottles: 1st estimate cross category	76.13	17.078	137
Bottles: 2nd estimate same category	69.34	18.183	137
Bottles: 2nd estimate cross category	67.57	20.041	137
Cans: 1st estimate same category	69.71	20.101	137
Cans: 1st estimate cross category	72.66	18.823	137
Cans: 2nd estimate same category	65.76	19.495	137
Cans: 2nd estimate cross category	66.87	19.205	137

Actively Openminded Thinking AOT-17

To investigate whether individual differences in cognitive style influence susceptibility to the NFI, a bivariate correlational analysis was conducted using the AOT-17 scale and the magnitude of the NFI which was computed as the difference between the environmental impact estimate for the non-recyclable-only condition and the estimate given when

recyclable items were added. Specifically, Magnitude of NFI = First Estimate - Second Estimate, where a higher magnitude value indicates a stronger NFI, as it reflects a greater reduction in perceived environmental harm following the addition of recyclable elements. Overall, AOT-17 scores were not significantly correlated with the magnitude of the NFI across any condition, including both same-category and cross-category conditions. However, a weak but significant positive correlation was found between AOT-17 scores and the NFI for cans, r (135) =.170, p =.047, suggesting that individuals who scored higher in open-minded thinking showed a greater resistance toward the NFI when evaluating cans. This pattern, however, was not observed for bottles or cross-category conditions. No association was found between the magnitude of the NFI and the four subscales of the AOT-17 (dogmatism, fact resistance, liberalism, and belief personification).

Further analysis entailed a series of multiple regression analysis which tested whether the AOT-17 subfactors could predict the NFI magnitude for different item conditions. None of these subfactors significantly predicted NFI magnitude for bottles, bottles + cans, cans, or cans + bottles (all p-values > .05; bottles, $F(4,132) = .755$, $p = .556$, $R^2 = .022$, bottles + cans, $F(4, 132) = 1.122$, $p = .349$, $R^2 = .033$, cans, $F(4, 132) = 1.138$, $p = .342$, $R^2 = .033$, cans + bottles, $F(2, 132) = .578$, $p = .679$, $R^2 = .017$). These findings are generally consistent with Experiment 1 and 2 and in contrast with Threadgold et al. (2022), who reported associations between open-minded thinking and susceptibility to the NFI. The lack of significant relationships suggests that the NFI is primarily driven by heuristic processing rather than cognitive style differences. Table 9 is presented to show all the AOT-17 scores and the subfactors with the magnitude for the NFI for each stimuli presentation.

Table 9. *Correlation matrix (Pearson correlation coefficients) for the AOT and its subscales and the magnitude of the NFI in the four conditions (bottles, bottles + cans, cans, cans + bottles) in Experiment 3.*

		Dogmatism	Fact resistance	Liberalism	Belief personification	AOT17
Magnitude of NFI for bottles	Pearson Correlation	.043	.025	.147	-.005	.063
	Sig (2-tailed)	.617	.774	.088	.950	.465
Magnitude of NFI for bottles + cans	Pearson Correlation	-.072	-.077	.081	.076	-.025
	Sig (2-tailed)	.406	.372	.350	.379	.779
Magnitude of NFI for cans	Pearson Correlation	.133	.104	.133	.101	.170*
	Sig (2-tailed)	.121	.225	.122	.240	.047
Magnitude of NFI for cans + bottles	Pearson Correlation	-.071	-.030	.081	-.039	-.041
	Sig (2-tailed)	.409	.725	.349	.649	.637

* Correlation is significant at the 0.05 level (2-tailed).

Working memory (OSpan, SymSpan)

For both the OSpan and SymSpan tasks, the absolute WMC score was computed (see Forster et al., 2015). This is the sum of only those trials in which the participant correctly recalled all items in the correct order. The formula therefore, is the total number of items correctly recalled only in fully correct trials. For example, if the participant correctly

recalled five full sets of three items but makes a mistake in other trials, their absolute score is 15 (3 × 5).

To assess whether WMC influenced NFI magnitude, separate multiple regression analyses were conducted, using OSpan and SymSpan scores as predictors. These analyses examined four conditions, corresponding to the different item pairings used in the study: Bottles + bottles, bottles + cans, cans + cans, and cans + bottles. The results revealed that neither OSpan nor SymSpan scores significantly predicted the magnitude of the NFI in any condition (bottles + bottles, $F(2, 128) = .776$, $p = .462$, $R^2 = .012$, bottles + cans $F(2, 128) = .286$, $p = .752$, $R^2 = .004$, + cans $F(2, 128) = .237$, $p = .789$, $R^2 = .004$, and cans + bottles $F(2, 128) = .191$, $p = .826$, $R^2 = .003$. This suggests that individual differences in WMC did not determine how strongly participants exhibited the illusion.

Similarly, correlational analyses were conducted to examine potential relationships between WMC and NFI magnitude. These analyses revealed no significant correlations, further indicating that WMC was not a key factor in shaping participants' environmental impact estimates.

Taken together, these findings suggest that the NFI emerges independently of working memory capacity. Whether an individual has a high or low WMC, their environmental judgements appear to be similarly influenced by the illusion, implying that the cognitive biases underlying the effect may not be driven by differences in executive function or attentional control. Table 10 is presented below for the Ospan and SymSpan relationship with the magnitude of the NFI.

Table 10.

Correlation matrix (Pearson correlation coefficients) for the OSpan, SymSpan and Composite WMC and the magnitude of the NFI in the four conditions (bottles, bottles plus cans, cans, cans plus bottles).

		Magnitude of NFI for bottles	Magnitude of NFI for bottles plus cans	Magnitude of NFI for cans	Magnitude of NFI for cans plus bottles
OSPAN	Pearson Correlation	-.079	-.040	.021	-.047
	Sig (2-tailed)	.359	.645	.808	.587
SYMSPAN	Pearson Correlation	-.107	-.065	.049	-.054
	Sig (2-tailed)	.226	.461	.582	.544
COMPOSITE WMC	Pearson Correlation	-.108	-.060	.023	-.073
	Sig (2-tailed)	.214	.491	.791	.400

* Correlation is significant at the 0.05 level (2-tailed).

AOT-17 and Working Memory capacity

To examine whether AOT-17 and WMC predict the magnitude of the NFI, four multiple regression analyses were conducted. The independent variables in these models were AOT-17 scores and combined WMC, measured through Operation Span (OSpan) and Symmetry Span (SymSpan) tasks. The dependent variable was the NFI magnitude across four conditions: (1) bottles + bottles, (2) bottles + cans, (3) cans + cans, and (4) cans + bottles. The results indicated that neither AOT-17 nor WMC significantly predicted the NFI magnitude in any of these conditions. Specifically, for bottles + bottles, the regression model was non-significant, $F(2, 132) = .859$, $p = .426$, $R^2 = .013$, suggesting that only 1.3% of the

variance in the NFI could be explained by AOT-17 and WMC. Similarly, for bottles + cans, the regression model was also non-significant, $F(2,132) = .418$, $p = .659$, $R^2 = .006$, indicating no meaningful relationship. The same pattern emerged for cans with cans, $F(2, 132) = 1.886$, $p = .156$, $R^2 = .028$, and for cans + bottles, $F(2, 132) = .589$, $p = .556$, $R^2 = .009$, demonstrating that neither AOT-17 nor WMC significantly influenced participants' susceptibility to the NFI.

To further investigate whether specific aspects of AOT-17 played a role in shaping the illusion, four additional multiple regression analyses were conducted, incorporating the AOT-17 subscales: Dogmatism, Fact Resistance, Liberalism, and Belief Personification, alongside combined WMC scores. However, none of these models yielded significant results. For bottles + bottles, the regression model was non-significant, $F(5, 129) = .674$, $p = .644$, $R^2 = .025$, indicating that only 2.5% of the variance in the NFI could be explained by these cognitive factors. The model for bottles + cans similarly failed to reach significance, $F(5, 129) = 1.009$, $p = .415$, $R^2 = .038$, as did the models for cans + cans, $F(5, 129) = .888$, $p = .492$, $R^2 = .033$, and cans + bottles, $F(5, 129) = .579$, $p = .716$, $R^2 = .022$. These findings suggest that individual differences in cognitive flexibility, belief reasoning, or resistance to misinformation do not systematically influence the NFI.

To assess whether WMC predicted AOT-17 scores, an additional regression analysis was conducted, testing whether combined WMC scores (OSpan and SymSpan) could account for variance in AOT-17 performance. However, the results revealed no significant relationship, $F(2, 133) = 1.171$, $p = .281$, $R^2 = .009$, indicating that WMC does not predict participants' ability to engage in actively open-minded thinking.

Taken together, these findings suggest that neither AOT-17 nor WMC plays a decisive role in susceptibility to the NFI. The results are consistent with previous research (Threadgold et al., 2022, Experiments 1 and 2), which has found weak or inconsistent links between cognitive reflection and environmental reasoning biases. This suggests that the NFI

may instead be driven by general heuristic processing, such as averaging biases, rather than domain-specific cognitive traits. Moreover, the absence of a significant relationship between WMC and AOT-17 indicates that these two cognitive constructs function independently, rather than interacting to shape environmental impact judgements. Building on the notion that individuals with high and low WMC may process information differently, as well as the flatlining pattern observed in Experiment 2, where the quantity manipulation did not yield significant effects, a median split was applied to the combined WMC scores to create two distinct groups. The median WMC score was determined to be 31, dividing participants almost evenly, with 60 individuals categorised as having low WMC and 75 individuals assigned to the high WMC group (see Table 11).

To investigate whether WMC influences the magnitude of the NFI, a three-way mixed repeated measures ANOVA was conducted. The design included two within-participant factors—item type (cans, bottles) and category type (same-category, cross-category)—and one between-participants factor, WMC group (low, high). This analysis aimed to determine whether participants' estimations of environmental impact varied as a function of WMC, particularly when assessing plastic bottles and tin cans before and after the introduction of recyclable materials.

The results indicated no significant main effect of WMC on NFI magnitude. Specifically, there was no significant interaction between item type and WMC category, $F(1, 133) = 0.232$, $p = .631$, $\eta^2p = .002$, indicating that WMC did not differentially affect the magnitude of the NFI for bottles versus cans. Similarly, there was no significant interaction between item type and category type, $F(1, 133) = 0.003$, $p = .956$, $\eta^2p = .000$, suggesting that environmental impact estimations remained stable whether the recyclable addition belonged to the same or a different category.

Additionally, the interaction between category type and WMC category was not significant, $F(1, 133) = 0.215$, $p = .644$, $\eta^2p = .002$, suggesting that working memory capacity

did not modulate the extent to which cross-category conditions influenced NFI magnitude. Finally, the three-way interaction between item type, category type, and WMC category was also not significant, $F(1, 133) = 1.850$, $p = .176$, $\eta^2p = .014$, reinforcing the conclusion that WMC did not play a critical role in shaping the illusion across different item and category conditions.

Overall, these results suggest that WMC does not significantly influence participants' susceptibility to the NFI, regardless of whether the recyclable items belonged to the same or different categories. This finding aligns with previous results, reinforcing the idea that the NFI operates largely as a heuristic-based bias, rather than being constrained by individual differences in cognitive capacity.

Table 11.

Combined WMC scores Means and standard deviations after a median split to provide low and high WMC category scores with the magnitude of the NFI in the four conditions (bottles plus bottles, bottles plus cans, cans plus cans, cans plus bottles).

	WMC category	Mean	SD	N
Same category Bottles	Low	8.28	17.25	60
	High	4.17	20.88	75
	Total	6.00	19.39	135
Cross category Bottles	Low	9.65	17.69	60
	High	7.05	16.00	75
	Total	8.21	16.76	135
Same category Cans	Low	4.12	20.43	60
	High	3.48	17.32	75
	Total	3.76	18.70	135
Cross category Cans	Low	7.87	18.23	60
	High	3.77	15.80	75
	Total	5.59	16.98	135

Discussion

The findings from Experiment 3 further elucidate the nature of the NFI and its cognitive underpinnings, while also raising questions about the role of item type, cognitive biases, and individual differences in environmental impact judgements. The results confirm that item type influences the magnitude of the NFI, with cans being consistently judged as having a lower environmental impact than plastic bottles. This pattern aligns with prior research suggesting that plastic pollution is perceived as more environmentally harmful than tin cans, potentially due to media coverage, environmental campaigns, and public discourse surrounding plastic waste (Ford, 2020; Foster, Jacobsen et al., 2022).

Crucially, the presence of recyclable items led to systematic reductions in perceived environmental impact, confirming the core characteristic of the NFI—a heuristic-driven miscalculation where individuals assume that adding eco-friendly elements reduces overall harm rather than summing the total impact of all items. However, category type did not significantly influence the NFI, meaning that the illusion persisted regardless of whether recyclable additions belonged to the same category (e.g., bottles + recyclable bottles) or a different category (e.g., bottles + recyclable cans). This reinforces the idea that the NFI operates independently of category-specific judgements and is instead driven by a generalised cognitive mechanism—such as averaging bias—rather than domain-specific reasoning about material properties.

A key objective of Experiment 3 was to explore whether cognitive capacity or reasoning style influences NFI susceptibility. However, despite extensive analysis, no significant relationship was found between NFI magnitude and scores on the AOT-17 scale or WMC. The AOT-17 scale, which assesses cognitive flexibility and resistance to bias, showed no predictive power in explaining NFI magnitude across any item conditions, contradicting previous research (Threadgold et al., 2022). Likewise, WMC, as measured by OSpan and SymSpan tasks, did not significantly predict NFI magnitude. Further, using

median split to create groups high- and low-WMC groups revealed no systematic differences in their environmental impact estimations. This null finding suggests that the NFI emerges independently of cognitive flexibility, working memory resources, or attentional control mechanisms. The presence of the illusion across both high- and low-WMC individuals implies that the cognitive distortions underpinning the NFI are not linked to executive function or individual differences in processing capacity. Instead, these results support the idea that heuristic-based, rather than capacity-based, processing underlies the effect.

One possible explanation is that both high- and low-WMC individuals rely on different but functionally equivalent heuristic strategies when processing environmental impact. Individuals with higher WMC may engage in a more systematic, arithmetic-based averaging, computing and arithmetic mean of harmful and eco-friendly components, despite this being an inappropriate strategy for environmental impact judgements. In contrast, lower WMC individuals may rely on qualitative heuristics, intuitively categorising actions as either "good" or "bad" and weighing them subjectively rather than numerically. If both high- and low-WMC participants apply some form of averaging heuristic rather than summation, the differences in their response patterns may be subtle, resulting in similar overall NFI susceptibility.

The evidence from this experiment strongly supports averaging bias as the primary cognitive mechanism underpinning the NFI. The fact that the NFI persists across item types and category conditions suggests that individuals do not sum environmental impact judgements but instead apply a heuristic averaging process. This aligns with prior research suggesting that individuals tend to integrate conflicting information (e.g., harmful, and eco-friendly elements) by mentally averaging their impact rather than considering their absolute summation (Holmgren et al., 2019; Andersson et al., 2024).

However, this experiment also challenges previous assumptions about how averaging bias operates. If pure arithmetic averaging were at play, then environmental impact estimates should show a predictable pattern. Specifically, participants should

estimate half the impact when an equal number of eco-friendly items are added to harmful ones. Instead, the results indicate that participants' estimates do not follow a straightforward numerical pattern, suggesting that qualitative averaging—where individuals intuitively balance "good" and "bad" actions—may be a more accurate explanation.

If qualitative averaging underlies the NFI, it raises important questions about how individuals perceive and integrate environmental information in real-world decision-making. Previous research has explored summative priming as an intervention, encouraging individuals to think in terms of absolute quantities rather than relative proportions. However, while this approach has been shown to reduce the NFI, it does not completely eliminate the illusion (Holmgren et al., 2021). This suggests that even when individuals are explicitly prompted to consider environmental impact additively, they may still default to heuristic simplifications.

Importantly, most environmental consequences unfold over time, requiring individuals to integrate cumulative impact rather than making static, one-time judgements. In real-world settings, recycling decisions often occur at different points in time—either prospectively (e.g., when purchasing a product and considering its sustainability) or retrospectively (e.g., when deciding how to dispose of an item). This introduces the concept of temporal dissonance, where the timing of a decision influences how individuals perceive environmental consequences. If individuals engage in heuristic averaging over time, they may systematically underestimate cumulative harm, particularly when improvements (such as increased recycling efficiency) are introduced after periods of inefficiency. Future research should investigate whether time delays influence the strength of the NFI, as well as whether interventions (e.g., numerical prompts or explicit impact framing) can mitigate its effects. The next experiment addresses this by shifting from a static, product-based NFI paradigm to a dynamic, time-dependent evaluation of environmental impact.

Experiment 3 provides strong evidence that the NFI persists across item types and category conditions, reinforcing the idea that generalised heuristic biases drive the illusion. However, despite testing potential cognitive moderators, individual differences in WMC and reasoning style did not significantly influence NFI susceptibility. These results suggest that the NFI is not constrained by cognitive flexibility or processing capacity but instead arises from a heuristic-driven tendency to mentally integrate environmental impact through qualitative averaging. If individuals apply qualitative averaging to balance "good" and "bad" environmental actions in static judgements, they may also do so when processing environmental impact over time. Rather than treating cumulative harm as an additive process, individuals might intuitively smooth out fluctuations, perceiving later improvements as offsetting prior damage. This raises the possibility that people systematically misjudge long-term environmental impact when improvements follow inefficiencies.

The implications of these findings are significant for environmental policy, public awareness campaigns, and sustainability interventions. If individuals consistently misjudge environmental impact due to heuristic distortions, then simply providing factual information about recyclability may not be sufficient to correct these errors. Instead, interventions may need to directly target cognitive biases, encouraging individuals to adopt summative rather than averaging-based reasoning. Future studies should explore how framing, numerical anchoring, and real-world decision-making contexts influence the NFI, helping to bridge the gap between cognitive biases and sustainable behaviour change. An important next step is to determine whether the NFI extends beyond immediate judgements to situations where environmental harm accumulates over time. Do individuals process long-term environmental impact in the same way they judge single-instance scenarios, or does heuristic averaging lead to systematic misjudgement of cumulative harm? Experiment 4 addresses this question by shifting from a static product-based NFI paradigm to a dynamic, time-dependent evaluation of environmental impact.

Chapter 6

Experiment 4: Time, Quantity, and Judgement Patterns in Perceived Environmental Impact

The negative footprint illusion (NFI) refers to the tendency for people to underestimate environmental harm when an eco-friendly component is introduced alongside an environmentally harmful component (Holmgren et al., 2019; Kusch & Fiebelkorn, 2019; Sörqvist & Langeborg, 2019). While this illusion has traditionally been studied in the context of immediate judgements of product/item impact, recent evidence suggests that it also extends to judgements made over time. Specifically, when participants estimate long-term environmental impact, they appear to rely on a heuristic averaging process rather than summing cumulative harm, leading to systematic underestimation of environmental damage.

Holmgren et al. (2019) investigated this effect using a CO_2 accumulation paradigm. In their first experiment, participants estimated atmospheric CO_2 concentration under two conditions. In the high condition, participants estimated CO_2 levels after five years, assuming a steady increase of 2PPM per year due to human activity. In the high + low condition, participants were given additional information that environmental interventions had reduced emissions to 1.4 PPM per year for an additional five years. Participants then estimated total CO_2 accumulation over the full ten-year period. Critically, despite the longer time-frame and greater overall emissions in the high + low condition, participants often gave lower estimates that in the high-only condition, demonstrating an averaging bias rather than an accurate cumulative judgement.

The findings suggest that individuals do not engage in a strict summation of CO_2 emissions over time. Instead, they appear to form an intuitive impression by averaging across high and low emission periods. This qualitative rather than quantitative approach leads to a systematic underestimation of cumulative impact. The effect persisted even when

symbolically significant wording (e.g., references to environmental protection efforts) was removed, suggesting that the bias is rooted in cognitive heuristics rather than in moral framing. Averaging bias can be conceptualised in two ways. First, quantitative averaging – participants compute a numerical average (e.g., averaging 2 PPM and 1.4 PPM instead of summing them). Second, qualitatively averaging – participants form a gestalt impression of the trend (e.g., interpreting the introduction of a lower-emission phase as meaning overall impact is lower). The current evidence aligns more closely with qualitative averaging, as the observed estimates do not follow precise arithmetic means but reflect a perceptual dilution of harm.

While averaging bias provides a strong explanation, other cognitive processes could theoretically influence environmental judgements over time. Environmental behaviours and their consequences are typically separated in time (Howard et al., 2019; UNEP, 2019; United Nations). Unlike an immediate product-based decision (e.g., judging the impact of a plastic bottle), environmental decisions often involve cumulative, delayed effects—for example, CO_2 emissions persist long after their initial release, and the impact of recycling is spread over extended periods. Critically, individuals do not experience these consequences in real-time but must infer them from abstract or retrospective information. Research suggests that when people evaluate experiences over time, they do not simply sum individual instances but instead rely on heuristic processes that integrate information into an overall impression (Asutay et al., 2021; Schreiber & Kahneman, 2000). This may explain why people fail to recognise the full environmental impact of temporally distributed events.

As the Holmgren et al. (2019) study and the present experiment shifts from static judgements of environmental harm to a dynamic, time-based scenario, it is crucial to consider additional cognitive processes that may influence how people integrate environmental impact over multiple time periods. While averaging bias provides a strong explanation, two alternative mechanisms—temporal discounting (Frederick et al., 2002;

Hardisty & Weber, 2009) and mental accounting (Thaler, 1985)—may also contribute to misjudgements in cumulative environmental impact. These accounts become particularly relevant in a temporally structured scenario, as they address how individuals process sequentially presented environmental information over time, rather than in a single-instance judgement.

Temporal discounting suggests that people devalue future events relative to immediate ones (Frederick et al., 2002; Hardisty & Weber, 2009). If this bias were at play, participants should discount the importance of later emissions (e.g., the additional five years at 1.4 PPM) rather than averaging them. However, participants did not merely ignore future emissions; rather, they incorporated them in a way that reduced their overall estimate. This suggests an averaging process rather than simple discounting.

Mental accounting (Thaler, 1985) holds that people treat events in separate categories rather than integrating them into a single judgement. If mental accounting were driving the effect, participants should consider the two periods independently rather than blending them. However, the fact that participants' estimates were lower than they should have been suggests they combined the two periods into a single impression—a signature of averaging.

Taken together, the findings of Holmgren et al. (2019) suggest that the NFI over time is primarily driven by an averaging bias rather than temporal discounting or mental accounting.

The same heuristic averaging process may extend beyond CO_2 emissions to recycling behaviours where individuals could misjudge the cumulative impact of inefficient recycling when followed by a more sustainable phase. If people rely on intuitive averaging, they may falsely believe that early inefficiencies in recycling are 'cancelled out' by later improvements, leading to a systematic underestimation of environmental harm. This has key implications for public messaging. For example, people may perceive short-term

inefficiencies in recycling as insignificant, assuming later improvements compensate for earlier harm. Similarly, awareness campaigns should emphasise cumulative impact rather than isolated improvements.

To further test the generality of the averaging bias, it is necessary to examine whether similar effects emerge when people evaluate recycling efficiency over time rather than immediate judgements about products/items (as in Experiments 1-3 of the current thesis). Moving beyond single-judgement paradigms, multi-step tasks that require participants to track environmental impact dynamically could provide greater ecological validity (Ahn & Picard, 2006; cf. Clayton & Myers, 2015; Thøgersen, 2006). A crucial question is whether people's judgements follow: an arithmetic summation model (e.g., treating two inefficient periods as strictly additive); an averaging model (e.g., assuming that improvements 'balance out' inefficiencies) and are susceptible to temporal discounting, leading them to undervalue future recycling efficiency gains. To address these issues, the following experiment manipulates recycling efficiency over time to examine how participants conceptualise cumulative environmental impact.

The following predictions were entertained: If averaging bias is operating, participants should systematically underestimate the total environmental harm when a period of inefficient recycling is followed by a period of efficiency. Further, participants should show greater misestimation when the efficient period is introduced later rather than earlier. If temporal discounting is at play, participants should devalue later recycling efficiency, meaning that judgements should be more accurate when efficiency occurs early but distorted when efficiency occurs later. Finally, if mental accounting plays a role, then participants should show less bias when explicitly cued to compare both time periods and fail to integrate early and late periods into a coherent judgement. Through testing these alternative explanations, it can be more precisely determined whether the NFI in long-term judgements results from an averaging heuristic or a broader temporal bias.

While previous experiments in this thesis have examined whether actively open-minded thinking (AOT-17) predicts sensitivity to the NFI, findings have been weak or non-significant. Thus, rather than treating AOT-17 as a core theoretical construct, this study includes it as an exploratory measure to assess whether individual differences in cognitive flexibility influence temporal environmental judgements.

AOT-17 measures tendencies toward cognitive reflection, openness to new evidence, and resistance to dogmatic thinking (Stanovich & Toplak, 2019). If the NFI over time is a fundamentally intuitive bias, it may persist across reasoning styles, suggesting that even those high in AOT-17 would still rely on heuristic averaging. However, if cognitive flexibility helps counteract heuristic biases, then individuals high in AOT-17 may be less susceptible to blending inefficient and efficient recycling periods into a single impression.

While previous findings suggest a limited role of AOT-17 in the NFI, this study explores whether temporal scenarios introduce greater variance in reasoning styles, potentially revealing new individual differences in susceptibility to heuristic averaging.

Method

Design

The study employed a 2 (Plastic Quantity: 10 kilograms, 20 kilograms) x 2 (Behaviour: continue, recycle) between-participants design. The dependent variable was perceived environmental impact, measured on a 1 – 100 scale. Participants were not shown numerical values; instead, the scale was visually presented from “very low environmental impact” (left) “very high environmental impact” (right).

Participants

A total of 151 participants (*M*_age = 26.40, SD = 8.74) were recruited from Prolific (www.prolific.com) (see Table 12 for gender classification and Table 13 for the demographic breakdowns across conditions). Participants met the following inclusion criteria: Born and

residing in the U.K; native English speaker, and no reported literacy difficulties. All participants received a small monetary honorarium for their participation.

Table 12

The classification of participants by gender

Gender	N
male	30
female	117
other	2
Non-binary	1
Prefer not to say	1

Table 13

The means and standard deviations for Age across gender classifications and experimental grouping for each of the independent variables

Independent variables		Total participants	Gender					Age	
			Male	Female	Other	Non-binary	Prefer not to say	Mean	SD
Control	10	30	22.65	23.76	19.00			23.60	6.80
	20	29	24.18	24.14		18.00		23.97	8.13
Experimental	10	47	28.40	29.26	37.00			29.26	9.52
	20	45	27.16	26.45			19.00	26.84	8.66
Totals		151	25.70	26.33	25.68	18.00	19.00	26.40	8.74

Materials and Procedures

Participants completed an online questionnaire designed to assess their perceptions of environmental impact. At the beginning of the study, they were presented with a brief statement outlining the purpose of the research before answering demographic questions regarding their age and gender. Following this, they proceeded to the main experimental task, in which they were asked to evaluate the environmental impact of a hypothetical waste disposal scenario.

Participants were presented with a vignette (**Appendix F**) describing Thomas Smith and his family, who resided in a suburban area and disposed of their plastic waste without recycling during the first half of 2019. The scenario stated that the Smith family, who had not previously engaged in environmentally conscious waste disposal, discarded 20 kilograms of plastic waste into a landfill between February and June. The text also indicated that this quantity of waste had been marked on the centre of a rating scale. Participants were then shown a slider scale labelled at its endpoints as “Very low environmental impact” and “Very high environmental impact,” though the numerical values corresponding to these labels (ranging from 1 to 100) remained hidden to encourage intuitive responses. After rating the environmental impact of this initial scenario, participants were randomly assigned to one of four experimental conditions, which varied in terms of whether the family adopted a recycling policy in the second half of 2019 (July–December) and the amount of plastic waste produced.

In Scenario A (Recycling Begins, Lower Waste Output), the suburban area where the Smith family lived introduced a recycling policy, and the family adopted the scheme. Consequently, their plastic waste output during the second half of 2019 was reduced to 10 kilograms. In Scenario B (Recycling Begins, Same Waste Output), the Smith family also adopted recycling; however, despite participating in the scheme, their waste output remained 20 kilograms during the second half of the year. In the control conditions, the Smith family

did not adopt the recycling scheme and continued their previous disposal habits. In Scenario C (No Recycling, Lower Waste Output), the family disposed of an additional 10 kilograms of plastic waste into a landfill in the second half of 2019. Finally, in Scenario D (No Recycling, Same Waste Output), the Smith family remained unwilling to recycle, continuing to dispose of 20 kilograms of plastic waste into landfill.

Participants rated the total environmental impact of waste disposal across both time periods using the same slider scale they had encountered in the initial scenario. Responses were recorded as scale movements from the anchored midpoint, allowing an assessment of whether participants perceived recycling as mitigating prior environmental harm. The study aimed to determine whether participants' judgements reflected an averaging bias, wherein they intuitively balanced inefficiencies against later improvements, or whether they engaged in strict summation, integrating cumulative waste over time.

After completing the environmental impact judgement task, participants proceeded to an individual differences measure designed to assess their cognitive flexibility and openness to revising beliefs. Specifically, participants completed the Actively Open-Minded Thinking (AOT-17) scale (Svedholm-Häkkinen & Lindeman, 2018), a 17-item questionnaire that measures resistance to dogmatism, willingness to engage with conflicting viewpoints, and openness to new evidence. The scale consists of four subscales: Dogmatism (e.g., *"Changing your mind is a sign of weakness."*), Fact Resistance (e.g., *"Scientific facts should not change people's beliefs."*), Liberalism (e.g., *"It is important to be open to different political viewpoints."*), and Belief Personification (e.g., *"A person's values are a reflection of their personality."*). Participants responded using a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree), with higher scores reflecting greater cognitive flexibility and openness to revising beliefs based on new evidence.

To ensure that metacognitive reflection did not influence initial environmental judgements, the AOT-17 scale was administered only after participants had completed the

environmental impact task. Finally, upon completing the study, participants were fully debriefed regarding the study's aims and hypotheses and received a small monetary honorarium for their participation through the Prolific crowdsourcing platform.

Results

Experiment 4 examined how recycling efficiency is evaluated over time, focusing on how individuals perceive cumulative environmental impact rather than making immediate judgements. The study employed temporal-based scenarios that depicted changes in recycling behaviour over a one-year period. To assess these perceptions, a two-way between-participants ANOVA (analysis of variance) 2 (Behaviour: control, experimental) × 2 (Plastic Quantity: 10 kg, 20kg) was conducted. The dependent variable was participant's estimated environmental impact of plastic waste when either recycled or disposed of in landfill.

Participants' judgement ratings were compared against a baseline score (midpoint of 50 on the scale, with numerical values hidden from participants). The results revealed a significant deviation from baseline $F(1,147) = 35.854$, $p < .001$, $\eta^2p = .196$. Lower scores reflected lower perceived environmental impact, while higher scores indicated greater perceived impact. In the experimental (recycling) condition, ratings were significantly lower than baseline ($M = 44.77$, $SD = 17.78$), whereas in the control (landfill) condition, ratings were significantly higher ($M = 72.41$, $SD = 17.78$).

No main effect was found for Plastic Quantity, $F(1,145) = .079$, $p = .779$, $\eta^2p = .001$, indicating that 10kg of plastic waste ($M = 4.82$, $SD = 21.58$) was perceived similarly to 20kg of plastic waste ($M = 4.71$, $SD = 21.32$) in terms of environmental impact. However, there was a significant main effect for Behaviour, $F(1, 145) = 88.329$, $p < .001$, $\eta^2p = .379$, with participants assigning significantly lower impact ratings to recycling ($M = -5.856$, $SD = 17.55$) compared to landfill disposal ($M = 20.97$, $SD = 15.88$).

No interaction effect was found between Plastic Quantity × Behaviour, $F(1,145) = .331$, $p = .566$, $\eta^2p = .002$, suggesting that the perceived environmental impact of plastic disposal was driven primarily by behavioural change (recycling vs. landfill), rather than the quantity of plastic waste. Across all conditions, participants consistently rated recycling as less environmentally damaging than continued landfill disposal, regardless of the amount of plastic waste

Actively Openminded Thinking AOT-17

Correlation Analysis

To assess whether individual differences in actively open-minded thinking (AOT-17) were associated with the NFI over a 12-month period, we computed the perceived environmental harm scores by subtracting baseline estimates from participants' judgements. A bivariate correlation analysis was then conducted to examine the relationship between the magnitude of the NFI for 10 kg, 20 kg, and combined 10 kg + 20 kg of plastic waste and AOT-17 scores, as well as its four subscales (dogmatism, fact resistance, liberalism, and belief personification). This analysis revealed no statistically significant correlations between AOT-17 scores (or its subscales) and the NFI across any of the weight conditions (see Table 14). These findings do not replicate previous results (Threadgold et al., 2022) but are consistent with prior experiments in this thesis.

Table 14.

Pearson Correlation Coefficients between AOT-17 Subscales and Environmental Impact Estimates for Recycling 10kg, 20kg or 10+20kg of Plastic Waste

		Dogmatism	Fact resistance	Liberalism	Belief personification	AOT17
10kg	Pearson Correlation	.008	.117	.009	-.170	-.004
	Sig (2-tailed)	.957	.434	.953	.253	.976
20kg	Pearson Correlation	.013	.004	.184	-.065	.055
	Sig (2-tailed)	.934	.980	.227	.673	.722
10kg + 20 kg	Pearson Correlation	.001	.049	.064	-.129	.008
	Sig (2-tailed)	.994	.643	.541	.221	.940

*. Correlation is significant at the 0.05 level (2-tailed).

Regression

To further examine whether AOT-17 and its subscales predicted perceived environmental harm, three multiple regression analysis were conducted. The dependent variable in each case was the judged environmental impact of 10 kg of plastic waste, 20 kg of plastic waste, and combined 10 kg + 20 kg of plastic waste.

In the first regression, AOT-17 subscale scores (dogmatism, fact resistance, liberalism, and belief personification) did not significantly predict perceived environmental harm for any of the plastic waste weight conditions: 10 kg + 20 kg, $F(4, 87) = .639$, $p = .636$,

R^2 = .029, 20 kg, $F(4, 40) = .506$, $p = .732$, R^2 = .048, and 10kg, $F(4, 42) = .507$, $p = .731$, R^2 = .046.

Similarly when AOT-17 total scores were used as a predictor, they failed to explain variability in perceived environmental harm: 10kg + 20 kg , $F(1, 90) = .006$, $p = .940$, R^2 = .000, 20kg, $F(1, 43) = .129$, $p = .722$, R^2 = .003, 10kg, $F(1, 45) = .001$, $p = .976$, R^2 = .000.

Summary

The results suggest that individual differences in actively open-minded thinking do not predict susceptibility to the NFI in the context of recycling judgements over time. Unlike previous studies (Threadgold et al., 2022), which found associations between cognitive flexibility and environmental decision-making, our findings indicate that the NFI operates independently of individual differences in open-mindedness. This suggests that heuristic biases in environmental impact judgements---such as averaging effects—may be more automatic and less influenced by reflective thinking styles than previously thought.

Discussion

The results of Experiment 4 provide further evidence for the NFI over time, supporting the averaging bias account (Holmgren et al., 2019) over alternative explanations such as mental accounting (Chatelain et al., 2018; Li et al., 2019; Zhang et al., 2021) and temporal discounting (Hardisty & Weber, 2009; Huang et al., 2024). Specifically, participants systematically underestimated the cumulative environmental impact of inefficient recycling when it was followed by a more efficient phase. Instead of treating the two phases as additive, participants appeared to mentally average the impact of both phases, leading to a distorted perception of environmental harm.

The key finding is that participants judged the total environmental impact to be lower in conditions where inefficient recycling was followed by a more efficient period, relative to a condition with continuous inefficiency. This aligns with previous work on the NFI, which suggests that people tend to average environmental costs rather than summing them

(Holmgren et al., 2019). To recap, averaging bias can occur in two forms: Quantitative averaging—where participants compute a numerical mean of high and low impact periods and Qualitative averaging—where participants perceive a reduced environmental burden due to the presence of an improvement, without engaging in explicit arithmetic calculations. The present results are more consistent with qualitative averaging, as seen in prior research (Andersson et al., 2024). Participants did not show evidence of strict arithmetic averaging (i.e., they did not simply compute an exact mean between the two period); instead, their estimates reflected a heuristic-driven dilution of harm when an efficient recycling period was introduced. A particularly striking result was that the amount of plastic waste (10kg vs. 20kg) did not significantly influence environmental impact judgements. If participants were engaging in quantitative averaging, one would expect a difference in judgements depending on the weight of plastic waste. However, the lack of such an effect suggests that participants were engaging in a holistic impression-based heuristic rather than systematically integrating numerical values.

The findings of Experiment 4 are at odds with both the mental accounting and temporal discounting accounts. Mental accounting predicts that people treat events in separate “mental categories” rather than integrating them into a single evaluation (Thaler, 1985). If this process were driving the results, one would expect participants to consider the inefficient and efficient phases separately, leading to an undistorted assessment of overall environmental harm. However, participants clearly integrated the two phases into a single impression, as evidenced by the systematic underestimation of cumulative impact. Furthermore, mental accounting does not predict why efficiency following inefficiency would lead to a lower perceived environmental impact. If participants were treating the two phases independently, they should have judged the second phase in isolation rather than allowing it to reduce the perceived harm of the first phase. This suggests that participants were not

compartmentalising time periods but rather forming a single integrated judgement consistent with averaging bias.

Temporal discounting (Frederick et al., 2002; Hardisty & Weber, 2009) predicts that people discount the importance of future events, meaning that later recycling inefficiency should be perceived as less impactful than earlier inefficiency. However, this was not the pattern observed. Instead of ignoring the later phase, participants factored it into their judgement in a way that diluted the impact of earlier inefficiency. This pattern is inconsistent with discounting but fully consistent with heuristic averaging. Notably, if temporal discounting were the primary mechanism, we would expect greater misestimation when the inefficient period occurred later rather than earlier—yet our results show that participant systematically misjudged the total impact, regardless of temporal ordering. This reinforces that it is the act of integrating two conflicting values (high vs. low environmental impact) that leads to misjudgement, rather than a simple devaluation of future events.

The role of individual differences in cognitive flexibility (as measured by AOT-17) was also explored, given prior research suggesting that more deliberative reasoning styles might mitigate heuristic biases (Stanovich & Toplak, 2019). However, consistent with findings from earlier experiments in this thesis, and at odds with Threadgold et al. (2022), AOT-17 showed no significant relationship with the magnitude of the NFI in the present experiment. This suggests that heuristic averaging processes are robust across reasoning styles, indicating that even individuals who typically engage in more reflective, analytical thinking are still susceptible to blending sequential environmental impacts into a single impression.

While these findings do not support a strong role for AOT-17 in counteracting the NFI, they align with other studies demonstrating that certain biases—especially those that emerge from perceptual or intuitive processes—may be resistant to individual differences in cognitive reflection (Threadgold et al., 2022). However, it remains possible that different interventions, such as explicit prompts to engage in summative rather than intuitive

reasoning, could mitigate this bias in high AOT-17 individuals. Future research could examine whether providing structured numerical breakdowns of cumulative environmental impact reduces reliance on heuristic averaging, particularly among those who typically exhibit greater cognitive flexibility.

The present findings have direct practical implications for public perceptions of environmental impact and policy communication. The tendency to average rather than sum environmental harm suggests that people may systematically underestimate the cumulative cost of inefficient environmental practices when a later “improvement” is introduced. This has important consequences for how individuals evaluate sustainability initiatives, particular in recycling behaviour.

An additional consideration is that participants’ perceptions may have been shaped by inferred researcher intent, consistent with applied relevance theory (Taguchi, 2002). If participants interpreted the study as aiming to highlight the benefits of recycling, they may have overemphasised the positive impact of behaviour change, leading to an underestimation of cumulative harm. This aligns with the broader finding that people often rely on contextual cues and perceived environmental purpose to guide their judgement (Cosin et al., 2000). Future studies should control for this by manipulating the framing of environmental information to assess whether participants make different estimates when explicitly instructed to focus on cumulative impact.

Given that participants systematically misjudged environmental impact over time, several future research directions are warranted. First, interventions designed to mitigate heuristic averaging should be explicitly tested. For example, providing visual accumulations of waste over time may counteract averaging effects as might encouraging numerical summation (rather than perceptual judgement). Second, it should be examined whether similar effects can be observed in different domains. For example, does the NFI over time extend to water consumption, energy use or carbon offsets? And would financial decisions

(e.g., debt repayment) show similar heuristic averaging? Third, temporal framing could be manipulation to investigate whether misjudgements are greater or smaller if the recycling period were spaced further apart and investigating whether the effect holds if the inefficient period comes after the efficient period could be theoretically revealing.

In conclusion, the results provide strong evidence that people systematically underestimate cumulative environmental impact when a period of inefficiency is followed by efficiency, consistent with the averaging bias account. This misjudgement does not align with mental accounting (which predicts compartmentalisation) or temporal discounting (which predicts devaluation of later events). Instead, participants appear to construct a single integrated judgement that leads to a distorted perception of long-term environmental harm.

The research highlights the cognitive challenges inherent in evaluating sustainability over time and underscores the importance of designing interventions that counteract heuristic biases. Policies and public communication strategies should emphasise the cumulative nature of environmental impact, ensuring that minor improvements in efficiency are not mistaken for full compensation of earlier inefficiencies.

Chapter 7

Experiment 5: Cognitive Nudging and Task Format Effects on the NFI

In Chapter 6, we examined averaging bias in the context of a family's short-term recycling behaviour, emphasising individual responsibility for managing environmental impact. In contrast, this chapter shifts the scope from a smaller context—focusing on individual responsibility and personal or small-scale recycling—to a larger context that encompasses collective responsibility, aiming to capture the global scale of environmental issues driven by collective human consumption.

This chapter concentrates on the global consumption of Waste from Electrical and Electronic Equipment (WEEE), a category of the WFH dry recyclate intended for household recycling (DEFRA, 2022). WEEE presents a widespread challenge driven by global consumption patterns, highlighting the environmental consequences of modern society's resource usage. As one of the fastest-growing waste streams, WEEE contributes significantly to environmental damage through pollution and resource depletion. Therefore, this study focuses on the amount of WEEE produced per person, presenting a scenario that underscores the shared responsibility humanity holds in reducing electronic waste and resource use. This shift from individual to collective responsibility allows us to explore whether participant's judgements of environmental impact are influenced by framing and scale. Prior research suggests that framing impacts environmental judgements (Spence & Pidgeon, 2010) and this chapter tests whether shifting from individual to collective frames can mitigate biases – in particular, the negative footprint illusion (NFI; Holmgren et al., 2018).

Rather than focussing on short-term habits (see Chapter 6) the WEEE scenario in this chapter utilises a complex temporal structure, presenting participants with 5-year and 10-year timeframes to judge cumulative environmental impacts of large-scale resource consumption. Long-term consumption patterns are often harder to assess accurately

(Damari & Kissinger, 2024), and transitioning to longer time scales enables an investigation into how people estimate environmental damage over extended periods. Previous research highlights the challenge of accurately assessing long-term environmental damage due to cognitive biases like temporal discounting (Hardisty & Weber, 2009) where people undervalue future outcomes. While temporal discounting might lead individuals to focus on more immediate environmental benefits or harms, the averaging bias (e.g., Holmgren et al., 2019) may encourage participants to perceive long-term environmental impacts through a simplified heuristic (Holmgren et al., 2018; Chapter 6). By averaging across time-periods, participants may underestimate cumulative damage, focussing instead on recent improvements in recycling practices. This reliance on heuristics suggests that environmental judgements may be shaped by Cognitive Miser Theory (Fiske, 1991), which posits that individuals often resort to simplified processing for complex judgements, especially when assessing impacts over extended timelines.

Vice-virtue categorisation (e.g., Chernev et al., 2010) and moral licensing theory (Sachdeva et al., 2009) provide further context for understanding judgements in a WEEE scenario. Participants may treat recycling as a "virtuous" action that offsets the environmental "vice" of waste production, implicitly assuming that efficient recycling practices compensate for inefficient ones. This implicit balancing act aligns with moral licensing, where pro environmental behaviours are seen as sufficient compensation for less sustainable actions. The WEEE scenario tests whether participants mentally compartmentalise efficient and inefficient recycling practices, thus failing to integrate them into a cumulative assessment—a phenomenon aligned with mental accounting theory (Thaler, 1999). If participants view these periods as separate accounts rather than a unified timeline, then they may underweight the environmental cost of the inefficient phase when it is followed by efficient practices.

However, it is possible that a multi-year scenario featuring easily understood waste quantities (e.g., 21 kg per person per year) may provide a framing that helps participants grasp the cumulative environmental harm from sustained high consumption rates, potentially triggering a summative mindset (Holmgren et al., 2021). Further, the WEEE scenario requires participants to consider the cumulative impact of society's actions, potentially altering how accountability is perceived compared to the family scenario adopted in Chapter 6. Another notable aspect of the design is the focus on per-person impact, which simplifies the large-scale environmental problem, making it more relatable and easier for participants to conceptualise. This approach helps bridge the gap between personal responsibility and global-scale problems while maintaining a level of abstraction that encourages broader thinking.

The negative footprint illusion has been shown to be robust across various scales (Camilleri et al., 2018; Gorissen & Weijters, 2016; Holmgren et al., 2018; Sörqvist & Holmgren, 2022) and response characteristics (e.g., tree compensation; Holmgren et al., 2018). However, previous research has not determined whether the negative footprint illusion manifests similarly across focal tasks with different demands for the same participants. In both studies of this chapter, participants will not only estimate the environmental impact of different scenarios, but they will also sort these scenarios from highest to lowest impact. Compared to the estimation task, the sorting task may reveal biases inherent in the judgement process, as it arguably requires participants to engage in more analytical thinking, potentially leading to different outcomes. If the negative footprint illusion in judgements is driven by the intuitive, fast system (Gorissen, 2018; Holmgren et al., 2019; Kusch & Fiebelkorn, 2019; Sörqvist & Langeborg, 2019; Threadgold.et al., 2022), while sorting tasks engage the more deliberate system (Kozhevnikov, 2007; Threadgold et al., 2022), then we might expect more accurate categorisations in the latter. Similarly, format-dependent judgement theories (Hsee & LeClerc, 1998) suggest that people may alter their

evaluative strategies depending on how options are presented. By comparing these tasks, we can explore whether the sorting task mitigates the NFI by encouraging more comparative, analytical processing, which could lead to normative assessments. This distinction is critical, as it suggests that intuitive responses may reinforce the NFI, whereas analytical engagement could help participants bypass this cognitive bias. Sorting the environmental impacts could highlight areas of misunderstanding or misperception that might not be evident in estimates. Overall, the sorting task may provide deeper insights into decision-making processes, informing interventions aimed at promoting more sustainable behaviours.

An important facet of this study is the use of a "nudge" or hint (e.g., Allcott, 2011)—an intervention aimed at guiding participants' cognitive processes toward more accurate assessments. Research on nudges in environmental reasoning highlights their potential to promote pro-environmental behaviours by leveraging choice architecture and social norms (Thaler & Sunstein, 2008; Bergquist et al., 2019). Studies have shown that nudges—such as presenting social comparisons in energy usage (Allcott, 2011), simplifying complex environmental decisions (Camilleri & Larrick, 2014), and using subtle cues to reduce plastic waste (Bruns & Perino, 2023)—can positively influence judgement and behaviour, though with varying effectiveness depending on context and presentation (Hummel & Maedche, 2019). Meta-analyses support the effectiveness of norm-based nudges, although achieving long-term change can be challenging as biases toward averaging or underestimating cumulative impacts remain strong (Byerly et al., 2018; Kaiser & Wilson, 2019; Sörqvist & Langeborg, 2019). Rather than focus on norm-based nudges, the current study aims to orient participants to (re)consider the computational processes underpinning their environmental impact decisions. Specifically, participants will answer a forced-choice question about whether they interpreted a question as asking for the *total* environmental impact for the time-period or the *average* environmental impact over that time-period. They

will then receive a hint that emphasises calculating the total environmental impact for the given time-period and will be asked to repeat their estimates. One of the significant challenges in addressing the negative footprint illusion is the tendency to average the impacts of efficient and inefficient practices (as discussed in Chapter 5) or the combination of environmentally friendly and conventional objects (as explored in Chapters 3-4). By prompting participants to reflect on their judgement processes, the aim is to bring cognitive processes to the forefront, encouraging critical thinking about their reasoning. The nudge to focus on total impact could help guide them toward a more accurate, cumulative assessment. Thus, this study investigates for the first time, whether a computational nudge that prompts participants to focus on total environmental impact can override intuitive averaging and encourage a summative perspective. If successful, this would provide evidence that nudges targeting the cognitive processing of environmental impact could mitigate biases like the NFI.

In the two experiments within this chapter, participants are asked to assess WEEE waste scenarios spanning a 5-year timescale with different annual waste quantities. By comparing judgements of environmental impact across timeframes and task formats, we test whether averaging bias, vice-virtue categorization, and cognitive defaults like mental accounting affect how participants process cumulative environmental harm. To enhance clarity, participants are prompted to reflect on whether they based their estimates on total or average impact over the timeline, followed by a computational nudge. This forced-choice reflection and subsequent nudge represent novel applications in the study of environmental cognition and aim to bridge the gap between intuitive and analytical processing.

If the nudge successfully mitigates NFI, it will underscore the potential for structured cognitive interventions to correct biased judgements in environmental decision-making. However, if the NFI persists despite the nudge, it would highlight the robustness of averaging bias and suggest that further investigation is needed to develop more effective interventions.

Given the urgency of global environmental issues, understanding the cognitive mechanisms underpinning these biases is essential for informing policy and public communication strategies. By examining WEEE through a lens of collective responsibility and long-term impact, this chapter provides a broader framework for understanding how people navigate complex environmental information and may ultimately contribute to more effective strategies for promoting sustainable behaviour.

Experiment 5A

Design

A within-participants study with one independent variable (Scenario Type) was presented to participants. The dependent variable was the environmental impact, with a scale of –100 to +100. The numerical value was not visible to participants. Participants saw a scale labelled from the left side as "very low environmental impact" (equating to –100) to the right side "very high environmental impact" (equating to +100).

Participants

The online survey Prolific was used to recruit participants. Returning to a simpler study design with fewer independent variables the sample size was based on a power analysis using GPower (Faul et al., 2007), which indicated that 42 participants would be needed to detect a medium effect with 80% power using an *F* test with alpha at .05. Therefore, 62 participants, self-reported English as their first language, were first tested (*M*_age = 23.03 years; *SD* = 3.86, 40 female, 21 male, 1 other) in the full experimental design, which included the nudge manipulation. To increase statistical power for the planned correlational and multiple regression analyses (e.g., relationships between scenario estimates and actively open-minded thinking), 62 further participants were subsequently recruited (*M*_age = 24.71; *SD* = 3.73, 44 female, 18 male). These additional participants completed only the scenario estimation task and the AOT-17 scale; they did not complete the experimental manipulation. The main experimental analyses are therefore based on the

initial 62 participants, while the full sample of 124 participants (62 experimental + 62 additional) was used for correlational and regression analyses. The study took approximately 15 minutes to complete (around 10 minutes for the participant completing on the estimates and AOT-17), equating to £2.25 per participant.

Materials and Procedures

This experiment was presented online via Prolific (www.prolific.com) where participants engaged in an online questionnaire about waste of electrical and electronic equipment. Waste of electrical and electronic equipment (WEEE) coming from household appliances, information technology and telecommunications equipment (e.g., fridges, laptop computers, mobile phones) is rising all over the world at increasing rates. Some reasons accounting for this are fast technological changes, consumers' desire for the latest electronics products and difficulties to repair existing equipment. It should be noted that WEEE is one of the fastest waste streams. In 2016, an average e-waste of 16 kg per person was generated in the European Union (EU) with the total amount in this region projected to reach more than 12 million tons by 2020. As a result, landfill sites are filling up with WEEE. A shortage of raw materials needed to manufacture these products (e.g., gold, copper, iron, aluminium) is envisioned for the years to come.

Your task

Below you will see three different scenarios lettered A, B, and C. Assuming the number of people comprising the population is the same for each scenario, your task is to estimate how each scenario influences the environment in terms of waste of electrical and electronic equipment (WEEE). Please read each scenario carefully before making each estimate. Each scenario has its own scale. The scale is labelled from the left side as "very low environmental impact" to the right side "very high environmental impact.

Scenario A. Over a 5-year period (2001-2006), the amount of WEEE per person was relatively high (21 kg per year) due to humanity's consumption and use of natural resources. Please estimate, to the best of your abilities, how this scenario influences the environment during this five-year time-period by using the scale below.

Scenario B. Over a 5-year period (2006-2011) the amount of WEEE per person was relatively low (11 kg per year) due to a new WEEE directive established by the European Union to reduce waste and recover raw materials. Please estimate, to the best of your abilities, how this scenario influences the environment during this five-year time-period by using the scale below.

Scenario C. Over a 5-year period (2001-2006) the amount of WEEE per person was relatively high (21 kg per year) due to humanity's consumption and use of natural resources. But after a new WEEE directive was established by the European Union to reduce waste and recover raw materials, another five-year period (2006-2011) followed when the WEEE per person was relatively low (11 kg per year). Please estimate, to the best of your abilities, how this scenario influences the environment during this ten-year time-period (2001-2011) by using the scale below.

After making an environmental impact estimate for each of the three scenarios participants then completed a sorting task whereby, they were told

Please sort the scenarios in terms of their total Environmental Impact from highest (top[1]) to lowest (bottom[3]). You can sort them into position by dragging them using your mouse or touchpad.

Scenario A. 21 kg of WEEE per person over a 5-year period (2001-2006)

Scenario B. 11 kg of WEEE per person over a 5-year period (2006-2011)

Scenario C. 21 kg of WEEE per person over an initial 5-year period (2001-2006), followed by 11 kg of WEEE per person over a subsequent 5-year period (2006-2011)

Following the sorting task, participants were then asked a forced-choice question about the decision strategy they used for the task. This was presented as follows:

> For the WEEE question, did you interpret the question as asking you to calculate the total environmental impact for the time-period or the average environmental impact over the time-period?
>
> Please choose:
>
> Total environmental impact for the time-period.
>
> Average environmental impact over the time-period.

After choosing one of the two options they were all given the same hint/nudge

> The appropriate interpretation of the question would lead to calculation of the total environmental impact for the time-period given. You will now have a chance to answer the question again in case you thought you should calculate the average environmental impact across the time-periods.

Participants then completed the same environmental impact judgement task.

After completing their estimates for the scenarios, participants completed the AOT-17.

Results

Estimates Task – Overall Sample

A repeated measures design with Scenario Type (21kg for 5 years, 11kg for 5 years, 21kg for 5 years + 11kg for five years) revealed a main effect of Scenario, $F(2, 246) = 168.264$, $MSE = 10.951$, $p < .001$, $\eta^2p = .578$. Paired samples t-test revealed a significant difference between Scenario A ($M = 4.895$, $SD = 0.261$) and Scenario B ($M = -2.815$, $SD = 0.346$), $t(123) = 16.127$, $p < .001$, Cohen's $dz = 1.448$, $BF_{01} = .000$, and between Scenario A and Scenario C ($M = 1$, $SD = 0.297$), $t(123) = 10.610$, $p < .001$, Cohen's $dz = 0.953$, $BF_{01} =$

.000. There was also a significant difference between Scenario B and C, $t(123) = -9.346$, $p < .001$, Cohen's $dz = -.839$, $BF_{01} = .000$. This pattern of results that ensued (A > C > B) follows that which would be expected from a NFI perspective if participants were averaging the environmental impacts of 21kg for 5 years and 11kg for 5 years across the ten-year period (see Holmgren et al., 2018, and Chapter 6).

Correlation and Multiple Regression

The magnitude of the NFI was computed as the difference between the estimates made for Scenario A (21 kg for 5 years) and Scenario C (21kg for 5 years + 11kg for five years). For each participants estimate values for Scenario C were subtracted from estimate values for Scenario A such that a positive score reflected a larger NFI. A Pearson's bivariate correlation revealed no significant relationship with any of the subcomponents of AOT ($r(124) = .123$, $p = .172$ (dogmatism), $r(124) = -.054$, $p = .553$ (fact resistance), $r(124) = -.171$, $p = .058$ (liberalism), $r(124) = .084$, $p = .355$ (belief personification), or the AOT scale as a whole, $r(124) = .001$, $p = .987$. A multiple regression was run to predict NFI Magnitude from dogmatism, fact resistance, liberalism, and belief personification. These variables did not significantly predict NFI Magnitude $F(4, 119) = 1.293$, $p = .277$, $R^2 = .042$. The remainder of the analyses in this chapter focus on the original set of 62 participants that were exposed to the nudge and repeated their estimates.

Estimates Task – Nudge Subsample

A 3 (Scenario Type: 21kg for 5 years, 11kg for 5 years, 21kg for 5 years + 11kg for five years) × 2 (Intervention: Pre vs. Post Nudge) within-participant analysis of variance revealed a significant main effect of Scenario, $F(2, 122) = 120.716$, $MSE = 16.358$, $p < .001$, $\eta^2p = .664$, and of Intervention, $F(1, 61) = 13.980$, $MSE = 2.723$, $p < .001$, $\eta^2p = .186$. There was also a significant interaction between Scenario Type and Intervention, $F(2, 122) = 12.160$, $MSE = 3.296$, $p < .001$, $\eta^2p = .166$. Follow-up Simple Effects Analysis revealed significant differences between all three scenarios at both levels of the intervention: At pre-

nudge the environmental impact rating for Scenario A (M = 4.694, SD = 2.714) differed significantly from Scenario B (M = -3.081, SD = 3.360; t(61) = 13.246, p < .001, dz = 1.682, BF_{01} = .000), and C (M = 1.194, SD = 2.913; t(61) = 7.00, p < .001, dz = .889, BF_{01} = .000), and Scenario B differed significant from C (t(61) = -9.326, p < .001, dz = -1.184, BF_{01} = .000). This pattern of results (A > C > B) coheres with what would be expected if the environmental impacts of 21kg for 5 years and 11kg for 5 years across a ten-year period were blended/averaged (see Holmgren et al., 2018, and Chapter 6).

At post-nudge the impact rating for Scenario A (M = 4.726, SD = 2.711) differed significantly from Scenario B (M = -3.145, SD = 3.534, t(61) = 14.133, p < .001, dz = 1.795, BF_{01} = .000), and C (M = 3.145, SD = 3.958, t(61) = 2.770, p = .007, dz = .352, BF_{01} = .284), and Scenario B differed significant from C (t(61) = -9.256, p < .001, dz = 1.175, BF_{01} = .000). Therefore, the nudge did not alter the pattern of results (A > C > B) that obtained pre-nudge.

The Simple Effects Analysis, did, however, reveal a significant difference between the environmental impact ratings for Scenario C whereby the ratings increased, t(61) = -4.840, p < .001, dz = -.615, BF_{01} = .001. The ratings neither increased nor decreased from pre- to post-nudge for Scenario A (t(61) = -.141, p = .888, dz = -.018, BF_{10} = 9.925), or B (t(61) = .221, p = .826, dz = .028, BF_{10} = 9.786). Therefore, while there was still evidence of the averaging of impacts in Scenario C, this appeared less pronounced post-nudge.

For the forced-choice question at pre-nudge (e.g., relating to whether they computed the environmental impact of the scenarios through the total impact for the time-period or the average environmental impact over the time-period) 35 participants reported that they computed the total, while 27 reported they calculated the average. To investigate whether the self-reported computation had any meaningful effect on the NFI, a 3 (Scenario Type) × 2 (Intervention) × 2 (Computation Type: Total vs. Averaging) mixed analysis of variance was undertaken. This revealed no between-participants main effect of Computation Type (F(1, 60) = .286, MSE = 20.854, p = .595, η^2p = .005), and the interaction was not significant

between Scenario and Computation Type ($F(2, 120) = .231$, $MSE = 16.567$, $p = .794$, $\eta^2p = .004$). However, the Scenario Type by Intervention manipulation was significant ($F(1, 60) = 4.389$, $MSE = 2.580$, $p = .040$, $\eta^2p = .068$. This arose because the group self-reporting averaging increased their environmental impact ratings *generally* from pre-nudge ($M = .593$; $SD = 1.457$) to post-nudge ($M = 1.630$; $SD = 1.553$, $t(26) = 3.599$, $p = .001$, $dz = -.693$, $BF_{01} = .040$) while the group self-reporting totalling did not ($M = 1.200$ [$SD = 2.121$] pre-nudge to $M = 1.533$ post-nudge [$SD = 2.412$], $t(34) = -1.716$, $p = .095$, $dz = -.290$, $BF_{01} = 1.915$). The three-way interaction between Scenario, Intervention and Computation Type was not significant ($F(2, 120) = 2.950$, $MSE = 3.194$, $p = .056$, $\eta^2p = .047$). Thus, the nudge did not remove the NFI for the group reporting averaging or the group reporting totalling.

Sorting Task

The participants sorted the environmental impact of the scenarios from highest to lowest. Given there were three scenarios, the participants could sort the scenarios into six possible orders (ABC, ACB, BAC, BCA, CAB, CBA) whereby CAB is the correct order and thus the normative response, and ACB represents the expected order if participants were falling prey to the NFI. A Chi-Square test of independence was conducted to examine the relationship between sorting patterns and the frequency of responses. The results indicated a significant association, $\chi^2(5, N = 62) = 39.42$, $p < .001$. All expected frequencies were above 5, indicating the assumptions of the test were met. Considering just participants' report totalling, a chi-square test of independence revealed a statistically significant association, $\chi^2(5, n = 35) = 27.572$, $p < .001$. Similarly, for participants reporting averaging, a chi-square test of independence revealed a statistically significant association, $\chi^2(5, n = 27) = 16.333$, $p = .006$.

The number of participants demonstrating each of the six possible orders can be seen in Table 16 below. Strikingly, only 11% of participants selected the correct order, while 40% selected the order that would be in line with the NFI. 11% of participants self-reporting

averaging choose the correct order, while 37% chose the order expected from an NFI perspective. This compared with 11% of participants selecting the correct order for the group self-reporting totalling, with 40% of participants in that group choosing the order expected from the NFI perspective.

Further inspection of the data revealed that 10 participants had no correct ranks, 34 had one correct rank and 0 had two, and 18 participants had three correct ranks.

Table 15

The Mean environmental impact estimations for the scenarios A, B and C pre-nudge and post-nudge for participants who self-reported a cognitive process of either totalling or averaging.

		Pre-Nudge			Post=Nudge		
		Scenario A	Scenario B	Scenario C	Scenario A	Scenario B	Scenario C
Total	*M*	4.543	-2.6	1.657	4.8	2.886	2.886
	SD	3.284	3.558	3.038	3.197	3.657	3.740
Average	*M*	4.889	-3.704	0.593	4.630	-3.222	3.481
	SD	1.761	3.036	2.678	1.964	3.434	4.273

Table 16

Six possible sorting orders and the frequency of participants choosing self-reporting averaging or totalling to assess environmental impact.

	Sorting Order of Scenarios in Relation to Their Environmental Impact					
	ABC	ACB	BAC	BCA	CAB	CBA
Participants who Averaged	2 (7%)	12 (44%)	3 (11%)	5(19%)	3 (11%)	2 (7%)
Participants who totalled	1 (3%)	13 (37%)	1 (3%)	13 (37%)	4 (11%)	3 (9%)
Response		NFI			Norm	
Total number of participants	3 (5%)	25 (40%)	4 (6%)	18 (29%)	7 (11%)	5 (8%)

The mean rank for scenario A was 1.742 (*SD* = 0.767), for B it was 2.516 (*SD* = 0.784), and for C it was 1.742 (*SD* = 0.651). The mean ranks appeared to show different patterns depending on whether participants self-reported totalling or averaging. For participants self-reporting totalling, the means demonstrated the pattern BAC, whereas for participants self-reporting averaging, the pattern was BCA, patterns consistent with neither normative responding nor the NFI. However, it should be noted that the data here are aggregations of sorting orders.

(Scenario A = *M* = 1.8 *SD* = 0.759 (totalling), *M* = 1.667, *SD* = 0.784 (averaging); Scenario B = *M* = 2.6, *SD* = 0.736 (totalling), *M* = 2.407, *SD* = 0.844 (averaging), Scenario C = *M* = 1.6, *SD* = 0.604 (totalling), *M* = 1.926, *SD* = 0.675 (averaging). Due to the small sample size when broken down by self-reported strategy, the following analyses are restricted to the whole sample (i.e., collapsed across self-reported strategy).

A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, and C. The results indicated a non-significant difference, $\chi^2(2, n = 62) = 24.774$, $p < .001$. Similarly, Kendall's coefficient of concordance (W) test was conducted to determine the level of agreement among raters. There was not a statistically significant agreement in the rankings, $W = .200$, $\chi^2(2, n = 62) = 24.774$, $p < .001$.

A Wilcoxon signed-rank test was then conducted to determine whether there was a significant difference in the participants' rank scores compared to the correct rank position. There was a statistically significant difference between the participants' rankings for Scenario A (Mdn = 2) and the correct ranking (2), $Z = -2.530$, $p < .001$ (based on negative ranks), Scenario B (Mdn = 3) and the correct ranking (3) $Z = -3.946$, $p < .001$ (based on negative ranks), and between Scenario C (Mdn = 2) and the correct ranking (1) $Z = -5.849$, $p < .001$ (based on positive ranks). It is important to note that the lower the rank, the more impactful the participants considered the scenario to be. For Scenarios A and B participants' ratings were significantly lower than the correct ranking suggesting that they ranked Scenarios A and B as more impactful than they really were. For Scenario C participants ratings were significantly higher than the correct ranking, suggesting that they ranked Scenario C as less impactful than it really was.

From the point of view of the NFI, the expected sorting pattern would be ACB – in line with the estimate data. A Wilcoxon signed-rank test was conducted to determine whether there was a significant difference in the participants' rank scores compared to the rank position expected from the NFI. There was a statistically significant difference between the participants' rankings for the three scenarios and the expected pattern based on the NFI. There was a significant difference between participants' ratings for Scenario A and the rank expected from the NFI (1) $Z = -5.289$, $p < .001$ (based on positive ranks), and between the participant's ratings for Scenario B and the rank expected from the NFI (3) $Z = -3.946$, $p < .001$ (based on negative ranks) and between participants' ratings for Scenario C and the

rank expected from the NFI (2) $Z = -2.921$, $p = .003$ (based on negative ranks). Thus, at odds with the NFI, participants tended to assign a higher rank to Scenario A compared to what would be expected from the NFI, suggesting they judged it as less impactful than what would be expected. Further, they tended to assign lower ranks for Scenarios B and C compared to what would be expected from the NFI – suggesting that they viewed them as more impactful than would be expected from an NFI perspective.

Comparison between Pre-nudge Estimate and the Sorting Task Data

To directly compare data from the estimates task with the pre-nudge sorting task data, participants estimates were rank ordered. For example, if participants rated the environmental impact of Scenario A as 8, Scenario B as 3 and Scenario C as 10, the rank order would be assigned as 2, 3, 1. For instances where the environmental impact was rated as the same for two scenarios, an average of the tied ranks was assigned. For example, if a participant rated Scenario A as 4, Scenario B as 4 and Scenario C as 1, the rank order assigned would be 1.5, 1.5, 3.

Not including the eight participants who had tied ranks, the distribution of the possible orders for the pre-nudge judgement task was as follows. A Chi-Square test of independence was conducted to examine the relationship between sorting patterns and the frequency of responses revealed a statistically significant association, $\chi^2(5, n = 62) = 164.222$, $p < .001$.

The mean rank for scenario A was 1.148 ($SD = 0.452$), for B was 2.833 ($SD = 0.466$), and for C was 2.019 ($SD = 0.412$). A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, and C. The results indicated a significant difference, $\chi^2(2, n = 62) = 76.704$, $p < .001$. Similarly, Kendall's coefficient of concordance (W) test was conducted to determine the level of agreement among raters. There was a statistically significant agreement in the rankings, $W = .710$, $\chi^2(2, n = 62) = 76.704$, $p < .001$.

To investigate if there is a relationship between the ranks from the environmental impact judgements and the sorting task responses, a Spearman rank correlation was

performed. This revealed an absence of a correlation between the rating and sorting task for Scenario A (ρ(62) = .223, *p* = .104), Scenario B (ρ(62) = .243, *p* = .077, and Scenario C (ρ(62) = -.060, *p* = .667). A Wilcoxon Signed-Rank Test was undertaken to test the differences between the ranks of environmental judgements and sorting task responses. There was a statistically significant difference between the participants' rankings for Scenario A and the ranking based on environmental impact judgements (Mdn = 1), *Z* = -4.206, *p* < .001 (based on positive ranks). Similarly, there was a statistically significant difference between the participant's rankings for Scenario B and the ranking based on environmental impact judgements (Mdn = 3), *Z* = -2.495, *p* = .031 (based on negative ranks), and for participant's ranking for Scenario C and the ranking based on environmental impact judgements (Mdn = 2), *Z* = -2.481, *p* = .013 (based on negative ranks). For Scenario A participants' ranking from the sorting task was significantly higher than the ranking computed from the judgement task suggesting that they ranked Scenario A as less impactful for the sorting against judgement task. For Scenarios B and C participants' rankings based on the sorting task were significantly lower than for the judgement task, suggesting that they ranked Scenarios B and C as more impactful within the sorting as compared to judgement task.

Comparison between Post-nudge Estimate and the Sorting Task Data

Post-nudge estimates transformed into sorting patterns in the manner described previously. Five participants had ties. The remaining 57 participants demonstrated the following frequency of sorting patterns in Table 17. A Chi-Square test of independence was conducted to examine the relationship between sorting patterns and the frequency of responses revealed a statistically significant association, χ2(5) = 86.053, *p* < .001.

Table17

Six possible sorting orders and the frequency of participants order of environmental impact for scenarios A, B and C pre nudge and again post nudge.

	Sorting Order of Scenarios in Relation to Their Environmental Impact					
	ABC	ACB	BAC	BCA	CAB	CBA
Pre nudge	4 (7%)	44 (81%)	1 (2%)	3(6%)	1 (2%)	1 (2%)
Post nudge	6 (11%)	31 (54%)	0	19 (33%)	0	1 (2%)
Response		NFI			Normative	

A Chi-square test for independence was conducted to examine if there was a change in frequency distribution from the scoring categories (e.g., ABC, ACB etc) from the pre-nudge judgement to the post-nudge judgement. The results indicated a significant difference in the frequency of responses, $\chi^2(5, n = 111) = 16.220$, $p = .006$. The conclusion remained the same when only the 50 participants without tied ranks at both pre-nudge and post-nudge were included in the analysis, $\chi^2(5, n = 100) = 13.095$, $p = .023$. These findings suggest that the frequency of the ACB pattern (indicating the NFI) *decreased* significantly from the pre-nudge to post-nudge estimate, while the frequency of BCA responses increased. Thus, although the response pattern indicating a NFI decreased following the nudge, the incidence of normative responses (e.g., CAB) did not.

For the post-nudge estimation data, the mean rank for scenario A was 1.368 (*SD* = 0.522), for B it was 2.877 (*SD* = 0.331), and for C was 1.754 (*SD* = 0.635). A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, and C. The results indicated a significant difference, $\chi^2(2, n = 62) = 70.035$, $p < .001$. Similarly, Kendall's coefficient of concordance (*W*) test was conducted to determine the level of

agreement among raters. There was a statistically significant agreement in the rankings, W = .614, $\chi^2(2, n = 62) = 70.035$, $p < .001$.

To investigate if there is a relationship between the ranks from the environmental impact judgements and the sorting task responses, a Spearman rank correlation was performed. This revealed a statistically significant correlation between the rating and sorting task for Scenario A ($\rho(62) = .280$, $p = .035$) and Scenario C ($\rho(62) = .280$, $p = .035$), but not Scenario B ($\rho(62) = .182$, $p = .177$.

A Wilcoxon Signed-Rank Test was undertaken to test the differences between the ranks of environmental judgements and sorting task responses. There was a statistically significant difference between the participants' rankings for Scenario A and the ranking based on environmental impact judgements (Mdn = 1), $Z = -3.402$, $p < .001$ (based on positive ranks). Similarly, there was a statistically significant difference between the participant's rankings for Scenario B and the ranking based on environmental impact judgements (Mdn = 3), $Z = -3.078$, $p = .002$ (based on negative ranks). There was no statistically significant difference between participant's rankings for Scenario C and the ranking based on environmental impact judgements (Mdn = 2), $Z = .442$, $p = .658$ (based on positive ranks). For Scenario A participants' ranking from the sorting task was significantly higher than the ranking computed from the judgement task suggesting that they ranked it as less impactful for the sorting against judgement task. For Scenario B participants' rankings based on the sorting task were significantly lower than for the judgement task, suggesting that they ranked Scenario B as more impactful within the sorting as compared to judgement task.

Comparison of rating at pre-nudge and rating at post-nudge with the scores converted into rank order for the 50 participants that had no ties at both pre- and post-nudge. Scenario A and the ranking based on environmental impact judgements (Mdn = 1), $Z = -2.673$, $p = .008$ (based on negative ranks) and similarly for Scenario C, $Z = -3.357$, $p = .002$

(based on positive ranks). There was no statistically significant difference between participant's rankings for Scenario B and the ranking based on environmental impact judgements, Z = -1.089, p = .276 (based on negative ranks). Participants ranked Scenario A as lower pre nudge than post-nudge, indicating that they perceived its impact as less high following the nudge. Participants ranked Scenario C as lower post-nudge than pre-nudge, indicating that the perceived its impact as greater following the nudge.

Surprisingly, then, the environmental impact judgements did not completely align with how participants sorted the scenarios. The evidence for a NFI was much weaker with the sorting task than with the judgement task. While a normative response was more likely in the sorting than estimates task, it was still infrequent. The nudge, though effective at reducing the incidence of response patterns indicative of the NFI, failed to promote normative responding.

Experiment 5B

Experiment B aimed to replicate Experiment 5A, with the addition of another scenario (D) where 21kg of WEEE per person over 5 years is followed by another 5 years of 21kg per person (a total of 10 years at 42kg per person). This addition (see also Chapter 6) serves as a control scenario to clarify participants' judgements and the potential influence of judgement biases, compared to the original variable scenarios. Replicating Experiment 5A with the inclusion of Scenario D in a within-participant design establishes a stable baseline for comparison. The consistency of 21kg across both time periods allows us to assess whether the presence of variability in quantities affects how participants judge environmental impact.

The inclusion of an unchanging impact level may lead to different patterns in sorting and judgement tasks, providing clearer insights into whether variability in quantities is relevant for the negative footprint illusion (NFI). Additionally, this stable 21kg scenario enables an assessment of bias in response consistency; it allows one to determine whether participants' tendency to categorise scenarios as "normative" is influenced by stability versus

change. If judgements still fail to align with this stable scenario, this will imply that the NFI is a deeply ingrained bias affecting perception even in the absence of variability.

Including a stable 21kg scenario also helps to observe the nudge's effect on vice-virtue categorization. If the nudge prompts normative responses in this scenario, it could suggest that NFI can be mitigated in the context of vice-virtue evaluations, helping guide future strategies to support consistent normative judgements in environmental contexts. Ultimately, the stable scenario clarifies whether participants rely on vice-virtue evaluations even without quantity fluctuations, as consistent categorisation would suggest a strong cognitive bias toward vice-virtue heuristics rather than averaging in environmental impact judgement.

Method

Design

This was the same as Experiment 5A apart from the introduction of a new scenario (Scenario D). Thus, the within-participants factor of Scenario now had four levels.

Participants

A University in the Northwest of England used an internal participant recruitment platform SONA. The sample size was based on a power analysis using GPower (Faul et al., 2007), which indicated that 48 participants would be needed to detect a medium effect (.40) with 80% power using an *F* test with alpha at .05. Sixty-four participants with a mean age of 34.5 years, (*SD*=7.7, 55% female) with English as their first language participated in the study. The study took 15 minutes to complete, course credits were granted.

Materials and Procedures

This experiment was presented via Qualtrics, where participants engaged in an online questionnaire. The materials and procedure were the same as Experiment 5A apart from the addition of a new scenario:

> Scenario D. Over a 5-year period (2001-2006) the amount of WEEE per person was relatively high (21 kg per year) due to humanity's consumption and use of natural

> resources. Despite the fact that a new WEEE directive was established by the European Union to reduce waste and recover raw materials, another five-year period (2006-2011) followed when the WEEE per person was still relatively high (21 kg per year). Please estimate, to the best of your abilities, how this scenario influences the environment during this ten-year time-period (2001-2011) by using the scale below.

The four scenarios were also included in the sorting task. Another difference was that following the nudge participants repeated the sorting task after they repeated their environmental impact judgements for the scenarios.

Results

Environmental Impact Judgements

A 4 (Scenario Type: A (21kg for 5 years), B (11kg for 5 years), C (21kg for 5 years + 11kg for 5 years), D (21kg for 5 years + 21kg for 5 years)) × 2 (Intervention: Pre vs. Post Nudge) within-participant analysis of variance revealed a significant main effect of Scenario, $F(3, 189) = 68.954$, $MSE = 17.657$, $p < .001$, $\eta^2p = .523$. However, there was no effect of Intervention, $F(1, 63) = 1.683$, $MSE = 7.803$, $p = .199$, $\eta^2p = .026$. The interaction between Scenario Type and Intervention was not significant, $F(3, 189) = 0.904$, $MSE = 6.344$, $p = .440$, $\eta^2p = .014$.

Follow-up t-tests demonstrated significant differences between all pairs. Scenario A ($M = 3.922$; $SD = 3.214$) differed significantly from Scenario B ($M = -1.625$; $SD = 3.740$; $t(63) = 9.809$, $p < .001$, $dz = 1.226$, $BF_{01} = 0.000$), Scenario C ($M = 1.172$; $SD = 3.348$; $t(63) = 6.174$, $p < .001$, $dz = .772$, $BF_{01} = 0.000$), and Scenario D ($M = 5.344$; $SD = 3.946$; $t(63) = -4.228$, $p < .001$, $dz = -.528$, $BF_{01} = 0.004$). Scenario B differed significantly from C ($t(63) = -5.488$, $p < .001$, $dz = -.686$, $BF_{01} = 0.000$), and D ($t(63) = -9.756$, $p < .001$, $dz = -1.219$, $BF_{01} = 0.000$) and Scenario C differed significantly from D ($t(63) = -8.278$, $p < .001$, $dz = -1.035$, $BF_{01} = 0.000$). Thus, participants' reported impact estimates were highest in D, then A,

followed by C and then B. This pattern conforms to exactly what would be expected if participants were averaging/blending the high and low impact quinquennial in Scenario C but totalling the two high impact quinquennials in Scenario D. Scenario A and C are thus inverted from what would be expected for a normative response.

For the forced-choice question at pre-nudge (e.g., relating to whether participants computed the environmental impact of the scenarios through the total impact for the time-period or the average environmental impact over the time-period) 39 participants reported that they computed the total, while 25 reported they calculated the average.

To investigate whether the self-reported computation had any meaningful effect on the NFI, a 3 (Scenario Type) × 2 (Intervention) × 2 (Computation Type: Total vs. Averaging) mixed analysis of variance was undertaken. This revealed no between-participants main effect of Computation Type ($F(1, 62) = .374$, $MSE = 49.702$, $p = .543$, $\eta^2p = .006$). The Scenario Type by Intervention interaction was not significant ($F(1, 62) = 1.452$, $MSE = 7.748$, $p = .233$, $\eta^2p = .023$. However, the Scenario Type by Computation Type interaction was significant ($F(3, 186) = 3.252$, $MSE = 17.048$, $p = .023$, $\eta^2p = .050$). This arose because the group self-reporting averaging rated the environmental impact of Scenario B ($M = -2.800$, $SD = 3.894$) as significantly less than the totalling group did (M -.872; $SD = 3.481$; $t(62) = -2.064$, $p = .043$, $d = -.529$, $BF_{01} = 0.782$). The three-way interaction between Scenario Type, Intervention and Computation Type was not significant, $F(3, 186) = .231$, $MSE = 6.422$, $p = .874$, $\eta^2p = .004$.

Sorting Task – Pre-Nudge

Inspection of the data revealed that 24 (37.5%) participants sorted the scenarios into their correct order (DCAB). 21 (32.8%) participants erroneously sorted the scenarios into the order expected from a NFI perspective (DACB). 4 participants had no correct ranks, 9 had one correct rank and 27 had two, no participants had three correct ranks, and 24 participants had 4 correct ranks.

The mean rank for scenario A was 2.422 (*SD* = 0.730), for B was 3.578 (*SD* = 0.940), for C was 2.578 (*SD* = 0.708), and for D was 1.422 (*SD* = 0.887). The mean ranks were similar regardless of whether participants self-reported using averaging (Scenario A = *M* = 2.538, *SD* = 0.756 (totalling), *M* = 2.24, *SD* = 0.663 (averaging); Scenario B = *M* = 3.564, *SD* = 1.021 (totalling), *M* = 3.6, *SD* = 0.816 (averaging), Scenario C = *M* = 2.410, *SD* = 0.715 (totalling), *M* = 2.84, *SD* = 0.624 (averaging), Scenario D = *M* = 1.487, *SD* = 0.885 (totalling), *M* = 1.32, *SD* = 0.9 (averaging). 14 of the 25 participants who self-reported using averaging (56%), demonstrated the response pattern mapping onto the NFI (DACB) while 5 of the 25 (20%) demonstrated the normative response pattern. In contrast 19 of the 39 participants reporting totalling (49%) demonstrated the normative response pattern (DCAB), while 7 (18%) of participants demonstrated the response pattern consistent with the NFI (DACB). A Pearson Chi-square test was conducted to examine the relationship between sorting order (DACB and DCAB) and self-reported strategy (averaging and totalling). The association was found to be statistically significant, $\chi^2(1, N = 45) = 9.64$, $p = .002$, indicating that participants' choice of sorting order was related to the strategy they used. Specifically, participants who sorted the scenarios as DACB, a NFI, were more likely to self-report use of an averaging strategy compared to those who sorted them as DCAB, the normative response. Due to the small sample size when broken down by self-reported strategy, the following analyses are restricted to the whole sample (i.e., collapsed across self-reported strategy).

A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, C, and D. The results indicated a significant difference, $\chi^2(3, n = 64) = 89.737$, $p < .001$. Similarly, Kendall's coefficient of concordance (*W*) test was conducted to determine the level of agreement among raters. There was a statistically significant agreement in the rankings, $W = .467$, $\chi^2(3, n = 64) = 89.737$, $p < .001$.

A Wilcoxon signed-rank test was then conducted to determine whether there was a significant difference in the participants' rank scores compared to the correct rank position.

There was a statistically significant difference between the participants' rankings for all scenarios and their correct rankings (A [Mdn = 2.5] and the correct ranking (3), $Z = -4.916$, $p < .001$ [based on negative ranks], (B [Mdn = 4] and the correct ranking (4), $Z = -3.236$, $p = .001$ [based on negative ranks], C [Mdn = 3] and the correct ranking (2), $Z = -5.026$, $p < .001$ [based on positive ranks], D [Mdn = 1] and the correct ranking (1), $Z = -3.482$, $p < .001$ [based on positive ranks]). For Scenario A and B participants' ratings were significantly lower than the correct ranking, despite the same median (Scenario B). This indicates a skew towards lower rankings – that is, participants ranked Scenario A and B are *more* impactful than they really are. The opposite pattern obtained for Scenario C and D. Despite the same median (Scenario D), participants' ratings were significantly higher than the correct ranking which suggests a skew towards higher rankings – participants ranked Scenario C and D as less impactful than they really are.

As mentioned previously, the expected pattern of rankings from an NFI perspective is DABC. When considering this pattern, 7 participants had 0 ranks correct, 4 participants had 1, 32 had 2, no participants had 3, and 21 participants had 4 ranks "correct".

A Wilcoxon signed-rank test was conducted to determine whether there was a significant difference in the participants' rank scores compared to the rank position expected from the NFI. There was a statistically significant difference between the participants' rankings for all scenarios and their correct rankings (A [Mdn = 2.5] and the NFI-derived ranking (2), $Z = -4.023$, $p < .001$ [based on negative ranks], (B [Mdn = 4] and the NFI-derived ranking (4), $Z = -3.236$, $p = .001$ [based on positive ranks], C [Mdn = 3] and the NFI-derived ranking (3), $Z = -4.115$, $p < .001$ [based on positive ranks], D [Mdn = 1] and the correct ranking (1), $Z = -3.382$, $p < .001$ [based on negative ranks]).

For Scenario A and D participants' ratings were significantly higher than the NFI-derived ranking, despite the same median (Scenario D). This indicates a skew towards higher rankings – that is, participants ranked Scenario A and D as less impactful than

expected from an NFI perspective. The opposite pattern obtained for Scenario B and C: Despite the same median scores (Scenarios B and C) participants' ratings were significantly lower than the NFI-derived ranking which suggests a skew towards lower rankings – participants ranked Scenario B and C as more impactful than would be expected from the NFI perspective.

Comparison between Pre-nudge Estimate and the Sorting Task Data

To directly compare data from the estimates task with the pre-nudge sorting task data, participants estimates were rank ordered as in Experiment 5A. Not including the twenty-four participants who had tied ranks, 23 (58%) participants scores followed the pattern expected from the NFI (DACB) while only 1 (3%) of the participants scoring patterns showed a normative response (DCAB).

Given that there were 24 possible order of responses, and forty eligible participants, a Chi-square test incorporating the 24 (sorting) categories, was not undertaken because > 20% of the expected frequencies were expected to be less than 5, and thus the test may not be valid. In descriptive terms, of the 23 participants reporting the NFI order DACB for judgements, 9 self-reported averaging while 14 self-reported totalling. The single participant reporting the normative response DCAB reporting totalling. In contrast, for the sorting task within the same reduced sample, 15 of the participants reported the NFI order, with 9 of these participants reporting averaging and 6 totalling, while 16 participants reported the normative response with 4 self-reporting averaging and 12 self-reporting totalling.

A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, and C and D. The results indicated a significant difference, $\chi^2(3, n = 40) = 71.580$, $p < .001$. Similarly, Kendall's coefficient of concordance (W) test was conducted to determine the level of agreement among raters. There was a statistically significant agreement in the rankings, $W = .597$, $\chi^2(3, n = 40) = 71.580$, $p < .001$.

To investigate if there is a relationship between the ranks from the environmental impact judgements and the sorting task responses, a Spearman rank correlation was performed. Note that this involved the reduced sample of 40 participants for which rank data were usable for both the judgement and sorting task. This revealed an absence of a correlation between the rating and sorting task for Scenario A ($\rho(40) = .204$, $p = .207$), Scenario B ($\rho(40) = .279$, $p = .081$, and Scenario C ($\rho(40) = -.177$, $p = .274$. However, a significant correlation between the rating and sorting task was found for Scenario D ($\rho(40) = .617$, $p < .001$).

A Wilcoxon Signed-Rank Test was undertaken to test the differences between the ranks of environmental judgements and sorting task responses. There was no statistically significant difference between the participants' rankings for Scenario A and the ranking based on environmental impact judgements (Mdn = 2), $Z = -1.868$, $p = .062$ (based on negative ranks). Similarly, there was a statistically significant difference between the participant's rankings for Scenario B and the ranking based on environmental impact judgements *(*Mdn = 4), $Z = -1.030$, $p = .303$ (based on negative ranks), or for participant's ranking of Scenario D and the ranking based on environmental impact judgements (Mdn = 1), $Z = -0.159$, $p = .873$ (based on positive ranks). However, there was a statistically significant difference between participant's rankings for Scenario C and the ranking based on environmental impact judgements (Mdn = 3), $Z = -2.394$, $p = .017$ (based on positive ranks): Participants' ranks for Scenario C were higher in the judgement task than in the sorting task meaning that they perceived the scenario as having a greater environmental impact in the sorting compared to judgement task. This ties in with the characteristics of the reduced sample whereby 16 participants (40%) exhibited a normative response, and 15 participants (38%) demonstrated a pattern of responding consistent with the NFI – a far more even distribution than for the judgement task.

Sorting Task – Post nudge

Inspection of the data revealed that 27 (42.2%) of participants sorted the scenarios into their correct order (DCAB). 16 (25%) of participants erroneously sorted the scenarios into the order expected from a NFI perspective (DACB). 10 participants had no correct ranks, 5 had one correct rank and 22 had two, no participants had three correct ranks, and 26 participants had 4 correct ranks.

The mean rank for scenario A was 2.625 (*SD* = 0.701), for B was 3.48 (*SD* = 0.959), for C was 2.375 (*SD* = 0.807), and for D was 1.516 (*SD* = 1.008). A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, C, and D. The results indicated a significant difference, $\chi^2(3, n = 64) = 75.619$, $p < .001$. Similarly, Kendall's coefficient of concordance (*W*) test was conducted to determine the level of agreement among raters. There was a statistically significant agreement in the rankings, $W = .394$, $\chi^2(3, n = 64) = 75.619$, $p < .001$.

A Wilcoxon signed-rank test was then conducted to determine whether there was a significant difference in the participants' rank scores compared to the correct rank position. There was a statistically significant difference between the participants' rankings for all scenarios and the correct rank position (A [Mdn = 3] and the correct ranking (3), $Z = -3.788$, $p < .001$ [based on negative ranks], (B [Mdn = 4] and the correct ranking (4), $Z = -3.668$, $p = .001$ [based on negative ranks], C [Mdn = 2] and the correct ranking (2), $Z = -3.396$, $p < .001$ [based on positive ranks], D [Mdn = 1] and the correct ranking (1), $Z = -3.573$, $p < .001$ [based on positive ranks]). Despite the same medians, for Scenario A and B participants' ratings were significantly lower than the correct ranking. This indicates a skew towards lower rankings – that is, participants ranked Scenario A and B are *more* impactful than they really are. The opposite pattern obtained for Scenario C and D. Despite the same medians, participants' ratings were significantly higher than the correct ranking which suggests a skew

towards higher rankings – participants ranked Scenario C and D as less impactful than they really are.

As for Experiment A, the participant rankings were compared with those expected from the NFI perspective. When considering this pattern, 5 participants had 0 ranks correct, 10 participants had 1, 33 had 2, no participants had 3, and 16 participants had 4 ranks "correct". A Wilcoxon signed-rank test was conducted to determine whether there was a significant difference in the participants' rank scores compared to the rank position expected from the NFI. There was a statistically significant difference between the participants' rankings for all scenarios and their correct rankings (A [Mdn = 3] and the NFI-derived ranking (2), $Z = -5.313$, $p < .001$ [based on negative ranks], (B [Mdn = 4] and the NFI-derived ranking (4), $Z = -3.668$, $p < .001$ [based on positive ranks], C [Mdn = 2] and the NFI-derived ranking (3), $Z = -4.878$, $p < .001$ [based on positive ranks], D [Mdn = 1] and the correct ranking (1), $Z = -3.573$, $p < .001$ [based on negative ranks]).

For Scenario A and D participants' ratings were significantly higher than the NFI-derived ranking. This indicates a skew towards higher rankings – that is, participants ranked Scenario A and D as less impactful than expected from an NFI perspective. The opposite pattern obtained for Scenario B and C whereby participants' ratings were significantly lower than the NFI-derived ranking which suggests a skew towards lower rankings – thus participants ranked Scenario B and C as more impactful than would be expected from the NFI perspective.

Comparison between Post-nudge Estimate and the Post-nudge Sorting Task Data

To directly compare data from the estimates task with the post-nudge sorting task data, participants estimates were again rank ordered. Not including the twenty-seven participants who had tied ranks, 21 (58%) participants scores followed the pattern expected from the NFI (DACB) while only 5 (14%) of the participants scoring patterns showed a normative response (DCAB).

A Friedman test was conducted to determine if there were differences in the ranks of Scenarios A, B, and C and D. The results indicated a significant difference, $\chi^2(3, n = 37) = 48.016$, $p < .001$. Similarly, Kendall's coefficient of concordance (W) test was conducted to determine the level of agreement among raters. There was a statistically significant agreement in the rankings, $W = .433$, $\chi^2(3, n = 37) = 48.016$, $p < .001$.

To investigate if there is a relationship between the ranks from the environmental impact judgements and the sorting task responses, a Spearman rank correlation was performed. Note that this involved the reduced sample of 37 participants for which rank data were usable for both the judgement and sorting task. This revealed an absence of a correlation between the rating and sorting task for Scenario A ($\rho(37) = .036$, $p = .832$). However, a significant correlation between the rating and sorting task emerged for Scenario B ($\rho(37) = .521$, $p < .001$, Scenario C ($\rho(37) = .478$, $p = .003$, and Scenario D ($\rho(37) = .762$, $p < .001$).

A Wilcoxon Signed-Rank Test was undertaken to test the differences between the ranks of environmental judgements and sorting task responses. There was no statistically significant difference between the participants' rankings and the ranking based on environmental impact judgements for Scenario A (Mdn = 2), $Z = -1.103$, $p = .270$ (based on positive ranks) Scenario B (Mdn = 4), $Z = -0.181$, $p = .856$ (based on positive ranks), or Scenario D (Mdn = 1), $Z = -0.541$, $p = .589$ (based on positive ranks). However, there was a statistically significant difference between participant's rankings for Scenario C and the ranking based on environmental impact judgements (Mdn = 3), $Z = -2.295$, $p = .022$ (based on positive ranks): Participants' ranks for Scenario C were higher in the judgement task than in the sorting task meaning that they perceived the scenario as having a greater environmental impact in the sorting compared to judgement task. Again, this ties in with the characteristics of the reduced sample whereby for the sorting task, 15 participants (41%)

exhibited a normative response, and 12 participants (32%) demonstrated a pattern of responding consistent with the NFI – a more even distribution than for the judgement task.

Assessing the Impact of the Nudge

To investigate whether there was a significant change in rank orderings from pre- to post-nudge, a Wilcoxon Signed-Rank Test was undertaken. There was a statistically significant difference between the participants' rankings between pre and post-nudge for Scenario A (Z = -2.194, p = .028 (based on negative ranks), but not for Scenario B (Z = -0.674, p = .500 (based on positive ranks), Scenario C (Z = -1.734, p = .083 (based on positive ranks) or Scenario D (Z = -0.860, p = .390 (based on negative ranks). The rank assigned to Scenario A was significantly higher following the nudge, indicating that post-nudge participants considered the environmental impact of this scenario to be lower.

Sorting behaviours DACB (NFI) and DCAB (Norm) were considered in a further analysis to determine whether individuals demonstrating sorting behaviour consistent with the NFI at pre-nudge (DACB) (NFI), changed to a normative response (DCAB) (Norm) post-nudge (or vice versa). Descriptively, 9 participants who sorted as DACB (NFI) continued to do so post-nudge, and 18 participants who sorted into DCAB continued to do so post-nudge. 8 participants who sorted into DACB (NFI) switched to DCAB (Norm) post-nudge compared to 5 participants who sorted into DCAB (Norm) and switched post-nudge to DACB (NFI). Of the 8 participants who switched from the NFI response to the normative response, 7 self-reported averaging pre-nudge and 1 self-reported totalling. Of the 5 participants who selected the normative response pre-nudge and then sorted via the NFI response pattern post-nudge, 1 self-reported averaging and 4 self-reported totalling.

McNemar's test was the first used analysis as it is a resource that specifically tests for differences in a dichotomous variable. McNemar's test was the most relatable analysis as we investigated a change in behaviour pre- and post-nudge. The results of McNemar's test were not statistically significant, p = .581, indicating no significant change in sorting

behaviour based on the nudge. During the investigations throughout this thesis, we observed the flatlining of data, a phenomenon where the data showed no significant change. This suggests that true information is hidden throughout the data, given the statistical significance of the results and variations between A, B, C and D and understanding if interventions work is potentially important; hence, a second analysis was undertaken. This time, we looked beyond the dichotomous relationship but towards homogeneity (a comparison of distribution using the categorical variable), independence (do the observations of the two variables exist independently of each other), and whether the observed frequency differs from the theoretical distribution- is it a good fit. A Pearson Chi-test was conducted. The Pearson Chi-Square test was statistically significant, $\chi 2(1, n = 40) = 4.18$, $p = .041$, suggesting a significant difference in sorting patterns before and after the nudge. Here, two things arise: we now have a statistically significant result, but it does not inform us where the relationship is and whether these contradictory analyses result from a small sample size. In the search for accuracy, we conduct a third analysis, this time using Fisher's exact test, which is specifically used for small sample sizes and makes exact calculations of probability with the given data rather than approximations. However, Fisher's Exact Test did not reach significance on the two-sided test, $p = .052$. These mixed results suggest that while there may be some evidence of a change in sorting behaviour, it is not robust across all statistical tests, and further investigation with a larger sample size may be needed to clarify the impact of the nudge. To determine if this could be a possible source of intervention to correct behaviour.

In relation to the rank orders that were derived from participants' estimates, only thirty participants produced ratings that were not ties at either pre-nudge or post-nudge. Of those participants 15 (9 self-reporting totalling, 6 averaging) that originally estimated in the NFI pattern at pre-nudge, did not change the pattern of those estimates post-nudge. The two remaining participants (1 self-reporting totalling, 1 averaging) that estimated in the NFI

pattern at pre-nudge switched their responses, but not to the normative response. Of two participants (1 self-reporting totalling and 1 averaging) that estimated at pre-nudge the normative pattern, one (that self-reported averaging) selected the NFI pattern at post-nudge. None of the participants left within the reduced sample changed their pattern of responding to the normative pattern after the nudge.

Discussion

The results from the WEEE scenario and the family scenario (Chapter 6) are highly comparable. This means that introducing the complexity of long-term environmental impact, and moving away from focussing on individual failure, did not alter how people perceived ecological damage. That is, the results suggest that people's judgements of environmental damage are similarly biased regardless of whether the scenario is framed in terms of individual failure (Chapter 6), or collective failure (this chapter) has consequences for messages regarding the requirement for systemic change. These findings suggest the robustness of the Averaging Bias (Holmgren et al., 2019) and Vice-Virtue Categorisation (Gorissen & Weijters, 2016; Threadgold et al., 2022), whereby participants mentally balance harmful and positive actions rather than summing cumulative impact.

The magnitude of the NFI was not associated with AOT (see also, Chapter 2 And 4). This offers important insights into the underlying cognitive processes that drive environmental judgements. The lack of association suggests that cognitive openness and flexibility—key components of AOT—may not directly influence to tendency to underestimate environmental harm when eco-friendly items or episodes are added to convention ones. This result is at odds with that reported by Threadgold et al. (2022) whereby better general analytic reasoning dispositions were associated with a reduced susceptibility to the NFI. The dissociation between NFI magnitude and general analytic reasoning observed in this study implies that the NFI operates independently of reflective thinking styles potentially relying more on heuristic processes than on deliberative ones.

A striking finding that was replicated across Experiment 5A to 5B was that the NFI, while robust in participant's estimates, was less well observed when participants were asked to rank the same scenarios from most to least environmentally impactful. However, the relationship between self-reported strategies and sorting outcomes, alongside the statistical significance in ranking discrepancies, underscores the capacity of the sorting task to reveal how participants interpret and evaluate scenarios relative to both the normative response and that predicted from the NFI. The Dual-Process Theory (Kahneman, 2011) may help explain this shift: sorting tasks likely engage analytical (System 2) processes, while estimation tasks rely on intuitive (System 1) processes. However, the scarcity of normative responses in the sorting scenarios, coupled with the general lack of normative responses in second estimates (Experiments A and B) and sorting responses (Experiment B), suggests that even if the sorting task promotes analytical processing, it does not consistently lead to accurate or 'normative' results. This finding aligns with Format-Dependent Judgement theories (e.g., Hsee & LeClerc, 1998) Hsee and LeClerc (1998) found that judgement behaviours shift based on presentation format, with responses differing significantly when options are assessed in isolation compared to side-by-side evaluation. This discrepancy suggests that while sorting encourages a comparative approach, it does not necessarily foster a normative or summative assessment. The divergence between estimates and sorting responses points to a cognitive gap between judgement and prioritisation, underscoring the complexities in how individuals process and evaluate environmental impacts. This highlights the need for further investigation into the cognitive mechanisms driving these discrepancies. Future research could benefit from qualitative analyses to examine the reasoning behind both judgements and sorting decisions, as well as experimental studies on how framing influences decision-making in environmental contexts (e.g., Moser & Dilling, 2007; Spence & Pidgeon, 2010). Overall, the sorting task sheds light

on the nuances of how individuals navigate environmental decisions, suggesting that judgements do not straightforwardly translate into prioritisation.

While there is some evidence that the nudge influences participants' sorting behaviours (and estimates), the results are not consistently strong across all analyses. The mixed outcomes—significant shifts for some scenarios and sorting behaviours, but not others—suggest that the nudge may have a limited or variable impact on the NFI. The failure of the sorting task to elicit normative responses even with nudges may reflect Mental Accounting Theory (Thaler, 1999) in environmental contexts. Participants appear to compartmentalise the efficient and inefficient phases of recycling as separate 'accounts' rather than integrating them holistically. This compartmentalisation may prevent a summative evaluation, leading participants to overlook cumulative impact, even when provided with prompts to sum total impact.

The results thus show that the NFI is surprisingly robust: It was resistant to influence by the nudge/hint that was provided. This casts doubt on whether nudges, at least targeting the computation process underpinning the assessment of environmental damage, will be effective behavioural interventions at counteracting misjudgements common in environmental decision-making in relation to the true scale of cumulative impacts.

The ineffectiveness of the nudge used within this study, that focusses on the computational strategy of the participant—contrasts with the effectiveness of nudges within other contexts such as energy usage (Allcott, 2011), and plastic waste reduction (Bruns & Perino, 2023). Within these contexts nudges tend to be more social- or norm-based (Byerly et al., 2018; Kaiser & Wilson, 2019) which might be a critical variable underpinning their effectiveness. Given that NFI is likely driven by averaging within a vice-virtue framework, a norm-based nudge may not be feasible or effective in this context. Thus, the results call for alternative nudging strategies beyond computational cues, potentially involving more nuanced, situational prompts that target deeper cognitive biases.

The observed dissonance between self-reported strategies (e.g., total vs. average) and participants' actual estimates further suggests limited insight into their cognitive processes, supporting Intuitive vs. Analytical Processing frameworks. Participants may rely on an intuitive, qualitative heuristic, perceiving recycling as inherently "green" without explicitly calculating cumulative impact. This may reflect the Moral Licensing Theory (Sachdeva et al., 2009), where positive actions (recycling) are perceived as compensating for negative actions (waste), creating an implicit offset that reduces perceived harm. The generally poor mapping between participant's self-reported computational strategy (totalling vs. averaging) and their tendency to manifest an NFI, suggests that the participants have very little insight in how they arrive at their decision. This might suggest that the averaging process underpinning the NFI is not an arithmetic process but is rather a qualitative process characterised by a general impression of environmental impact rather than a precise calculation. This qualitative approach may involve heuristic judgements, where participants rely on the perceived 'greenness' of recycling actions without explicit numerical reasoning. Such an interpretation suggests that the NFI arises from intuitive processing, where participants treat the presence of recyclable items as offsetting the environmental harm of non-recyclable items rather than explicitly calculating an aggregate or average impact. This suggestion coheres with the findings of Andersson et al. (2024), where arithmetic averaging was not consistently applied and points to computations based on general impressions of environmental impact rather than an explicit calculation, consistent with Cognitive Miser Theory (Fiske, 1991), which posits that individuals often rely on simplified judgements to manage complex information.

However, this reasoning must be reconciled with findings that priming for summative or quantitative operations reduces the NFI (Holmgren et al., 2021). A possible resolution is that the NFI may function as a cognitive default, one that can be overridden when cues prompt a more analytical approach. This implies that the process underlying the NFI, such

as averaging, is a flexible yet generally uninsightful one in the context of environmental impact judgements. Future work could explore cognitive prompts that encourage a summative perspective, as well as interventions targeting public understanding of the limits of recycling as a compensatory action. Such interventions could address public misunderstandings, as individuals may believe that recycling can fully offset environmental harm, despite the continued environmental costs associated with recycling processes (Gu et al., 2017). That individuals with high cognitive flexibility (as measured with the AOT scale) are still prone to intuitive biases in environmental judgements, indicates that the NFI persists across varying levels of reflective thinking. The repeated lack of an association between NFI and analytic thinking suggest that interventions aimed at reducing the NFI might need to target specific biases in environmental reasoning rather than general thinking dispositions.

Chapter 8

General Discussion: Reassessing the Averaging Bias and Its Implications for Recycling Behaviour

Summary

This thesis investigated the cognitive mechanisms underpinning the negative footprint illusion (NFI) through five experiments focussed on recycling-related decisions. The findings confirm the robustness of the NFI in domains with high ecological validity. Critically, the NFI was not constrained by item category and consistently emerged when participants evaluated combinations of conventional and recyclable items—particularly when quantities were large (e.g., 40 conventional + 20 recyclable), replicating the A + B < A pattern seen in prior work (Andersson et al. 2024). In contrast, smaller quantities (e.g., 10 or 20 items) often produced stagnant estimates, indicating a “zero footprint” illusion. Importantly, individual differences in actively open-minded thinking (AOT-17) and working memory capacity did not predict susceptibility to the illusion, suggesting that the NFI is less about cognitive ability or thinking style and more rooted in general heuristic biases.

Emotional factors—specifically valence and arousal—were considered as potential modulators of the NFI, but the results did not support this hypothesis. While recyclable items elicited higher arousal ratings, this emotional engagement did not translate into greater or reduced susceptibility to the illusion. This aligns with Kahneman’s (2011) suggestion that, “emotion looms large in intuitive judgements,” yet it appears that in this case, the emotional salience of recyclability did not influence the cognitive bias. Instead, the persistence of the NFI regardless of affective response strengthens the argument for a generalised averaging bias, likely driven by heuristics or qualitative evaluations rather than numerical reasoning. Emotional responses (arousal) might be expected to influence System 1 processes—but the fact they do not in this case suggests that specific affective cues are less potent than structural heuristics like vice–virtue categorisation. Emotional salience has been shown in

other domains to increase heuristic reliance, particularly when judgments are made under time pressure or uncertainty (Kahneman, 2011; Slovic et al., 2007). In the context of recycling, one might expect that emotionally charged cues—such as guilt about waste or pride in recycling—could bias impact judgments. Yet the current findings suggest that such affective states are not sufficient to override or modulate the deeper cognitive simplifications involved. This interpretation is consistent with findings from Experiments 4, 5A, and 5B, where there was no support for alternative explanations such as mental accounting (Thaler, 1999) or temporal discounting (Frederick et al., 2002). These results point towards a robust, domain-general process of cognitive simplification in environmental judgements.

In addition to item-based and affective evaluations, Experiments 4, 5A, and 5B extended the NFI paradigm to examine environmental judgements across time. These studies revealed that the NFI persists in temporal contexts, such that participants underestimated cumulative environmental harm when periods of inefficient behaviour (e.g., high electronic waste generation) were followed by periods of involvement (e.g., more sustainable recycling). This finding suggests that the averaging bias generalises beyond static item-based decisions and operates even when information is distributed across time. These findings challenge alternative explanations such as temporal discounting (Frederick et al., 2002) and mental accounting (Thaler, 1999). Furthermore, Experiment 5 introduced a cognitive nudge designed to shift participants from an intuitive averaging process to a more normative summation calculation. While this nudge promoted some reflection, it did not eliminate the NFI, suggesting a striking resistance to correction. The illusion persisted even when participants were explicitly encouraged to consider total environmental impact. Taken together, these findings underscore the robustness of the NFI and raise concerns about the limits of individual-level cognitive interventions in correcting environmentally faulty reasoning.

Experiment 1

Experiment 1 (Ch. 3) tested whether the NFI. previously demonstrated in contexts such as houses and transport (Holmgren et al. 2018a, 2018b), would generalise to more commonplace consumer items—specifically, plastic bottles. Participants made environmental impact judgements for conventional items alone and for combinations of conventional and recyclable items. Consistent with the NFI, estimates were lower for the mixed condition, despite the total quantity increasing—replicating the A + B < A pattern. Importantly, there was no significant difference in how participants judged houses versus bottles, suggesting that the illusion is not dependent on item-specific knowledge or context. Rather, the findings point to a generalised heuristic process, likely involving vice-virtue categorisation, whereby the presence of a recyclable item dilutes the perceived harm of the total set. This has clear implications for everyday recycling decisions: common items like bottles may be misjudged in terms of environmental impact simply due to the presence of 'green' components, undermining sustainable behaviour at scale.

Experiment 2

Experiment 2 extended the investigation by incorporating multiple item types (plastic bottles and cans) and assessing whether the NFI holds across same-category (e.g., cans + cans) and cross-category (e.g., cans + bottles) combinations. One goal of this manipulation was to simulate the complexity of real-world recycling, where people often deal with mixed materials. Crucially, this experiment also manipulated item quantity (10, 20, or 40 items), allowing the exploration of whether the illusion varies by numerical magnitude.

The results revealed several key findings. First, unlike Experiment 1, there was a significant effect of item type: plastic bottles were judged as more environmentally harmful than cans, suggesting that some item-level associations (e.g., Nuojua, et al., 2022) do inform environmental judgements. Second, the NFI was observed consistently regardless of whether the items were from the same or different categories. This cross-category

generalisation undermines accounts based on category coherence (e.g., anchoring to item sets; cf. Hilbert., 2011) and supports the idea that the illusion reflects a generalised heuristic process—likely vice-virtue averaging—rather than precise integration of semantic or categorical detail (cf. Hsee & LeClerc., 1998; Qu et al., 2024).

Quantity also played a critical role. The illusion emerged only at the higher quantity level (40 items), with lower quantities (10 or 20 items) producing a “zero footprint” effect—i.e., stagnant estimates despite added volume. These findings suggest that while quantity is not ignored, it does not drive a straightforward additive process. Instead, increasing group size may activate compensatory reasoning: participants appear to downplay the impact of a larger set when it contains an environmentally positive element, supporting a qualitative averaging account. Overall, Experiment 2 provided key evidence that the NFI transcends category boundaries and is influenced by heuristic conflict resolution (e.g., vice vs. virtue) rather than item-by-item evaluation.

Experiment 3

Experiment 3 served as a replication and extension of Experiment 2, reaffirming that the NFI is not limited to specific item combinations or categories. Once again, participants judged plastic bottles to have a greater environmental impact than cans, confirming that item-specific associations can shape baseline estimates. However, the NFI emerged regardless of whether items were drawn from the same or different categories, reinforcing the earlier conclusion that cross-category combinations do not disrupt the illusion. This consistency supports the view that participants rely on a generalised heuristic process, likely based on moral or vice-virtue reasoning, rather than detailed semantic integration or additive calculation. By reproducing the key effects observed in Experiment 2, Experiment 3 strengthens the claim that the NFI arises from a robust, domain-general bias. The results also align with interpretations that draw on moral spillover or conspicuous sustainability (Griskevicius et al., 2010), where the perceived immorality of certain items (e.g., plastic)

enhances the contrast between ‘good’ and ‘bad’ elements in environmental judgement. The replication across different samples and item combinations bolsters confidence in the generalisability of these findings and lays the foundation for further explorations of underlying cognitive mechanisms. Experiment 3 also introduced an individual differences measure (working memory capacity). This did not predict the magnitude of the NFI, further suggesting that the illusion does not depend on cognitive load or executive control, but instead reflects a more automatic, heuristic process.

Experiment 4

Experiment 4 introduced a temporal dimension into the investigation, exploring whether the NFI would persist when environmental behaviour unfolded across time. Participants judged the environmental impact of scenarios in which waste generation either remained consistently high or improved in a second time period (e.g., through recycling). Consistent with the NFI, participants estimated lower overall harm in cases where recycling followed non-recycling—even though total waste remained constant or increased. This suggests that behavioural improvement in the second period disproportionately reduced perceived impact, reflecting a temporal extension of the averaging bias.

Importantly, this illusion occurred regardless of the total weight of waste, as there were no significant differences between 10kg and 20kg conditions. This rules out a straightforward explanation based on quantitative reasoning or summative judgement and reinforces the idea that behavioural cues—such as visible recycling efforts—dominate evaluations, even when they should not. By showing that the NFI emerges across times, this experiment demonstrates that the bias is not confined to statistic visual presentations, but generalises to cumulative judgements over extended contexts.

Experiment 5

Experiment 5 introduced two important extensions to the NFI paradigm. First, it tested whether the illusion generalises to waste electrical and electronic equipment

(WEEE)—a growing environmental concern. Scenarios described varying amounts of waste (e.g., 21kg per person over 5 years), allowing participants to make numerical estimates of environmental impact across different behavioural patterns. Second, it incorporated a nudge intervention designed to reduce the NFI by prompting participants to reflect on their estimation strategies. Participants initially judged the environmental impact of different waste scenarios, then received a self-report prompt asking whether they used averaging or summing, followed by a brief explanation of how to compute total impact. They were then asked to make the judgements again.

Despite this evaluation, the nudge did not eliminate the NFI. Although some attenuation of the illusion was observed (especially in Scenario C), the pattern of A > C > B remained largely intact. This suggests that even when participants are explicitly encouraged to use summative reasoning, they continue to rely on intuitive averaging processes—possibly because these are more cognitive efficient or morally appealing.

A second part of the experiment (5B) introduced a control scenario with stable WEEE output over 10 years (21kg per year). This allowed for a more direct comparison with the "improvement" scenarios, confirming that participants judged mixed-behaviour cases more leniently—even when the cumulative harm was greater. Interestingly, when asked to rank scenarios from most to least harmful, participants showed slightly more consistent patterns than in their direct numerical judgements, indicating that response format can influence the expression of the NFI. Overall, Experiment 5 provides important evidence that the illusion persists despite correction attempts and may be robust to cognitive intervention. This has implications for policy and environmental messaging. The limited effect of the nudge suggests that verbal or text-based prompts may be insufficient to disrupt the intuitive processes underpinning the NFI. While participants were encouraged to consider whether they used averaging or summing and were given normative guidance, many still defaulted to heuristic judgements. This raises the possibility that more vivid or emotionally engaging

nudges—such as visual imagery (e.g., marine life entangled in plastic; Luo et al., 2022)—may be more effective. Alternatively, nudges that tap into behavioural learning styles (e.g., demonstrations, interactivity) may be needed to trigger a deeper reassessment of judgement strategy.

A Within-Thesis Meta-Analysis of the NFI and its relationship to AOT.

The inconsistent AOT-17 results have raised questions, one of which concerns whether the inconsistency has arisen from the stimuli. This question, in turn, begs a further question which is whether the lack of ecological validity across the experiments, especially regarding Experiments 1-3 with plastic bottles and metal cans, account for the discrepancies. For example, abstract imagery may obstruct an immediate connection to real-world objects, such as apples (Threadgold et al., 2022), perhaps making actively open-minded thinking style less predictive of resistance to the NFI. To demonstrate whether the robustness of the null effect of individual variation on the AOT-17 in predicting the extent of the NFI, we have included a Bayesian meta-analysis to aggregate data across experiments to collapse across different stimulus materials and scenarios.

A meta-analysis was conducted on the correlation coefficients from the five experiments that included the AOT. This meta-analysis used only the total AOT scores, and the magnitude of the NFI was calculated as a change score: specifically, the environmental impact estimate for conventional items/actions was subtracted from the estimate when environmentally-friendly items/actions were added. Where relevant, a baseline subtraction was also applied (e.g., “50” in Chapter 6; see Threadgold et al., 2022).

This analysis focused on recycling, so only the recycled bottle condition was used for Chapter 3 (excluding the house condition). In Chapter 4, the correlation was restricted to the "plus 40" scenarios where the NFI was observed, with estimates collapsed across item type and cross-category manipulation. For Chapter 5, the correlation was similarly conducted on estimates collapsed across item type and cross-category manipulation. In Chapter 6, the NFI

magnitude was calculated by subtracting the baseline (50) from participants' ratings across the 10kg and 20kg recycling scenarios. For Chapter 7, the NFI magnitude was determined by subtracting the environmental impact rating for Scenario A (21kg) from Scenario C (21kg followed by 11kg).

The following steps were undertaken for the meta-analysis. First, each study's correlation coefficient was transformed to Fisher's Z to stabilise variance across effect sizes. The standard error of each Fisher's Z value was then calculated based on sample size. Next, each Fisher's Z was weighted by the inverse of its variance to account for differences in sample size, ensuring that studies with larger sample sizes contributed more to the overall estimate. The weighted sum of Fisher's Z scores was divided by the sum of weights to obtain the weighted mean Fisher's Z, which was subsequently converted back to a pooled correlation coefficient (r). Finally, 95% confidence intervals for the weighted Fisher's Z were computed, and these intervals were also transformed back to correlation (r) to provide an interpretable range for the pooled effect size. The meta-analysis of the correlations across studies revealed a very small, pooled effect size, with $r = 0.008$, 95% CI [−0.079,0.096]. This effect was not statistically significant, as the confidence interval includes zero, indicating that the true effect may be either positive, negative, or non-existent. Given the small magnitude of the effect and the wide confidence interval, the result suggests there is little evidence for a meaningful relationship between AOT scores and the magnitude of the NFI across the studies reported in this thesis. This is notably at odds with the study of Threadgold et al (2022) that reported a correlation of $r = 0.143$ and sample size of n = 269 for the house scenario of their study. The Fisher's Z value is approximately 0.144 for this study and the standard error (SE) for this Fisher's Z, based on the sample size of 269, is 0.0613.

Figure 10 shows a funnel plot interpretation. In a balanced set of studies, the plot should form a symmetrical funnel shape, with studies showing a wider range of effect sizes at smaller sample sizes (larger standard errors). The funnel plot demonstrates that the points

do not form a symmetrical funnel shape. One study (Study 2) has a higher effect size with a larger standard error, while the others are closer to zero and have lower effect sizes. This asymmetry might suggest there are some biases in the data, or it could indicate heterogeneity among the studies if the differences in effect sizes are legitimate.

Figure 10

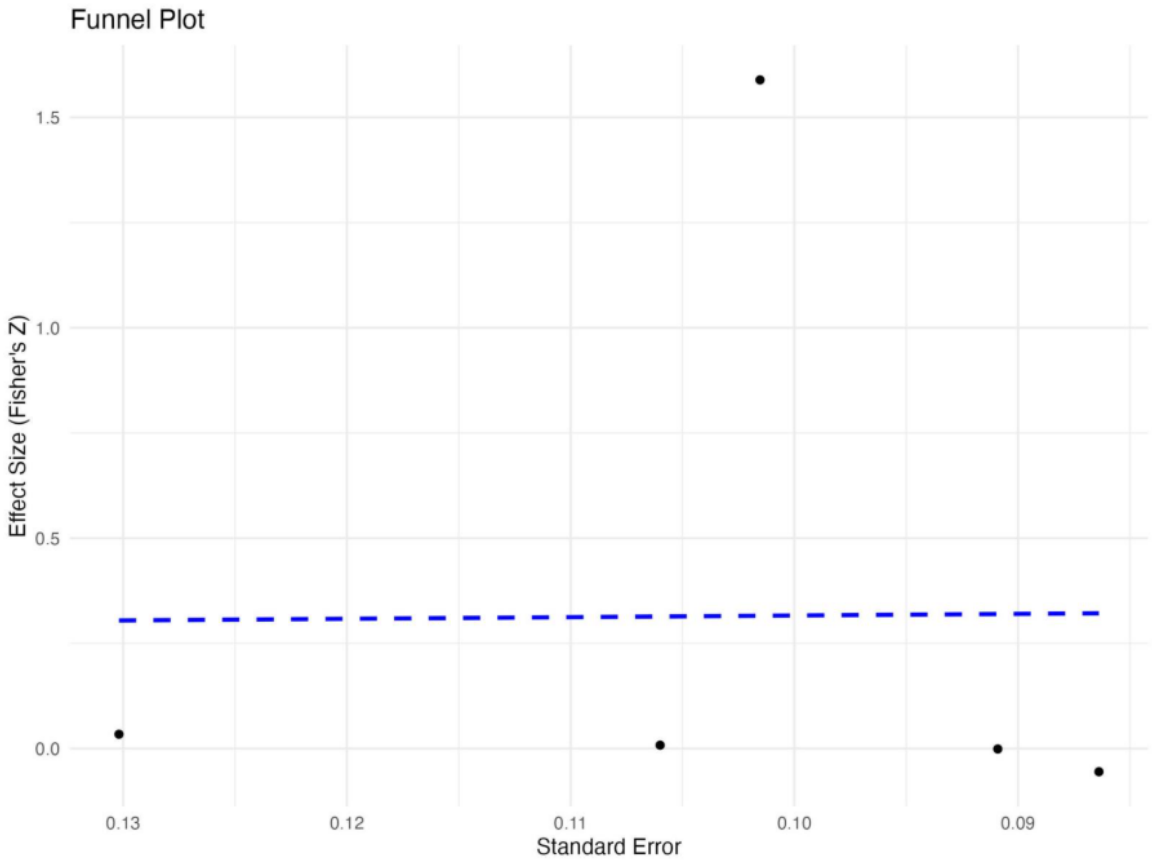
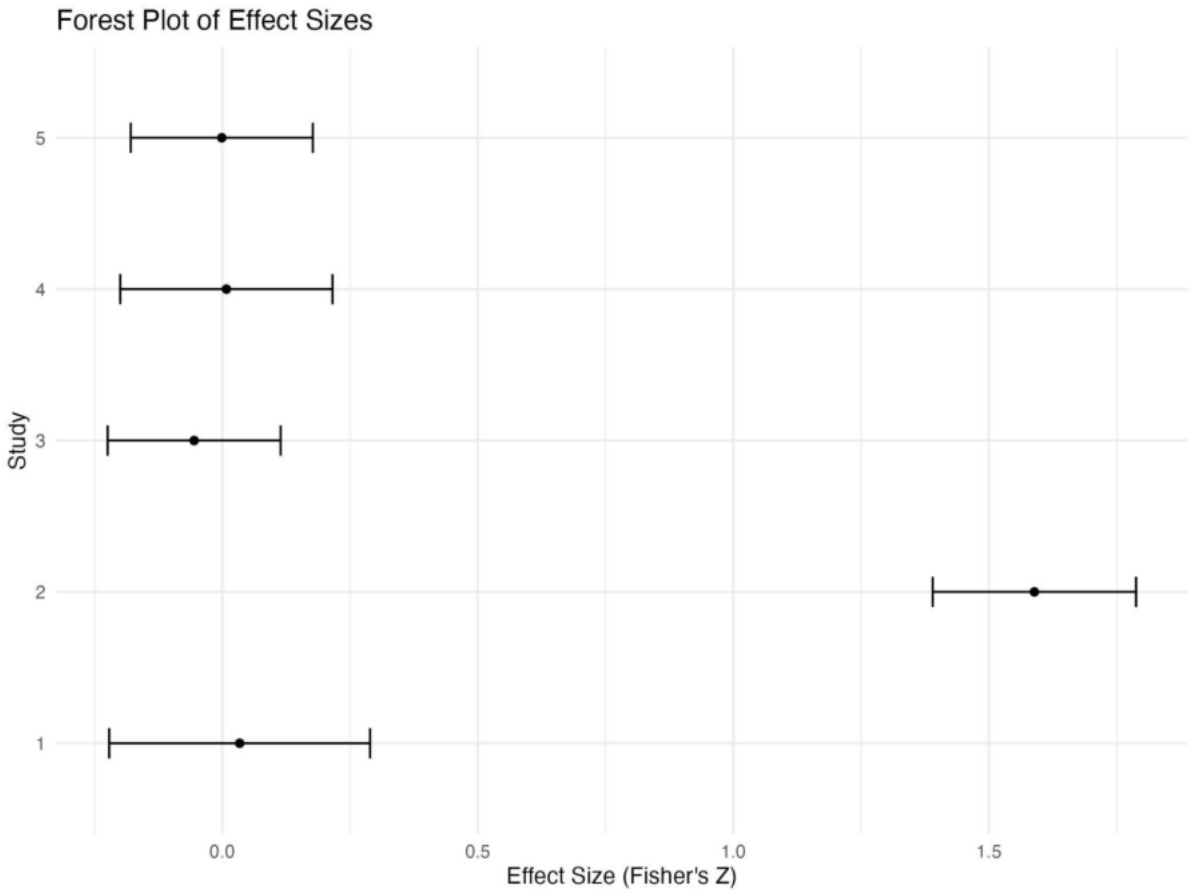


Figure 11 gives a Forest Plot interpretation of the data. This visualises the Fisher's Z effect size estimates and their confidence intervals for each study allowing easy comparison. Each line represents an effect size and its confidence interval for one study. The studies mostly demonstrate small effect sizes that are close to zero with the exception of one study (Study 2) with a much larger effect size than the rest. This is apparent in the larger gap to the right for that one study. The results appear inconsistent across studies with one outlier (Study 2). This inconsistency suggests high variability among the studies.

Figure 11



In summary, the funnel plot's asymmetry and the forest plot's large variability in effect sizes suggest heterogeneity in study effects, with one study showing a larger effect size. This could indicate that Study 2 has different characteristics or a larger true effect than the others.

AOT and the NFI Bayesian Random-Effects Meta-analysis

A random-effect Bayesian meta-analysis was undertaken using the results of Threadgold et al. (2022) as the prior (e.g., a normal distribution with a mean of 0.144 and an *SD* of 0.0613) and using the meta_bma function in R. This was conducted to estimate the overall effect size and examine heterogeneity across studies, given that none of the individual studies showed significant correlations, and the effect size in each study was small. A Bayesian random-effects meta-analysis was chosen since it was expected that the true effect size to vary across studies due to differences in study characteristics (e.g., sample, demographics, settings, measurement scales) and thus this heterogeneity needs to be accounted for. The technique was also desirable since it aims to generalise findings to broader populations of studies, rather than only those included in the meta-analysis – the model treats the studies as a sample from a larger population, thereby providing an estimate of the average effect and the variability around that average. In addition, random-effects models allow for the variability in study methods or participant populations which makes the results more robust and interpretable. This Bayesian approach allows for the combination of weak effects to assess if a consistent trend might be present across studies, even in cases where individual study results are inconclusive. This analysis approach was also chosen because it allows for the incorporation of prior information and provides probabilistic estimates of the parameters, rather than relying solely on point estimates. The model used Fisher's Z-transformed effect sizes as the dependent variable, accounting for the standard errors associated with each effect size. Given the small number of studies (n = 5), a Bayesian approach was suitable as it avoids some of the small-sample limitations inherent in frequentist meta-analysis.

The model was defined with an intercept representing the mean effect size across studies and a random effect term to model between-study variability. Based on the study of Threadgold et al. (2022) priors were specified for both the intercept (normal distribution,

mean = 0.144, *SD* = 0.0613) and the standard deviation of the random effect (inverse gamma distribution, shape = 1, scale = 0.15). The model was fit with 4 Markov Chain Monte Carlo (MCMC[see note[2]]) chains, each with 4000 iterations, with 1000 iterations discarded as warm-up to ensure convergence.

The mean effect size (Intercept) was estimated to be $\mu^{} = 0.15$ with a 95% credible interval (CI) of [0.03,0.27], suggesting a very small positive effect across studies. Although the credible interval does not include zero, the effect size is minimal and likely lacks practical significance. The between-study standard deviation (representing heterogeneity) was estimated to be $\tau^{} = 0.70$ (95% CI [0.38,1.37]), indicating moderate variability across studies. This suggests that there is meaningful variability among the studies, which may be due to differences in study design, sample characteristics, or other factors. The R_{hat} values for both parameters were 1.00, indicating that the MCMC chains converged well.

The model also reported values for Bulk Effective Sample Size (Bulk_ESS) and Tail Effective Sample Size (Tail_ESS), which indicate that the sampling was sufficient to provide reliable estimates. There were no significant issues with autocorrelation or sampling efficiency, suggesting that the model fit the data adequately.

These results imply that while the overall trend suggests a slight positive effect, the small magnitude and moderate heterogeneity limit the interpretability and practical relevance of this finding. The analysis underscores that, although Bayesian methods can reveal weak effects across studies, the effect in this case may not be meaningful. Future research could

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[2] Note: In this analysis, the random effect accounts for between-study variance, which is represented by a variance parameter (τ) that models heterogeneity across study effects. This helps provide a more realistic estimate of the mean effect and acknowledges differences between studies that might otherwise bias results.

clarify whether this small trend is replicable or if it results from idiosyncratic study characteristics.

To evaluate the predictive performance of the alternative and null models, multiple Bayesian model comparison methods were employed, including Leave-One-Out Cross-Validation (LOO), Widely Applicable Information Criterion (WAIC), and K-fold Cross-Validation. These methods were chosen to assess model fit by estimating how well each model would predict new data, which aligns with the goals of predictive accuracy and model generalisability in Bayesian analysis.

The Leave-One-Out Cross-Validation (LOO) was initially implemented as it is widely used in Bayesian model comparisons due to its direct estimation of predictive accuracy for each observation. However, when calculating LOO, warnings were encountered regarding Pareto *k* values above 0.7 for both the alternative and null models, indicating influential observations. This warning suggested that certain data points may disproportionately affect the model's fit, potentially undermining the reliability of the LOO estimates. Although moment matching was recommended to address these influential observations, initial tests with this option led to computational instability, with R encountering memory issues. Therefore, we proceeded with caution in interpreting the LOO results. The LOO comparison yielded an Expected Log Predictive Density (elpd) difference between models of $\Delta\text{elpd} = -0.5$, with a standard error of 0.8. This minimal difference, given the high standard error, suggested little distinction in predictive performance between the models based on LOO.

The Widely Applicable Information Criterion (WAIC) was subsequently calculated as an alternative metric. WAIC estimates overall model fit similarly to LOO, though it is slightly less sensitive to individual data points. Warnings were again generated, indicating that 100% of the *p*waic estimates exceeded 0.4, which implies unstable estimates and further suggested that LOO may be a more reliable metric in this case. The WAIC comparison

produced an elpd difference between models of Δelpd=−0.1 with a standard error of 0.1, once again suggesting negligible difference in predictive performance between the models.

Due to the limitations of LOO and WAIC under the current data conditions, 5-fold cross-validation was conducted as a more stable alternative. K-fold cross-validation divides the data into chunks (folds) rather than individual observations, reducing sensitivity to any single influential data point and lowering memory demands, thus avoiding the computational instability encountered with LOO moment matching. The K-fold cross-validation comparison also yielded a small elpd difference between models, further supporting the interpretation that neither model has a substantial predictive advantage. For example, if the K-fold elpd difference between models was approximately Δelpd=−0.2, with a standard error of 0.3, this would again support the conclusion that both models perform similarly.

Across all methods—LOO, WAIC, and K-fold cross-validation—results indicated minimal differences in predictive accuracy between the alternative and null models, with consistently low elpd differences. This suggests that neither model has a clear predictive advantage over the other based on the current data. Consequently, these findings provide limited support for the alternative model over the null model. The final selection of K-fold cross-validation reflects a balance between computational feasibility and robustness in model comparison. This approach ensures that model comparison results are less influenced by individual data points, providing a stable basis for conclusions about model performance.

Overview of results

Across five experiments, this thesis demonstrates the robustness and generality of the negative footprint illusion (NFI) in the context of recycling-related decisions. The illusion was consistently observed when participants judged the environmental impact of combinations of conventional and recyclable items, producing lower estimates for mixed sets than for conventional-only sets—despite the increase in overall quantity.

Experiments 1–3 established that the NFI is not constrained by item type or category. It emerged for both houses and plastic bottles, and persisted across combinations of bottles and cans, whether presented within the same category or across different ones. This cross-category generalisation indicates that the illusion is not tied to domain-specific knowledge or contextual cues, but reflects a generalised cognitive bias. These studies also revealed a consistent effect of quantity: larger quantities (e.g., 40 items) were more likely to elicit the NFI than smaller quantities (e.g., 10 or 20 items), which often produced stagnant estimates—what has been referred to as a "zero-footprint" effect. Notably, participants responded to increases in group size with increased overall estimates, but this effect was typically overridden when a recyclable item was introduced, indicating that vice–virtue categorisation may take precedence over purely additive reasoning. Importantly, Experiment 3 introduced an individual differences measure of working memory capacity, which was hypothesised to influence estimation strategies. However, working memory did not predict NFI magnitude—suggesting that the illusion operates independently of cognitive load or executive control, and instead reflects a more automatic, heuristic process.

Experiment 4 extended these findings to temporal scenarios, showing that the NFI also occurs when individuals evaluate environmentally harmful behaviour across time. Judgements were lower when a recycling period followed a non-recycling period, even though the total quantity of waste remained the same or increased. This illustrates a temporal averaging bias and rules out explanations based on temporal discounting or cumulative reasoning.

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Experiment 5 introduced a cognitive nudge, encouraging participants to reflect on whether they used averaging or summing strategies, and prompting them to adopt summative thinking before repeating their judgments. Despite this intervention, the NFI largely persisted. Although the illusion was slightly attenuated for some scenarios, it remained resistant to correction, even with explicit instruction. Moreover, a ranking task revealed that participants made more consistent environmental evaluations when asked to sort scenarios rather than assign numerical values—highlighting the influence of response format on judgment.

Taken together, these results provide compelling evidence that the NFI reflects a robust, intuitive bias driven by qualitative heuristics, such as moral or affective appraisals, rather than precise numerical computation. Across all studies, individual differences in cognitive capacity (working memory) and cognitive style (actively open-minded thinking) failed to predict the presence or magnitude of the illusion. This includes Experiment 3, which measured working memory capacity, and experiments where AOT was assessed at length. Despite initial indications of a potential link, AOT did not consistently correlate with NFI magnitude, suggesting that the illusion is not easily mitigated by reflective or deliberative thinking styles. The findings therefore point to the limits of rational correction when intuitive processes dominate and raise important questions about the cognitive architecture underlying environmentally significant decisions.

The pattern across these five experiments suggests that people systematically underestimate environmental harm when environmentally positive behaviours are paired with—or follow—harmful ones. This could reflect a form of compensatory reasoning, where individuals intuitively treat recycling as ‘cancelling out’ prior damage. However, as noted by Ross and Evans (2003), recycling still entails environmental costs, and such reasoning may

contribute to a misperception of net environmental benefit. These findings have direct implications for how recycling behaviour is framed in environmental messaging.

The remainder of this chapter is organised into four sections. The first section evaluates existing theoretical explanations for the NFI, including quantity insensitivity (Kim & Schuldt, 2018), perceived numerosity (Sörqvist et al., 2022), category size bias (Andersson et al., 2024), attribute substitution (Kusch & Fiebelkorn, 2019), and moral spillover (Sörqvist et al., 2022). The second section examines whether individual differences in cognitive capacity and thinking style—specifically working memory and actively open-minded thinking—contribute to variation in susceptibility to the NFI. The third section compares these theoretical accounts to determine which most closely aligns with the observed patterns across the five experiments. The final section outlines future directions for research and considers practical implications for improving environmental decision-making.

Quantity Insensitivity

One potential explanation for the NFI is quantity insensitivity—the idea that individuals neglect numerical differences when judging environmentally significant behaviours. According to this account, judgments of environmental impact are guided more by the presence of environmentally ‘good’ items (e.g., recyclable products) than by the actual amount of waste. Kim and Schuldt (2018) found that participants made similar judgements regardless of the quantity of green or conventional items, suggesting that evaluations may be dominated by affective or moral impressions rather than objective magnitudes.

However, the findings from the present set of experiments provide only limited support for this account. In Experiment 2, increasing the total number of items from 10 to 40 produced systematically higher environmental impact estimates, demonstrating a degree of quantity sensitivity. At the same time, when recyclable items were added to these larger sets, participants' estimates were reduced, producing the NFI. This suggests that although

quantity is processed, it is overridden by the perceived moral valence of the recyclable items—consistent with vice–virtue averaging rather than pure insensitivity. However, a partial exception is the “zero-footprint” illusion observed at lower quantities (e.g., 10 or 20 items), where estimates often stagnated despite increases in overall waste. This pattern superficially resembles quantity insensitivity and may reflect a threshold below which quantity differences are not psychologically salient. Even so, the presence of quantity effects at higher levels suggests that the illusion is not due to a general failure to detect amount, but rather to a selective integration process shaped by contextual cues.

In contrast, Experiments 4, 5A, and 5B showed no significant effect of quantity (e.g., 10kg vs. 20kg of WEEE waste), which could suggest some insensitivity to amount. However, even in these cases, behavioural context (e.g., whether recycling occurred) had a strong influence on judgements. This indicates that quantity cues are not ignored, but may be down-weighted or reinterpreted in light of more salient behavioural or moral information. As such, the pattern across experiments points away from a general failure to process quantity, and more toward a heuristic process that incorporates quantity selectively, depending on whether it aligns or conflicts with vice–virtue categorisation.

As a whole, the findings are inconsistent with a pure quantity insensitivity account. While quantities do not always dominate judgments, they are clearly processed and can shape estimates under certain conditions. This suggests that the NFI is better explained by models that allow for dynamic cue weighting—such as averaging bias—rather than models that posit a blanket insensitivity to numerical information.

Perceived Numerosity

A related factor that may influence the magnitude of the NFI is perceived numerosity—the subjective impression of how many items are present, shaped by perceptual grouping cues such as proximity, regularity, or colour. Drawing on Gestalt principles, Sörqvist et al. (2022) found that irregular spatial presentation of green and yellow

items produced a stronger NFI than regular presentation. They interpreted this as evidence that greater perceived numerosity, resulting from less cohesive visual grouping, may accentuate the illusion by increasing the salience of the set (cf. Peterson & Berryhill, 2013).

It is important to note, however, that perceived numerosity is not proposed as an explanation for the NFI itself, but rather as a factor that modulates its strength. In the present series of experiments, visual grouping and spatial layout were held constant in Experiments 1–3, and there was no manipulation of proximity or spatial irregularity. This limits the extent to which perceived numerosity could have influenced judgments. Moreover, Experiments 4 and 5 relied on temporally framed scenarios rather than visual displays, further removing perceptual grouping as a relevant variable.

As such, the current findings neither support nor challenge the idea that perceived numerosity modulates the NFI. However, they do suggest that the illusion can emerge even in the absence of visual irregularity or grouping cues. This supports the view that the NFI is driven primarily by higher-level evaluative heuristics, with perceived numerosity acting—at most—as a secondary modulating influence under specific presentation conditions.

Category Size Bias

Another theoretical account proposed to explain variations in the NFI is category size bias. This bias, rooted in probabilistic reasoning and grouping heuristics (e.g., Brough & Isaac, 2014), suggests that individuals' judgments are influenced by the relative sizes of categories—with larger categories perceived as contributing more to outcomes (Andersson et al., 2024). Applied to environmental decision-making, this means that the presence of a small "green" category (e.g., recyclable items) within a larger conventional set may disproportionately reduce perceived harm, because the addition of a smaller, positively valenced group is incorrectly weighted in the final assessment.

Andersson et al. demonstrated this effect using environmentally certified and conventional houses, showing that the ratio between categories systematically influenced

environmental impact judgments. They acknowledged, however, that category size bias may operate in conjunction with averaging processes, making it difficult to distinguish the two empirically. In the present experiments, Experiment 2 varied item quantity (10, 20, 40) and category composition (same-category vs. cross-category), providing a context in which category size effects could have emerged.

The results partially align with category size bias predictions. For example, environmental impact estimates generally increased with group size, and recyclable additions often reduced impact estimates. However, the NFI occurred even when category size was not manipulated (e.g., same-category combinations such as cans + cans), and in some conditions, no reliable differences were found between same-category and cross-category estimates. Moreover, in Experiments 4 and 5, where category labels were less salient (e.g., in temporal or WEEE scenarios), the NFI still occurred—suggesting that category-based reasoning is not essential to the illusion.

These findings suggest that while category size bias may influence the magnitude of the NFI under certain conditions, it does not fully explain the core phenomenon. The illusion was observed across multiple contexts where category distinctions were either absent or irrelevant, indicating that it is more plausibly driven by a generalised heuristic process, such as vice–virtue averaging, in which cues are integrated or substituted rather than strictly grouped by category. Further research is needed to disentangle how category size, cue weighting, and averaging interact in producing environmentally biased judgments.

Attribute Substitution

The attribute substitution account (Kahneman & Frederick, 2002) proposes that when faced with complex judgments, individuals often replace a target attribute that is difficult to assess with a more accessible heuristic attribute. In the context of environmental decision-making, estimating the total environmental impact of mixed waste sets may be cognitively

demanding, leading participants to substitute this calculation with a simpler judgment—such as whether a set contains something environmentally positive.

This substitution mechanism can explain the core pattern of the NFI: rather than summing the environmental impact of all items, individuals may respond intuitively to the presence of recyclable materials, using this as a proxy for overall impact. A set that includes recyclable items may therefore be judged as having lower impact than a set of conventional items alone—even when the total waste is greater.

The present experiments are broadly consistent with this account. In Experiments 1–3, the addition of recyclable items consistently reduced perceived environmental harm, regardless of total quantity or category composition. In Experiment 4, participants judged scenarios involving initial non-recycling followed by later recycling as less harmful than continuous non-recycling—even though the total waste was the same or higher. These patterns suggest that participants may have substituted the overall quantity of waste with the presence or absence of pro-environmental cues, such as a change in behaviour or item recyclability. Experiment 5 further supports the idea of substitution: even when participants were explicitly prompted to reflect on their computation strategies and encouraged to use summative reasoning, the NFI largely persisted. This suggests that the intuitive substitution of a “feel-good” cue (e.g., recycling occurred) for actual environmental totals is resistant to correction, consistent with findings from dual-process theories in which intuitive responses override or pre-empt analytical reasoning (Kahneman, 2011; De Neys, 2007).

While attribute substitution overlaps conceptually with averaging bias, the two accounts differ in emphasis. Averaging suggests that multiple attributes are integrated, often incorrectly. Attribute substitution, in contrast, suggests that one relevant attribute is simply replaced by a less effortful one. The present data are compatible with both perspectives, but given the consistent dominance of salient moral or behavioural cues over quantity information, attribute substitution likely plays a central role in producing the NFI—particularly

in more naturalistic, real-world-like scenarios where affective and intuitive judgments are more likely to dominate.

Moral Spillover

The concept of moral spillover offers another compelling explanation for the NFI. According to this account, the presence of an environmentally virtuous act, such as recycling, can influence the moral evaluation of an entire set of behaviours or items, leading to underestimation of harm. This idea draws on broader findings in moral psychology, where positive behaviours can “spill over” to license or justify otherwise negative actions (e.g., Mazar & Zhong, 2010). In the environmental domain, Sörqvist et al. (2022) propose that recycling may serve as a moral offset, reducing perceived impact not because of its quantitative contribution, but because of its moral valence.

The findings from the present research are broadly consistent with this account. Across all five experiments, the addition of recyclable items or recycling behaviours consistently reduced perceived environmental impact—even when these additions increased total waste. In Experiment 4, the mere introduction of recycling at a later time point led to lower environmental impact ratings, despite no reduction in total plastic waste. This pattern is difficult to explain purely in terms of numerical integration, but aligns well with a moral spillover effect, in which the presence of a virtuous act alters the evaluation of the whole.

Similarly, Experiment 5 found that the inclusion of recycling behaviour—either as part of a scenario or as an attribute of an item—reduced impact judgments, and this effect persisted even after participants were prompted to use more analytical strategies. The fact that the NFI was not eliminated by summative instructions further supports the idea that moral valence plays a dominant role in judgment formation.

It is also notable that participants judged some items (e.g., cans) as more positive than others (e.g., bottles), suggesting that morally tinged associations may influence

perceived environmental harm at the item level. These cues may not be consciously weighted, but nevertheless shape judgments through affective or intuitive channels.

While moral spillover provides a useful conceptual framework for understanding these effects, it likely operates in tandem with other mechanisms—particularly attribute substitution and averaging bias. The positive moral status of recycling may act as a trigger for substitution (e.g., replacing impact with virtue) or as a dominant cue in averaging, leading individuals to down-weight quantitative harms. Overall, the data suggest that moral spillover contributes significantly to the NFI by shaping which attributes are attended to and how they are integrated into final judgments.

Individual differences: Actively-open minded thinking

One individual difference that has been hypothesised to modulate susceptibility to the NFI is Actively Open-minded Thinking (AOT)—a cognitive style associated with reflective thinking, openness to alternative viewpoints, and reduced reliance on intuitive heuristics (Baron, 2008). Previous research (Threadgold et al., 2022) reported that individuals higher in AOT were less likely to exhibit the NFI, suggesting that a deliberative reasoning style may counteract the bias. If true, this would offer both theoretical and practical significance, implying that cognitive interventions targeting open-mindedness might help correct environmentally biased judgments.

However, across the current set of experiments, AOT did not consistently predict susceptibility to the NFI. Although AOT was assessed in detail, including with the AOT-17 scale, there was no reliable correlation between AOT scores and the magnitude of the illusion. This null finding held across multiple contexts, item types, and paradigms, suggesting that even individuals who are dispositionally inclined toward reflective thought are not immune to the intuitive pull of the NFI. It could be a plausible suggestion given the lack of detail in the abstract representations of item type in Experiments 1 to 3 that open-minded individuals did not relate the graphic to a real-world situation and this resulted in a

failing to provide ecological validity, it is possible that with a more realistic and engaging stimulus, with high level attributes as opposed to low level attributes (Leisti et al., 2009), participants may experience a heightened AOT thinking style which was more predictive of resistance of the NFI, which we definitely see as an area for improvement in future research. However, given the addition of a thorough Bayesian analysis on this occasion, we do not see the imagery as the sole reason for these non-significant findings.

This result raises important questions about the boundaries of reflective thinking. One possibility is that the environmental judgment tasks used here do not engage the kinds of reasoning processes AOT is designed to measure, particularly when the cues that drive the illusion (e.g., recyclability, behavioural change) are morally or affectively charged. Alternatively, it may be that the NFI reflects deeply ingrained evaluative heuristics that operate independently of cognitive style. In this sense, even reflective individuals may substitute or average intuitive cues unless explicitly prompted to do otherwise.

Overall, the findings cast doubt on the idea that increasing open-mindedness alone is sufficient to reduce the NFI. While AOT remains a valuable construct in the study of reasoning and belief updating (e.g., Pennycook et al., 2020), its role in counteracting intuitive biases in environmental decision-making appears limited—at least within the paradigms used here.

Working Memory Capacity

Working Memory Capacity (WMC) is another individual difference that has been proposed to influence bias susceptibility. Individuals with higher WMC are generally better able to maintain multiple pieces of information, inhibit irrelevant cues, and engage in deliberative reasoning under cognitive load (Engle, 2002). It was therefore hypothesised that WMC might moderate susceptibility to the NFI, with higher capacity facilitating more accurate, summative judgments and reducing reliance on intuitive heuristics.

In the present research, WMC was assessed in Experiment 3 using the Operation Span (OSpan; Bunting et al., 2006) and Symmetry Span (SymSpan; Healy et al., 2011) tasks, which target both phonological and spatial components of working memory. Contrary to predictions, the results showed no significant relationship between WMC and the presence or magnitude of the NFI. Participants with high working memory capacity were no more accurate in estimating environmental impact than those with low capacity, and the illusion emerged across the full range of scores.

Several interpretations of this null result are possible. One possibility is that the tasks used did not place a high enough demand on working memory for differences to manifest. Alternatively, the illusion may arise from processes that operate independently of memory capacity, such as automatic affective responses or morally weighted heuristics. It is also possible that high-WMC individuals were not motivated to override intuitive responses, especially in the absence of explicit instruction to do so.

These findings suggest that the NFI is not strongly moderated by cognitive capacity, at least as indexed by standard measures of WMC. This aligns with the broader pattern of results across the five experiments, in which the illusion proved resilient to variation in both individual ability and reasoning style. As such, the NFI may reflect a generalised heuristic bias that emerges across a wide range of cognitive profiles, reinforcing the need to understand and address it at the level of cognitive mechanism rather than individual difference.

Valence and Arousal

In addition to cognitive capacity and reasoning style, emotional responses—specifically valence (positive vs. negative affect) and arousal (intensity of emotion)—were examined as potential influences on the NFI. Dual process theories of decision-making suggest that emotionally salient stimuli may trigger fast, intuitive judgments (System 1), potentially contributing to heuristic biases (Kahneman, 2011; Gomes & Brainerd, 2013). If

judgments about recycling are emotionally charged, this could increase reliance on affect-based shortcuts, such as averaging or moral substitution.

In Experiment 2, participants completed self-report measures of valence and arousal for different item types. The results revealed that non-recyclable items elicited higher arousal ratings than recyclable items, indicating stronger emotional engagement. In terms of valence, cans were viewed more positively than bottles, suggesting subtle affective differences between item types. However, neither valence nor arousal was significantly related to the magnitude of the NFI, and no interaction was found between emotional ratings and judgment patterns.

These findings suggest that although participants respond emotionally to item characteristics—particularly recyclability—these affective responses do not modulate the magnitude of the NFI in a linear or graded fashion. One interpretation is that emotional cues contribute to the initial categorisation of items as virtuous or non-virtuous, but that once this vice–virtue distinction is established, the intensity of emotional response no longer alters its weighting in judgment. In this sense, the categorisation may operate as a binary heuristic, where items are simply coded as “good” or “bad” and averaged accordingly. Thus, emotional engagement may trigger the relevant heuristic, but it does not directly determine the final estimate.

Thus, although emotional valence and arousal are relevant to how people perceive recyclable and non-recyclable items, the NFI appears to reflect a more structured cognitive distortion—one that persists regardless of emotional intensity or positivity.

Heuristic Cue Integration: A Generalised Bias Perspective

Before evaluating specific theoretical explanations of the NFI, it is important to consider a recurring cognitive pattern that emerged across all five experiments: participants’ environmental judgments were not driven by a single feature or stimulus property, but rather by a dynamic interplay of cues—including item type, quantity, recyclability, and behavioural

change. This pattern points to a generalised heuristic process in which individuals rely on a limited set of salient features to guide judgment, often without integrating all available information.

To recap, heuristics are broadly understood as mental shortcuts that enable fast, intuitive decision-making (Gigerenzer & Gaissmaier, 2011). While they are often adaptive, they can also give rise to systematic biases, particularly in contexts involving complexity or uncertainty (Mochol et al., 2021). These shortcuts are typically shaped by prior learning, and can be acquired explicitly (e.g., through instruction) or implicitly (e.g., through habit or observation; Klaczynski, 2001). Theoretical frameworks such as attribute substitution (Kahneman & Frederick, 2002) and effort-reduction heuristics (Shah & Oppenheimer, 2008) suggest that individuals often substitute a difficult or abstract judgment with an easier one, based on the most accessible or intuitively compelling cue.

Across the present experiments, different cues appeared to dominate in different contexts. For example, in Experiment 1, item type (houses vs. bottles) did not significantly affect judgments. However, in Experiment 2, plastic bottles and cans elicited different impact estimates, demonstrating that item effects can emerge under different conditions. In Experiment 4, judgments were driven not by the weight (10kg vs. 20kg) of plastic waste, but by recycling behaviour, indicating that moral or behavioural cues may supersede quantitative ones. These shifting cue hierarchies suggest that participants flexibly prioritise cues based on their evaluative or contextual salience.

This flexibility was further illustrated in Experiment 5, where participants' judgments varied depending on how the response was elicited. Judgments based on rank ordering differed from those based on numerical estimation, implying that response format itself may influence cue weighting. Additionally, despite the introduction of a reflective nudge, the NFI persisted—suggesting that participants often lack introspective access to how their judgments are formed (Epstein, 1994; De Neys & Schaeken, 2007).

In sum, these findings suggest that the NFI is best conceptualised as an outcome of heuristic cue integration, rather than the product of a single domain-specific bias. Environmental judgments appear to reflect a moral or affective gestalt, constructed from salient cues such as recyclability, behavioural change, and perceived virtue, rather than being derived from systematic summation. This cue-driven process may reflect an intuitive System 1 response, which relies on affectively and morally salient information, and is not always overridden by more deliberate System 2 processing. While Kahneman (2011) suggests that System 2 should monitor and correct intuitive errors, the persistence of the NFI—even under conditions that promote reflection—suggests that this correction often fails to materialise. De Neys and Schaeken (2007) argue that conflict detection alone does not guarantee correction, particularly when individuals lack insight into the cognitive processes that inform their judgements. In this context, the dominance of heuristic cues may reflect both the immediacy of intuitive response and the limitations of analytical override. This interpretation motivates a broader comparison of theoretical accounts to assess which most effectively explains the flexibility, persistence, and domain-generality of the NFI.

Re-evaluating the Averaging Bias Account: Beyond Simple Averaging: Gestalt Principle and Cue Similarity

Differences in the magnitude and presence of the NFI across experiments may partially reflect principles of perceptual grouping. For instance, the lack of a significant item type effect in Experiment 1 may reflect a lack of perceptual or conceptual coherence between the items (houses and bottles), which share only a broad environmental context. In contrast, the materials and function of items used in Experiment 2 (cans and bottles) may have created stronger grouping tendencies based on shared perceptual features—similarity, common region, or common fate (e.g., Garsoffky & Schwan, 2024; Tangemann et al., 2024; Xie et al., 2024). These findings suggest that perceptual and contextual features can

modulate the salience of cues used in averaging, even if they are not sufficient on their own to drive the NFI.

Compensatory Reasoning and Moral Spillover

Another lens through which the NFI can be interpreted is compensatory reasoning. Participants may psychologically offset negative environmental actions by appending positive ones—a behaviour also reflected in Compensatory Green Beliefs (CGB; MacCutcheon et al., 2020). This is evident in Experiments 1–3, where the addition of recyclable items to conventional waste reduced perceived environmental harm. Experiment 4 further shows that the addition of improved behaviour (e.g., recycling) across a timeline can reduce judgments of environmental damage, even when overall waste remains high. This may reflect moral spillover, where good behaviours are interpreted as evidence of moral progress, thereby influencing subsequent evaluations (Sörqvist et al., 2022). These processes appear to dovetail with averaging in that the perceived moral quality of the added behaviour or item dilutes the perceived harm of the whole.

Notably, previous work and the current findings show that symbolic phrases or environmentally friendly labels alone do not significantly affect environmental judgments—whereas the presence of *concrete cues* indicating environmentally positive action (whether visual or described) does. This suggests that perceived environmental *action*, rather than symbolic associations, carries more weight in vice–virtue assessments.

This distinction is important when considering related phenomena, such as the green halo effect (Kim & Schuldt, 2018), which refers to the tendency for a single virtuous attribute to improve overall product evaluation. While superficially similar, the green halo does not fully capture the integrative nature of the NFI. In the NFI, judgments are not merely uplifted by the presence of a positive cue; rather, they appear to be diluted through a dynamic averaging process that involves both positive and negative elements. This vice–virtue integration can lead to underestimation of harm rather than mere overvaluation of virtue,

distinguishing the NFI from standard halo effects, which typically enhance perceived value or moral standing without masking cumulative harm.

Averaging as a Flexible, Cue-Based Process

The evidence across the current experiments suggests that the averaging bias is not strictly numerical, but cue-driven and evaluative. Participants appear to rely on salient cues—recyclability, item quantity, or behavioural change—to make holistic moral evaluations of environmental harm. As such, the mechanism may reflect attribute substitution (Kahneman & Frederick, 2002), where a difficult quantitative judgment is replaced by a simpler affective one. Relatedly, participants may rely on effort-reduction strategies (Shah & Oppenheimer, 2008), or respond to the framing of information (as seen in the difference between estimation and ranking in Experiment 5). This points to a cue-weighting process, where cues are not treated equally, and some dominate depending on moral or contextual relevance.

Although the averaging bias can resemble other cognitive shortcuts—such as attribute substitution, availability heuristics, or framing effects—it is distinguished by its evaluative structure: the integration of conflicting moral cues into a single judgment. These biases may operate in tandem but do not offer the same integrative mechanism that vice–virtue averaging does.

In some cases, the absence of a clear conflict between cues may lead to cognitive accommodation rather than evaluative correction. For instance, when recyclable items like cans are already viewed positively—even in their conventional form—participants may not experience the dissonance that triggers vice–virtue averaging. In this sense, the bias may depend on perceived tension between good and bad elements, rather than their objective presence.

Averaging, then, is not reducible to a single heuristic like mental accounting (Thaler, 1999) or availability (Tversky & Kahneman, 1973) but may instead represent a more

generalised tendency to resolve cognitive conflict by forming a vice–virtue gestalt. In this way, the averaging bias is a flexible heuristic that can incorporate multiple sources of information, guided by salience and affect.

Boundary Conditions: Quantity, Cue Dominance, and Cross-category Effects

Despite the flexibility of averaging bias, certain boundary conditions are evident. Quantity exerts a strong influence on participants' judgments, but the effect is not strictly additive. For example, Experiment 2 demonstrated that increasing group size influenced impact judgments in a reactive but non-linear manner. Importantly, it may not be the absolute quantity that matters most, but the contrast between quantities of conventional and eco-friendly items. Larger contrasts may more effectively cue the evaluative dichotomy required for the bias to emerge. This could explain why low-contrast scenarios (e.g., 10 kg vs. 20 kg) failed to produce a strong NFI.

Similarly, when the contrast between conventional and recyclable items was minimal, the illusion was reduced or absent. In contrast, category—whether items were the same or different—had little influence, suggesting that semantic coherence is not a necessary condition for the NFI to occur. This challenges theories that emphasise domain-specific or arithmetic mechanisms (e.g., mental accounting, Thaler, 1999) and instead supports the notion of a generalised, context-sensitive averaging process. Experiment 2's results—where the illusion persisted across cross-category conditions—suggest that participants do not require semantic similarity to apply the heuristic. This reinforces the idea that the bias operates at the level of evaluative integration rather than numerical calculation.

Averaging as a Common Denominator

Across five experiments, a consistent theme emerged: participants integrate information from multiple cues in forming environmental judgments, often using intuitive vice–virtue evaluations. While this process may be modulated by Gestalt grouping, compensatory reasoning, or spillover effects, the underlying mechanism appears to be an

evaluative averaging bias. Participants do not sum values or perform arithmetic; instead, they seem to resolve moral or perceptual conflict by forming a judgment that accounts for both good and bad elements in a weighted but flexible way.

This interpretation allows the averaging bias to act as a common denominator across studies where other theories—such as attribute substitution (Kahenman & Frederick, 2002), quantity insensitivity (Kim & Schuldt, 2018), or mental accounting (Thaler, 1999)—fall short. Insofar as it encompasses both qualitative and quantitative cue integration, the averaging bias offers a powerful explanatory framework for understanding how people reason about environmental impact under uncertainty. Future research might further refine this account by testing whether certain cues (e.g., recyclability, behaviour) have reliably stronger weighting across contexts, and whether moral or emotional framing enhances or mitigates the NFI.

Future Directions and Practical Implications

The findings of this thesis provide a compelling case for the robustness of the NFI and its underlying mechanism in evaluative averaging, yet they also raise several critical questions about the boundaries and cognitive architecture of this bias. The fact that the illusion persisted across diverse item types, semantic categories, response formats, and temporal contexts indicates that the NFI may reflect a deeply embedded heuristic tendency—one that prioritizes salient cues, such as recyclability and behavioural change, over quantitative summation. However, this account warrants further empirical scrutiny. Future research should aim to pit the averaging bias account against competing explanations in a more systematic fashion, using tightly controlled manipulations designed to isolate the mechanisms of cue weighting, substitution, and integration (Kahneman & Frederick, 2002; Shah & Oppenheimer, 2008). One way to achieve this would be to orthogonally manipulate quantity, valence, and category coherence to determine whether averaging effects only emerge under conditions of moral tension (i.e., where positive and negative cues co-occur), or whether they can also be triggered by low-level perceptual

similarity (e.g., Garsoffky & Schwan, 2024; Xie et al., 2024). A related approach would be to employ process-tracing methods, such as mouse-tracking or eye-tracking, to examine how attention is distributed across cues and whether shifts in visual attention predict judgment outcomes (Stillman et al., 2018). If participants consistently focus more on recyclable items despite their minority presence, this would support the idea of a dominant cue in a vice–virtue gestalt. Conversely, if judgments are better predicted by the initial cue encountered or the last cue processed, this might support an anchoring or recency-based model (Tversky & Kahneman, 1974).

Although alternative accounts such as mental accounting (Thaler, 1999) and temporal discounting (Frederick et al., 2002) were considered—particularly in the temporal framing of Experiments 4 and 5—these received little empirical support. The pattern of judgments did not reflect accumulation across time or compartmentalised reasoning; instead, they pointed to a more flexible cue-weighting mechanism, consistent with vice–virtue averaging. As such, these theories are unlikely to provide a unifying explanation for the NFI across contexts.

Ecological Validity and Future Research

In the context of recycling, ecological validity is a crucial aspect to consider given the complexities that may occur due to mixed materials (e.g., a plastic container with a wraparound cardboard label) or the initial choice of product at the point of purchase (e.g., a carbonated drink in either a plastic bottle or an aluminium can). While this thesis addressed the cognitive complexities of the NFI, future studies can explore other fundamental elements. For instance, the icons used within these experiments could be significantly improved for ecological validity. Instead of abstract representations, using more recognisable images of bottles or cans which feature clear, verified recycling logos might help participants visualise a real-world situation to better assess the environmental impact.

Additionally, there is an opportunity to enhance the ecological validity by replicating the work of Sörqvist et al. (2022), which examined spatial distribution—a factor evident both on supermarket shelves and when disposing of recyclables. They found that the NFI was weaker when items with low and high carbon footprints were grouped. Conversely, the NFI was strong when items were displayed in an irregular spatial distribution. This approach could be applied in recycling contexts by using realistic imagery and displays to encourage the disposal of recyclable materials.

Furthermore, the daily schedules of consumers could introduce another layer of complexity in recycling decisions, such as time constraints (e.g., school drop-offs and collections, childcare, or work routines may impact recycling behaviours). Incorporating these time pressures into experiments, comparing a time-limited response with no time limit, would help determine whether participants rely on intuitive thinking (System 1) or more deliberative reasoning (System 2) when making decisions about recycling. This understanding of consumer routines and their impact on recycling behaviours enlightens us and equips us with the knowledge to design more effective strategies.

Thinking-out-loud investigations, where participants discuss their thought processes (Olson et al., 2018), would better aid the understanding of recycling, environmental impact, and item types and quantities. In an investigation into internal and external communication of sustainability within companies, a semi-structured interview utilised qualitative analysis found that participants considered sustainability to be either important or very important (Offermann et al., 2024). Using a similar approach, we can aim to comprehend how participants perceive and evaluate recyclable materials and the NFI. Quantities are an important factor in understanding the precise point in cognitive processing which the NFI occurs. In Experiment 2, participants estimates for large quantities increased when quantities increased however, the addition of environmentally positive items reduced estimates. It would be interesting to understand why participants saw the addition as a

reduction in harm. A thinking-out-loud analysis may bring forth information that research has yet to consider. Exploring individuals concerns regarding the environment and recycling which could impact legislation if sales strategies rely on the NFI. For example, sales techniques may offer discounts for purchasing multiple products, which can result in an excess of recyclable packaging. Understanding when environmental harm is underestimated would help address faulty cognitions—perhaps utilising a metacognitive analysis approach, taking a bird's-eye view of cue integration (Ackerman, 2023). Further research could also draw more directly on dual-process theories, for example, by manipulating cognitive load or time pressure (e.g., Sörqvist & Holmgren, 2022) to determine whether the NFI is indeed a product of System 1 intuitive reasoning—as suggested by its resistance to correction via summative instruction (De Neys, 2006; Kahneman, 2011). Experimental designs that encourage or inhibit analytic processing (e.g., via concurrent memory tasks or metacognitive prompts) could help distinguish whether vice–virtue averaging is a fast, default heuristic or a strategic simplification adopted under uncertainty. Additionally, neurocognitive techniques such as EEG or fNIRS might be employed to measure conflict detection (e.g., anterior cingulate cortex activation) when participants confront competing cues (Botvinick et al., 2001), helping to delineate when and how cue conflicts are resolved.

Critically, the boundaries of averaging need to be more precisely defined. As the current work shows, item quantity plays a complex and non-linear role: increases in group size tend to raise impact estimates, but this effect can be attenuated or reversed when recyclable items are introduced. Is this a true arithmetic averaging effect, a qualitative dichotomisation, or a form of compensatory reasoning? Future studies could incorporate numerical transparency interventions, where the actual total impact of items is made salient either before or after judgment, to determine whether feedback corrects the illusion—or whether the averaging persists even in the face of contradiction (Holmgren et al., 2019).

Beyond this theoretical scope, the practical and applied implications of the NFI are significant. If people systematically underestimate environmental harm when pro-environmental behaviours are presented alongside harmful ones—whether in consumer decisions, corporate communications, or public policy—then well-intentioned messaging may inadvertently legitimise environmental degradation (cf. MacCutcheon et al., 2020; Sörqvist et al., 2022). For instance, product advertisements that highlight eco-friendly packaging or offsets may obscure the broader carbon or waste footprint, promoting a “green halo” that reduces accountability (Kim & Schuldt, 2018). Similarly, recycling campaigns that celebrate behavioural change without contextualising it within overall waste generation may give rise to complacency, rather than motivating sustained reductions (Mazar & Zhong, 2010).

While this thesis has focused on the NFI as a specific cognitive bias, it was originally motivated by a broader question: why do individuals fail to act in accordance with their environmental intentions—particularly when it comes to recycling? Viewed in this light, the NFI is not just a curiosity of judgment but a potentially serious barrier to sustainable behaviour. If individuals intuitively believe that adding recyclable items reduces the overall harm of their consumption—even when it does not—this may promote complacency and undercut the motivation to reduce waste more broadly. In this way, the NFI contributes to a larger constellation of cognitive, motivational, and contextual factors that impede effective recycling behaviour.

This broader framing highlights the need for interventions that go beyond closing informational gaps or addressing practical barriers. Instead, they must also tackle the intuitive distortions that shape how people perceive the consequences of their actions. The present findings suggest that unless these biases are targeted directly—through emotionally engaging nudges, culturally resonant cues, or long-term educational reform—efforts to

improve recycling behaviour may be undermined by precisely the heuristics they aim to exploit.

Evidence from Experiment 5 reinforces this concern. Even when participants were explicitly prompted to reflect on their reasoning strategies and encouraged to use summative rather than intuitive averaging processes, the illusion largely persisted. This suggests that standard informational or reflective nudges may be insufficient to overcome the bias. Instead, interventions may need to disrupt default cue prioritisation or fundamentally reframe how environmental impact is presented. One promising approach is to use emotionally salient visual prompts or norm-based cues—such as the marine conservation-themed images used by Luo et al. (2022), which led to a 17% reduction in plastic waste disposal. Such strategies may engage affective processing more directly than verbal prompts, and thereby shift the weight given to environmentally harmful cues in intuitive judgment.

Additionally, future work should explore varied nudge formats tailored to diverse cognitive profiles. Drawing on Gardner's (1983) theory of multiple intelligences, researchers might examine whether linguistic, visual, kinaesthetic, or interpersonal prompts yield differential effects depending on the user. For example, cumulative feedback interfaces showing net environmental impact, interactive simulations, or gamified educational modules could appeal to different user preferences and more effectively correct intuitive errors.

It would also be fruitful to explore individual developmental trajectories in the acquisition and weighting of environmental heuristics. Longitudinal or cross-sectional studies could examine whether certain types of environmental knowledge (e.g., understanding the full life cycle of waste, or the limits of recycling) reduce reliance on affective cues or symbolic gestures. This might inform education initiatives aimed at building intuitive models of environmental harm that are more accurate—and more resistant to vice–virtue illusions (Gorissen & Weijters, 2016). Similarly, foundational heuristic knowledge may vary by context and culture, which affects cue prioritisation. For example, as demonstrated in classic base

rate studies (De Neys, 2007), culturally familiar cues—such as the perceived gender of a name—can override statistical reasoning. Applied to environmental contexts, this suggests that people may prioritise familiar or socially reinforced cues (e.g., “recyclable” labels or eco-symbols) over quantitative information, particularly when these cues align with local norms or media messaging. This highlights the need to design environmental interventions that consider cultural norms and pre-existing knowledge structures.

Conclusion

This thesis provides the most comprehensive demonstration to date of the NFI in the domain of recycling-related decisions. Through five empirically grounded experiments, it establishes that the NFI is not a domain-specific anomaly but a robust, generalised cognitive bias. Crucially, the illusion was shown to transcend item categories (e.g., cans and bottles), persist across judgment formats (e.g., ranking vs. estimation), and extend into temporal contexts involving sequences of environmental behaviours. This pattern of findings suggests that people’s environmental judgments are not governed by additive or summative reasoning, but instead reflect an intuitive cue integration process—driven by evaluative heuristics such as vice–virtue categorisation.

The thesis breaks new theoretical ground by reframing the NFI not simply as a failure of quantity processing (e.g., Kim & Schuldt, 2018), nor as an instance of isolated attribute substitution (Kahneman & Frederick, 2002), but as a flexible and fallible cue-weighting mechanism that prioritises moral salience over objective magnitude. While previous studies have hinted at the influence of moral spillover or compensatory thinking (e.g., MacCutcheon et al., 2020; Sörqvist et al., 2022), this work systematically evaluates and rules out competing explanations such as mental accounting (Thaler, 1999), category size bias (Andersson et al., 2024), and working memory limitations. Instead, it provides a compelling body of evidence for a generalised averaging bias that operates not through arithmetic computation, but through the intuitive integration of morally valenced cues—where the

presence of ‘good’ elements downplays the perceived harm of ‘bad’ ones, regardless of actual quantity.

This account has significant implications for dual-process theories of cognition. While System 1 processes are often associated with speed and error (Kahneman, 2011), this research suggests they may also be structured by learned, morally-inflected heuristics that are resistant to correction—even under explicit instruction or reflection (cf. De Neys & Schaeken, 2007). The failure of a reflective nudge in Experiment 5 underscores the difficulty of displacing these default strategies, and points to the limits of informational interventions.

From an applied perspective, the thesis highlights the urgent need to design environmental communications and policies that anticipate—and counteract—intuitive distortions in judgment. When individuals systematically underestimate cumulative harm due to the presence of “green” cues, this can lead to serious consequences: corporate greenwashing, consumer complacency, and underinvestment in sustainability. To address this, future interventions must go beyond information provision. Instead, they should harness affectively engaging nudges (e.g., Luo et al., 2022), culturally calibrated framing strategies, and possibly long-term educational reforms aimed at reshaping foundational heuristic knowledge (Gardner, 1983; Gorissen & Weijters, 2016).

Overall, this thesis refines and extends existing accounts of environmental judgement by elaborating a cue-based model of vice-virtue averaging. It clarifies the processes by which people misjudge environmental impact, demonstrating that such errors stem from intuitive evaluative integration rather than from simple arithmetic failure or symbolic associations. By identifying the robustness of this heuristic and its resistance to cognitive correction, the thesis offers a valuable framework for guiding future interventions and research in environmental decision-making.

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Appendices

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Appendix A.

Participant Information Sheet
An investigation into the cognitive and behavioural mechanisms of recycling behaviours

Dear Participant,

We would like to invite you to take part in our online research experiment, in a location of your own convenience with no need to attend a laboratory.

Before you decide, we would like you to understand why the research is being done, and what it would involve for you. Please take the time to read the following information carefully. Talk to others about the experiment if you wish. Please email Sarah Ormesher, (SOrmesher@uclan.ac.uk) or Dr Kathleen McCulloch (KMcCulloch@uclan.ac.uk) if there is anything that is not clear, or if you would like more information.

This study will take no longer than 30 minutes.

It is widely understood that recycling and reducing carbon footprint is a better course of action for the environment. However, regardless of expertise, we all at times choose not to recycle or opt for a less environmentally friendly purchase. There are many explanations for this behaviour; many answers pivot around bias. This study aims to investigate the cognitive biases that can hamper positive action. We are looking at your thought process and the current understanding you have regarding particular words and practices.

What is the purpose of the experiment?
The purpose of the experiment is to answer a series of questions relating to the environmental impact of different objects.
Why have I been chosen?
We would like to invite anyone over 18 years old to take part in the study.
Do I have to take part?
No, it is up to you to decide whether or not to take part. You are free to withdraw from this experiment at any point before submitting your final answers, by simply closing your browser.
What will happen to me if I take part?
The experiment will involve completing surveys related to judgement of environmental impact and questionnaires about perception and attitudes related to the environment. Further instructions will be provided on starting the task.

What are the possible disadvantages and risks of taking part?
There are no disadvantages of taking part. Many people find such tasks fun, if a little tiring at times.
What are the possible advantages of taking part?
There is no immediate benefit from this experiment and we do not anticipate that the findings will benefit you directly. However, the information we gather will help to inform the scientific community about how we make judgements.
What if there is a problem?
We do not anticipate any problems during this experiment. If you have any questions, please contact the researcher on the details provided above. If you do not wish to speak to the researchers, and you wish to speak to someone independent of the research, please contact the Ethics Office using the following email (OfficerforEthics@uclan.ac.uk).
Will my taking part be kept confidential?
Yes. All information gathered during this experiment will be anonymous and will be kept strictly confidential. The data will be accessible only to the researchers involved in the project, and it will be stored on password-protected computers for a maximum of seven years, according to UCLan data requirements.
What will happen if I do not wish to carry on with the experiment?
You are welcome to withdraw from the experiment, without having to give any reason, at any point up to submitting your final answers. Once you have submitted your final answers, it will no longer be possible for you to withdraw your responses because they will become anonymized and stored with other anonymised data according to UCLan data requirements.
What will happen to my data?
The data will be combined together into means so that any individual responses are non-identifiable. The overall findings will be published in a journal as part of a peer-reviewed publication and presented at conferences.
Who has reviewed the experiment?
This experiment has been reviewed and approved by the Science Ethics Review Panel at the University of Central Lancashire.
Thank you for taking the time to read this information sheet

Appendix B.

***The AOT-17 Questionnaire*.**

Table 2. Factor loadings in CFA Model 4 Study 1.

Item	Latent factor F1	F2	F3	F4	Source
Factor 1: Dogmatism					
23. I believe that loyalty to one's ideals and principles is more important than "open-mindedness". (R)	**.64**				O-v
32. I believe that the "new morality" of permissiveness is no morality at all. (R)	**.59**				O-v
24. Of all the different philosophies which exist in the world there is probably only one which is correct. (R)	**.52**				Dogm
8. I think there are many wrong ways, but only one right way, to almost anything. (R)	**.89**	−.49			Cat
39. I believe letting students hear controversial speakers can only confuse and mislead them. (R)	**.45**				O-v
7. I believe we should look to our religious authorities for decisions on moral issues. (R)	.20	.29			O-v
Factor 2: Fact resistance					
33. One should disregard evidence that conflicts with your established beliefs. (R)		**.64**			Bel
15. It is important to persevere in your beliefs even when evidence is brought to bear against them. (R)		**.61**			Bel
19. Certain beliefs are just too important to abandon no matter how good a case can be made against them. (R)		**.68**	−.22		Bel
37. Beliefs should always be revised in response to new information or evidence.	−.68	.90			Bel
41. People should always take into consideration evidence that goes against their beliefs.	−1.14	1.28	.48		Flex
Factor 3: Liberalism					
18. I consider myself broad-minded and tolerant of other people's lifestyles.			**.58**		O-v
4. A person should always consider new possibilities.			**.40**		Flex
27. I believe that the different ideas of right and wrong that people in other societies have may be valid for them.			**.42**		O-v
Factor 4: Belief personification					
11. There are a number of people I have come to hate because of the things they stand for. (R)				**.73**	Dogm
3. I tend to classify people as either for me or against me. (R)	.27			**.40**	Cat
31. My blood boils over whenever a person stubbornly refuses to admit he's wrong. (R)				**.44**	Dogm

Note: Loadings in boldface are included in the sum variables used in subsequent analyses. R = reflected item, O-v = openness-values, dogm = dogmatism, cat = categorical thinking, bel = belief identification and flex = flexible thinking.

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the shortened scale (Cronbach's $\alpha = .75$) was lower than of the 41-item original, $t(2733) = 24.47$, $p < .001$, but still acceptable.

(Svedholm-Häkkinen & Lindeman, 2018)

Appendix C

Debrief Sheet

An investigation into the cognitive and behavioural mechanisms of recycling behaviours.

Thank you for taking part in our research study. Your time is very much appreciated. The research you have participated in aims to investigate the cognitive and behavioural mechanisms that impede recycling behaviours. The founding concept is based on a unique paradigm known as the Negative Footprint Illusion (NFI). Regardless of an individual's expertise, adding an eco-friendly item to an estimate of carbon footprint, the overall damage to the environment is underestimated. The NFI is prevalent in food consumption, house, and car studies. We want to see if it also relates to general recycling. In this research study, you were asked to estimate the carbon footprint or environmental impact of houses and plastic bottles and then complete questionnaires about your perception of environmental issues.

You will never be identified in any findings of this experiment, nor will it be possible to link the findings back to you. We want to remind you that this is the final opportunity to withdraw your data from the experiment. If you wish to withdraw, simply close your browser. By clicking the confirm button below, you are submitting your responses anonymously, and as such, they will no longer be able to be withdrawn.

If you have any questions, please contact Sarah Ormesher, SOrmesher@uclan.ac.uk or Dr Kathleen McCulloch, KMcCulloch@uclan.ac.uk. If you are unhappy or have concerns about any aspect of the project and do not wish to contact the research team, you can contact the University Officer for Ethics (OfficerforEthics@uclan.ac.uk). They are entirely independent of the research and will respond to your queries or concerns. Thank you for taking part in this experiment. Your time is very much appreciated.

Appendix D.

Figure D1.
Conditions.

10 non-recyclable cans, 10 non-recyclable cans +20 recyclable cans.

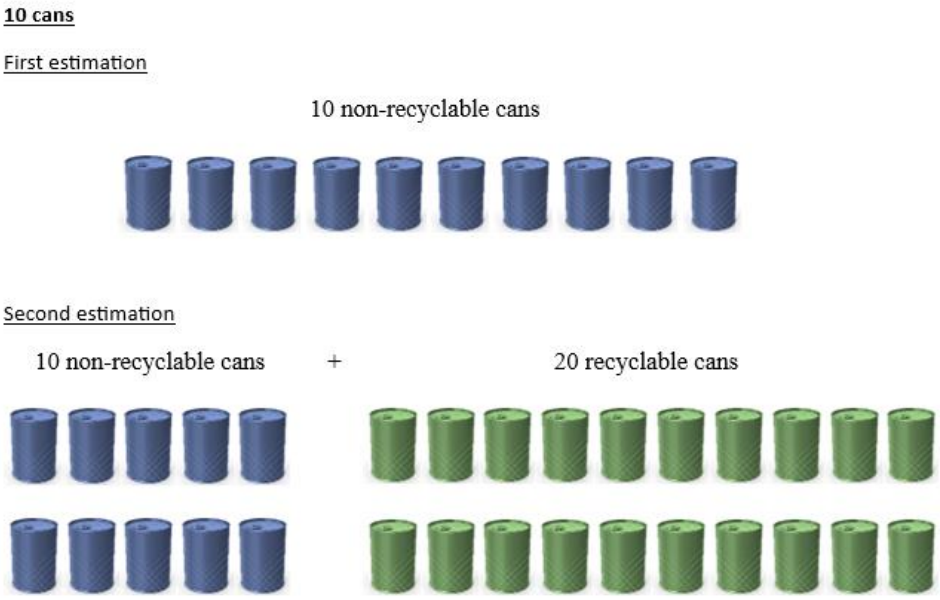


Figure D2.
10 non-recyclable plastic bottles, 10 non-recyclable plastic bottles + 20 recyclable plastic bottles.

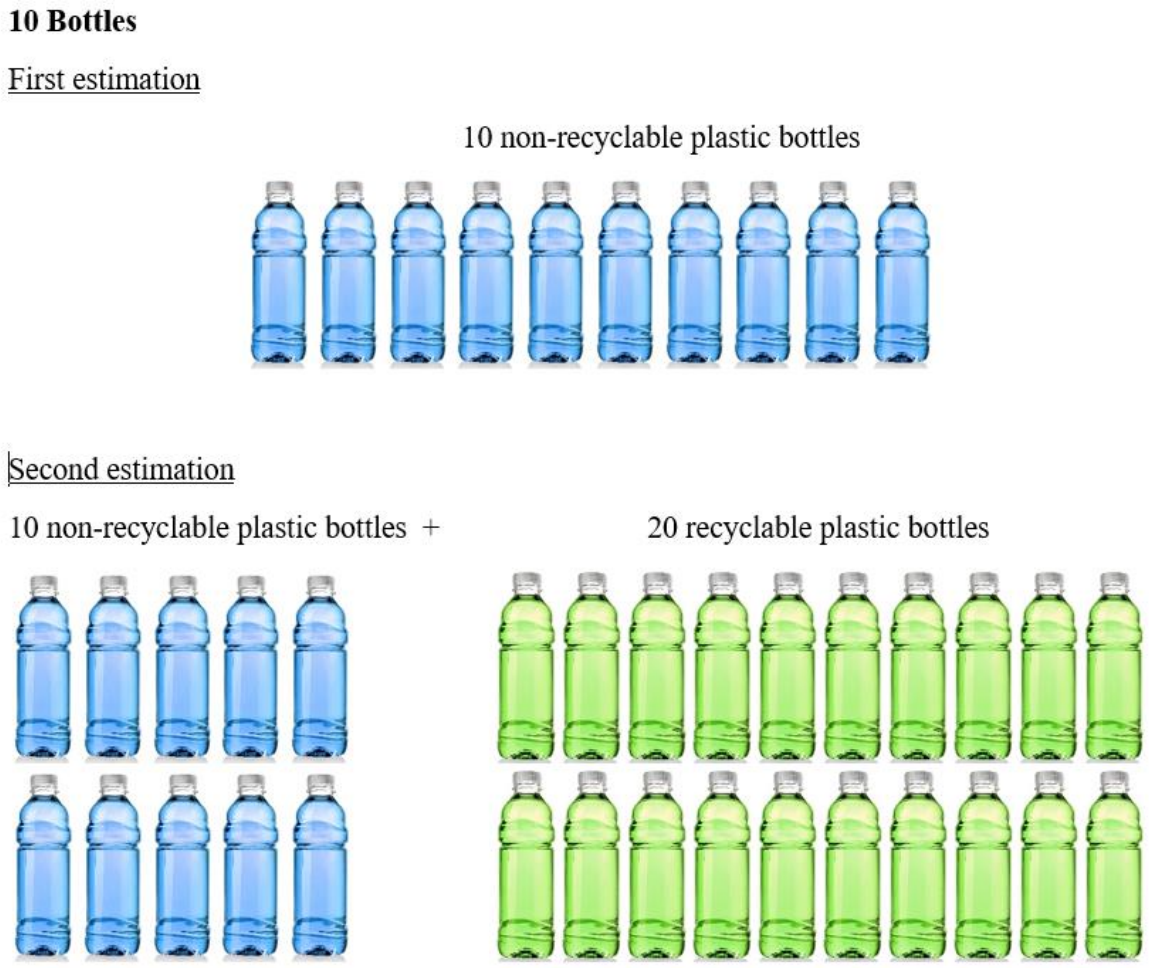
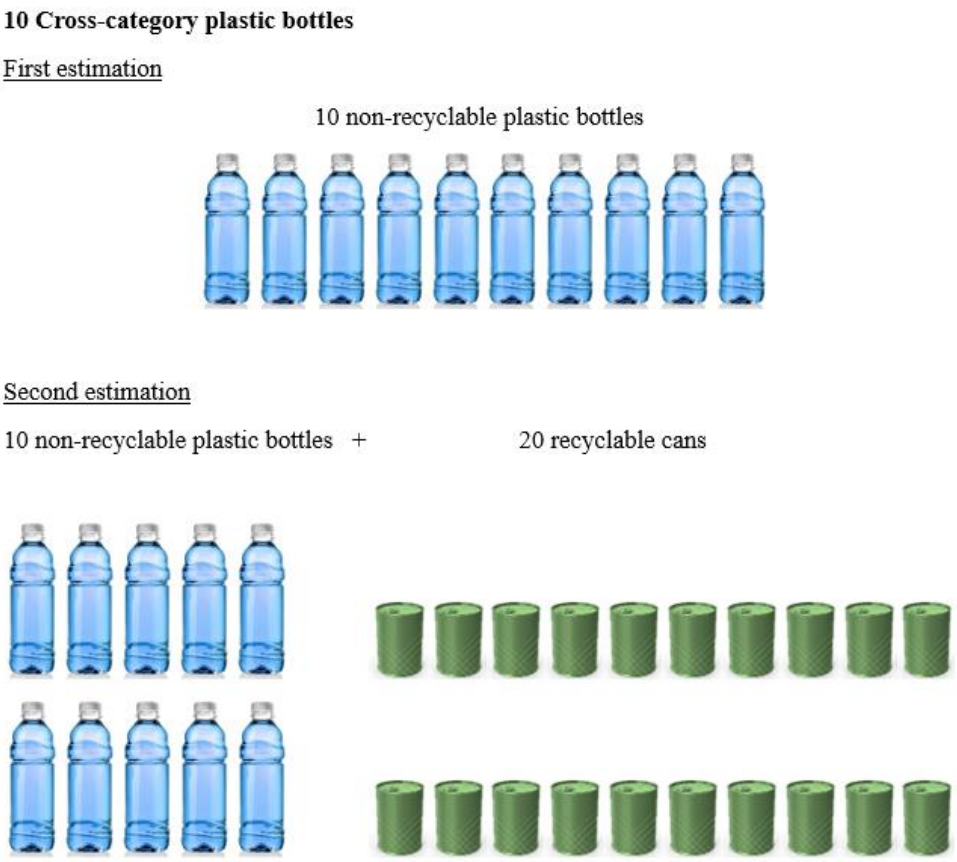


Figure D3.

10 non-recyclable plastic bottles, 10 non-recyclable plastic bottles + 20 recyclable cans.

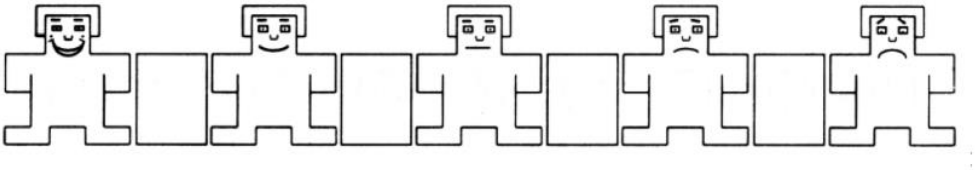


Appendix E

Valence and Arousal stimuli

The images below depict happiness and sadness. Please use the scale below to describe how you feel about **non-recyclable bottles.**

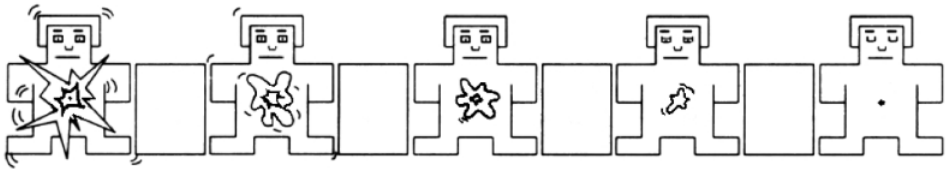
Mark the number of the figure that corresponds to how you feel. You may use the boxes in between the figures to make a more fine-grained assessment.



1 2 3 4 5 6 7 8 9

The images below depict different levels of arousal. Please select the number below that best describes how you feel about **non-recyclable bottles.**

Select the number of the figure that corresponds to how you feel. You may use the boxes in between the figures to make a more fine-grained assessment.



1 2 3 4 5 6 7 8 9

Appendix F

Experiment 4

Vignette
Thomas Smith is a 40-year-old accounting manager at a large supermarket chain in London. He lives together with his 39-year-old wife in a small suburban area just outside of London with their two children Michelle and Amy (ages 6 and 8). During the first half of 2019 (from February to June) the Smith-family was not environmentally conscious and threw plastic waste together with their regular rubbish in the same bin (which ended up in a landfill site). The plastic waste that ended up in a landfill site during the first half of 2019 was 20 kilograms and is marked on the centre of the scale below.

Scenario A
After the suburban area, where Thomas and his family live, introduced a recycling policy for plastic waste, Thomas and his family started recycling during the second half of 2019 (from July to December). The plastic waste during this period was 10 kilograms. Please estimate, on the scale below, the total environmental impact for the first half of 2019 and the second half of 2019 (when the family started to recycle their plastic waste) taken together.

Scenario B
After the suburban area, where Thomas and his family live, introduced a recycling policy for plastic waste, Thomas and his family started recycling during the second half of 2019 (from July to December). The plastic waste during this period was 20 kilograms. Please estimate, on the scale below, the total environmental impact for the first half of 2019 and the second half of 2019 (when the family started to recycle their plastic waste) taken together.

In the control scenarios, the Smith family continued their previous behaviour:

After the suburban area, where Thomas and his family live, introduced a recycling policy for plastic waste, Thomas and his family were unwilling to start recycling during the second half of 2019 (from July to December) because they considered the scheme too time-consuming. The Smith-family was not environmentally conscious and continued to throw plastic waste together with their regular rubbish in the same bin (which ended up in a landfill site). The plastic waste that ended up in a landfill site during this period was 10 (Scenario C)/20 (Scenario D) kilograms.