Information Filters

Learn from Personal and Social Experience

A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy in Psychology

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*Or how subjectivity explains “the” learning mechanism.
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Declaration

The thesis is my own work that is submitted in support to my application for the degree of Doctor of Philosophy in Psychology at the University of Warwick. The thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma at a university. This work has only been submitted for this doctoral programme and has not been submitted at any other institution. The thesis does not contain any materials previously published or written by another person except where due reference is made in the text; all substantive contributions by others to the work presented are clearly acknowledged.
Abstract

People learn and make decisions by selectively gathering, processing and communicating information – a complex chain of actions prone to bias. In doing so, people do not only interact directly with the environment to gather information, but also with other individuals. Indeed, social context allow more efficient learning and decision-making by mitigating individual limitations. In this thesis, personal and social learning are viewed as two complementary levels of information filtering – a recursive process, the base case of which being individual (subjective) experience via sampling. Identity representing subjectivity in a learning process is a filtering parameter on both levels. A well-established phenomenon in risky decision-making – Description-Experience Gap – was used to explore the difference of personal and social learning. Firstly, newly developed decisions-from-observation and decisions-from-description experimental paradigms showed that decision-making by social and personal experience are similar learning processes, with communication tending to decrease personal experience bias by over-reporting it. Secondly, decisions-from-description paradigm with either present or absent social source showed that people assume social source even when it is absent. Lastly, identity (mis)alignment between social source and receiver showed to affect evaluation of the source, but not the evaluation of information they delivered. Overall, by comparing and combining personal and social learning strategies, and by performing Bayesian meta-analysis, this thesis shows that personal and social levels of information filtering are closely related with identity playing a mediating role. The experimental results also suggest that personal and social information filters are two different perspectives constituting a single complementary process necessary for efficient decision-making.
## Abbreviations

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<td>DE</td>
<td>Description-Experience (gap)</td>
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<td>DfD</td>
<td>Decisions from Description</td>
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<tr>
<td>DfDE</td>
<td>Decisions from Described Experience</td>
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<tr>
<td>DfE</td>
<td>Decisions from Experience</td>
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<td>EV</td>
<td>Expected Value</td>
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<td>OSF</td>
<td>Open Science Framework</td>
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<td>RL</td>
<td>Reinforcement Learning</td>
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<td>RPE</td>
<td>Reward Prediction Error</td>
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<td>ToM</td>
<td>Theory of Mind</td>
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Chapter 1: Introduction

Learn from other’s mistakes. – Russian Proverb

‘Broken telephone’ – a game highlighting people’s tendency to produce errors in communication.

Goals, resources, biases, heuristics, and how these apply to self and others – is what people (should) think about most of the time.

In our era of constant information exchange, efficient learning is becoming increasingly difficult. This is because with increasing amount of information, learning rate must increase as well. To understand how to navigate these seemingly infinite information streams, individuals have to be selective about what, how, and from whom to learn to adjust behaviour (Simon, 1971). One of the ideas that account for these problems is information processing framework, which is a way of describing how individuals interact with information (Lindsay & Norman, 2013). Information processing framework focuses on the cognitive mechanisms once information is already acquired. Individuals, however, not only process information, but selectively gather,
manipulate and communicate it in various ways. In this thesis, the idea of information processing is developed further by adding agency (decision-making), subjective experience (outcomes), and social context of individuals, which is better described as *information filtering*. An information filter, an individual in this case, continuously selects specific information (signal) and removes redundant information (noise) from the information stream, which is unavoidable and beneficial for learning and decision-making (Chen, 2003; Grüter, Leadbeater, & Ratnieks, 2010; Rendell et al., 2010; Rendell et al., 2011; Schöbel, Rieskamp, & Huber, 2016; Sharanand & Maes, 1995; Sikder, Smith, Vivo, & Livan, 2020a). Information filtering is dependent on (social) environment, identity, personal experience of an individual among other layers, and works as attention bias towards specific stimuli, such as reward. For example, research in cognitive, behavioural and computer science show that people perceive the same information differently depending on its environment or information format, resulting in biased learning and communication (Dutt, Arló-Costa, Helzner, & Gonzalez, 2013; FeldmanHall & Shenhav, 2019; Lieder, Griffiths, & Hsu, 2017a). The overall aim of the thesis was to understand the interaction of personal and social learning under the framework of information filtering, and how the two are the same are on the same spectrum of “learning”. This was specifically explored in risky decision-making. The aim of the thesis was to understand: (1) the difference between personal and social learning (learning, decision-making, communication), (2) whether information that is not acquired from the environment is perceived as social (having a source), and (3) how identity affects evaluation of information (subjectivity)
1.1 Information Filters

There is more information than any individual can ever learn and make sense of. Therefore, one must be strategic about what information to learnt (Grüter et al., 2010; Heyes, 2016b; Körding, 2007; Rendell et al., 2010; Shadanand & Maes, 1995). The idea of information filtering has been mentioned in the psychology literature before, but has not been given enough attention so far (e.g., McConnell, 2011; Rendell et al., 2010; Thompson, 1988). People are selective learners – what any of us learns and communicates depends on at least two different levels – personal filter (e.g., learning from environment) and social filter (e.g., learning from a specific other) (Toelch, Bruce,

![Diagram](image)

Figure 1.1. An information filter processes information from personal and social experience. Gathered information from personal and social experience goes through different layers of filtering such as an agent’s surrounding environment, their identity, and their habits, resulting in a specific learning outcome that is manifested in decision-making and communication.
Newson, Richerson, & Reader, 2013; Toelch et al., 2009). These two filtering levels are necessary and sufficient for an individual to navigate information flow in the environment. Given that consistent biases are observed in individual and group behaviour, information filtering might be used as a way to understand why these happen. For example, selective information gathering on an individual level manifests as over-confidence and information avoidance, but on a group level, polarisation manifests as informational cascades, filter bubbles or echo chambers (Bikhchandani, Hirshleifer, & Welch, 1992; Flaxman, Goel, & Rao, 2016; Pilditch, 2017).

Information filtering is a simple idea: the act of gathering and compressing information, measuring or categorising it by some principle and then providing it to others in some form (Chen, 2003; Stordal, Karlsen, Nævdal, Skaug, & Vallès, 2011; Thompson, 1988). An individual as an information filter (Figure 1.1), processes personally and socially selective information (signal) and avoid unwanted information (noise) to then apply to personal decision-making or/and communicate to others. Information goes through different layers of filtering such as individual’s surrounding environment, including other individuals, habits, and identity. These filtering layers results in a learning outcome: a decision and/or communication.

Human behaviour can be described as a multi-dimensional dynamic system and be represented as a model with state-space parameters limited in time (Schumitsch, Thrun, Bradski, & Olukotun, 2005; Stordal et al., 2011). This system produces information in the form of actions or representations that can be used by others (Gershman & Daw, 2017; Ng & Russell, 2000). By making selective choices, individuals filter information and then act as social source to others, helping receivers to avoid costly exploration and exploit what already known (Behrens, Hunt, Woolrich, & Rushworth, 2008; Heyes, 2016b; Madsen, 2013). Thus, receivers can skip the step of
filtering information through personal experience, and instead filter social sources to select the appropriate one to learn from. In this way, agents can learn directly from the behaviours of others, who have proven to be successful (Benjamin & Budescu, 2015; Grüter et al., 2010; Heyes, 2016b). Thus, people can sample actions not only from personal experience but also by using samples and representations generated by others via observing them (Chapter 2) or by exploring the outcomes (products) of others’ choice (Chapter 3; Vuilleumier, 2005). The gathered and processed data is then applied to personal decisions, which in turn produces observations for others (Rendell et al., 2010).

Information filters is a model to describe human behaviour, i.e., how individuals (1) learn information and (2) process it, then, use it to (3) make decisions that can be represented in some form (i.e., decision outcome, description), which then can be (4) communicated to others. The impact of this chain of information filtering was explored in Chapter 3, which looked at described experience, with those data representing fully the process of noise reduction from skewed sampling. Formally, information filters can be viewed as a numerical approximation to the nonlinear Bayesian Filtering problem or Sequential Monte Carlo Method (Gustafsson, 2010). Information filters use sampling to represent the posterior distribution of a given noisy behaviour and partial observations of it, and then update their prediction in an approximate (statistical) manner. Thus, an information filter can be described as a dynamic system that reduces noise in gathered data by some principle (i.e., previous experience, identity). The main problem of such filter is that a large number of samples is needed to closely approximate the posterior probability density of the system. But this problem can be overcome by the recursive structure of social learning, by which an agent can receive an infinite number of compressed or modified samples created by others (e.g., via network or
generations). In other words, individuals can learn on the level of limited personal filtering, by sampling the environment directly by personal experience or using observing others doing so, or on the level of potentially unlimited social filtering – by sampling social sources.

1.1.1 Personal and Social Levels of Learning

People learn in different ways, but the main categories of learning are personal (i.e., subjective or individual) and social, from one other or group of others, including aggregated knowledge (Ho, MacGlashan, Littman, & Cushman, 2017; Krafft et al., 2016). Figure 1.2 represents these two general categories of learning – by personal trial-and-error (i.e., individual learning; e.g., Hertwig & Erev, 2009) or by interaction with others (i.e., social learning) (Boyd, Richerson, & Henrich, 2011; Heyes, 2016; Olsson, Knapska, & Lindström, 2020; Rendell et al., 2011). Learning from personal experience is the process of reaching an understanding based on interaction directly with the environment by living through events (e.g., Hertwig, Hogarth, & Lejarraga, 2018). Social learning, on the other hand, is the process of learning that is facilitated by interaction with other individual or their products, such as descriptions (Heyes, 1994; Rendell et al., 2011). In this thesis, a broad definition of social learning is used: social learning is distinguished from personal learning by presence of information source and its direct or indirect interaction with information receiver. Both personal and social learning have own trade-offs regarding how information is received, processed and communicated, resulting in biased behaviour. For adaptive advantage, learning flexibly by switching between personal and social learning is essential (Kang et al., 2009). Social learning generally follows the same principles as learning from personal learning, but navigates a more complex environment – social environment, which contains other agentic individuals, i.e., with personal goals and subjective experience.
Thus, to successfully navigate social level of environment, social learning requires additional learning mechanisms, such as model-based mentalising and meta-cognitive processes, such as theory of mind (Heyes, 2016; Olsson, Knapska, & Lindström, 2020). Social information is a more recent cognitive function as compared to learning from personal experience, and is more resource-efficient (e.g., time shortcuts) and prevents costly mistakes (e.g., by avoiding unnecessary risks) (Kendal et al., 2018; Rendell et al., 2011).

Figure 1.2. Even though there are multitude of learning strategies, these can be generally classified into two tightly related modes of learning: personal and social.

Biases might be considered as distortions in human cognition and behaviour that might lead to potential suboptimal behaviour. But, biases in information gathering, processing and communication reflect human cognitive processes which in turn are substantial contributors to human culture (Kalish, Griffiths, & Lewandowsky, 2007). The biases can emerge from any stage of information filtering: from biased perception,
experience and processing, to biased storage and communication of information (Xiao, Coppin, & Van Bavel, 2016). For example, personal experience biases how information is learnt and is further distorted by memory (Lieder et al., 2017a; Ludvig, Madan, & Spetch, 2014; Madan, Ludvig, & Spetch, 2014; Pleskac & Hertwig, 2014). Social information is also biased by identity, skewing information consumption (i.e., echo chambers, filter bubbles) contributing to social-level reality distortion (Effron, 2018; Flaxman et al., 2016; Pilditch, 2017). Social source bias is an example of information filtering – the information coming from others with high perceived reliability, such as in-groups, can be learnt without evaluating information itself (Bonaccio & Dalal, 2006; Bonnie & Earley, 2007; Farrell & Lewandowsky, 2010; Leong & Zaki, 2017; Lewandowsky, Ecker, & Cook, 2017; Xiao et al., 2016).

Social learning is an essential part of human adaptation and is one of the key factors in human progress over the last 50,000 years (Boyd & Richerson, 2009; Chamley, 2004; Perreault, Moya, & Boyd, 2012; Richerson & Boyd, 2004). Indeed, social learning theory suggests that much of human behaviour is acquired not through individual trial-and-error learning as in the form of classical or operant conditioning, but via learning from others (Bandura, 1971; Heyes, 2016a; Perreault, Moya, & Boyd, 2012b). This view fits within the framework of bounded rationality: social learning can be seen as a heuristic in personal decision-making (Gigerenzer et al., 2008; Krafft et al., 2016; Kvam & Hintze, 2018; Simon, 1955; Simon, 1979). Humans and other animals learn in various ways starting from direct observation and finishing with more abstract forms of communication such as verbal expressions (Galef & Heyes, 2004; Heyes, 2016b). When engaging in social learning, people are receivers of information, but a receiver can also be a social source when sharing received information. When people act as receivers they seek and apply information from others to own personal
understanding of reality. When people act as social sources, they seek receivers to provide personally (or socially) gathered information, e.g., sharing a summary of travel experiences. People share opinions, experiences, “life-hacks”, and teaching material on platforms such as YouTube, Reddit, Medium, and other social media platforms, channels and forums. This knowledge sharing not only saves time and energy to figure something out, but it advances social knowledge in general.

Social learning uses information from the experience of others, thereby decreasing the uncertainty in the environment, helping to select an appropriate action (Aronson, Wilson, Akert, & Sommers, 2005). In risky choices, it is beneficial for some activities (e.g., driving) to be learnt from social experience rather than personal trial-and-error, which decreases costly mistakes, time or other resources in the learning process (Chamley, 2004; Pachur, Hertwig, & Rieskamp, 2013; Rendell et al., 2010). In the case of costly mistakes, social learning is particularly important because some activities can result in potential unusually costly outcomes (e.g., death), which are to be avoided at all costs in personal experience. Receivers of information can thus have a choice to skip the risky exploration stage and exploit whatever is already being indicated by others (Daw, O’Doherty, Dayan, Seymour, & Dolan, 2006; Rendell et al., 2010; Rieucau & Giraldeau, 2011; Schöbel et al., 2016; Wilson, Geana, White, Ludvig, & Cohen, 2014).

The most optimal way of gaining knowledge is to flexibly use personal and social learning (Bonnie & Earley, 2007; Kang et al., 2009; Rieucau & Giraldeau, 2011). This flexibility is beneficial because if cooperative, information sharing and learning can be very efficient (Cummings, 2004; Gallotti & Frith, 2013; Toma & Butera, 2009). In the same time, the benefit of cooperation comes at the cost of innovators. Information exchange can be viewed as a social dilemma: innovators spend most of their time on
personal learning – exploring – to then share collected information they collect, so others can use the outcome of innovations by using and applying – exploiting – the information obtained from them (Heyes, 2016; Rendell et al., 2011; Toelch, Bruce, Meeus, & Reader, 2011). Social source thus is the intermediary between information in the environment and efficient learning of receivers. Different social learning strategies have evolved that are useful in different circumstances, such as “copy when uncertain”, “copy the majority”, “copy the most successful”, and “learn from personal experience at least sometimes” (Heyes, 2016; Legare & Nielsen, 2015; Muthukrishna, Morgan, & Henrich, 2015; Wisdom, Song, & Goldstone, 2013). A social source communicates information that was itself acquired socially or personally, and these learning strategies define information filtering on social level (Demsky, 2020; Körding, 2007).

### 1.1.2 Recursive Structure of Learning

A recursive procedure is where (at least) one of its steps is used in a new instance of the same procedure, and in a social learning context, different people in different circumstances can be that new instance. Learning is a recursive process – it is defined in terms of sampling different instances – to come up with an optimal decision-making process, which is then repeated and shared with other individuals, thus building up on the initially gathered information (i.e., exemplar or base case). Following such a recursive process, an initial direct experience can be described by and thus define all consequent experiences that are based on descriptions and/or memory of these (Perreault et al., 2012). Imagine you visited a local bakery for the first time and bought a bread. You like it and decide to leave a review on the bakery’s website. On the website, other people have left reviews too. By reading the reviews, you realise that your bread was not an outlier – the bakery on average makes excellent bread. In this example, you and others experienced essentially the same thing – trying out bread and
describing the same experience in many different instances. This example is sampling by using experience of others via communication (Hauser, Chomsky, & Fitch, 2002; Pachur et al., 2013). Simply reading the information, however, is not a recursive process in itself – one needs to build on the initial information and augment it. Thus, recursion enables more effective learning if others share their personal experiences.

In computer science, recursion is defined as a method of solving a problem where the solution depends on figuring out the solutions to smaller instances of the same problem (Avigad & Brattka, 2014). Thus, a method is recursive when it can be described by two properties: (a) it has a base case — an initial scenario determining conditions of the function and (b) a recursive case — a set of rules that distil all consecutive cases toward the base case. This is also the idea of reinforcement learning, specifically in temporal difference learning, where a value is learnt from a subsequent value, which was also learnt from a subsequent value and so on, all the way to the reward (Sutton & Barto, 1998). The parallel recursion idea comes from learning from others who learned from others, all the way to the person who had the initial experience. Learning through sampling is essentially the inferential process in the form of acquiring samples personally from the environment or from communication with others (Perreault et al., 2012; Rendell et al., 2010). Thus, the key aspect of recursion is that it always has an initial or base condition, which specifically differentiates recursion from regression theories (e.g., Kanter & Steiger, 1974). The idea of recursion or social reinforcement in learning is that, in principle, an individual can learn infinite amount of information from others, but one needs to filter out the noise for learning to be adaptive. Although the idea of recursion simplifies learning to a repetitive process of several steps, it represents the tendency of people as an intelligent entity to seek, categorise and modify information to resolve uncertainty (Achiam & Sastry, 2017; Mirza, Adams, Friston, &
People can reason about others’ motivations and goals (Pfeiffer & Foster, 2013; Tolman, 1948) and also use this reasoning ability recursively: we can consider what others believe about our own beliefs (Baker, Saxe, & Tenenbaum, 2009; Cosmides, 1989; Hawthorne-Madell & Goodman, 2019a). All these ideas about social interaction can be thus be described as a recursive process (Yoshida, Seymour, Friston, & Dolan, 2010).

1.2 Social Influence is Learning

From an information theory perspective, receiver’s behavioural adjustments given social information can be described in terms of choice imitation or goal emulation (Charpentier, Iigaya, & O’Doherty, 2020; Toelch, Pooresmaeili, & Dolan, 2018). Depending on identity, which is a subjective perception of the environment, mimicking productive behaviour or acquiring information from others (e.g., a group or more experienced individuals) must be specific to the receiver and context in order to achieve personal goal, while saving resources (e.g., Curio et al., 1978; Galef, 1996; Thornton and Clutton-Brock, 2011). Thus, by directly learning from others or being indirectly influenced by them, it is possible to make personally best choices without costly interaction with the environment and putting yourself at risk of making a costly error.

There are two broad definitions of social influence: informational and normative (Deutsch & Gerard, 1955; Toelch & Dolan, 2015). Social informational influence is usually distinguished from normative social influence (e.g., conformity) on the behavioural level and is defined as influence which nudges one to accept information obtained from others as evidence about reality (Deutsch & Gerard, 1955; Toelch & Dolan, 2015). Normative social influence, on the other hand, focuses on the receiver’s outcome behaviour – leading to behaviour that complies to the behaviour of others
(Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009; Nyborg et al., 2016). On a neuro-computational level, informational and normative social influences are represented by similar mechanisms (e.g., Toelch & Dolan, 2015). Informational as well as normative social influences can be described more generally as instances of social learning – both influences reflect learning information from or about others in light of which behaviour can be adjusted (Denrell & Le Mens, 2007; Montgomery & Casterline, 1996; Toelch & Dolan, 2015). The two social influences can also be described in terms of conformity bias, which is likely to be a universal aspect of social agents (Boyd & Richerson, 1982, 1985; Henrich & Boyd, 1998).

Conformity via social learning biases, such as prestige bias, facilitates a distribution of (preferably) preferable behaviour through the whole population, such as adaptive innovation as described above. From an evolutionary point of view, a strong reliance on adaptive social information acquired by conformity is adaptive, but, when the frequency of social learning increases within population, the value of it decreases, and more personal learning is needed for a group to thrive (Rendell et al., 2010). That is, if everyone copies the behavior of each other and no one learns from personal experience directly from environment, individual adaptability can substantially decrease (Anderson & Holt, 1997; Rieucau & Giraldeau, 2011). Thus, exploiting the knowledge of others indefinitely is a bad learning startegy that can result in maladaptive behaviours such as information cascades (Bikhchandani et al., 1992; Huber, Klucharev, & Rieskamp, 2013; Yudkowsky, 2017). Thus, simply copying others is not beneficial, instead one needs to pay attention to learning process itself (i.e., meta-learning) by choosing appropriate learning strategies in a given environment.

Navigating social information requires additional mechanisms compared to personal learning. People are exceptionally adept at reasoning about another person who
is the source of information — an ability known as Theory of Mind (ToM). ToM is involved in perspective taking and the ability to represent the mental states of others, such as beliefs and intentions (Carlson, Koenig, & Harms, 2013; Frith & Frith, 2011). When people communicate deliberately, as in teaching and cooperation, the processes underpinning ToM allows individuals to understand one another with a high degree of precision (Wang, 2015). Apart from teaching, people can also infer what others believe about the world and integrate these beliefs into own worldview. One computational account of the inference process involved in personal and social learning demonstrated subtle interactions between information and ToM attributes, such as a learner’s intuitive understanding of confidence, reliability, and knowledgeability of the social source (Gershman, Gerstenberg, Baker, & Cushman, 2016). These attributes are then used to interpret the other person’s choices, weighing them against the receiver’s own direct evidence. Thus, ToM contributes to both learning (i.e., reception of information) and social influence (i.e., compliance), which can eventually be equated to the same fundamental process – gathering information from others to adjust one’s own behaviour. The robustness with which one can gather information and adjust behaviour according to the environment might be particularly important in situations involving risk, especially where there is at least some possibility of a significant danger or loss.

1.3 How Social is Risk?

On an individual level, people often miscalculate the occurrence of events, particularly ones that are extreme and happen with low probability. This miscalculation is potentially most often encountered in risky decision-making due to the intrinsic format of risky events: their probability of occurrence often correlates with their magnitude (Johnson & Tversky, 1983; Gigerenzer, Hoffrage, Mellers, & McGraw,
There are many reasons for this miscalculation: people can be biased in how they sample the environment, how this sampling is represented in memory, and how these samples are used to make decisions (Barberis, 2013; Ludvig, Madan, & Spetch, 2014; Stewart, Chater, & Brown, 2006; Tversky & Kahneman, 1992; Ungemach, Chater, & Stewart, 2009). The idea of biases as a miscalculation is debated as actually a rational aspect of an individual behavioural repertoire, because it saves resources (i.e., time) in individual learning (e.g., Gigerenzer et al., 1995, 2008; Lieder et al., 2017). Even though learning and choice can be biased when making a risky choice, this distortion in risk perception might nevertheless be adaptive. Specifically, as discussed in this thesis, the biases on personal level are likely to be complemented by biases on social level, overall improving adaptability of social intelligent agents.

The human mind evolved with experienced frequencies as the quantitative input and thus is perhaps better able to make decisions based on small samples, because for an individual in the real world, events happen in a countable way (Brase & Hill, 2017). However, individuals can fail to encounter information about rare events as encountering them require specific search strategies (Hills & Hertwig, 2010; Wulff & Hertwig, 2018). These individual search strategies can be improved with the help of others because rare events can be estimated better from a higher number of samples. Indeed, one of the reasons people formed and lived in groups is to better manage uncertainty and risks (Denrell & March, 2001; Fehr & Fischbacher, 2003; Toelch, Bruce, Meeus, & Reader, 2010). Within groups, individuals can learn from personal trial-and-error and from others depending on the situation at hand. When there is a low risk of danger (i.e., stable environment), relying on the knowledge acquired through personal learning might be reasonable in day-to-day situations, but when risk is high,
relating on learning from others is more adaptive (Heyes & Pearce, 2015). With social learning comes the problem of judging the value and reliability of communicated social information and one’s own experiences (Boyd et al., 2011; Pachur et al., 2013). The research has started to address the idea that social learning can be key in understanding risky decision-making (Hertwig et al., 2018; Kopsacheilis, 2019; Pachur et al., 2013). The problem of social learning about risk can be directly addressed by looking at a well-established phenomenon in risky decision-making research – the Description-Experience gap.

1.3.1 Description-Experience Gap

One of the most known phenomena in risky decision-making is known as the Description-Experience (DE) gap (Hertwig, Barron, Weber, & Erev, 2004; Hertwig & Erev, 2009; Wulff, Mergenthaler-Canseco, & Hertwig, 2018). The DE gap describes

![Figure 1.3. Basic paradigms for (A) Decisions-from-Experience and (B) Decisions-from-Description as often used in risky decision-making research. Note that in the Description condition (B), there is no sampling: participants simply learn the outcomes and probabilities directly, here expressed as a percentage.](image-url)
the difference in how people make risky choices depending on the way they encounter information. The two paradigms of learning about risks described in DE gap, differ in how the information is learned: by directly experiencing the odds and outcomes or by an explicit description of those same odds and outcomes. The first risky decision-making paradigm is known as Decisions-from-Experience (Experience), in which as Figure 1.3A shows, participants do not know about potential outcomes and probabilities – they can only sample options and by receiving feedback in the form of outcomes (e.g., monetary) learn to then estimate corresponding probabilities. In Experience, when learning probabilities and outcomes from personal experience, people act as if they underweight rare events (Hertwig et al., 2004; Hertwig & Erev, 2009). The second decision-making paradigm is known as Decisions-from-Description (DfD), as figure 1.3B shows. In this paradigm, participants are presented with the choice problem with precisely stated outcomes and their probabilities. In DfD, participants tend to make
decisions as if they overweight the rare outcomes relative to their probability (Figure 1.4; Barron & Erev, 2003; Hertwig et al., 2004; Kahneman & Tversky, 1979). The difference in risky choice between the two paradigms is believed to happen because participants implement different strategies in the decision-making process depending on how the choice problems are encountered: in description, statistical thinking is required, whereas in experience – heuristic thinking (Gigerenzer & Brighton, 2009; Volz & Gigerenzer, 2014). Other possible reasons include sampling and memory specificities, although it still can be explained by adaptation to different kinds of information (Hertwig & Erev, 2009; Plonsky, Teodorescu, & Erev, 2015).

Depending on the learning mode – through Description or Experience – this information is perceived and processed differently even though formally equivalent information has been gathered (Camilleri & Newell, 2013). When rare events are experienced from an individual perspective, the probability remains uncertain until the last sample, but even then, there is no guarantee that the future will follow the past, nor that the probability is stable and will not change. Experience only allows one to estimate the natural frequency, as compared to explicitly stated probabilities in description (Rakow & Newell, 2010). In description, however, the frequencies are modified – the information about real-life events is transformed to a probability. This transformation is the result of information filtering, corresponding to how information is gathered, processed and communicated by intelligent agents.

Information format is often examined using sampling and memory, but not as the ability of people to gather, process (modify, e.g., “pack”) and then communicate information depending on communicative intent. For example, the estimated frequency of events is represented in memory as samples of events which affects how these events are recalled (Camilleri & Newell, 2013; Stewart et al., 2006; Zhu, Sanborn, & Chater,
Indeed, DE gap is a unique phenomenon to explore personal and social learning, because of the bias to underweight or overweight the same information depending in what format it is provided. These two biases might be an adaptive complementary mechanism by which individuals learn, process and communicate about rare risky events. Decisions from experience and description paradigms were given main emphasis in the thesis because of the idea that personal and social learning might complement (mirror) each other, given difference in agency and difference in learning strategies between individual vs. social levels. The use of social information in personal decision-making has been mainly studied by looking at why individuals use social information, generally described as cues about social source (i.e., prestige bias). Yet, there is still no overarching theories that successfully explain social learning as a complementary mechanism in personal learning, which can explain why people adapted to have certain biases. This thesis specifically focuses on one well-established bias in risky decision-making research – DE gap – to understand how information about rare events is gathered, processed and communicated. Thus, this thesis is concerned about the cognitive mechanism of social learning and decision-making.

1.3.2 Risk Communication

In risky choice, people act as if they underweight rare events when they learn about those events from experience, but overweight those same rare events when learning about them from descriptions (Hertwig & Erev, 2009; Hertwig, Pachur, & Kurzenhäuser, 2005; Wulff & Hertwig, 2018). This gap might not simply be due to the format of information – either personal or social – but also because the same frequency of events appears differently from individual and group perspectives. On the group level, uncertainty of personal experience can be decreased by information sharing between individuals experiencing the same event differently (FeldmanHall & Shenhav, 2018).
Thus, communication might be the link between experiencing an event from personal and social perspectives (Cho & Scherer, 2003).

One potential reason people communicate is to share the perception of risks needed to make decisions that would increase chances of encountering valuable events or avoiding disastrous ones (Hintze et al., 2015; Cho & Scherer, 2003; Wang, 2008). When people experience rare events, they tend to underweight them because they happen rarely. But, many risky events are often skewed in terms of perception of extremity (Lieder et al., 2017; Ludvig et al., 2014; Zacks, Tversky, & Iyer, 2001). People’s perception of risk is mediated by social interaction – when propagated through communication chains, risk information can be amplified and become more intense (Jagiello & Hills, 2018; Kasprow, Kasprow, Pidgeon, & Slovic, 1988; Moussaid, Brighton, & Gaissmaier, 2015). Coincidently, probability is overweighted and remembered better of extreme events (Konstantinidis, Taylor, & Newell, 2017a; Lieder, Griffiths, & Hsu, 2018; Ludvig, Madan, McMillan, Xu, & Spetch, 2018; Ludvig et al., 2014; Madan et al., 2014). Most people are not faced with extreme events, such as natural or technological disasters, still there is a great demand to manage the potential consequences of such events on a group level (Bostrom, 2013; Ord, 2020). Because there is a mismatch in how risks are perceived and acted upon, it could be beneficial to take advice on how to handle extreme events if they happen (Bonaccio & Dalal, 2006; Garcia-Retamero & Galesic, 2012; Yaniv, 2004; Yaniv & Milyavsky, 2007).

A strategy that people often use to optimise behaviour for gaining rewards and avoiding losses in uncertain situations is to efficiently learn from and communicate to others. People can receive information about risky events from others who have previously encountered these events in personal experience and then described them in the form of an abstract representation (Hütter & Ache, 2016). People can also receive
representations of the same event from different individuals and aggregate these judgments of individual social experiences to make their own decisions. Because people can learn from personal or social experience interchangeably and also communicate learnt information to others, people can use the representations of learned experience and communicate them, further fostering social knowledge about events (Heyes & Pearce, 2015). Information about rare events is a special case in communication, as rare events have an inherent skewed reward structure which in turn skew attention as well as the need to communicate about them to receive a reward or avoid loss (Dunne, D’Souza, & O’Doherty, 2016; Leuker et al., 2018; Newell, Rakow, Yechiam, & Sambur, 2016). Risks, both – gains and losses – especially, large and extremely rare are better understood social level, due to a more efficient learning. That is, rare events, and especially, extreme rare events are memorized better and therefore are likely to be communicated more often to others as intrinsically important information.

1.3.3 Biases in Frequency Estimation

People perceive rare events differently depending on the relevance, context, and value it possesses for that individual (Slovic & Peters, 2006; Hertwig et al., 2004). From the perspective of personal experience of encountering rare events, people must pay particular attention to rare events that are subjectively important and pay less attention to rare events that are less important. Indeed, emotional events are remembered better and for longer than unemotional events because of the subjective importance it bears to the individual (LaBar & Cabeza, 2006; Yonelinas & Ritchey, 2015). In the context of decision making, some particularly emotional events can be overweighted and remembered better than others (Charpentier, De Neve, Li, Roiser, & Sharot, 2016; Kahneman & Tversky, 1984; Ludvig, Madan, & Spetch, 2015; Yechiam, 2018). Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978) investigated how well
people estimate the frequencies of lethal events they might potentially encounter in life, such as accidents, diseases, or disasters. Their findings highlighted two general biases: (1) participants over-estimated small frequencies of event occurrence and under-estimated larger ones, and (2) participants exaggerated the frequency of some specific causes and under-estimated the frequency of others, at any given level of objective frequency. These effects are not only due to the encountered frequency itself, but also due to cognitive and memory biases. When people make judgements when recalling events, several biases can play a role in shaping that recall: primacy-recency effect, saliency, and availability biases (Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993; Murdock, 1962; Rakow, Demes, & Newell, 2008). Thus, people are likely to exaggerate the occurrence of salient rare events (e.g., acts of terrorism), and simultaneously underestimate more mundane but more likely ones (e.g., dying from diabetes).

Subjective gains and losses are also known to be perceived differently (Kahneman & Tversky, 1984; Sokol-Hessner, Camerer, & Phelps, 2013; Yechiam & Hochman, 2013). Rare wins make people to overweight the actual chances of winning but also exaggerate very slim chances of losses, such as the occurrence of unusual lethal events (e.g., dying from a rare disease) and underestimate larger ones (e.g., getting into a car crash) (Lichtenstein et al., 1978). These biases in learning and remembering risk contribute to skewed memory samples. Because the perception of risk can be mediated by social interactions, the frequency of an event can perhaps be either overweighted or underweighted depending on the meaning it bears not only to an individual, but also to the group they belong to as well. For example, one can have no personal information about events, but rather learn about them from others – then, one can still adjust
behaviour by keeping vigilant in order to avoid a big loss or be more persistent in
searching to encounter a big gain (Cho & Scherer, 2003).

1.4 Social Information

The neurobiology of rewards and values in social decision making (Ruff & Fehr,
2014) suggests that social learning is a form of associative learning in which cues come
from conspecifics rather than from the environment (e.g., Wilkinson, Kuenstner,
Mueller, & Huber, 2010). Thus, social information is the information not only coming
from others, but also about others. People gather social information to understand how
credible the social source is in order to evaluate whether the information they deliver is
sufficiently worthwhile to be processed and applied in personal decision-making
(Behrens et al., 2008). When people use advice to make decisions, learning about source
reliability is similar to traditional learning processes; however, when personal
information is encountered in addition to the given advice, redundant information is still
taken into consideration (Collins, Percy, Smith, & Kruschke, 2011). This suggests that
when people learn from the combination of personal information and advice from others
– the context naturally encountered in daily life – redundant information is not ignored,
but rather accumulated. Thus, mutually supportive information from different types of
sources is treated as confirmatory rather than as redundant, which might explain biases
in human choice when either of the learning modes is used.

Social information has a reliable influence on people’s judgement, which can
enhance and supplement personal decision-making. For example, people often make up
their mind based on personal information and then use social information to calibrate
their decisions (Puskaric, von Helversen, & Rieskamp, 2017). Li, Delgado, & Phelps
(2011) showed that when instructed social knowledge is available, people readily use
this information and make better decisions compared to using only personal information. The study also showed that when this social information was used by participants, the model that well describes personal learning by experience, reinforcement learning (RL), was not as successful in predicting participants’ behaviour nor the brain activation pattern in the social learning task. Although there is some overlap between personal and social learning processes, social learning engages additional brain pathways and complex mechanisms such as model-based mentalising and ToM (Olsson et al., 2020a). Written descriptions, for example, are unique to humans, and in this thesis, it is assumed that for written information people use both – mentalising and meta-cognitive processes. Mentalising being perspective-taking, whereas meta-cognition is knowing about knowing such as planning, thought monitoring (Frith & Frith, 2012). Indeed, there are several computational models that specifically describe the social type of learning comparing it to the asocial type (Burke et al., 2010; Legare, Sciences, & 2015; Olsson et al., 2020; Toelch & Dolan, 2015). In these, social learning matches personal learning but has additional mechanisms responsible for the social aspect of learning accounting for the interaction with others, including the consideration of cooperation strategies and important parameters of the social source, such as reliability.

### 1.4.1 Learning about Risk from Others

Personally experienced occurrences are inherently uncertain as is reflected in the perception of rare events: risk can vary depending on the subjective perception of the event, relative framing, environment and other factors (Johnson & Tversky, 1983; Slovic & Peters, 2006). Interacting with others, however, is one of the most inherently uncertain behaviours that people can undertake. There are a multitude of unknowns: how to express oneself to others, whom to trust, or whether to engage in a risky
behaviour with others. According to this account, to communicate advantageously, both social source and receiver must efficiently communicate and learn, respectively, about rare events. Here, availability bias can play the role of an enhancer of memory retrieval that contributes to a salient representation of rare events (Keller, Siegrist, & Gutscher, 2006; Lieder et al., 2017a; Madan et al., 2014; Pachur et al., 2013). This availability-induced enhancement can also serve as a cognitive compensating mechanism that deals with small samples in risk (Plonsky et al., 2015; Ungemach et al., 2009). Because most people are part of a social group, they are likely to communicate memorable risky events to others. If information is important for an individual, it can also be important for others with the same principle behind wisdom-of-the-crowd phenomena: people want others to be wise so that everyone benefits from information sharing (Larrick, Mannes, & Soll, 2012; Yaniv & Choshen-Hillel, 2012).

People also perceive events differently depending on an event’s subjective value. If a rare event bears some importance and evokes an emotional response, then that event is likely to be overweighted in the memory of that individual. More memorable or emotionally charged events are also likely to be communicated more (Brady, Wills, Jost, Tucker, & Van Bavel, 2017; Kramer, Guillory, & Hancock, 2014). Subjectively judged, unimportant events can thus be dismissed as there is no value in being applied to personal experience or communicated to others who might benefit from it. In the same way, as in the wisdom of the crowd, there is the idiosyncratic noise associated with a single judgment, but shared experience of others could cancel it out. The only prerequisite is to provide reliable, or at least truthful, information (Hahn, Harris, & Corner, 2009; Harris, Sildmäe, Speekenbrink, & Hahn, 2019). Risk aversion, in particular, can be an adaptive mechanism for avoiding losses when living in groups (Hintze et al., 2015). Because under-sampling produce skewed representations of rare
events in experience – many do not experience rare events. People who experience a rare-extreme event may exaggerate its occurrence in communication, which might be an adaptative strategy to avoid rare significant losses or draw attention to large gains. Thus, the effort of many individuals in the form of personal experience and its subsequent reporting might be needed to manage these rare events, which is easier done in a social setting. Based on the idea that social learning is more adaptive than personal learning, some arguments regarding why some people act as if they overweight small probabilities in social communication (description) are considered in Chapters 3 and 4, while Chapter 2 of the thesis looks at observational learning.

1.4.2 Learning from Observation

A significant proportion of learning in humans and many other species happens by observing others—a learning strategy which is also at the core of human learning in development and culture (Cattaneo & Rizzolatti, 2009; Hertwig et al., 2018; Heyes, 2017; Heyes, 2016a; Rendell et al., 2011). When learning from personal experience, dopamine neurons encode a reward prediction error (RPE)—the difference between how rewarding an event was expected to be and how rewarding it actually was (Schultz, Dayan, & Montague, 1997). But, when people observe someone else, neurons encode not only the RPE after the outcome was revealed, but also the expected value of an observed choice (Burke et al., 2010; Hill, Boorman, & Fried, 2016). This suggests that people learn by observing others, at least in part through the encoding of RPEs that are specific to learning from observation as people do from learning by personal experience.

People are able to learn by observing others and have specific neurons that underpin the ability to learn from observation (Gallese & Goldman, 1998). These sets of neuronal cells help people to understand what others are doing and feeling. These
neurons, called mirror neurons, detect certain mental states of others and facilitate the activation of the same muscular groups as those used by observed others. Mirror neurons fire not only for action understanding, but also to analyse specific actions features relevant to generating appropriate behaviours (Caggiano, Fogassi, Rizzolatti, Thier, & Casile, 2009; Gallese & Goldman, 1998). These neurons are activated when actions performed by self but also when matching actions are performed by others, creating a bridge between minds (Williams, Whiten, Suddendorf, & Perrett, 2001). Thus, the neuronal imprint of social learning can be viewed as simulating others’ physical and mental representational models of the world. Mental representations, however, can be also transferred to an indirect, more abstract form, by using verbal or written descriptions. Observational learning in the context of risky decision-making is explored in Chapter 2.

1.4.3 Learning from Description

People can encounter the experience of others indirectly, through products created by others, such as verbal descriptions, and effectively learn from doing so (Bonnie & Earley, 2007; Heyes, 1994; Pachur, Suter, & Hertwig, 2017). Abstract descriptions can be viewed as the simplification of personal experience within the environment in order to record and communicate it (Brumann, 1999; Richerson & Boyd, 2004). In risky decision-making, descriptions are externalised symbolic representations of any kind of knowledge that can be causal, procedural, or episodic (Hertwig et al., 2018). Descriptions can be written or spoken words, numbers, or images. Even though internal representations of the world are not descriptions, when these become available to others in the form of stories, warnings, or testimony, they become descriptions. Importantly, producing descriptions from one’s own experience decreases the multidimensionality of personal experience – it is difficult to convey all
the perceptual and affective cues and associations in verbal form. In other words, descriptions are typically partial symbolic representations of an event, which relies on other people to summarize the information, thereby becoming indirect knowledge. In contrast, in experience, an understanding of a situation is achieved by interacting with the environment, which is a form of direct knowledge.

People use personal and social information to varying degrees depending on the state of environment. Descriptions can be used in combination with personal experiences, or they can be ignored if personal information is more useful and not costly to acquire (FeldmanHall & Shenhav, 2019; Kendal, Coolen, van Bergen, & Laland, 2005; Weiss-Cohen, Konstantinidis, & Harvey, 2020). Descriptions, however, are almost always encountered in situations when there is no direct social information (observation) is available. Specific trade-offs of different learning strategies suggest that social information is usually used in combination with individual experience. Animals use social information only under certain conditions, following certain social learning strategies: they may use social information when uncertain, or when acquiring (sampling) individual information is costly, or when the information acquired from individual experience is outdated, or when errors in individual experience are substantial.

Descriptions of experience are a special type of social learning because they can be constructed from imagination and memory: descriptions can be viewed as an extension of working memory, which become the content of recursive attention, processing or reflection, guiding the planning of future-oriented behaviours (Lou et al., 2011). Subsequently, what is maintained in working memory based on personal experience serves as a base when producing descriptions. Because personal experiences can be skewed due to selective sampling, cognitive biases, and memory limitations,
they can affect future-oriented states (i.e., goals) in predictable ways. Thus, descriptions are a modification of information gathered from experience which construct personal and social goal-directed behaviour. Paying attention to specific attributes of the social source of descriptions, such as their identity, can be particularly efficient in simplifying information stream from the environment that the receiver is confronted with.

The use of social information in personal decision-making literature has been mainly studied by looking at efficiency and biases. Also, little is known in terms of how social learning differs from personal learning in risky decision-making, but this research direction is emerging (e.g., Hertwig et al., 2018; Schöbel, Rieskamp, & Huber, 2016). This thesis focuses on social learning as being complementary to personal learning, using behavioural (risky decision-making) and subjective information evaluation methods (attitude, beliefs etc.), thus filling in the existing gap in information theory, decision-making, and social learning literature. Here, personal experience (as discussed below) is considered as a base case, whereas social experience is considered as a more complex structure – an interaction between information source and its receiver. Therefore, in this thesis, social learning was given more attention and, in addition to comparing with personal learning, explored from two perspectives, unique to social information – source presence and source-receiver identity (alignment).

1.5 Social Source

Selective news reporting and other forms of misinformation shows that specific information gets more attention than other (Balliet, Wu, & De Dreu, 2014; Frimer, Skitka, & Motyl, 2017; Thomas, McGarty, & Mavor, 2009). Understanding the difference in how people perceive a social source and the information they deliver based on their identity is of particular interest for understanding how people process social
information. If the ultimate goal for a receiver is to choose the best learning strategy, the receiver needs to infer which social source is most likely to share the most valuable information. For example, learning who is the expert and follow their advice could be a useful shortcut in understanding the world. Expertise, however, is often not the primary criterion for social source selection, but identity (Van Bavel & Pereira, 2018). Identity is the main attribute by which a social source is judged and is based on categorization of others into in-groups and out-groups. This categorization a simple evolutionary principle based on kin selection, reciprocal altruism, and competitive altruism (Parks, Joireman, & Van Lange, 2013; Silk & House, 2016). When people lived in tribes, the need to distinguish people by attributes other than social identity was minimal (Quinn, Bellovary, & Cole, 2019). Because the pool of social information is vast, the specific identity of a social source can be viewed as a shortcut to obtaining relevant-to-self information (Federico & Ekstrom, 2018; Harris, Hahn, Madsen, & Hsu, 2015). The central question of this thesis is how people learn from others, be that another person, group, organisation, or algorithm. All these social sources deliver acquired information, which are always manipulated by others. In Chapters 4 and 5, this idea is explored by looking at the social source in an abstract form, as other – as opposed to personal, self – which can be generalised to an individual, group, organisation or an algorithm.

1.5.1 Identity as Information Filtering Parameter

People have difficulty in perceiving pure information without associating any context attributes, such as its source, to the informational content. Indeed, information source is fundamental to the evaluation of information itself (De Martino, Bobadilla-Suarez, Nouguchi, Sharot, & Love, 2017a; Harris et al., 2015; Laidre, Lamb, Shultz, & Olsen, 2013; Martin & Marks, 2019). It can be challenging for people to eliminate the
contextual information such as where and how a description was acquired, which might be even more challenging when information is acquired by directly observing others. As the result, people readily associate information with the context in which it is acquired, whether social or non-social, which then constitutes an episodic memory (Greenberg & Verfaellie, 2010; Yonelinas & Ritchey, 2015). The limited ability of people to perceive information without contextual cues is not surprising: if considering ecological perspective, there are only a few instances when information can be received with no identifiable source, with the exception of personal learning which is perceived directly from the environment. Thus, information is inevitably characterised by its source – the messenger delivering it – with reliability playing a mediating role in establishing information value (Jarvstad & Hahn, 2011; Toelch, Bach, & Dolan, 2014). The problem of sourceless information is examined in Chapter 4, where sourced vs. unsourced information is used in risky choice. For example, consider the following scenario. When you come back to your desk after a break at your workplace, you see a note: “Healthy food choices such as eating fruits and vegetables have not only physical but also mental health benefits and might be a long-term investment in future well-being” (Wahl et al., 2017). By trying to consider who might be the source of this information, one might better understand how valuable the information is (Harris et al., 2015; Jarvstad & Hahn, 2011). Is it a note from one of your caring colleagues or is it a marketing leaflet from a local shop? Additionally, to evaluate information by its social source, people constantly make assumptions about those who speak to them: how similar they are, whether they possess relevant expertise, how attractive physically or socially (i.e., status) they are (Petty & Cacioppo, 1986).

The social source of information can matter even more than the received information itself (for a review, see Van Bavel & Pereira, 2018). There might, however,
be a simple mechanism behind this social source perception based on which aspects of the source are judged: whether the source can be described as more similar or dissimilar to the receiver in specific attributes, including cultural background or personal preferences. However, most decision-making research is conducted without specifying the source of information that participants receive, which might limit our understanding about learning in risky choice (Harris et al., 2015). As will be shown in Chapter 4, if information does not possess attributes of a source, people still readily guess a source. In this way, people make sense of the information using social-source identity as a shortcut to judgments of reliability that might be a direct proxy for consistency of information quality.

1.5.2 Reliability of Social Information

People receive and communicate information about controversial topics such as political events, climate change, immigration, gun control, and drug legalisation on a regular basis. These topics often lead to polarisation of the receivers’ views, who are prone to confirmation bias and overconfidence (de Witt, 2015; Frimer et al., 2017; Haslam & Reicher, 2015; Kahan, Peters, Cantrell, & Slovic, 2017; van Prooijen & Krouwel, 2019). This polarisation stems from receivers who fail to adjust their attitudes, beliefs, feelings, and ultimately behaviour, according to the quality and amount of received information (Nyhan, Porter, Reifler, & Wood, 2017; Rutjens, Sutton, & van der Lee, 2018; Thorson, 2016). One reason for this failure to adjust is that people pay close attention to who is delivering information and, consequently, might ignore valuable information coming from dissimilar-to-self social sources (Balliet, 2010; Frimer et al., 2017; Golman, Hagmann, & Loewenstein, 2015). Indeed, the social environment has a significant influence on individual beliefs, attitudes, and behaviour,
with an identity alignment being a primary attribute for receiving valuable information for personal judgment (Shamay-Tsoory, 2019; Van Bavel & Pereira, 2018).

Social platforms make it easier for people to fall into filter bubbles and echo chambers of information. Because people search for information relevant to their personal identity, they look for social sources that categorise information in a predictable way (Flaxman et al., 2016; Pilditch, 2017). One example of such filtering is through political identity as shown in Figure 1.5, which depicts a range of news reporting outlets categorized by political bias and reliability. If a person associates themselves with some expressed attribute, for example in the form of alignment with liberal political views, then they would also seek out more information about liberal values such as individualism (Frimer et al., 2017). Simultaneously, by being associated with an attribute, one can signal this association to others by having a certain identity.

![Figure 1.5](http://www.adfontesmedia.com)

**Figure 1.5.** Different news sources classified on the Left to Right economic spectrum and attributes. Retrieved from: [http://www.adfontesmedia.com](http://www.adfontesmedia.com)
linked with one’s social self (Chen, Urminsky, & Bartels, 2016; Cross, Hardin, & Gercek-Swing, 2011; Strohminger, Knobe, & Newman, 2017). A recent survey with around 2,000 participants showed that increasing the visibility of publishers is ineffective and can be counterproductive in addressing misinformation on social media (Dias, Pennycook, Rand, 2020). This study found that providing information about publishers increases the chance that a reliable headline would be mistakenly seen as unreliable and vice versa. Thus, the use of social source identity might bias reliability – one of the negative consequences of highlighting social-source attributes for receivers.

In social media, political polarization occurs because political identity is one of the strongest identities that people hold on to – the categorization that in turn produces a strong preference for specific information (Van Bavel & Cunningham, 2010; Van Bavel & Pereira, 2018; Xiao et al., 2016). Identity, thus, can obscure information and skew perception (Van Bavel & Pereira, 2018; Xiao et al., 2016). Biased information perception then can emerge from selective exploration of political values guided by social sources (Frimer et al., 2017; Van Bavel & Pereira, 2018). In-group theory recognises this dynamic between groups (Hewstone, Rubin, & Willis, 2002). For example, a person’s beliefs and attitudes about information are often shaped by the group of people with whom they associate themselves (Cohen, 2003). These associations, by which people judge self and others when receiving information, can be based on extremely simple identity elements. Some of these identities can include occupation, hobbies, preferences, political and economic orientation, or even a birth date. Relatedly, Walton, Cohen, Cwir, & Spencer (2012) studied the concept of “mere belonging”, which is a minimal social connection with others. Mere belonging is described as a sense of social connectedness with (unfamiliar) others that can make
people acquire the motivations of these others as their own. Thus, identity too can be built on mere belonging – a simple associative attributes with others.

Most of the research looking at sources of information has examined the effects of social identity on individual decision making (e.g., Moutoussis, Dolan, & Dayan, 2016; Yaniv & Milyavsky, 2007; Harris et al., 2015; Mannes, Soll, & Larrick, 2014; Hartman & Weber, 2009). Little evidence has yet been produced to understand the dynamic between minimal identity alignment between a receiver and a social source and the perception of the social source and the information they deliver. Chapter 5 directly examines how identity alignment of a social source influences perception of the information they deliver.

1.6 Current Thesis

This thesis provides a novel perspective on learning, specifically, that learning directly relies on both personal and social information, the proposed mechanism being information filtering. Chapter 2 and Chapter 3 explored individual vs. social learning, by looking at personal learning or from another individual by observing them or using their described experience. Chapter 4 explored the role of social source – whether its presence (or absence) in choices-from-description information makes a difference to decision-making. The experiments in Chapter 4 involved risky choices from experience paradigm – sampling with a final choice. Chapter 5 explores identity alignment between social source and receiver. Since social source and receiver both have agency that guides subjective experience, they also possess identity associated with this experience. In this chapter, how social source with an identity that aligns or misaligns to that of the receiver affects information evaluation was investigated. In Chapter 5, self-reporting
measures were used to evaluate the identity alignment manipulation. In this case, identity alignment was explored as a modulating factor of information filtering.

The thesis contains three levels of understanding of what information filtering is: (1) the difference (if any) in risky decision-making learning by personal or social experience, (2) the role of social source in risky decision-making, (3) identity social source and the receiver.
Chapter 2: Risky Decisions from Personal and Social Experience

Learning happens every time people interact with the environment: trying out new food, making financial decisions, or playing sports. In these instances, the environment provides us with feedback that can be viewed as positive or negative reinforcement, which adjusts behaviour accordingly (Sutton & Barto, 1998; Thorndike, 1898). For example, at work, one can make choices that more often than not lead to praise. A praise can be in the form of annual bonus, which is an example of a reward that acts as an incentive – a positive reinforcer. This reinforcement encourages one to sustain the actions that were initially rewarded. But what happens when we observe the actions and work habits of others and the rewards they receive? When people learn information from others, be that through a direct observation, tutorial, or an ad (Bandura, 1971; Frith & Frith, 2012), it can be described as social learning, or information transfer from one agent to another (Cloninger, 1981). As receivers, people can learn from others by encountering others directly and observing their experience (Hill, Boorman, & Fried, 2016). People can also learn via interacting with artefacts from others, including verbal descriptions or video footage. In this thesis, observational learning is viewed specifically as learning directly from the experience of others. The aim of this chapter is to explore the difference between the two modes of learning – personal or social experience – in risky choice using observation learning in a decisions-from-experience paradigm.
2.1 Observing Experience of Others

The ability of individuals to learn from others and the outcomes that follow is an effective learning strategy, which is prevalent across many species (Bandura & Walters, 1977; Heyes, 2016; Myers, 1970; Smolla et al., 2016). One prominent way people learn from others is by gathering information through observing other people experience (Bandura, 1971). This information gathering from others is a highly efficient strategy because people can infer the best strategy for themselves without having to do the work themselves. For example, when observing others playing videogames, via streaming or in real life, we receive information about actions, from which the goals of the player can be inferred. This is the premise of Inverse Reinforcement Learning – to infer the reward function of others by observing what they do (Abbeel & Ng, 2000; Baker et al., 2009).

Social information can come from learning something from personal experience or from experience gathered from others (Behrens et al., 2008; Ernst Fehr & Fischbacher, 2005; Maynard Smith, 1976). Learning by observing others is much faster and more efficient, especially when information is conveyed by someone who shares truthful information — a process that requires cooperation (Bowles, Choi, & Hopfensitz, 2003; Swol & Sniezek, 2005). For example, watching an informed and cooperative social source intentionally convey a well-thought through example via a demonstration (e.g., teaching) is more useful than information received from a random social source or from a deceptive one (Shafto, Goodman, & Frank, 2012). Thus, cooperation and appropriate communication are essential for efficient information-sharing required for efficient learning (Chamley, 2004). Additionally, this dependence on others in learning provides some cues about potential biases an individual can have,
such as accepting social information too readily, which can lead to social herding (Denrell & Le Mens, 2015; Mahmoodi, Bahrami, & Mehring, 2018).

Observing others has a great influence on our choices because social learning is deeply ingrained in the human brain. When observing others, specific brain regions – the dorsolateral prefrontal cortex (dLPCF) and ventromedial prefrontal cortex (vmPFC) – are engaged (Burke et al., 2010). The dLPCF encodes executive functions such as working memory, planning, and abstract reasoning, whereas the vmPFC primarily encodes values for personal decision-making, but is also involved in social decision-making. These brain regions are active when people model and predict the actions others make and the outcomes they receive. These two regions also correlate with two distinct prediction errors in reinforcement learning that are derived from observing others: observational action prediction errors are encoded by the dLPCF and observational outcome prediction errors are encoded by the vmPFC. Observational action prediction errors represent the difference between actual actions and the predicted actions of others, whereas observational outcome prediction errors represent the difference between the actual outcome received by others and the predicted outcome. This simulation of other’s reward prediction errors processed is identical for valuation of the self and simulated-other (Burke et al., 2010; Suzuki et al., 2012). These brain regions underpin the human ability to simulate the mental states of others to be able to predict others’ actions and according outcomes, to then use this information in personal decision-making. Overall, on a neural level, people generally use the information gleaned from the choices made by others similarly to how they use information from their own risky decisions.

Observing others making choices does not mean that the observers will choose exactly the same choices, but rather, the observed choices and outcomes are used to
inform personal preference. This process is not simple copying, but a comparison-based adjustment of personal preferences: selective choices of others increase the subjective value of the observed chosen options which are then more likely to be selected in personal decisions (Chung, Christopoulos, King-Casas, Ball, & Chiu, 2015; Suzuki, Jensen, Bossaerts, & O’Doherty, 2016). For example, if we observe others behaving in a risk-seeking or risk-averse fashion, we become in turn more or less prone to risky behaviour (Michael et al., 2020; Suzuki et al., 2016). Thus, the value of chosen options is dependent on individual risk preferences and then adjusted by the observed choices of others: objectively the same risky choice made by observed others may be perceived as a gentle nudge for a risk-seeking observer or a strong push for the risk-averse observer (Chung et al., 2015). This effect of adjusting behaviour also appears in the frequency of the observed choices, suggesting that people generally use the information about the choices of others as they do from their own risky decisions (Michael et al., 2020; Suzuki et al., 2012). In this chapter, I capitalize on this type of social learning by investigating, in two experiments, how people make risky choices when the odds and outcomes are learned from observed experience—presenting the opportunity to both emulate the goals and sampling actions of another person.

2.1.1 Description-Experience Learning Gap

In risky decision-making, there are two main approaches used to evaluate how people make choices. One is termed Decision from Description (DfD) and the other Decisions from Experience (Experience). These approaches represent two general ways of how people can learn about risk (Hertwig et al., 2018). In DfD, a decision-maker is provided with a symbolic summary of a choice problem, which is used to make a decision. In Experience, a decision-maker does not have any prior knowledge about a choice problem, but instead makes choices and receives feedback to learn about a choice
problem. There is a robust difference in risky choice when people make choices learning about outcomes and their probabilities via DfD or Experience. When the odds and outcomes are learned through explicit descriptions, people tend to overweight rare events (Hertwig et al., 2004; Kahneman & Tversky, 1979). In contrast, when people learn the odds and outcomes from personal experience, they act as if they underweight the rare events. This reversal of risk preference depending on information format is a phenomenon known as the Description-Experience Gap (Hertwig & Erev, 2009). This gap is a remarkable feature of risky decision-making, which has been mainly attributed to reliance on small samples in memory when making decisions from experience (Erev, Ert, Plonsky, Cohen, & Cohen, 2017; Hau, Pleskac, & Hertwig, 2010).

In this chapter, the DE gap is looked at through the lens of information sampling about risky decisions via personal and social learning. Decisions from experience can be viewed as learning by directly interacting with the environment (i.e., trial-and-error), whereas decisions from description rely on learning from information in which a social source (the one who created the description) acts as an intermediary between the receiver and the environment. Thus, experience is a more direct way of gathering information from the environment, but description is the result of a social source gathering information from the environment or interacting with another description or personal experience. Social learning thus uses information collected and mediated by another person(s) so as to be intentionally or unintentionally transferred to someone else. In the current study, one possible cause for the gap between description and experience is investigated, whereby the gap is supposed to reflect a difference between personal and social learning. In two experiments, participants made choices based on learning from personal experience vs. learning from the experience of others by observing a partner’s actions. We hypothesised that this difference between two
learning modes (social vs personal) would lead to differential weighting of rare events, similar to what is usually observed in the DE gap.

**2.2 Experiment 1**

Experiment 1 examines risky choices when learning from personal experience versus when learning from directly observing the experience of another person. To make the observation condition, a decisions-from-experience (Experience) was taken as a base case – the simplest form of learning. In Experience procedure, people learn about pairs of options by sampling (e.g., Hertwig & Erev, 2009). After sampling, people make a choice between the two options—where one option is typically safer and the other one riskier. In our variation on the standard task, on some rounds, participants instead observe samples drawn by another individual (partner) and then make a final decision based on this social experience. Following from the logic that observing the experience of others is analogous to deciding from description, then people should act as though they underweight rare events less when observing—possibly even acting as if they overweight the rare event. Thus, the first hypothesis is that when people learn from others, the underweighting of rare events will be reduced and will be significantly lower than for learning from experience (H1). Second, the social component may create a competitive environment, whereby people seek to secure a higher return than the other participants. Thus, we hypothesised (H2a) that participants may be more risk-seeking and competitive when they observe others. Alternatively, people are often more risk averse for others than themselves (e.g., Charness & Jackson, 2009). This increased risk aversion might translate into the social scenario here, leading people to be more risk-averse when learning from others (H2b). Lastly, in line with the previous literature on Experience, people should act as if they underweight rare events when learning from
personal experience, acting risk averse (H3). All the above hypotheses were preregistered\(^1\).

2.2.1 Methods

Participants

For the experiment, 102 participants were recruited in sessions of 2-8 participants via the SONA system from a paid participant pool at the University of Warwick. The number of participants was determined before the experiment through a power analysis with 80% power to find a medium effect size \((d = 0.4)\) at the 5% significance level. Participants were randomly divided into pairs for the experiment. The number of participants in a session was sometimes uneven, so not all participants could be paired up. For the six participants who did not have a pair during the session they attended, they performed a similar computer version of this study. The data from those participants were not included in the analysis. From the participants who were successfully paired, 16 participants were excluded from the analysis: 6 were excluded because they could not complete the task due to a computer error and 10 were excluded based on the pre-registered exclusion criteria (see below), leaving 80 participants \((M_{age} = 23.3 \pm 2.3, 56\) women). Participants were paid a show-up fee of £3 plus a variable bonus conditional on luck and their choices ranging from £0 to £22 with a mean bonus of £2.97. The research was approved by the Department of Psychology Research Ethics Committee at the University of Warwick. The methods, hypotheses, sampling plan, exclusion criteria, and planned analyses were all preregistered on the Open Science Framework (OSF) at: [https://osf.io/ucemz/](https://osf.io/ucemz/). Code for experiments and analysis as well as the raw data are available at the same link.

\(^1\) The hypotheses from the preregistration were re-arranged in this chapter.
Design

The study had both a within-participants element and a matched-design element. First, within-participants, we compared the risky choices based on a participant’s own sampling from the different options against choices made by that same participant based on observing another participant sampling. Given the stochasticity in the sampling from a random distribution and differences in choices made during the sampling phase, this comparison is likely made about situations with slightly different experienced outcomes and probabilities. As a result, this analysis was supplemented with a matched-design comparison. Here, we compared the choices of the observed with the observer; in this case, their experience with the options was identical, but the experience was obtained from different roles. No description condition was used for design simplicity, to see how adding a social aspect – experience but without agency – affects risky choice.

Materials

The experiment involved binary choice problems between a safe option providing a Medium payoff (M) with certainty and a risky option providing a High payoff (H) with probability P and a zero payoff otherwise. Thus, the choice problems that were used in the study can be represented as follows: M with certainty – safe option, and H with probability P or 0 otherwise (with probability 1-P) – risky option. The experiment consisted of a standard decisions-from-experience sampling protocol using 5 different choice problems detailed in Table 1. Each choice problem was between one risky and one safe option. The risky option had one rarely occurring outcome, with either 5 or 10% probability, and the safe option always provided the same medium outcome. In two choice problems, the rare outcome was high outcome, and in two choice problems, the rare outcome was zero. Thus, high outcomes could happen as a rare event and as a common event, ensuring no confounding of risk-seeking and
underweighting of rare events; the safe option always yielded the medium (M) outcome. Low outcomes were always zero. The expected values were the same for risky and safe options in Problems 1-4. In Choice Problem 5, the safe option always yielded an outcome which was higher than either possible outcome on the risky option; this was a trick problem, serving as a manipulation check (#5 in Table 2.1) with a clearly dominant safe option to ensure that participants were properly incentivised and paid attention to the task. For each option, outcomes were randomly drawn without replacement from a set of 40 possible outcomes, with 2 (5%) or 4 (10%) rare events (i.e., shuffled outcomes). Participants experienced each choice problem twice—once when they sampled for themselves, and once when they observed their partner sampling from the same choice problem.

Table 2.1. The five choice problems that were used in the experiment.

<table>
<thead>
<tr>
<th>Risky</th>
<th>Safe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem</td>
<td>H</td>
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<tr>
<td>1</td>
<td>22</td>
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<tr>
<td>2</td>
<td>20</td>
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<td>3</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>5 (trick)</td>
<td>3</td>
</tr>
</tbody>
</table>

Procedure

The experiment was performed on Windows 10 computers in the Warwick Psychology Behavioural Testing lab using PsychoPy software version 1.90.3 (Peirce, 2009). Participants were first presented with a summary of the study and, if they agreed with the terms and conditions of the study, they provided informed consent by signing
the consent sheet. Participants initially sat back-to-back facing their computers. The experiment began with instructions on the computer screen of each participant’s computer. As can be seen in Figure 2.1, participants started each round at their own computers and then were informed whether, in the upcoming round, they were to sample for themselves (Experimenter) or their partner would sample and they would observe (Observer). When a participant sampled for themselves, they stayed at their own computer and waited for their partner to sit next to them to observe. When participants were informed that they needed to observe their partner, they moved to sit next to their partner’s computer.

Figure 2.1. Schematic representation of the experimental set up. Participants played the choice problems in pairs. In the sampling phase, one of the participants in a pair sampled the doors using the arrow keys, while the other participant observed them. For the final choice, the participant who observed went back to their own computer, so that each participant made their final choice without observing what the other chose.

Figure 2.2. The computer screen during sampling choice problems. Participants repeatedly chose between two doors and received feedback about the selected door. Each trial involved a choice between one door that always led to a fixed medium payoff and a second door that led to two possible outcomes - High and Low payoff - with a specific probability (see Table 1). Choices were followed by immediate feedback about a potential payoff for that door (i.e., partial feedback).
As illustrated in Figure 2.2, on each trial, participants were presented with pictures of two doors, and they indicated which door they wished to sample by using the keyboard arrow key (left or right arrow) for the corresponding door (see Ludvig & Spetch, 2011). Selections were immediately followed by feedback for 1.2 s, which showed the points corresponding to that door only. Feedback was only given for the chosen door as in the sampling paradigm (Hertwig & Erev, 2009). One participant (the experiencer) sampled 40 times from the two options using the arrow keys, while the observer observed the selections; both participants observed the feedback after each selection. After the round finished, the observer moved back to their computer and indicated their preferred option based on the 40 viewed samples, as a single final decision. Participants did not observe each other’s final decisions. During the task, participants were asked not to talk nor directly intervene in any way in their partner’s selections.

Each participant experienced the five choice problems described above twice, once by sampling from the options themselves while their partner was observing them (Decisions from Experience; Experience), and once by observing their partner’s sampling from the same five choice problems (Decisions from Observed Experience; Observation). The order of these ten rounds (5 Experience and 5 Observation) was randomly shuffled for each pair. Each round had a different pair of door images representing the two options. This shift was necessary to limit the possibility that participants recognized that the choice problems were repeated in the observed and experienced conditions and only differed in terms of the sampling differences between the participants. Nevertheless, in the qualitative feedback after the experiment, only about a third of the participants reported they recognized playing the same choice problems twice. The sampling selections, final choices, and observed outcomes in both
conditions were recorded. The pay-out for participants depended on the final choices—out of the ten choices they made, one of their chosen options was randomly selected and then played out using the generative odds as given in Table 1. This outcome served as a bonus in addition to the show-up fee. This incentive scheme made all final choices incentive compatible.

### 2.2.2 Analysis

The within- as well as between-subject independent measure was whether participants learned outcomes and their probabilities from personal experience or from observing others. The dependent measures were the proportion of risky choices and the underweighting of rare events. The proportion of risky choices was defined as the ratio of the number of times the risky option was chosen in the final decision. The proportion of risky choices was calculated across the first 4 choice problems in each condition (see Table 1). The degree of underweighting was defined as the sum of safe choices made in Problems 1-2 (where the rare event was a large win) and risky choices made in Problems 3-4 (where the rare event was a zero outcome) divided by four, the overall number of choice problems. The proportion of risky choices and degree of underweighting were calculated for each individual participant.

All statistical comparisons were made twice: once within-participant and once with matched participants. The within-participant comparison pitted the final choices in Experience against those in Observation or the same participant. The matched-participant comparison pitted the final choices for the observed in their Experience and the observer in their Observation. The data from all non-excluded participants was tested for normality using a Kolmogorov-Smirnov test because the number of subjects was above 30 and tested for equality of samples variances with Levene's test. A one-sample Kolmogorov-Smirnov test showed that both variables – proportion of risky
choices and underweighting of rare events were not normally distributed ($D(79) = 0.5$, $p < .01$). The samples that participants made, however, were drawn from the same distribution both for proportion risky ($D(79) = 0.13$, $p = 0.56$) and for underweighting of rare events ($D(79) = 0.13$, $p = 0.56$). Levene's test for equality of variances showed that the variability in the two conditions for both proportion of risky choices ($F = 1.65$, $p = .2$) and underweighting of rare events ($F = 0.18$, $p = .67$) were not reliably different. Because the data did not meet the requirements for a parametric test (i.e., the data was not normally distributed), Wilcoxon tests for within-subject comparison were performed instead. As a robustness check, standard t-tests were also performed and yielded qualitatively similar results. All data analysis was conducted in RStudio (Version 1.2.5033). Effect sizes were calculated as Cohen’s d, and mean differences are presented with 95% confidence intervals. The data analyses followed the pre-registered plan with the exception of exploratory analysis which is clearly acknowledged.

### 2.2.3 Results

The main hypothesis of the current study (H1 above) was that, given the proposed mapping between personal and social learning, decisions from observed experience (Observation) would differ from decisions from experience (Experience) and be more similar to decisions from description (i.e., less underweighting of rare events). As shown in Figure 2.3A, participants tended to underweight rare events in Observation less (54.0±3.1%) than in Experience (59.7±3.0%), exhibiting more random behavior, but this trend was non-significant in a one-tailed test ($z = 1.95$, $d = 0.20$, $p = .051$, $BF = 6.40$; in favor of the null). The direction and mild effect are in line with the hypothesis that learning from observation might be similar to description (H1). Specifically, in Observation, participants did not reliably act as if they underweighted rare events, but rather acted as if they had no preference for the safe or risky option ($z$
= 0.11, \( d = 0.14, p = .18, BF = 1.49; \) in favor of the null). It was also hypothesized that participants are more risk-seeking when observing others (H2a), or more risk-averse when learning from others as compared to learning from personal experience (H2b). Figure 2.3B shows that people were non-significantly more risk-seeking in observation (46.6±3.0%) as compared to experience (40.3±3.1%; \( z = 1.77, d = .23, p = .076, BF = 1.56; \) in favor of the null). Overall, deciding from observation led participants to be slightly more risk-seeking compared to deciding from personal experience, thereby slightly decreasing the usual bias observed in decisions from experience literature. Thus, participants also exhibited more random behaviour – no preference as per expected value.

![Figure 2.3](image-url)

Figure 2.3. Mean proportion of (A) underweighting and (B) proportion risky choices of rare events across all choice problems for Observation and Experience conditions. The dashed line represents chance level. Error bars represent 95% CI.

When comparing proportion of risky choices from Observation against chance level (H2a), participants were not risk-seeking as would be assumed from Description – participants did not choose significantly differently from chance level (\( z = 1.13, d = \)
0.13, \( p = .258, BF = 3.42; \) in favor of the null). However, in choices from experience, participants also acted as would be expected from the literature, by underweighting rare events. As hypothesized (H3), when comparing the proportion of risky choices in Experience against chance level, participants were risk-averse, choosing the risky option significantly less often than chance level (\( z = 3.07, d = 0.35, p = .002, BF = 13.55, \) in favor of the alternative). Overall, the results suggest that when people learn from observed experience from other, they act similarly to learning by personal experience.

The matched-sample analysis controlling for the variability in the encountered sampling showed a similar picture as in the paired comparison, but with slightly statistically more robust results. People underweighted rare outcomes similarly in Observation and Experience condition (\( z = 1.67, d = 0.17, p = .09, BF = 2.10; \) in favor of the null), and also chose the risky option with similar frequency in the observed as compared to experienced condition (\( z = 1.75, d = 0.23, p = .081, BF = 2.10; \) in favor of the null) These results mirror the within-participant analysis, which implies that the mild difference between the two conditions was not due to encountering different samples in the two conditions, but rather an additional mechanism.

*Low- and High-Outcome Choice problems*

As part of an exploratory analysis, the data was split based on the choice problem type – high-value (£22 and £20) or low-value (£0) rare choice problems (see Table 2.1). As shown in Figure 2.4, participants chose the risky option significantly less often in choice problems with the high-value rare outcomes than in those with low-value rare outcomes, \( W(n=80) = 621, d = 0.3, p = .007. \) This indicates that the two choice problems are distinct, allowing further analysis looking at the difference in Observation and Experience within these two subsets of the choice problems.
Sampling

As depicted in Figure 2.5, the sampling rate between the choice problems differed ($\chi^2(3, N= 80) = 117.3, p < 0.001$). People tended to sample the safe option more often in Choice Problems 1 and 2 (see Table 1), which were the problems with a high-value rare outcome (£22 and £20, respectively), as compared to Choice Problems 3 and 4, which were the choice problems with a low-value rare outcome (0). A binomial logistic regression confirmed the proportion of samples for the risky option predicted the final choice in the choice problems with a high-value rare outcome (1 and 2), $z= 2.66, d = 0.6, p = .008$, as well as in the choice problems with a low-rare outcome (3 and 4), $z = 2.9, d = 0.7, p = .003$, meaning that the more people chose the safe or risky option during sampling the more likely they were to choose the safe or risky in the final trial, respectively. Participants’ sampling pattern also predicted not only one’s own final

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.4.png}
\caption{Proportion of risky choices for all choice problems across participants in Observation and Experience conditions. The error bars represent 95\% CI. Dashed line represents chance level.}
\end{figure}
choices ($z = 6.57, d = 2.2, p < .001$), but also the observer’s ($z = 3.87, d = 1.0, p < .001$) final choices.

Figure 2.6 shows how the frequency distribution of the actual experienced probabilities of rare events in different choice problems differed from the scheduled probabilities of the choice problems (cf. Table 1). Few participants experienced the actual probability of the rare events in either of the choice problems. Choice problems 1 and 3 had a probability of 10% for the rare outcomes, which were £22 and £0 respectively. Only 13 participants experienced close (in the range of 9-11%) to the predicted probability of rare events for the £22 outcome in Choice Problem 1, and only 17 participants experienced the £0 (low-value rare) outcome in Choice Problem 3 in the same 9-11% range of occurrence. Choice Problems 2 and 4 had a scheduled probability of 5% for the rare outcomes, which were £20 and £0 respectively. In these choice

![Figure 2.5. Sampling rates of choosing the risky option for each choice problem (only Experience condition) and the final choice. Choice Problems 1 and 2 are high-value rare outcome choice problem, and Choice Problems 3 and 4 are low-rare outcome choice problems.](image-url)
problems, 18 and 19 participants experienced £20 and £0 in the range of 4-6% chance in sampling.

These deviations from the scheduled probabilities, as seen in Figure 2.6, significantly predicted choice. The more people encountered high-value rare events during sampling the more likely they were to choose risky option ($z = 2.98$, $d = 0.71$, $p = .003$) as were their partners who were observing those same events ($z = 4.85$, $d = 1.29$, $p < .001$). In low-value rare outcome choice problems, the direction was the opposite: people gambled less in the final choice in experience ($z = 3.82$, $d = 0.94$, $p < .001$) as did their partners ($z = 2.78$, $d = 0.65$, $p = .006$), based on the proportion of rare events encountered. Thus, sampling alone – choosing safe or risky option during the sampling phase – could predict the final choice.
2.2.4 Discussion

In observation condition, participants chose more riskily and underweighted rare outcomes less when learning about the choice problems through observation than when learning about the choice problems by personal experience; however, the trend was non-significant in both cases. Additionally, sampling – both the proportion of choosing risky or safe as well as the probability of encountering rare events in sampling – reliably predicted not only personal final choice, but also the choice of the partner who observed the sampling. The core results from the previous literature on Experience were replicated, whereby people acted as if they underweight rare events, making them risk-averse when the rare events are big wins and risk-seeking when the rare events are relative losses (Hertwig et al., 2004; Plonsky et al., 2015; Regenwetter & Robinson, 2017). Participants, however, did not underweight rare events in observation. The results suggest that when personal and social (of another person) information is used people exhibit less bias in risky decision-making.

The results were in line with the previous literature on Experience because participants acted as if they underweighted rare events, acting risk-averse whenever the rare events were big wins (H1). However, the hypothesis that participants may be more risk-seeking when they observe others (H2a) does not hold up as well as the idea that people might be more risk averse when learning from others (H2b). Notably, when learning from observing others, participants’ bias decreased – they did not underweight rare events as is usually observed in decisions from experience (H3) or overweight the rare event as is usually observed in decisions from description (Kahneman & Tversky, 1979). Risky choice in Observation was not different from chance level, meaning that people did not have a clear preference for either risky or safe choices as the expected value of the two outcomes would suggest.
To further investigate the results, the data was split based on the choice-problem type. There were two types: choice problems where the rare outcome was either high in value (£22 and £20) or low in value (£0). An interesting pattern emerged in high-value rare outcome choice problems. When observing high-value rare outcome choice problems, people choose more riskily and underweighted rare events less in this condition. In the low-value rare outcome choice problems, however, people chose almost identically when learning about choice problems by personal experience or observing others’ experience. Experiment 2 addresses the comparison between observation and experience using only high-value rare outcome choice problems.

2.3 Experiment 2

The direction of the results in Experiment 1 suggests that risky choices when learning from Observation may be more similar to those when learning from Description, but the comparison between the conditions was not statistically significant. Indeed, in a post-hoc analysis, there was a significant difference between the observation and experience conditions, but only when looking at the subset of choice problems with high-value rare outcomes. Experiment 2 directly follows up Experiment 1 by focusing on the case with “rare treasures” (i.e., only high-value rare outcomes). Two choice problems from Experiment 1 were used again (Choice Problems 1 and 2), and three novel choice problems and one catch choice problem were developed. Following from Experiment 1, this experiment was aimed to replicate the pattern of less underweighting of high-value rare events in learning from observation. Learning by social experience can lead to the same risk preferences as learning by personal experience, so there might be no difference in risky choice between the two conditions (Null Hypothesis). Thus, given the logic that deciding from descriptions is similar to
observing the experience of others, people should act as though they are more risk-seeking as compared to personal experience (H1).

### 2.3.1 Methods

The methods of Experiment 2 were mostly identical to the methods of Experiment 1 with some modifications that are explained below. As in Experiment 1, the key comparison was between the final decisions based on observed or personal experience.

#### Participants

The results in the previous study showed that the effect size of the mean difference between learning from observation or personal experience for the proportion of risky choices and underweighting of rare events was $d = 0.27$ in the high-value rare outcome lotteries. Thus, a power analysis using GPower 3.1 (Mayr, Buchner, ErExperiencelder, & Faul, 2007) using these results from Experiment 1 showed that with the effect size of $d = 0.27$, power of 0.8, one-tailed, and error probability $\alpha = 0.05$, the sample size should include a minimum of 98 participants for a within-participant design. Accordingly, 145 participants were recruited in groups of 2-8 and data collection was stopped following the session when the 49th pair of participants fulfilled the exclusion criterion (see below). From the collected sample, 9 were excluded from the analysis as they had no partner and performed a substitute computer task. Based on the pre-registered exclusion criteria, 34 participants were excluded: either they did not follow the instructions or they themselves failed to pick the dominant option on the catch trial in either the Experience or Observation conditions or their partner failed to do so. During the experimental task, a further 4 participants did not complete the task due to a software error. The final sample consisted of 98 participants, ($M_{age} = 21.7\pm0.7$, 46 women). All participants were paid £3 as a show-up fee with a chance to make an
additional bonus up to £22 (mean bonus was £1.86), conditional on their choices and the probability of those choices. The sampling plan, hypotheses, methods, and analysis plan were all preregistered at: https://osf.io/37reu/.

**Materials**

The experiment consisted of a simple decisions-from-experience sampling protocol using six different choice problems. Table 2.2 details the six choice problems. Each choice problem was between one risky and one safe option.

*Table 2.2. The six choice problems that were used in the experiment.*

<table>
<thead>
<tr>
<th>Problem</th>
<th>Rare</th>
<th>P(Rare)</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>22</td>
<td>0.1</td>
<td>2.2</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>0.05</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>16.7</td>
<td>0.06</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>12.5</td>
<td>0.08</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>0.1</td>
<td>2</td>
</tr>
<tr>
<td>6 (trick)</td>
<td>2</td>
<td>0.1</td>
<td>4</td>
</tr>
</tbody>
</table>

The risky option had one rarely occurring outcome, with 5, 6, 8 or 10% probability, and the safe option always provided the same medium outcome. In contrast to Experiment 1, here, in all the choice problems, the rare outcome was always the high outcome. This modification to the design was included to further explore why people might underweight rare events less in observation than in experience, which was the case for both choice problems with high-value rare outcomes in Experiment 1. Thus, rare outcomes appeared only with low probability (P); the safe option always yielded the medium outcome. Low outcomes (not shown) were always zero. The expected
values were the same for risky and safe options in Problems 1-5. As a manipulation check, there was one trick problem (#6 in Table 2) with a dominant safe option to ensure that participants were properly incentivised and paid attention to the task. The outcomes occurred in a random order, based on the predefined probability of either 5, 6, 8 or 10%.

Procedure

The procedure of Experiment 2 was similar to Experiment 1. The experiment was performed on Windows 10 computers in the Warwick Psychology Behavioural Testing lab using PsychoPy software version 1.90.3 (Peirce, 2009). When participants arrived, they were given a short description of the task and also read a summary of the study. If participants agreed with the terms and conditions of the experiment, they provided informed consent. Initially, participants sat back-to-back to each other, facing their computers. The experiment began with instructions on the computer screen of each participant’s computer. Participants started each round at their own computers and then were informed whether, in the upcoming round, they were to stay at their own computers and sample for themselves (experiencer or observed), or they need to turn around and observe their partner’s sampling (observer). As in Experiment 1, in this experiment, participants were presented with pictures of two doors, and they indicated which door they wished to sample by using the keyboard arrow key (left or right) for the corresponding door (see Ludvig & Spetch, 2011). Selections were immediately followed by feedback for 1.2 s, which was only given for the chosen door as in the sampling paradigm (Hertwig & Erev, 2009).

The experiencer sampled 40 times from the two options using the arrow keys, while the observer observed the selections; both participants observed the feedback after each selection. After the round finished, the observer moved back to their
computer, and both participants indicated their preferred option based on the 40 viewed samples, as a single final decision. Participants did not observe each other’s final decisions. During the task, participants were asked not to intervene in any way in their partner’s selections. Each participant experienced the six choice problems described above twice, once by sampling from the options themselves while their partner was observing them (Decisions from Experience, Experience), and once by observing their partner’s sampling from the same five choice problems (Decisions from Observed Experience, Observation). The order of these 12 rounds (6 Experience and 6 Observation) was randomly shuffled for each pair. Each round had a different pair of door images representing the two options – this limited the possibility that participants recognized that the choice problems were repeated in the observed and experienced conditions and only differed in terms of the sampling differences between the participants. The sampling selections, final choices, and observed outcomes in both conditions were recorded. The pay-out for participants depended on the final choices—out of the twelve choices they made, one of their chosen options was randomly selected and then played out using the generative odds as given in Table 2.2. This outcome served as a bonus in addition to the show-up fee making all final choices incentive compatible. The experiment lasted about 30 minutes.

Data Analysis

Kolmogorov-Smirnov and Levene's tests were performed to assess differences in the distribution and variance of samples in each population. The distribution between the two conditions was not different ($D(98) = 0.112, p = .568$), and the variances between the conditions were also not reliably different ($F(1,194) = 3.01, p = .085$). Thus, paired-sample and matched-sample t-tests for within and between-subject comparison were performed accordingly.
2.3.2 Results

As Figure 2.7A shows people were significantly risk-averse in the Experience condition, acting as though they underweighted rare events, \( t(97) = -4.51, d = 0.46, p < .001, BF = 1295.85, \) in favour of the alternative. People were also risk-averse in Observation condition, choosing the risky option significantly less often than chance level, \( t(97) = -3.36, d = 0.34, p = .001; BF = 27.80, \) in favour of the alternative. The main hypothesis of the current experiment was that decisions based on observational learning would exhibit a pattern more similar to that generally observed with decisions from description. Specifically, based on the previous results, we predicted that participants would overweight high-value rare outcomes more and thus select more riskily in observation than in experience. Overall, people again chose the risky option slightly more often in Observation (40.3±5.3%) than in Experience (36.7±5.9%) condition, but the difference was non-significant in a one-tailed paired t-test, \( t(97) =1.43, d =0.14, p = .078; BF = 2.59, \) in favour of the null. This result was supplemented

![Figure 2.7](image.png)

*Figure 2.7.* Mean (±95% CI) proportion of risky choices across all choice problems for the Observation and Experience conditions (A). Proportion of individuals who picked the risky option for each choice problem in the Observation and Experience conditions (B).
by a matched-sample t-test analysis, which controls for the sampling the participants encountered, the picture is the same for the paired comparison. The difference between the conditions was also non-significant, $t(97)=1.25, \; d=0.12, \; p = .106; \; BF = 3.28$, in favour of the null.

**Sampling**

Figure 2.8 depicts the relationship between the samples one observed and the final choice they made: A binomial logistic regression showed that the proportion of risky choices in sampling reliably predicted the final choice both in the experience condition ($z = 7.07, \; d = 2.06, \; p < .001$) and in the observation condition ($z = 4.96, \; d = 1.17, \; p < .001$). Sampling did not reliably differ between the five choice problems, $\chi^2(3, \; N = 80) = 6.92, \; p = .078$. On average, the probability of experiencing the rare event was lower the scheduled probability, except one of choice problem (10%a).

![Figure 2.8](image-url)

*Figure 2.8.* The proportion of risky choices in sampling phase for each choice problem, split by what the eventual final choice was. The panels on the right indicate the scheduled probability of the rare event in each choice problem.
Figure 2.9 shows the frequency distribution of the experienced probabilities of rare events in different choice problems compared to the actual probabilities of the choice problems. The rate of encountered rare events in personal sampling predicted participants' own final decisions ($z = 7.86, d = 2.65, p < .001$), as well as the final choice of the partner, who was observing the sampling ($z = 6.39, d = 1.71, p < .001$).

![Figure 2.9. Frequency distribution of the actual experienced probabilities of rare events in different choice problems. Note the high number of participants who encountered no rare events during the sampling phase and then also chose safe. The black vertical line represents the mean of the actual encountered rare-event probabilities across participants. The panels on the right are the scheduled probabilities for each choice problem. *In Choice problem 10%, one participant chose the risky option only once and got a rare outcome, which yielded a proportion of 1 (not shown on the plot).]

2.3.3 Discussion

The results of current experiment confirmed the direction of results in Experiment 1 – in Experiment 2 in decisions from observation, participants still underweighted rare events showing no difference between choices from experience and observation conditions. In this experiment, risky choices from observation and personal experience were investigated by looking at high-value rare outcome choice problems only. In observation, people showed slightly less underweighting (bias) of rare events...
as compared to decisions-from-experience (except Choice Problem 2), in the direction of random choice as expected value would suggest. The results also replicated the literature on decision-from-experience: participants underexperienced rare high-value events and, as a result acted, as if they underweighted rare events by being risk-averse. The probability of rare events occurrence and proportion of risky choice in sampling predicted the final choice in both personal and social expedience. The results of Experiment 2 also provide evidence for the idea that sampling plays an important role in overlapping personal and social learning affecting decision-making.

Social learning as compared to personal learning has specific distinctions that might be reflected in the results. First is that the experiencer’s sampling was inadvertently responsible for what both the experiencer and observer encountered in sampling, and in turn, influenced both partners’ final choice. Second, exploring options in hypothesis testing, by acting to obtain information versus passively receiving it, might be an important factor in decision-making (Sadeghiyeh, Wang, & Wilson, 2018). Observation can be viewed as a passive-learning or information-reception process, which lacks personal exploration; in this case, the information gathering is limited by their partner’s choices (Denrell & Le Mens, 2007; Markant & Gureckis, 2013). Even though there is a perceptual difference in who chooses an option, the difference between Observation and Experience was not significant, suggesting no, or only a mild role of active selection in risky choice in one-to-one social learning. Sampling or learning by selection introduces a hypothesis-dependent sampling bias, which leads to participants under-experiencing rare events and consequently acting risk-averse (Sadeghiyeh et al., 2018). Thus, on its own, learning from personal experience might not be particularly effective: one disadvantage of self-directed learning (equated with Experience here) is biased information collection due to the hot-stove effect and related emotional charge.
(Blanchette & Richards, 2010; Denrell, 2007; Denrell & March, 2001). Learning by actively selecting options can have a larger hedonic value than when learning from passively receiving information (Fernandez-Duque & Wifall, 2007). This hedonic effect might also have driven the slight difference in the outcomes between conditions.

In both experiments in the current chapter, the sampling was not directly incentivized, but participants could still experience the ups and downs of the sampling experience—more so if they were experiencing it personally in choice. Because participants in Observation were not directly involved in sampling, they may have been slightly less sensitive to outcomes and thus showed a smaller underweighting bias.

There is some advantage of selection as compared to the reception of options (active learning), which not only provides better engagement in tasks, although it does play a role, but it can direct information gathering based on ongoing hypothesis. This selective or hypothesis-based choice, however, can also be maladaptive: people might select only the choices that confirm, but not those that disprove a hypothesis or belief (Denrell & Kovács, 2015; Denrell & March, 2001), exhibiting confirmation bias and information avoidance (Frimer et al., 2017; Golman et al., 2015; Klayman & Ha, 1987b). But, in a risky setting, passive learning can be an advantage – the absence of personal engagement allows people to better avoid affective sampling bias, hot stove effect, recency bias (although still be influenced by it), and thus perform better in tasks (Chi, 2009; Gureckis & Markant, 2012; Markant & Gureckis, 2013). Observing others has been shown to decrease these biases, because observers tend to engage in analytical thinking more and dependent more on probabilities than the participants who actively chose (Godker, Jiao and Smeets, 2019; Fernandez-Duque and Wifall, 2007; Sadeghiyeh, Wang and Wilson, 2018). However, observers can also be more optimistic when estimating the probability of winning or losing as they might tend to over-value
low probability gains and under-value high probability losses, as is usually observed in DfD literature (Hertwig & Erev, 2009; Nicolle, Symmonds, & Dolan, 2011; Ungemach et al., 2009). Overall, the results of Experiment 2, suggest that participants in observation were slightly less risk-averse in high-rare outcome choice problems than when choosing from personal experience, suggesting a potential for improved decision-making according to expected value.

2.4 General Discussion

The results showed that learning from observation is similar to learning from personal experience. In two experiments, people underweighted rare events slightly less when encountering rare events from the experience of others, but overall acted the same in both conditions. In Experiment 1, in the observation condition participants showed no high or low rare-event underweighting bias, but there was no difference between Observation and Experience conditions. In Experiment 2, risky choices from observation and personal experience were further explored using high-value rare-outcome choice problems (“rare treasures”) only. In this experiment, there was a non-statistically significant difference between decisions from observation and decisions from experience, and participants in both conditions underweighted rare events. Overall, participants made choices from observation similarly to choices from experience, however adding a social aspect – another person – in Experience decreases rare event underweighting bias.

In both experiments, the sampling pattern of experiencer – both the proportion of samples of the risky option and occurrence of rare events – strongly predicted the final choice, both for themselves and others. This suggests that unincentivized selections of observed individual in exploration can significantly predict observer’s
choice. Overall, the results suggest experiencing choice problems via a social source possesses attributes of both personal experience, but also social learning from description when it comes to risky choice and rare values. Social learning, and observational learning in particular, can potentially play a role of a compensating mechanism or a learning strategy to improve personal decision-making. Even though social learning does not allow active hypothesis testing, it allows to avoid selective sampling and related biases in personal decision-making.

2.4.1 Social Environment or Social Experience?

The novel characteristic of Observation protocol used in the two experiments of this chapter was social attribute involved in learning and decision from experience paradigm. Social aspect on risky choice had a mild effect, which can potentially be explained by two complementary mechanisms of social learning – social context (environment) and social information. Social context can significantly affect personal decision-making (Izuma & Adolphs, 2013; Mahmoodi et al., 2018; Misyak, Noguchi, & Chater, 2016). For example, if we observe others being risk-seeking, we are likely to adjust personal risk preferences in becoming also more risk-seeking (Michael et al., 2020; Suzuki et al., 2016). The social context of the task used in the current study, could create a competitive environment, perhaps inducing risk-seeking in the context where others are present, similar to how choosing for others can be explained by competitive motives (e.g., Olschewski, Dietsch, & Ludvig, 2019). Any competitive motives, however, would manifest in both conditions because the social aspect – a partner – was always present during sampling (Figure 2.1). The competitive motives thus cannot fully explain the mild difference observed between the two learning conditions. The second mechanism potentially responsible for the slight overweighting in observation as compared to experience is the social experience – social information. Indeed, the social
experience predicted choice in observation, with both the proportion of risky samples and frequency of rare events in sampling acting as strong predictors of eventual choice. This result suggests that observation can be viewed as personal experience with additional noise, which is likely associated with the lowered engagement in exploration during sampling, but which removes sampling bias resulting in underweighting (Loomes, 2015; Zhu, Sanborn, & Chater, 2020).

The learning of other’s preferences (i.e., social context) might also be an important element because in choosing options in sampling, the experiencer also directs exploration and encountering of rare events. The effect of social context can be small if the goals or preferences of others are not clear (e.g., Baker et al., 2009; Michael et al., 2020). The alignment with other’s risk preference happens when other’s choices maximise personal utility and have the least distance between one’s risk preferences and others’ choices. In the experiments, participants were aware of their partners goals, thus no emulation of others’ goals was needed, rather learning personal risk preference by observing partner’s risk preference based on their sampling could be responsible for the similarity between the two conditions (Baker et al., 2009). Thus, the process of making decision based on observed experience was not simple copying to conform, but a comparison-based adjustment of one’s own preferences. Indeed, because the choices of the partner were selective, they increased the subjective value of these options in observers (Chung et al., 2015; Suzuki et al., 2016), with social preference adjusting individual risk preference. This effect of adjusting behaviour can also be seen from the frequency of the observed choices, suggesting that people might have identified the bias in partners’ sampling and slightly adjusted for it in personal decision-making. In Experiment 1 and 2, the sampling of others affected participants’ personal choice, but
left some space for personal adjustment of underweighting bias towards chance level as the expected value would suggest.

2.4.2 Probability and Choice Outcome

There are several candidate mechanisms behind the DE gap, including the proportion of risky choices in sampling and the experienced frequency of rare events in sampling. The choice pattern in sampling can determine what option people pick in the final choice (Hau et al., 2010). Indeed, this was also observed in the two experiments: people were more likely to pick the option they or their partner selected in personal experience. There is also growing evidence that experience in sampling can be a strong predictor of choice (e.g., Hau et al., 2010; Hills & Hertwig, 2010; Plonsky, Teodosescu, & Erev, 2015; Wulff et al., 2018). Some of the social learning mechanisms (see below) suggest that the observers would choose similarly to those whom they observed (Rakow et al., 2008). This is in line with the idea that information received by observation significantly influences receiver’s choice (Toelch et al., 2018). In both experiments in this chapter, how often participants experienced a rare outcome, be that high or low, predicted the final choice of the observer. This finding fits with the research stating that choice is dependent on the frequency of experienced event occurrence and their subsequent availability in memory (Erev et al., 2010; Ludvig et al., 2015; Madan et al., 2014). If in experience, participants’ final choices were guided by personal sampling, then it also means that participants in observation were dependent on their partner risk-preference (Michael et al., 2020). By inferring partner’s risk preferences participants could apply their risk strategy to personal judgement when making decisions, and indeed this is what was found.

The pattern of risky choice could also be viewed from the perspective of the proportion of rare events. If people are insensitive to the probability of rare events,
then the magnitude of the rare events could potentially drive the choices in experience as the two are often correlated (Konstantinidis, Taylor, & Newell, 2017b; Leuker et al., 2018; Ludvig et al., 2014). That might also be because the rare risky outcomes were comparably higher than safe or common risky events. Indeed, attention in learning from experience seem to be directed to the outcome rather than probability of these events (Kellen, Pachur, & Hertwig, 2016; Konstantinidis et al., 2017a). As predicted (H1), even though participants did not act as would be predicted by equivalence to decisions from description, the direction of risky choices were in line with this idea. Furthermore, the results suggest that choice in sampling and probability of rare events both significantly affect final choice.

**2.4.3 Hypothesis Testing: Selection vs. Reception**

In two experiments, learning from observing others’ experience led to a slight reduction in risk-averse behaviour in observation and a smaller underweighting bias compared to partner’s experience, but overall both conditions did not differ. The difference between the agency to choose an option and hypothesis-dependent sampling can potentially explain why the difference between the conditions was only mild – the two counterbalance each other (Markant & Gureckis, 2013). Hypothesis-dependent sampling bias reflects how sample selection happens – by passive information gathering or by active selection of what information to gain (Markant & Gureckis, 2013; Wilson et al., 2014). In hypothesis testing by selection, a learner actively decides which samples to collect in order to test a certain hypothesis (Klayman & Ha, 1987a; Skov & Sherman, 1986). In hypothesis testing by reception, a learner is in a passive mode of inference where they need to make sense of the information that is received to which they have no or only partial control (Bruner, 1961). Social information is often passively received, modulating receivers’ preferences and choices (Chung et al., 2015; Van Bavel &
Pereira, 2018), including risky choices (Suzuki et al., 2016). In observational learning, several cognitive mechanisms are at play: trial-and-error learning from the observed experience, emotional valence and ToM. These processes play a role in hypothesis selection vs. reception as well as impacting the social psychological distance that could explain the mild effect of social learning on risky decision-making.

Active hypothesis testing, as well as psychological distance, play the role of social mediators that filter information in sampling, and given the same goal, others’ experience can be as valid as personal experience. In this way, in observation, the observer keeps track of what their partner choses and receives, and then monitors consistency with their own personal risk-preference. Based on an actor/observer account, the experiencer – actor in this case – could actively test their hypothesis by selecting options in sampling, influencing the probability of encountering a high-value rare event. Because all samples that were chosen and witnessed by the experiencer were also tracked by the observer and both partners had the same goal, similar learning mechanisms were likely at play. Indeed, the neural mechanisms behind RPE updating in social (observational) and asocial (personal) learning work in similar ways, but exhibit a difference between social or asocial action prediction errors and social or asocial outcome prediction errors, which are reflected in distinct brain pathways and regions (Burke et al., 2010). Thus, when individuals have the same goal, the learning mode – from personal or social experience – does not matter significantly but can still help to adjust social choice via distancing oneself from risk. Similarly, the results can be viewed from the perspective of personal learning as updating one’s RPE when observing the outcomes of others, as in passive or off-policy learning (Abbeel & Ng, 2004; Markant & Gureckis, 2013). Thus, the differential prediction errors in Experience
as compared to Observation could potentially serve as a transition step from asocial to social learning that might at least partially explain the DE gap in risky choice.

2.4.4 Learning about Preferences and Goals

Given that participants knew their partner’s goal (to maximise received value in their final choice), observing partner’s actions could be considered more resource-efficient for which less active hypothesis testing is required. Since in this experiment, in observation, participants passively receive information given the aligned goal of their partner. When observing others, people can either receive information about actions that others make by inferring what goal they try to achieve based on actions (what these actions lead to?) or copy actions of others without knowing which goal they try to achieve (are these actions adaptive?). Passive hypothesis testing against the observer’s preferences can be beneficial because a learner can abstract oneself from the emotional valence and make a choice to evaluate whether the current hypothesis has been disconfirmed. If so, they need to generate a new hypothesis that is consistent with the new data. This slight increase in cognitive load might explain the decrease of underweighting bias in one of the experiments and the overall trend towards indifference between safe and risky options as per the expected value.

Another alternative is that participants might not be as attentive to the task during observation because they were not directly involved in deciding what option to sample. Markant and Gureckis (2013) showed that selecting what to learn, as compared to passively observing what another person learns, improves learning performance due to enhanced motivation, attention, and engagement. To account for this, a future experiment could potentially make the sampling phase consequential: Partner A would do the sampling, but Partner B would receive the consequences. Because agency and outcomes would be perceived by different participants, personal and social experience
could be distinguished further. Specifically, whether it was the emotional impact of outcomes or active engagement that drives any differences in choice. A hypothesis-dependent sampling bias can also be related to the psychological distance from a decision, whereby observation is a passive mode of learning, which might influence the types of representations and preferences involved in decision-making (Michael et al., 2020; Trope & Liberman, 2010a). Participants could be slightly more risk-seeking when observing because, in observation, someone else experienced the risk, and hence the risk related to the outcome was not fully absorbed during sampling. Although, there was no real risk in the sampling phase as that part was not incentivized and the information was equally useful to both partners. In addition, low value rare outcomes would have less impact on the experiencer and social distance may not matter in that case. So, this logic seem to hold only for high-value rare-outcome choice problems, as underweighting between observation and experience were identical in low-value rare-outcome choice problems (see Figure 2.4). Even though there was a similar trend in Experiment 2 when only looking at high-value rare-outcome choice problems, the effect was consistent even though marginal. Potentially, a low-value rare-outcome could impact both observers and experiencers, but a rare high outcome only impacts the experiencer due to the extremity of the outcome and the potential emotional charge (Konstantinidis et al., 2017a; Madan et al., 2014; Xu et al., 2018; Zaki, Kallman, Wimmer, Ochsner, & Shohamy, 2016). Furthermore, this effect is likely to be relative, because in Experiment 2, only the very highest outcomes produced a greater difference between the decisions based on different learning modes. This suggests that given similar goals, risk preferences based on observational learning likely depends on more basic elements of the choice situation, such as the proportion of risky samples and the magnitude and frequency of rare events.
2.4.5 Limitations and Next Steps

The results from this chapter suggest that social experience has the potential to decrease the bias of personal learning in underweighting rare events. The current experiments have limitations that left some research ideas unaddressed. In the first experiment, the value of the rare outcome (high or low) influenced whether there was a difference between decision from experience or observation. One possibility would be to introduce some problems with rare, large losses (rare disasters). Similar to Experiment 1, underweighting of large losses leads to risk aversion, which is opposite to what happens with underweighting big wins. So, this would also allow a clean distinction between effects on risk preference and the effects on rare-event weighting that was not addressed in Experiment 2. Additionally, because losses can have a strong emotional impact, they can potentially have a larger differential impact due to the social distance induced by observation. Future investigations could benefit by expanding the range of outcome considered to include losses to disentangle the effect of attention to outcome and risk-seeking in sampling.

In these experiments, the repetition of the choice problems across observation and experience was camouflaged by making outcomes similar across different problems (see Tables 1 and 2). The assumption was that participants would not readily realise they were playing the same choice problem in both conditions. However, there was no direct measure included to check if this was true or not. When participants were experiencing the same choice problem by themselves, the final choice might have not been based solely on their sampling but on what they had previously observed – the sampling by their partners. Similarly, they could use their own experience when making the final choice after observing their partner. Future experiments could address this limitation by introducing a distribution of outcomes rather than a two-outcome binary
option. Finally, even though deciding from observation was paralleled with deciding from description, no direct comparison was made between the two. Deciding from observation in these experiments was only compared to deciding from experience, as this was the main idea – to introduce a social aspect to an asocial learning paradigm. Future research could address this by directly comparing all three conditions to perhaps allow a more detailed conclusion about the difference between choices from Observation and choices from Description.

2.4.6 Conclusion

Two experiments showed that people make risky decisions similarly when learning from personal experience and social observational experience, suggesting that one-to-one social learning, observation, in this case, is similar to learning from personal experience. There was a mild but persistent trend of decreasing underweighting bias in observation as compared to experience with a particular effect of rare treasures as compared to low-value outcomes. This effect can potentially be explained by the first step of abstraction from personal experience – no agency – that introduces passive hypothesis testing and psychological distance in gaining information. Given that the current study showed that learning from observation, a type of social learning, was almost identical to learning from experience, it is of interested to compare decisions from experience to decisions from description more directly. Next chapter looks at how learning from described experience differs from personal experience in learning about risks.
Chapter 3: Choices from Described Experience

The ability to accumulate experience and share it with others in the form of abstract representations is a useful learning shortcut and is considered to be one of the key factors contributing to social progress (Heyes, 2017; Rieucau & Giraldeau, 2011). Abstract social information comes in different forms: as anecdotes from life, advice, teaching material, scientific reports, surveys, and many others. Social information can come directly from others who share personal experience from memory or demonstration, or indirectly as a product received from social source, such as summarised information (Heyes, 1994). This latter form – social information as a summary – can be viewed from the perspective of information compression by expressing complex information about personal experience in a concise form (Harris et al., 2019; Kahneman & Tversky, 1984; Nieder & Miller, 2003; Tessler, Bridges, & Tenenbaum, 2020).

Information that is gathered by personal experience is typically weighted more heavily in decision-making than social information, but both can be combined or used interchangeably in decision-making depending on the environment (Behrens et al., 2008; Huber et al., 2013; Kendal et al., 2005; Suzuki et al., 2012). When personal judgment is considered alongside correct social information, people perform better in tasks than when only using personal information (Li, Delgado, & Phelps, 2011; Rendell et al., 2010; Yaniv & Choshen-Hillel, 2012). Indeed, a reinforcement-learning (RL) model that successfully describes individual trial-and-error learning, does not correspond as well to participants’ behaviour and brain activity in social learning,
suggesting RL cannot fully represent the dynamics of social learning, even though the same mechanisms are involved (Behrens et al., 2008; J. Li, Delgado, & Phelps, 2011b). This is because social learning requires a more complex decoding, as compared to individual learning, in which various brain regions are involved. During social learning, the dLPFC, which is responsible for executive functions such as attention, working memory, planning, and social reasoning, interacts with the vmPFC, the reward-learning circuit of the brain. The interaction of these brain regions allows social, symbolic information, such as a summary of experiences, to be received and taken into account in personal decision-making (BarsaleyClo, 1999). Thus, personal and social information are distinguished in the brain and make separable contributions to the decision-making process.

Information, especially in a compact, symbolic form, is a crucial component that underlies decision-making process. Learning about risk through encountering symbolic information from others can be very efficient in directing a receiver’s behaviour (Kendal et al., 2018; Rieucau & Giraldeau, 2011). Indeed, social learning enables individuals to make a choice effectively without any personal experience. For social learning to work, especially in situations with high uncertainty, people need to use social sources strategically by decoding social information appropriately (Heyes, 2016b; Pachur et al., 2013) as social information can distort reality (Hills, 2018; Lewandowsky et al., 2017; Sikder, Smith, Vivo, & Livan, 2020b). This chapter describes an experiment that looked at how people transform personal experience into a described form (in percentages) for others to make decisions from. In addition, the experiment examined whether the underweighting of rare events is present when using the described experience of others. The aim of this experiment was to understand how
people transform personal experiences in the description form intended for communication and application in personal decision-making by another person.

3.1 Communication of Risk

Even though the origins of communication (language) are uncertain, it is viewed as the link between individuals leading to more cooperation and group-forming (Betsch, Böhm, & Korn, 2013; Johnson, 2002). Individuals exchange information about risks and readily adjust risk preferences depending on the behaviour of others (Helfinstein, Mumford, & Poldrack, 2015; Izuma & Adolphs, 2013; Kopsacheilis, 2019; Olsson, Knapska, & Lindström, 2020b). In groups, people are dependent on each other, so communication about risks can modulate individual behaviour, which can increase or decrease risk perception of the group (Balliet, Tybur, & Van Lange, 2016). People perceive rare events differently depending on the value it bears to an individual via emotional response representing subjective importance (Slovic & Peters, 2006; Hertwig et al., 2004). Because perception of risk is mediated by social interaction (Cho & Scherer, 2003), the frequency of the event can be either overweighted or underweighted depending on the meaning it bears to an individual within a social context. An individual is less likely to communicate information to others, if its judged as not valuable (Kasperson, Kasperson, Pidgeon, & Slovic, 1988; Kasperson & Kasperson, 1996). Thus, how people communicate about risk to others depends on how they perceive risks themselves. This might be considered a bias on individual level, but this can be adaptive for communication on social level (Jenkins, Harris, & Lark, 2018; Kasparsen et al., 1988; Kasperson & Kasperson, 1996; Keller et al., 2006).

If information is difficult to communicate and interpret its meaning, then its value is lost for individuals within a group. From a source’s perspective, they need to
abstract information about risk in a way that would allow effective communication which would promote appropriate behaviour (Morgan, Fischhoff, Bostrom, & Atman, 2002). From a receiver’s perspective, they need to understand information about risk in a way that would allow to adjust personal behaviour proportionally to the risk to gain rewards and avoid losses. Thus, there is an interplay between social source communicating about risk efficiently and receiver interpreting risk information appropriately based on limited, abstract information.

3.1.1 Risk Perception

Individuals perceive objective the same event differently depending on various factors, such as past experience, environment, and individual differences. Individual risk perception is determined by subjective understanding and perception of risk, rather than by direct interpretation of objective numbers (e.g., Mata, Frey, Richter, Schupp, & Hertwig, 2018). For example, individuals differ in the ability to comprehend numeric information and this affects how individuals use information to make a decision. In a study by Peters et al. (2006), high-numerate and low-numerate participants were tested on how they perceive risk in different formats. In this experiment, high-numerate participants perceived risk similarly in both frequency format (10 out of 100) and probability format (10% out of 100%); however, low-numerate participants perceived risk as higher in the frequency rather than probability format. Moreover, low-numerate participants were directed more by non-numeric sources of information, such as emotions. Thus, perception of risk can be segregated across population based on individual differences.

Risk perception is heavily dependent on the format and context used to make a decision (Cosmides & Tooby, 2013; Gigerenzer et al., 1995). Specifically, in the DE gap, people underweight experienced risks, but overweight described risks. Even
though some argue that people are inaccurate in how they perceive risk, whether people are good at probability and frequency judgements is debated (Barberis, 2013; Ludvig, Madan, & Spetch, 2014; Stewart, Chater, & Brown, 2006; Tversky & Kahneman, 1992; Ungemach, Chater, & Stewart, 2009). Indeed, some research suggests that apparent biases in human risk judgments are rational responses to specific contexts especially if viewed from an ecological perspective (Gigerenzer et al., 1995, 2008; Lieder et al., 2018; Otworowska, Blokpoel, Sweers, Wareham, & van Rooij, 2017). In decision-from-experience, people calibrate frequency of experienced outcomes very well with potential slight overweighting (e.g., Ungemach, Chater, & Stewart, 2009). Thus, choosing “as if” one underweights rare events in experience can happen without biased frequency judgment. Other research in decisions-from-experience also shows that people over-report rare risks (Hertwig et al., 2005; Kaspersen, Kaspersen, Pidgeon, & Slovic, 1988; Lundborg & Lindgren, 2002; Moussaïd, Brighton, & Gaismaier, 2015). Both are possible depending on the difference in how one perceives risk and how it is modulated to produce probability estimation, with social factors are likely to modulate individual risk perception (Frewer, Miles, & Marsh, 2002; Kaspersen & Kaspersen, 1996). Take for example, slot machine gambling. The potential payouts for playing a slot machine can vary significantly, but the majority of wins are very small. One study found that a slot machine had 82% of the wins for only 10 credits (50 cents), and the majority of wins were less than the amount people wagered on that spin (Harrigan & Dixon, 2009). If we leave the hooks of addictive procedures aside (e.g., timing of winning, lighting), the appeal of gambling to people can potentially be explained by the perception of rare positive outcomes: people think that the probability of winning is higher than it actually is, leading to excessive gambling. Such as the presentation of wins can sway people to overweight the actual chances of winning (Spetch, Madan,
Liu, & Ludvig, 2020). Still, losses are weighted much more than even very big wins, and thus losses are often obscured in gambling industry (McDermott, Fowler, & Smirnov, 2008; Tversky & Kahneman, 1986).

There are two general biases that emerge in risky decision-making: (a) participants over-estimate small frequencies and under-estimate larger ones and (b) participants exaggerate the frequency of some specific causes and under-estimate the frequency of others, at any given level of objective frequency (Lichtenstein et al., 1978). The reason for this skewed representation of risks is that people do not come up with the average experience based on all samples, but rather, pay attention to specific samples. People simultaneously overestimate slim chances (e.g., dying from a rare disease) and underestimate larger chances (e.g., getting into a car crash). People also tend to exaggerate memorable or unusual event occurrence (e.g., acts of terrorism), and underestimate mundane ones (e.g., getting diabetes) These cognitive and memory biases result in skewed memory samples (Lieder et al., 2018; Madan, Ludvig, & Spetch, 2015; Madan et al., 2014; Rakow et al., 2008). One of these biases is a recency bias (Rakow et al., 2008) where people base judgments on events that are remembered better, which are usually recent or emotional events (see also the “peak-end rule” by Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993). In addition, people can simultaneously overestimate the probability of rare events in their judgments and underweight the probability of the same rare events in their choices (Szollosi, Liang, Konstantinidis, Donkin, & Newell, 2019). Overall, people’s judgement of risk is complex and dependent on individual perception, which in turn affect how information about risk is communicated.
3.1.2 Transforming Experience to Description

In risky decision-making literature, risk is defined as an event with a known probability and outcomes (Aven & Renn, 2009; Mata et al., 2018; Rakow & Newell, 2010). Risk can be viewed from two different perspectives – objective (pre-set by nature) or subjective (individually perceived). Subjective risk is defined in terms of individual differences (e.g., numeracy) and the factors specific to that individual, such as previous experience (sampling), specific domain (e.g., health, gambling, or finance) and personal significance (Blanchette & Richards, 2010; Frey, Pedroni, Mata, Rieskamp, & Hertwig, 2017; Weber, Blais, & Betz, 2002). Subjective risk also depends on the factors such as how risk is framed (i.e., loss or gain), how recently it occurred (i.e., a minute ago or 10 years ago), and what emotional response it elicits (i.e., neutral vs. strong emotional response) (Blanchette & Richards, 2010; Hertwig et al., 2004; Johnson & Tversky, 1983; Murdock, 1962; Tversky & Kahneman, 1981). Thus, when risk information is transformed in memory in a communication form, it captures all of the above attributes and subjective interpretation of risk, reflecting the biases of social source.

Memory and attention, which are interdependent cognitive functions, are particularly important for frequency estimation and rely on individual differences, and arousal (i.e., emotions). Due to attention and memory limitations, subjective information about risks can be further modified when communicated (Heyes, 1994; Pleskac & Hertwig, 2014; Pope, 2007; Urai, De Gee, Tsetsos, & Donner, 2019; Vuilleumier, 2005). Risk probability estimates tend to regress to the mean frequency within the set of risks (e.g., lower for higher probability, and higher for lower probability (Hertwig et al., 2005). The same cognitive mechanisms that underlie frequency encoding are also at play when experiencing events (Zacks & Hasher, 2012).
Further, the communication of this “frequency knowledge” depends on cognitive biases when transformed from experience to described form, for example directed by extremity or saliency bias and subjective value it bears to the individual (Fisher & Keil, 2018; Ludvig et al., 2018). In particular, emotion can be viewed as amplifier in communication theory that intensify or attenuate signals during the transmission of information from source to a receiver (Guback & DeFleur, 1968; Kasperson et al., 1988). Such adaptation is described in the Amplification of Risk Theory that looks at personal experience and direct or indirect communication as factors of amplification (Kasperson, Kasperson, Pidgeon, & Slovic, 1988). This can be especially useful if the encountered risks are detrimental, because receivers can efficiently adapt individual behaviour without doing sampling personally, which would put themselves at risk (Heyes, 1994; Kendal et al., 2018; Rendell et al., 2011).

Behavioural response to risk is intrinsic to risk communication as it creates complex interaction between individuals. The variation in population response to risk communication is based on the subjective risk perception of individuals in the population. Moreover, the distribution of behavioural responses on the population level can change the actual probability of a risky event going forward, because individual behaviour can generate consequences that increase or decrease risk on social level (Kasperson, Kasperson, Pidgeon, & Slovic, 1988). A population of risk information receivers can be divided into different categories of behavioural response: Some individuals keep neutral and account appropriately for risk in their actions, whereas others can become anxious and exaggerate the risk (Sunstein, 2020), still others may disregard risk information and thus underestimate the risk. This pattern of population risk perception, as expressed in behavior (e.g., hand sanitisation, self-isolation), happened during the Covid-19 pandemic creating reinforced waves in the number of
infection cases (Patel-Carstairs, 2020). Because risk perception, communication, and behavioural response are inter-linked, these can be viewed as parts of social risk perception virtuous cycle resulting in reinforced waves on social level.

Subjective importance of a risky event might be perceived in terms of personal gain or loss, but also as a guide for communicating about that particular risk to others. The fact that individuals act as if they underweight the probability of rare events in personal experience due to under-sampling, but make accurate frequency estimates suggests a mechanism that accounts for this under-experience and impacts how individuals communicate about personally encountered risks to others and, in turn, perceive communications (Benjamin & Budescu, 2015; Fox & Hadar, 2006b; Hills & Hertwig, 2010; Wulff & Hertwig, 2018). From the perspective of personal experience of encountering rare events, people must pay particular attention to rare events that are subjectively important and pay less attention to rare events that are subjectively less important. Indeed, on individual level, emotional events are remembered better and for longer than unemotional ones because of the importance to the individual (LaBar & Cabeza, 2006; Yonelinas & Ritchey, 2015). Similarly, some particularly emotional events can be overweighted and remembered better than others in the context of decision making (Charpentier, De Neve, Li, Roiser, & Sharot, 2016; Kahneman & Tversky, 1984; Ludvig, Madan, & Spetch, 2015; Yechiam, 2018). Thus, people are likely to exaggerate the occurrence of specific rare events, and simultaneously, underestimate more mundane but likely events as they bear different individual value that is implied in communication of the encountered events.

3.1.3 Current Experiment

In Chapter 2, a classic form of social learning—observational learning—was used to explore the difference between learning from personal experience versus
learning from social experience, i.e., observation. This decisions-from-observation paradigm was used in two experiments, where participants made decisions from observing their partners sampling from different options. The results showed that learning from observation is similar to learning from personal experience, but with a mild difference in the direction of decisions from description: When observing, people underweighted rare events less. In this chapter, another novel paradigm is introduced to understand the social underpinnings of learning about risk, using abstract descriptions. The decisions-from-described-experience (DfDE) paradigm examines how people generate and use abstract social information. In this experiment, there are two key questions examining how people (a) summarise personal experience about risk for others and (b) use the descriptions generated by another person in personal risky decision-making. The experiment compared risky choice in three conditions: directly from personal experience, from a described experience, or from an objectively described risk information.

Two opposing predictions can be made in terms of how people generate descriptions based on personal experience and subjective perception of rare events. First, people may generate descriptions by retrospectively estimating the frequency of rare events based on the overall number of samples they experienced (samples; what happened). Second, people may project their experience to the future if they need to decide again (goal; what will happen) (Barbey & Sloman, 2007; Sirotka, Kostovičová, & Vallée-Tourangeau, 2015). Based on the work on the accuracy of frequency estimates, descriptions of experience could be treated as frequency estimates, and people thus should report well-calibrated or even over-reported descriptions (Lieder, Griffiths, & Hsu, 2017b; Ungemach et al., 2009) (H1a). Alternatively, people may transform their own experience to descriptions directly, and thus under-report event
probabilities (H1b). Another prediction of the experiment is that the DE gap would be replicated – people would act as though they underweight rare events when learning from experience and overweight them when deciding from objective description (H2). That means that in Experience, participants should choose a safe gain more often, and in Description, people should choose a safe probable loss option more. In terms of how people use descriptions made by others, participants might overweight rare events, as they tend to do in standard described problems (H3a). Alternatively, if described experience understates the frequency of rare events (see H1b), this systematic distortion may result in less overweighting of rare events. Consequently, participants using these described experience will be less risk averse for losses and less risk seeking for gains as compared to the Description condition (H3b). Lastly, described experience may be treated as simple description (H4). Then, when using them, participants would be more risk-seeking for gains and more risk-averse for losses as compared to Experience as they would with standard descriptions. The experiment was pre-registered on the Open Science Framework (OSF) including hypotheses, sampling plan, exclusion criteria, and initial analysis at: https://osf.io/dt36r/

3.2 Methods

3.2.1 Participants

The sample size of the current experiment was set by the University of Warwick Psychology undergraduate participant pool, and as many participants from this pool were recruited as possible in the available time frame. The final data was collected from 152 participants; of these, 6 were excluded due to a bug in the experimental code, 11 were excluded because they or their partner either did not follow the instructions (e.g., did not wait for their partner) or did not finish the experiment. Further, seven
participants failed to pick the risky option in the trick choice problem (#7), and thus both they and their partners were also excluded from the analysis. All exclusions were made data blind and according to the pre-registered plan. Following exclusions, 118 participants were left, out of whom 105 were females, 12 were males and one identified as a transgender male. The mean participant age in the sample was 19.11.8 years old. Gender and age information was collected to characterise the demographics of the sample at the beginning of the experiment, but these were not used in the main analyses as variables. Participants received course credit and a chance to partake in a raffle for a £30 prize, based on their choices and a random draw. The exclusion rate was consistent with the previous experiment, where about 25% of the tested sample was excluded. Power analysis indicated that with 118 participants for a two-tailed test with error probability $\alpha = 0.05$ for a within-participant design, the power of the experiment was 0.56 for an effect size of $d = 0.28$ as calculated using $pwr$ package in R. This effect size was drawn from an earlier study in the sequence (Chapter 2), which compared people’s choices from observed or experienced rare outcomes.

### 3.2.2 Design

The experiment used a within-participant design. The first independent variable was the source of learning about the choice problem: Description, Described Experience or Experience. The second independent variable was the domain of choice problem: gain or loss. The dependent variables were the proportion of final risky choices and the frequency estimates as reported in a description to another participant. The within-participant comparison pitted the final choices from Described Experience against those from Experience and Description for the same participant (see below). The dependent measure was the indicated frequency of rare outcomes in the described experience condition, where the absence of an outcome altogether was taken as indicating a 0
percent chance. There was no restriction on the written percentages that participants created, such that they could potentially not sum to 100. Therefore, the frequency of rare outcomes as indicated on the description were analysed as percentages stated by participants. The second dependent measure was the proportion of risky choices and was calculated for each participant separately for the Described Experience, Experience, and Description conditions choice problems (for each of the two types of problems: gains vs. losses), yielding six measures.

3.2.3 Materials

The experiment involved a sequence of binary choice problems between a risky option and a safe option, as detailed in Table 1. In each choice problem, a safe option provided a medium payoff, and the risky option provided a high payoff with a given probability (.1, .05) and a low payoff otherwise.

Table 3.1. The seven choice problems with the outcomes and probabilities (P) used in the experiment.

<table>
<thead>
<tr>
<th>Problem</th>
<th>Risky</th>
<th>Safe</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>-100</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>-20</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>-200</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>220</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>7 (trick)</td>
<td>10</td>
<td>5</td>
</tr>
</tbody>
</table>

The experiment consisted of a simple decisions-from-experience sampling protocol using these seven different choice problems (Table 1). The choice problems all had a rarely occurring outcome, with either .05 or .1 probability. Choice Problems 1-3 were in the loss domain, whereas Choice Problems 4-6 were in the gain domain.
The expected values were the same for both the risky and safe options in Choice Problems 1-6. As a manipulation check, there was one trick problem (#7 in Table 1) with a dominant risky option to ensure that participants were properly incentivised and paid attention to the task.

3.2.4 Procedure

The experiment was performed on Windows computers in the Warwick Psychology Behavioural Testing lab using PsychoPy, version 1.90.1 (Peirce et al., 2019). The experiment lasted around 30 minutes. Participants were presented with a summary of the study and, if they agreed with the terms and conditions, they provided informed consent. Participants were randomly allocated to pairs to perform the task. Partner pairs of participants sat next to each other facing their own computer screens; partners’ screens were shielded by a sidewall so they were not able to see each other’s sampling and final decisions. The experiment began with instructions on the computer screen of each participant. If there was an odd number of participants in a session, then one participant was randomly chosen to perform an alternative task. The data from these non-paired participants were not included in the data analysis. To become familiar with the task, participants first played a practise round before they began with the main task.

![Figure 3.1. Schematic of the experimental setup. In the sampling phase, participants chose between two doors and received feedback about the selected door. Each trial involved a choice between one door that always led to a fixed medium payoff and a second door that led to high/low payoffs with specific probabilities (see Table 1). Choices were followed by immediate feedback about the potential payoff for the selected door.](image)
The main task consisted of 7 rounds. In each experimental round, participants sampled a choice problem (Experience condition) followed by a single consequential choice for that choice problem. As illustrated in Figure 3.1, on each trial, participants were presented with pictures of two doors, and they indicated which door they wished to sample by using the left or right arrow keys for the corresponding door (see Ludvig & Spetch, 2011). Selections were immediately followed by feedback for 0.6s, which showed the points corresponding to that door only. For risky options, each outcome was independently and randomly selected based on the generative probabilities for that door (as in Table 1). Feedback was only given for the chosen door following the sampling paradigm (Hertwig & Erev, 2009). Participants sampled from the two options 40 times and then made one final consequential decision for that round. There were 7 rounds altogether. No feedback was provided after these final, consequential decisions.

Figure 3.2. Experimental conditions. Participants encountered four tasks. First, for 7 rounds, they Experience (E) some outcomes, described that Experience for their partner, and made decisions from the Described Experience (DE) of their partner in each round. After having made the final choices and descriptions for all seven of these choice problems, they were presented with the same problems again, but with the objective descriptions (D).
Only after that final decision, participants were asked to describe their experience of the choice problem they had just played; they wrote their description on a sheet of paper (see Appendix 1) and exchanged it with their partner. The participants, then, used the described experience received from their partner to make another choice for this problem (the Described Experience condition, DE). In the Experience condition, participants based their final choice only on their sampling, but in DE, participants could only base their final decision on the description generated from sampling by their partner. So, as can be seen in Figure 3.2, participants first made decisions based on sampling in the Experience condition. Then, they were asked to write down the outcomes they saw for each option and the corresponding probabilities in percentages. Next, they made a choice using their partner’s descriptions in the Described Experience condition. After all the experience rounds were complete, participants were presented once again with the same problems, but this time with the objective description of the problems in the Description condition.

*Figure 3.3. Example of the choice problem format in the Description condition. During the task, participants were not allowed to discuss their choices with each other (except through the written descriptions) nor intervene in any other way in their partner’s selections.*
In each round, both participants sampled from one of the choice problems in Table 1, which were randomly shuffled. Thus, in most rounds, participants experienced and wrote a description of one choice problem and made another final decision based on the described experience of another problem. The format of the form given to participants to describe their experience choosing in each choice problem indicated to participants to report only the number of points in percentages, with 100% being absolute certainty (see Appendix 1 for a sample form). All choice problems were decided upon three times—once from experience (DfE) and once from described experience (DfDE)—and finally a third time in a later round during which they were presented with the same problems, but in an explicitly described (DfD) format using the true generative probabilities for the experienced choice (see Table 1). Figure 3.3 shows one such described choice problem: in addition to explicitly stating the outcomes and their odds, the options were also represented with doors as in the Experience condition. This ensured that the final choices across all conditions were presented with as consistent a format as possible; the doors also served as a means of distracting participants from recognizing that the same choice problems were used across conditions because different door images appeared for these choice problems.

Prizes were allocated as follows: Participants started with 1000 raffle tickets at the beginning of the task. Participants earned raffle tickets probabilistically: the more points participants won, the more raffle tickets they earned (see Table 1) and thus the higher their chance to win the prize. This set-up was necessary to ensure that the task was incentive compatible. Participants were told that their chances of winning the prize did not depend on the number of raffle tickets other participants earn because the raffle tickets of each participant were independently randomly selected from a fixed number of raffle tickets (100 000). Therefore, the probability of each person winning the
voucher was independent of the choices made by others to prevent any competitive motives. The reward for participants depended on their consequential final choices. When all data was collected, the winners of the raffle were identified - two participants ended up being selected to win a prize of a £30 Amazon voucher.

3.2.5 Analysis

The within-participant independent measure was whether participants learned outcomes and their probabilities from personal experience, from the described experience of others, or from description. The dependent measures were the proportion of risky choices, described probability of the risky option, and the degree of underweighting of rare events. The proportion of risky choices was defined as the ratio of the number of times the risky option was selected when presented against the safe option. The proportions of risky choices were calculated across the problems in each condition. When a choice problem had a rare gain, participants could choose the riskier or safer option. If participants chose the risky option more often, they behaved as though they were overweighting the rare gain event, but if participants chose the risky option less often, they behaved as though they were underweighting the rare gain. This logic was reversed for losses. The degree of underweighting was thus defined as the sum of the risky choices made in the Loss domain in problems (#1-3) and the safe choices made in the Gain domain in problems (#4-6) divided by six, the overall number of choice problems. The proportion of risky choices and degree of underweighting were calculated for each participant. The within-participant comparison pitted the final choices in DfE against those in the DfDE and DfD for the same participant.

3.2.6 Normality of Data

The data from all non-excluded participants was tested for normality using a Shapiro-Wilk test and Levene's test for equality of samples variances. The Shapiro-
Wilk test showed that all three variables–the description of rare events \((W = 0.86, p < .01)\), proportion of risky choices \((W = 0.86, p < .001)\), and underweighting of rare events \((W = 0.91, p < .001)\)–were not normally distributed. The samples, however, were drawn from the same distribution as shown by a Kolmogorov-Smirnov test for the description of rare events in loss and gain domain \((D = 0.14, p = .23)\), proportion risky choices between experience and described experience \((D = 0.07, p = .94)\), and description and described experience \((D = 0.27, p < .92)\). The underweighting of rare events variable was also drawn from the same distribution between experience and described experience \((D = 0.26, p = 0.92)\), but not between description and described experience \((D = 0.26, p < .001)\). Levene's test for equality of variances showed that the variability in the three conditions for proportion of risky choices \((F = 0.2, p = 0.81)\) were the same, but the variance was different between conditions in the underweighting of rare events \((F = 12.45, p <.001)\).

Because the data did not meet the requirements for a parametric test (i.e., the data was not normally distributed), a Wilcoxon signed-rank test for within-subject comparison was performed instead. These tests were not pre-registered, but they are direct substitutes for the parametric tests. All data analysis was conducted in RStudio. Effect sizes were calculated as Cohen’s \(d\), and mean differences are presented with 95% confidence intervals. The data analyses followed the pre-registered plan in terms of hypothesis testing but used the alternative statistics to match the non-normality of the data.
3.3 Results

3.3.1 Description of Experience

After participants sampled the choice problems’ outcomes and learned about the probabilities of outcome occurrence, they were asked to write their estimates down on the provided form (see Appendix 1). The difference between the frequency estimates that participants provided to their partners based on their experience was compared with the objective percentages of the rare outcomes occurring in those choice problems. One of the predictions was that the described probabilities for rare outcomes will be well-calibrated or higher than the objective probabilities (H1a), and indeed this is what people did. Even though a large proportion of participants did not encounter the rare events in accordance with their probability (see below), on group level, participants still overestimated the likelihood of rare events in their descriptions against the mean of all events ($V = 4809, d = 0.41, p < .001, \mu = 0.067; BF = 1032.6$, in favour of the alternative). Figure 3.4 and Figure 3.5 show how, in particular, people tended to over-report rare losses ($M = 0.10 \pm 0.01, V = 5701, d = 0.40, p = .029, \mu = 0.067; BF = $).

![Figure 3.4](image)

*Figure 3.4.* Mean probability description of rare outcome Loss and Gain domains. Dashed line represents the average probability across the choice problems within each domain ($\mu = 0.067$). Error bars represent 95% CIs.
2335.02, in favour of the alternative), but less so rare gains ($M = 0.09 \pm 0.02, V = 3586, d = 0.22, p = .084, \mu = 0.067; BF = 1.8782$, in favour of the alternative) in descriptions of their experience compared to the objective probabilities. As per Hypothesis 1a, descriptions of experience were treated as frequency estimates, and people overestimated probabilities in their descriptions. This result provides strong evidence against Hypothesis 1b that stated participants would under-report rare events in accordance to the choices participants make in experience. Participants did not encounter rare events in every choice problem, which is to be expected in a limited partial-sampling paradigm (Fox & Hadar, 2006a). Figure 3.6 shows the probability distributions of objectively encountering the rare event and how participants reported this experience in each choice problem. The mean reported probability of rare event per each choice problem is presented in Table 3.2 below. Participants clearly indicated a higher proportion of rare events in their descriptions than what they actually encountered ($W(n=118) = 6497, d = 0.48, p < .001, BF = 3.1e+20$, in favour of the alternative).
A large proportion of participants did not experience rare events – ranging from 8% to 55% for a specific choice problem. In two choice problems where rare event occurred with 10% probability, 7.6% of participants did not encounter rare loss, and 27.1% did not encounter rare gain. In the choice problems where rare event occurred with 5% probability, 43.2% and 28.0% did not encounter rare loss, in Choice Problems 2 and 3 respectively, and similarly, 55.1% and 46.6% of participants did not encounter rare gain, in Choice Problems 5 and 6. Accordingly, participants over-reported the probabilities in the loss domain more than in the gain domain.

*Figure 3.6. Probability distribution of encountered rare events and how it was reported by participants. The dashed lines represent objective probabilities of rare events in the two type of choice problems – loss and gains (see Table 1). The numbers shown are from all participants – both those who did or did not encounter a rare event during sampling. Note that on the graphs, the probability distribution of described rare events does not show stated probabilities higher than 0.3, which appeared a total 36 times across choice problems.*
Table 3.2. The probability of encountered rare events for each choice problem.

<table>
<thead>
<tr>
<th>Choice Problem</th>
<th>Domain</th>
<th>Rare Outcome</th>
<th>Objective Event Occurrence</th>
<th>Mean Encountered Occurrence</th>
<th>Mean Reported Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>-100</td>
<td>10%</td>
<td>5.6 ± 0.7%</td>
<td>15.0 ± 2.7%</td>
</tr>
<tr>
<td>2</td>
<td>Loss</td>
<td>-20</td>
<td>5%</td>
<td>2.4 ± 0.5%</td>
<td>6.3 ± 1.5%</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>-200</td>
<td>5%</td>
<td>2.9 ± 0.5%</td>
<td>8.3 ± 2.1%</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>20</td>
<td>10%</td>
<td>4.5 ± 0.9%</td>
<td>12.9 ± 3.2%</td>
</tr>
<tr>
<td>5</td>
<td>Gain</td>
<td>220</td>
<td>5%</td>
<td>1.9 ± 0.5%</td>
<td>5.4 ± 2.0%</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>200</td>
<td>5%</td>
<td>2.1 ± 0.4%</td>
<td>7.3 ± 2.7%</td>
</tr>
</tbody>
</table>

3.3.2 Replication of the Description-Experience Gap

In Experience, people usually underweight rare events and act as though they are risk-averse for gains, but risk seeking in losses. In contrast, in Description, people act more riskily for rare gains, but are more risk averse for rare losses (Hertwig & Erev, 2009). Next, we looked at the decisions based on the two classic forms of learning about risk—from Descriptions and Experience separately in loss and gain domains. Participants chose more riskily in Experience as compared to Description in the Loss domain ($W(n=118) = 4952, d = 0.56, p < .001; BF = 12154.6$, in favour of the alternative), but this pattern was reversed in the gain domain ($W(n=118) = 8308.5, d = 0.44, p = .003; BF = 171.812$, in favour of the alternative). Overall, there was no full replication of DE gap: people did not act as if they overweighed rare events in Description, but they did choose as if they underweighted rare events in Experience (Hertwig & Erev, 2009). For these choices, in both groups, choice domains were compared with the chance level. In experience, participants were indeed risk-averse for
gains ($M = 0.23 \pm 0.04, z = 8.84, p < .001$) and risk-seeking for losses ($M = 0.72 \pm 0.05, z = 8.373, p < .001$). In Description, however, people were neither risk-seeking for gains ($M = 0.36 \pm 0.64, z = 0.42, p = 1$), nor risk averse for losses ($M = 0.52 \pm 0.07, z = 0.98, p = .327$).

### 3.3.3 Choices from Described Experience

Participants chose differently in described experience as compared to description, similarly to experience. Specifically, according to Hypothesis 3b, in losses, participants chose the risky option more often in described experience ($M = 0.73 \pm 0.05$) than description ($M = 0.52 \pm 0.07, W(n=118) = 6095.5, d = 0.52, p < .001; BF = 9.85$, in favour of the alternative), and in gains, participants chose non-significantly less riskily in described experience ($M = 0.29 \pm 0.05$) than in description ($M = 0.36 \pm 0.06, W(n=118) = 9667.5, d = 0.15, p = .052; BF = 1.06$, in favour of the null). When compared against experience, in the gain domain, people made non-significantly more risky decisions with described experience than in experience ($W(n=118) = 7711, d = 0.22, p = .122; BF = 3.083$, in favour of the null). In the loss domain, people chose similarly for both described experience and experience ($W(n=118) = 7067, d = 0.04, p = .831, BF = 9.25; in favour of the null$). This result did not confirm the proposed predictions of Hypothesis 4, which stated that DfDE would be similar to DfD.

As part of an exploratory analysis, the difference between all three conditions was explored. Figure 3.7 presents the proportion of risky choices between conditions in the six different choice problems. There was a significant difference between all three conditions in underweighting of rare events ($\chi^2(2) = 20.2, p < .001$), driven by the

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2 The p-value of 1 indicates that the results went in the opposite direction compared to the prediction tested in a one-tailed test.
difference between description and experience ($M_{\text{rank difference}} = 55.12, p = .003$) and description and described experience ($M_{\text{rank difference}} = 4.87, p = .001$). Overall, the pattern of choices in each condition was consistent: risky choice in described experience and experience was similar. Overall, choices in Described Experience were similar to the Experience condition in risky choice.

![Figure 3.7. Proportion of risky choices for all choice problems across participants in Description, Described Experience, and Experience conditions. Letters “a” or “b” distinguish the lotteries that had the same probability but different outcomes (see Table 1). Error bars represent 95% CIs.](image)

### 3.4 Discussion

This experiment showed that overall, participants over-reported the probability of rare events when describing experienced risky outcomes. Surprisingly, this over-reporting, in choices from described experience, led people to act similarly to personal experience, even though the format of the information in both, described experience and description was the same. These decisions from Described Experience seem to possess elements of both decisions based on info from Experience and Description, with
losses and gains affected in different ways. The main idea of this experiment was to better understand two ways people learn about risk comparing choices from description and from personal experience. For this, we introduced a task that had the two learning modes: descriptions of personal experience, i.e., described experience. The main aim of the experiment was to understand whether people over-report or under-report the probabilities encountered in personal experience, and how this affects choice. The fact that people underweight rare events in personal experience but over-report them to other suggests about the potential dissociation between personal experience and communication in the form of reporting of rare events.

The key finding of the experiment is that even though participants experienced rare events less often, they reported them as happening more often. This effect was driven by participants who encountered rare events correcting for others’ absence of this experience. A considerable proportion of participants did not experience rare events, but the ones who experienced them compensated for the absence of experience in others by overweighting encountered risky events in description. As a result, the mean estimated frequencies in the described experience exceeded both objective (preset) and experienced frequencies of rare events. However, on the group level, participants making choices using described experiences decided similarly to what they choose when they made choices from personal experience. Participants might have overweighted rare events in decisions from described experience, but because a large proportion of participants received information that made those events seem less rare, overweighting on the group level was disguised. Thus, there might be a different dynamic between information communicated individual-to-individual and information that was aggregated or normalized as in Description condition, usually discussed in DE gap literature. Overall, in this experiment, choices from described experience closely
represented choices from personal experience of the communicator suggesting that there might not be usual DE gap between one-to-one communication. Moreover, one-to-one communication seem to decrease the usual underweighting of rare events in personal experience bias.

The finding that people over-report risk in personal experience are in line with the Amplification of Risk Theory which demonstrates that information is intensified or amplified in a social context (Kasperson & Kasperson, 1996). Participants tended to overweight rare events when describing experience, especially losses, but did not act as if they overweighted the same rare events in personal experience. Indeed, when participants used described experience from others to make choices, their decisions were closer to the choices from experience rather than from objective descriptions. These results suggest the discrepancy between experiencing rare events and describing them can stem from an interaction of personal and social learning: across participants, rare events were under-sampled, but over-reporting them in description compensated for this under-sampling bias by creating another bias of over-reporting rare events in communication. This personal-social mirror effect is a complementary mechanism in learning that is useful to consider when looking at other biases decision-making, such as confirmation bias.

Information gathering, processing, and transforming from one form (e.g., personal perception) to others (e.g., abstract – demonstrated, written) can be viewed as information compression (Fisher & Keil, 2018; Nieder & Miller, 2003). Because social learning is often more efficient than personal learning, group level learning is required. Potentially, this overestimation is a compensating mechanism serving a correcting function in information compression across population (social setting). Indeed, the choices from Described Experience and Experience were similar, and choices in
transformed – described – experiences resulted in the same behavior as in experience but with the direction of receiving more gains and receiving fewer losses.

3.4.1 Describing Experience

Participants overweighed rare events in their probability descriptions, over-reporting rare losses more than rare gains as compared to objective probabilities, even though they acted as if they underweighted the same rare events when experiencing them in sampling. In the experiment, participants sampled each choice problem first, and then, after making a final decision, were asked to write the outcomes and corresponding probabilities for their partners to then make a final decision of the just-experienced choice problem. Because participants could make only a limited number of samples, they encountered the rare events less than the scheduled probability in accordance to what is usually reported in the literature (Fox & Hadar, 2006b; Wulff & Hertwig, 2018). Because rare events are typically under-experienced in sampling, a mechanism that accounts for this biased sampling would be beneficial in communication on the group level. Because a proportion of participants did not encounter rare events at all, the over-reporting of rare events was driven by a proportion of participants who did experience the rare event.

A potential mechanism for the rare-event over weighting when communicating personal experience could be increased attention to rare events, which drives a memory bias for those rare events. Losses are known to increase attention and enhance the reliance on deliberate and controlled cognitive processing (Yechiam & Hochman, 2013). This extra attention would modulate the memory of rare events, especially large losses, contributing to the over-estimation of encountered events in sampling, and, in turn, resulting in risk amplification when that risk is communicated. Indeed, Madan, Ludvig, & Spetch (2014) showed that extreme outcomes – the highest and the lowest
in a given context – are overweighed in memory. Further, this overweighting correlated with risk preference in decisions from experience. Madan et al. (2017) suggested that this memory bias might account for at least some of the differences between description and experience. In that work, the memory bias for losses was bigger than for gains, which can possibly explain why rare losses are overweighted more than rare gains, as observed here. The results here also fit with the findings by Lieder, Griffiths, & Hsu (2018) who found that the frequency with which an outcome can be recalled is biased by its utility. Overall, people might over-report rare events to correct on a social level for those who are likely to under-encounter (and those under-report) these rare events.

The perception of rare events can play a significant role in the overweighting of events in communication. From an emotional perspective, both large gains and large losses are emotionally salient leading to loss-aversion in general and risk-aversion for gains (Hertwig & Volz, 2013; Pfabigan, Alexopoulos, Bauer, Lamm, & Sailer, 2011; Sokol-Hessner et al., 2013). Slovic, Finucane, Peters, & Macgregor (2012) highlighted the beneficial aspect of emotional experience in risk, which seems to have adaptive benefits for survival. Decisions made from experience rely on images and associations that are linked by experience to emotions that help categorise when something good or bad is happening. Crucially, affective reactions are also in play in seemingly objective domains, such as financial investment decisions (Holtgrave & Weber, 1993). People also tended to believe that others have more intense experiences than they personally do, suggesting a priori overestimation of others’ evaluations of experience (Jung, Moon, Nelson, Lei, 2020). People also were shown to misjudge the preferences of others’ and ignore the trade-offs others make in evaluations. Thus, the over-reporting of rare-event frequency in this experiment might be generally adaptive in a group setting for risk communication and decision-making.
The perception of gains and losses might be expected to be asymmetric if viewed from a group-selection perspective and reciprocity of sharing information (Mohtashemi & Mui, 2003; Smith, 1964). On that view, absolute losses (e.g., death or significant hardship) can be more detrimental than gains (e.g., winning a fortune or gaining authority) can be beneficial (Hintze et al., 2015). As a result, if risk is communicated to others, amplifying losses might be more important than amplifying gains (Wang, 2008). Additionally, this logic implies that participants might amplify encountered risky-loss event to avoid it more in the future on a group level (de Houwer, Barnes-Holmes, & Moors, 2013; Den Ouden, Kok, & de Lange, 2012). Participants also tended to amplify the encountered risky gain event to potentially encounter it more or less in the future, on an individual or group level. Because personal experience affects subsequent choice, it might be adaptive to adjust memory for events bearing negative or positive value. This process of mirror biasing is reciprocal (i.e., personal-other) and can be viewed as an individual adaptation to social level. As people learn from others, they also communicate to others (Csibra & Gergely, 2006). This is because social learning requires reciprocity, and communication about events is part of cooperative behaviour that includes information sharing to improve adaptation of a group (Leibo, Zambaldi, Lanctot, Marecki, & Graepel, 2017; Tomasello, 2010). Because, in nature, large resource patches can provide food far beyond the environmental average and the need of a single individual (Smolla, Tucker Gilman, Galla, & Shultz, 2015), sharing social information can be particularly adaptive where reward distribution is skewed or costly.

3.4.2 Replicating the DE Gap

The DE gap has been mainly attributed to sampling bias (Fox & Hadar, 2006a), but such sampling bias has been shown to have only a mild role: the gap persists even
when sampling error is eliminated suggesting that other mechanisms are likely involved, such as recency effects, estimation error, and information format (Hertwig & Erev, 2009; Ungemach et al., 2009; Wulff & Hertwig, 2018). Participants were indeed more risk-seeking for losses in Experience than in Description but were more risk-seeking for gains in Description than in Experience. The results partly replicated the findings from the literature that people act as if they overweight rare events in description and underweight them in experience (Hertwig & Erev, 2009; Wulff & Hertwig, 2018). However, there was a divergence from the expected results driven by the fact that participants acted as though they underweighted rare gains in Description. When looking at the two conditions separately, participants were risk-averse for losses not only in Experience, but also in Description, contrary to what is usually found in the literature (Dutt et al., 2013). Still, participants acted as if they underweighted rare events in both gains and losses in Experience more as compared to Description: People acted as if they underweight rare events in personal experience and thus were risk-seeking when the rare events are relative losses (Hertwig & Erev, 2009; Wulff & Hertwig, 2018). In other words, participants exhibited the expected underweighting of rare events in Experience but deviated from expectation in the Description condition (Barberis, 2013). Thus, the results replicated the previous literature on DE gap, but only in Experience; in Description, participants exhibited risk-aversion rather than risk-seeking for rare gains and had no bias for rare losses.

In the current experiment, choices from Description could be potentially described by the unusual format of the Description used in the current experiment: alongside outcomes and their probability, participants were shown door images, after they already had experience with the identical problems twice in Experience and Described Experience. Additionally, this effect might be due to the fact that participants
made choices from Description only after all choices in both Experience and Described Experience were made. This might also be a limitation of the current experiment, because participants might have learnt the outcomes and guessed that the probabilities from previous conditions, biasing judgements in Description as compared to Experience and Described Experience conditions. Nevertheless, the general pattern was in the direction as per the DE gap literature.

3.4.3 Choices from Described Experience

As the experiment showed, the DE gap might not occur solely due to salience of extreme events and memory limitations per se, but rather these mechanisms might be a part of a wider compensating mechanism in social risk communication by transforming subjective risk perception to an abstract communicative form. The same mechanism that is responsible for de-biasing of social information for personal use (e.g., others experiencing everything more intensely than ourselves, Jung et al., 2020) can be also responsible for the overweighting of small probabilities in description. In this experiment, people chose differently in the gain and loss domains when comparing described experience and objective descriptions. Specifically, in Described Experience, participants were more risk averse for gains, but more risk seeking for losses – the opposite to what is usually observed in Description, although in the same direction. Even though the mean described probability was a third higher than the objective probability presented in Description. In Described Experience, for gains, people tended towards more risky decisions than in Experience, but choices for losses in both conditions – Described Experience and Experience – were similar. For this, a social learning mechanism, either implicit (written) or explicit (observation), might be responsible. Because the outcomes randomly occurred throughout 40 trials, the results cannot be attributed to recency effect. Further, participants did not treat the Described
Experience identical to Description despite the fact that both – Described Experience and Description – were represented in abstract format using explicitly stated outcomes and their probabilities. Still, there were some differences between the two description formats: One had no representation of doors and was handed by their partner who created the description on the spot, and the other was provided by the experimenter on the computer screen. This suggests that people might be sensitive to the attributes of abstract social information in description format.

The key finding of this experiment is that even though described experience had the same format as DfD (risk represented in %), it was the direct result of personal experience transcribed to a symbolic representation. Described Experience thus possessed the attributes of personal experience, in particular, that there is no certainty about the full (objective) outcome distribution being reflected in sampling of the partner to make an accurate decision. Instead, people correctly infer and adjusted their behaviour to account for this social filtering of personal experience which was transferred to descriptions. With only a single social source, this behavioural adjustment might be particularly pronounced because a single social source is more likely to transform their experience to description in a biased way. Thus, the communication of individual experience might be counterbalanced in interpersonal communication to adjust for the skewness of experience on social level. In future experiments, it would be of interest to explore the described experience direction further by using different sources of personal (subjective) experience in choice.

People might adjust to the biases of a social source by integrating social information as an information filter layer, which would account for attributes of the social source attributes, such as their reliability (Hahn, Merdes, & von Sydow, 2018). In this way, the bias attributed to the gathering information about rare events from
personal experience is mirrored when gathering social information. The results of the experiment partly confirmed the hypothesis that social learning can contribute to some of the biases usually observed in individual risky decision-making. This result suggests a connection between personal subjective experience and objective, abstract information: that information is transformed for communication which combines the two learning modes. As in personal experience, in described experience, the probabilities are estimated rather than known with certainty. As in description, described experience can be judged by the reliability of the information and the social source (Harris et al., 2015; Jarvstad & Hahn, 2011).

To account for the biased perception of the information coming from social sources, specific cognitive mechanisms, such as abstract concepts, categorical inference, and the ability to combine internal symbols in novel, productive ways as well as sensitivity to statistical dependency are involved (Niedenthal, Barsalou, Winkielman, Krauth-Gruber, & Ric, 2005; Whalen, Buchsbaum, & Griffiths, 2013). In social learning, many factors are taken into account, including prior accuracy, expertise and reliability of the social source (Jarvstad & Hahn, 2011; Whalen et al., 2013). In some instances, however, people do not judge social information based on these factors but simply copy others’ behaviour (Cook, Den Ouden, Heyes, & Cools, 2014; Heyes, 2016a; Williams et al., 2001). Similarly, in the current experiment, the mechanism might be similar to but with less intensity than is observed in informational cascades (e.g., Huber, Klucharev, & Rieskamp, 2013). Taken together, the results point to an interesting pattern: when participants decided from Described Experience, they chose as if they were choosing from personal Experience, but in the direction to what is usually observed in Description condition.
3.4.4 Limitations

This experiment looked at three different ways people learn about outcomes and their probabilities – experience, described experience, and description. A key limitation is a potential order effect: the choice problems in the description format were posed after all the choice problems in experience and described experience were finished. Second, participants knew that their descriptions would be used by their partner, so they were aware of the communicative intent of their descriptions. A good addition to this experiment might have been to have people estimate the frequency without the communicative intent. In this case, people might make more calibrated, not overestimated, descriptions (Benjamin & Robbins, 2007) or they might still be biased based on regression to the mean in their estimates (Fiedler & Unkelbach, 2014). Then, the experiment might have been better able to determine whether the overreporting of rare events was a fundamental misperception of risks or arose from the social element.

A third limitation stems from the fact that the probabilities in the described experience were different from the probabilities in the description – the probabilities in these two conditions were not matched nor yoked. Thus, the differences in the choices between conditions may solely emerge from the effectively different choice problems. However, this is unlikely because the effect went in the opposite direction – e.g. rare losses were reported to appear more frequently than they were objectively encountered, yet participants using this Described Experience made more – not fewer – risky choices. The distortion stems from several factors: people tend to reference belief-consistent information, the selection of predictive or emotionally silent information that amplifies information about risks, and herding that impairs objective assessment and reduces exploration for novel solutions (Hills, 2018).
Finally, participants were asked to state the occurrence of rare events in percentages, not in a free form or as a frequency. People, however, do not find probability estimation intuitive because in natural settings, people are usually faced with natural frequencies, e.g., “it happened only once in past 20 years” (Cosmides & Tooby, 1996; Teigen, Juanchich, & Riege, 2013). Thus, participants also could be confused about the task, even after explaining what probability is before the experiment. But, one of the most compact and precise forms of information about a real-life risky events that people deal with often comes in probability (percentages), e.g., “10% chance” (Cosmides & Tooby, 2013; Teigen et al., 2013; Wisdom et al., 2013). So, this format was chosen in this research, but more formats need to be considered more formats of descriptions, such as text responses, comments, or reviews. Natural language processing techniques can be used to assess this type of natural (although online) information sharing – personal communication of risk using the key phrases like “almost impossible” or “pretty doubtful” would be useful (Stewart et al., 2006).

3.4.5 Conclusion

In the current experiment, even though participants tended to under-sample rare events, they over-reported the probability in their description. Based on the results from this experiment, risky decisions from described experience were found to combine the features of personal experience and description from risky-decision literature. Because individuals are biased to underweight rare events in experience, over-reporting of rare events in description might represent a mediator mechanism in interpersonal learning – amplifying rare events in personal experience when communicating about them. In this experiment, the over-reporting of experienced rare event probabilities compensated for the proportion of people who under-experienced rare events. This effect of under-experiencing and over-reporting of rare events might be even more pronounced on the
population level. Overall, the current experiment offered a novel view on the DE gap and the transition of information about risk from experience to description. Next chapter explores the effect of social source presence on how people use information.
Chapter 4: Information Source in Risky Choice

In today’s world replete with unverified information, a good adage might be: before accepting information, one should always check the source. People, however, do not routinely verify how reliable a source of information is, which might create systematic biases (Lewandowsky et al., 2017; Sikder et al., 2020a). People can make decisions based on information obtained from others that is acquired directly, such as by observation or utterance, or indirectly, by encountering information in written, spoken, or visual form (Hahn et al., 2009; Madsen, Hahn, & Vorms, 2017). All information obtained by a person can be either asocial or social, where asocial information is often personal learning by trial-and-error (i.e., from experience), and social information is the information obtained from others (Behrens et al., 2008; Heyes, 2016b; Madsen, 2013). A social source of information can communicate experience that was itself acquired socially or personally, thereby filtering this information (Demsky, 2020). In this experiment, how people make decisions using information about risks is investigated by presenting probabilities of different outcomes with a social source is present or absent (obscure). The aim of the experiment is to explore whether people would treat information differently if it has a social source or not.

4.1 Information Source

Not all information consists of raw facts scattered in the environment, but also information is often delivered by a social source, for example as personal experience, as discussed in the previous chapters (e.g., Sarkka, 2013). In this chapter, the effect of
social source presence on risky choice is explored. The social aspect of information matters for at least two reasons. The first reason is the reliability of sourced information, which is dependent on social source attributes, such as expertise and trustworthiness (Harris et al., 2015). Indeed, receivers of information readily judge social sources by attributes in addition to judging the quality of the information that they deliver (Hahn, Oaksford, & Harris, 2012; Harris et al., 2015). The judgment about social source helps the receiver to further evaluate delivered information (Madsen et al., 2017; Pariser, 2011). Indeed, social sources have a significant effect on people’s perception and judgement of social information. Identifying a social source produces a bias: people rate plausible information from distrusted social sources as having lower accuracy, but rate implausible information from trusted social sources higher (Dias, Pennycook, & Rand, 2020). The second reason is the content of information is intrinsically dependent on social source, which can be neutral, positive, or negative in terms of feedback or reinforcement (Behrens et al., 2008; De Martino, Bobadilla-Suarez, Nouguchi, Sharot, & Love, 2017b; Harris et al., 2015; Hawthorne-Madell & Goodman, 2019a). Social information coming from a social source who gathered directly from environment or by interacting with another social source, or the products created by them, e.g., abstract descriptions (Heyes, 2016b; Rendell et al., 2010). Social source attributes, such as identity, are important because they bias information perception of the receiver (Cohen, 2003; Hartman & Weber, 2009; Lakoff, 2002). For example, if the receiver aligns with the social source, they perceive them differently compared to misaligned social source. When the source is clearly defined, people adjust to that source. This adjusting can be also viewed as a process of debiasing and adjusting to personal experience. Thus, a social source can be described as a (social) information filter possessing personal or social information and having specific attributes that directs its information gathering.
The pattern of information gathering of social sources depends on individual biases to which people are prone to, such as uncertainty- or loss-aversion and over-confidence (FeldmanHall & Shenhav, 2019; Hintze et al., 2015; Johnson & Fowler, 2011). Because people need to learn from others effectively, adjusting to social source can be an effective learning strategy to avoid unreliable information. This chapter looks at how people judge and decide based on risk information coming with or without a clearly identifiable social source.

4.1.1. Social Information Filtering

The information that a social source provides can vary in utility, and thus varied effects on a receiver’s decision-making and behavior. Social information can be reliable or deceptive, novel or outdated; can take the form of learning material, advice, or opinion (e.g., Behrens, Hunt, Woolrich, & Rushworth, 2008; Bonaccio & Dalal, 2006; Moutoussis, Dolan, & Dayan, 2016; Yaniv & Milyavsky, 2007). Several studies have examined how a social source of information affects decision-making in terms of expertise and trustworthiness (Gershman, Pouncy, & Gweon, 2017; Hahn et al., 2012; Harris et al., 2015; Mannes, Soll, & Larrick, 2014). Some research suggests that the source of information might be given more weight in receivers’ decision-making than the information itself (Van Bavel & Pereira, 2018). Indeed, in some circumstances, people do weight social goals, e.g., belonging, more than objective goals, such as accuracy. Figure 4.1 illustrates how this distortion can result in the tendency to give a higher weight to social goals than accuracy goals when receiving social information. In
this case, a receiver’s judgement about a social source is more heavily skewed to the belonging and social attributes of information than the ability to provide accurate information (Graham et al., 2011; Xiao et al., 2016). Thus, social information value depends on the weight given to different sets of goals–either socially-related goals or information-related goals. When the former outweighs the latter, more value is given to less accurate information. Despite the importance of the social source in evaluating information, most research on risky decision-making is conducted without specifying the source of information given to participants when making a decision. Given the impact of described experience observed in Chapter 3, the potential effects of the social source of descriptions in risky decision-making may prove useful in understanding how people choose based on explicit descriptions. This chapter is dedicated to understanding the effect of social source in risky choice.

4.1.2 Decisions from Description

This experiment uses the decisions-from-description (DfD) paradigm to explore how social source modulates risky choice (Hertwig & Erev, 2009; Kahneman & Tversky, 1979). The DfD paradigm typically consists of binary choice problems between a risky and a safe option, which are provided as explicit descriptions of possible
outcomes and their associated probabilities. These descriptions are provided without any indication of the source of information. When using such descriptions, people generally overweight rare events. A simple DfD paradigm was used as it represents a basic one-shot decision based on social information. The DfD paradigm is often contrasted with DfE, which relies on personal experience. In DfD, people usually overweight rare events, but in personal learning (trial-and-error; Benjamin & Budescu, 2015; Hertwig, Barron, Weber, & Erev, 2004), people usually act as if they underweight rare events. This systematic difference that might be potentially rooted in the degree of “socialness” of information, whereby experience is purely asocial, but descriptions, by their very nature, have some element of social construction. Thus, it might be advantageous to treat described information as a form of social information.

If we assume that all descriptions of events are ultimately generated from the experiences of people and then communicated (Francis, 2017; Tomasello, 2010), an adaptive agent would adjust for a potential transmission error of that information because of social source (Kendal et al., 2018; Muthukrishna et al., 2015; Stubbersfield, Dean, Sheikh, Laland, & Cross, 2019). Transmission errors assume the introduction of variability when receiving information from a social source that can be moderated by specific identity attributes, such as expertise and risk-preference, and that information coming from them can vary in reliability (Harris et al., 2015; Mata et al., 2018; Mishra & Lalumière, 2011; Muchnik, Aral, & Taylor, 2013). Thus, DfD can be treated as social information containing a source that might be making a transmission error. One potential example of cognitive adjustment to the transmission error of a social source in a positive way is the tendency of receivers to pay more attention to the sources that are perceived as more knowledgeable and trustworthy than others (Harris et al., 2015; Hovland & Weiss, 1951). Indeed, it pays out to be selective about social sources because
different information varies in utility for each receiver, and thus has varied contribution learning and behaviour (De Martino et al., 2017a; Hawthorne-Madell & Goodman, 2019a; Heyes, 2016b).

4.1.3 Social Learning Strategy

As discussed in earlier chapters, the DE Gap can potentially arise because people systematically under-explore the distribution of gains and losses, i.e., undersample, when learning from direct interaction with the environment (Fox & Hadar, 2006b; Hau et al., 2010; Wulff et al., 2018). This is because personal exploration is costly in terms of time and resources and is therefore pressured to be as efficient as possible: to diminish the number of samples, but still learn efficiently (Berger-Tal, Nathan, Meron, & Saltz, 2014; Hills et al., 2015; Lieder et al., 2018; Sanborn, Zhu, Spicer, & Chater, 2020). Furthermore, risk aversion is potentially an adaptive mechanism for avoiding losses, when living in small groups (Hintze et al., 2015). One of the ways that sampling from personal learning can become “cheaper” and gaining in efficiency is to incorporate sampling of others (Balliet et al., 2016; Chamley, 2004; Lieder et al., 2018; Rendell et al., 2011).

To be adaptive, the mechanism that integrates social information from others should take into account this under-sampling and the resultant distortion of probability estimation, which can percolate through to distort any subsequent communication. This adaptation, however, can be viewed as part of a strategy for managing the interaction between personal and social learning about rare events. For example, a strategy to “exaggerate the impact of personally significant events”, similar to the “copy when uncertain” or “copy when experience is costly” social learning strategies, can be at play (Heyes, 2016b; Toelch, Bach, et al., 2014). Even though the value of information about events can be subjective and vary based on factors such as emotional charge or a noisy
environment, the experience of a social source should possess at least some value to the receiver as compared to no information about the event (Blanchette & Richards, 2010; Sharot & Garrett, 2016). In this way, the DE Gap could be the manifestation of the interaction between individual and a social learning adaptation identified in risky decision-making.

The majority of risky decision-making research presents information without an explicit source, providing no social attributes by which participants could judge the potential reliability of social information. In other words, if there are no clear social attributes, such as expertise or trustworthiness to which to adjust in the learning process, people still assume something about the social source. Absence of social attributes is potentially an unnatural way of receiving social information, and thus a source might be inferred (Collins, Hahn, von Gerber, & Olsson, 2018; Hahn et al., 2012), based on other attributes in the environment. Indeed, learning and decision-making are known to be sensitive to context, so the behaviour in these domain is also context-dependent (Hertwig & Pedersen, 2016; Madan, Spetch, Machado, Mason, & Ludvig, (in press); Olsson et al., 2020b; Stewart, 2009). This could be a potential reason for the overweighting bias in decisions from description: information that comes without an identifiable source is still treated as social information. Thus, the pattern of risky choices observed in decisions from description might be a behavioural adjustment to the transmission error of social sources as a bias related to social learning.

4.1.4 Current Experiment

The overall aim of this study was to examine how people’s risk preference and judgement of information reliability (Hawthorne-Madell & Goodman, 2019a) depends on the presence or absence of the source of information. In this experiment, two groups of participants made risky decisions based on information with (Sourced group) or
without (Unsourced group) a specified social source. For Unsourced group, choice problems with no source information was provided as is usually done in DfD (by presenting probability and odds). For Sourced group, additional source information was presented as coming from a particular person (see Fig 4.2). Participants were then asked about their personal perception of the presented social source and information. The experiment explores whether the presence of a social source results in a perception of a transmission bias by receivers. This bias would presumably result in Source group to overweight rare events in risky choice from Description.

We had several hypotheses for this experiment. First, described information might already implicitly indicate a social source, thus adding an explicit social source to the information might have no effect (Null). Alternatively, sourced information might be a more natural way to receive social information, and thus it can potentially be interpreted and applied more easily by receivers, leading to improved decision weights and less bias of overweighting of rare events. Therefore, sourced information could be perceived as more social than unsourced information, leading people to overcompensate for any bias in the individual experience of a social source. Further hypothesis was that social source might matter only for rare events due to differential probability weighting on individual and social level (e.g., Benjamin & Budescu, 2015; Newell et al., 2016). To test this hypothesis, the experiment used two types of choice problems (common and rare) to disentangle the effects of social source and rarity of events. Following this logic, we hypothesized that people would overcompensate for the bias to underweight rare events in experience (see Chapter 2) by choosing more riskily in rare, but not in common, choice problems (H1).

Another possibility is that the presence of a social source may trigger competitive motives in the receiver and thus make participants more risk-seeking across
all – rare and common – choice problems (H2) (Olschewski et al., 2019). Further, as in the existing risky-choice literature (Kahneman & Tversky, 1979), a bias toward overweighting of rare event in DfD is expected to be replicated, which corresponds to Unsourced group in the current experiment. Given the choice problem set shown in Table 4.1, in Unsourced group, people should be more risk-seeking for rare gains and thus pick the risky option more often than chance level as in the classical DfD conditions (H3). Moreover, the introduction of a social source may decrease the bias which is usually observed in DfD and would make participants in Sourced group gamble less for rare outcomes as compared to Unsourced group (H4 only follows if H3 is true). Finally, in terms of reliability perception, participants may judge unsourced information as more reliable than information that has a stated social source due to the absence of social source attributes by which they can adjust their judgments (H5). All hypotheses, methodological details, and the analysis plan were pre-registered at the Open Science Framework (OSF): https://osf.io/9hd2x/

4.2 Methods

4.2.1 Participants

A total of 266 participants were tested, based on a power analysis which indicated that with a medium effect size ($d = 0.4$), and a significance level at $\alpha =.05$, 133 participants per group (two groups) were required for 90% statistical power. Participants were recruited using the Prolific Academic crowdsourcing platform (https://www.prolific.ac/). Participants received a reward of £0.50 for completion of the task. The average completion time was 4 min; the maximum allowed time was 10 min. Of the tested participants, 69 (25.2%) failed to pick the dominant option in both manipulation checks (see below) and were thus excluded from the analysis. The final
number of participants used in the data analysis was 199 with 97 participants in the Sourced and 102 participants in Unsourced group (108 females, 91 males); 20.1% of them were 18-24 years old, 42.7% were aged 25-34, and 22.6% were aged 35-44. All participants provided informed consent, and the study was approved by the University of Warwick Psychology Department’s ethics committee.

4.2.2 Materials and Procedure

Participants were randomly assigned to one of two groups. Participants in both groups were presented with 12 descriptions of binary risky choice problems and asked to select their preferred option. In Sourced group, participants were informed that the probabilities used in the choice problems were reported by specific others, as shown in

Figure 4.2. An example of the information and source presented in Sourced group. All pictures of faces accounted for gender, race, age and facial expressions (see Appendix 3). In Unsourced group, only the part below the picture was presented (“Please, choose…”). Pictures were randomised by gender, age, and ethnicity. A full list can be viewed in the OSF link (see above). The pictures were obtained by Google image search labelled as “Non-commercial reuse with modification”.

This person had played the gamble and then reported the probabilities presented to you below.

Scott

Please, choose your preferred option from the choices below.

- **100% chance of receiving £8**
- **50% chance of receiving £13 or £5 otherwise**
Figure 4.2. In Unsourced group, participants were “not given any additional information and were only given the two choices with the outcomes and the corresponding probabilities with no picture.

<table>
<thead>
<tr>
<th>Choice Problem</th>
<th>Event</th>
<th>High Outcome</th>
<th>P(High Outcome)</th>
<th>Low Outcome</th>
<th>Risky Expected Value</th>
<th>Safe Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rare</td>
<td>303</td>
<td>0.01</td>
<td>3</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>81</td>
<td>0.04</td>
<td>6</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>Rare</td>
<td>29</td>
<td>0.05</td>
<td>9</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>53</td>
<td>0.02</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>30</td>
<td>0.1</td>
<td>0</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>Common</td>
<td>10</td>
<td>0.5</td>
<td>2</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>13</td>
<td>0.5</td>
<td>5</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>Common</td>
<td>15</td>
<td>0.5</td>
<td>5</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>7</td>
<td>0.5</td>
<td>1</td>
<td>4</td>
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<tr>
<td>10</td>
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<td>6</td>
<td>0.5</td>
<td>0</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

*Table 4.1. Choice problems used in the experiment.*

Table 4.1 lists the choice problems in the experiment: There were 12 choice problems in total, two of which were trick problems (see below). All the choice problems consisted of a choice between a safe option (fixed reward) and a riskier option, which led to one of two possible outcomes with stated probabilities. Five choice problems had rare events \((p < .1)\), and five only included common events \((p = .5)\). The risky and safe options had varied differences in expected values (from -2 to +2), thus encouraging a distribution of risky choices across participants. In addition, two of the choice problems were manipulation checks, where there was a clearly dominant option (£8 with \(P = 1\) vs. £6 with \(P = 0.03\) or £0 otherwise; £7 with \(P = 1\) vs. £12 with \(P = 0.5\) or £9 otherwise). Each choice problem appeared one at a time in random order for each participant.
For the Rare choice problems, a probability of 0.1 or lower was used for the risky options. For the Common Problems, a .5 probability for each problem was used. After making all decisions, participants were asked to provide their degree of confidence in the provided information using a 0-100 slider bar, with 0 representing “very unreliable” and 100 representing “very reliable”, i.e., complete confidence in the provided information (Jarvstad & Hahn, 2011), with the slider bar started at 50. After all choice problems were presented, participants were asked a free-text question regarding what they thought was the source of the provided probabilities for the risky options. This final question was to explore whether learning about the choice problems from others explicitly (see also Chapter 3) would be more beneficial information than simple probabilities for making their choices. This question provided information as to what type of descriptions people were looking for in this type of problem and whether they were interested in learning more information after receiving either explicitly social or asocial information.

4.2.3 Data Analysis

The independent variables were the source of information (unsourced, sourced) and the problem type (Rare vs. Common). The dependent measures were the proportion of risky choices and the reliability scores. The proportion of risky choices was defined as the ratio of the number of times the risky option was chosen when presented against the corresponding safe option (see Table 4.1). Means and confidence intervals were calculated across the sample for each group (sourced/unsourced) and condition (rare/common). As pre-registered, a two-way ANOVA was employed to test for three effects: main effect of group, main effect of condition, and their interaction. A $p$ value less than .05 was taken as statistically significant. If there was a significant interaction, then follow-up post-hoc tests were applied: two paired and two unpaired t-tests with
Bonferroni’s correction. All tests were performed using RStudio using `tidyr`, `lsr`, `stats`, and `Rmisc` packages. The degree of reliability was defined by the value indicated by the participant using the slider bar (0-100%). The question was asked about the information of all the risky choice problems provided to the participant within each group. To test the influence of information source on the reliability score, a simple two-sample t-test was used.

The response to the open-source exploratory question were coded post-hoc manually using the classification into five domains based on participants’ answers. The categories included the answers that people described in their answers. The first category was that participants assumed that the data did not come from other people’s experience but was instead generated specifically for this study by the researchers. The second was previous participants as mentioned in the experimental instructions. In this case, participants assumed that the data was collected from the experience of other people performing similar experiments. The third category was online resources–some participants assumed that the data was taken from internet: online casinos, generative odds, dice, bookkeeper, etc. The fourth category of answers was ambiguous answers. In this category, participants who provided unclear answers, which could be assigned to more than one of the three domains above or none of them. Lastly, some participants stated that they did not know where the data is coming from or who might be responsible for the provided information. Of particular interest were the responses of participants in Unsourced group as they provided answers reflecting the default assumptions about the ‘unsourced’ information usually presented in decisions from description.
4.3 Results

4.3.1 Proportion of Risky Choices

The first comparison was made between the participants in Sourced and Unsourced groups to test whether participants treated the provided information about the choice problems differently depending on whether social source was present or absent. A two-way mixed ANOVA tested the main effects of the group, choice problem type, and the interaction of the two. Figure 4.3 shows how people chose the risky option with similar proportion in the Sourced (44.4 ± 3.8%) and Unsourced (43.1 ± 3.8%) Groups ($F(1,197) = .22$, $p = .64$, $\eta^2_p = .001$; $BF = 0.12$, in favour of the null), meaning that the presence of a source alone did not reliably affect overall risky choice.

![Figure 4.3](image)

*Figure 4.3. Mean proportion of risky choices for rare and common problems in Sourced and Unsourced groups. Error bars indicate 95% CI for the means.*

Overall, participants gambled significantly more in rare compared to common lottery type ($F(1,197) = 11.58$, $p < .001$, $\eta^2_p = .056$; $BF = 19.4$, in favour of the alternative). There was also an interaction between the choice problem type and group ($F(1,197) = 5.85, p = .016, \eta^2_p = .014; BF = 2.36$, in favour of the alternative). Follow-up post-hoc pairwise comparisons with Bonferroni’s correction showed that, in Sourced group, people gambled significantly more often in rare compared to common problems ($t(96) = 4.13, p < .001, d = .59, 95\%$ CI = [.30, .88]; $BF = 235.7$, in favour of the alternative). But, there was no difference between rare and common problems in
Unsourced group that represented DfD procedure ($t(101) = .71, p = .46, d = .10, 95\% CI = [-0.18, .37]; BF = 7.14, in favour of the null), thus DE gap was not replicated in this experiment. Social information (in Sourced group) potentially made the information more believable, and thus prompted participants to choose more riskily, but only in rare choice problems as was predicted by H1. These results contradict H2 that sourced information makes people gamble more overall and H4 that sourced information makes people gamble less in rare choice problems. In Unsourced group, participants chose the risky option less than half of the time in common problems ($M = 0.39 \pm 0.03; t(101) = 4.13, p < .001, d = 0.58, 95\% CI = [.30, .86]; BF = 238.98, in favour of the alternative), but not reliably so in rare problems ($M = 0.48 \pm 0.05; t(101) = 1.64, p = .11, d = -0.23, 95\% CI = [-.51, .05]; BF = 2.50, in favour of the null); this finding provides evidence against H3, which stated that people in Unsourced group would choose significantly more than chance level in rare choice problems. These results imply that participants only in Sourced group were sensitive to the probability of outcomes (rare vs. common) as was predicted, but the usual effect of over weighting of rare events was not observed in Unsourced group, which in this experiment was equivalent to a standard DfD.

As an exploratory analysis, risky choice in Sourced group was also compared against the chance level of gambling 50% of time. People in Sourced group reliably chose the risky option less than half of the time in common problems ($t(96) = 6.44, p < .001, d = .92, 95\% CI = [.63, 1.22]; BF > 1000, in favour of the alternative), but there was no difference between participant choice and 50% chance in rare problems ($t(96) = .69, p = .49, d = 0.10, 95\% CI [-.18, .38]; BF = 7.1, in favour of the null). Overall, the results show that when presented with sourced information about risky choice problems, people select the risky option more often in rare as compared to common problems;
when no source information about the gambles was presented, people chose equally in rare and common problems.

4.3.2 Individual Choice Problems

As a further analysis, risky choice within each problem was compared across groups to assess whether specific choice problems drove the difference between the choices in rare and common choice problems. Indeed, there was a significant difference between the Sourced and Unsourced group only in Problem 1 ($\chi^2 (1, 199) = 8.24$, $p = .004$, Cramér’s $\phi = .20$), with means of 75.3% and 55.9%, respectively (Fig. 4.4). However, the direction of the difference between the groups was the same across all rare choice problems.

Risk preference for each of the 10 choice problems was investigated across the two groups in post-hoc comparisons. As would be expected given the differences in expected values, risky behaviour appeared in descending order starting from Problem #1 to #5 in the rare choice problems and also from Problem #6 to #10 in the common
choice problems. The risk preference differed systematically between the choice problems in both rare ($\chi^2 (4, N = 199) = 137.2, p < .001, \text{Cramer's } \phi = .37$) and common ($\chi^2 (4, N = 199) = 412.0, p < .001, \text{Cramer's } \phi = .64$) choice problem types. Further, a post-hoc contingency table test (Beasley & Schumacker, 1995; García-pérez & Núñez-antón, 2003) was performed to confirm that the proportion of risky choices was significantly different from the mean in rare ($M = 48.3\%$) and common ($M = 39.2\%$) problem types (see Appendix 2 for all reported values). There was a descending pattern of proportion of risky choice as per EV, but not in Choice Problems 3 and 8, where the proportion of risky choices did not significantly differ from the mean (Fig. 4.4). This pattern, however, appeared only for common problems, but not for rare problems, where Choice Problem 4 was also non-significantly different from the mean. This EV difference between safe and risky choices were overridden by bias within 1 EV point. Interestingly, participants played almost in similar patterns despite the large EV difference between these choice problems (2 points difference going from Choice Problems 2, 3 and 4). This might imply that the overweighting of rare events happened in this range of EVs, when, for example Choice Problems 4 and 9, where the EV difference was -1 are directly compared.
4.3.3 Reliability

The degree of reliability of the information was defined by the value indicated by the participant using the slider bar (0-100). Participants were asked to indicate how reliable they thought the information was for the probabilities used in the problems. Figure 4.5 shows how people rated unsourced information as more reliable (67.1 ± 4.4%) than sourced (54.6 ± 5.0%) information, \( t(192) = 3.70, p < .001, d = 0.53, CI = [0.25, 0.82]; BF = 80.48, \) in favour of the alternative), supporting Hypothesis 5.

*Figure 4.5. Reliability scores for Sourced and Unsourced groups. Error bars represent 95% confidence intervals of the mean. \(* p < .001.\)

*Figure 4.6. Reliability score of social source and proportion of risky choices of participants in Sourced and Unsourced groups.*
In an exploratory analysis, the relationship between perceived reliability and risky choice of information was examined. Figure 4.6 depicts the relationship between the proportion of risky choices and the perceived reliability of information in both Sourced and Unsourced groups. There was a mild, not statistically significant, correlation between reliability and risky choice across groups \((r(197) = -.13, p = .062, 95\% \text{ CI } [-.26, .01])\). When people rated the information as less reliable, they tended to take more risky choices, but only in Unsourced group \((r(97) = -.20, p = .04, 95\% \text{ CI } [.003, .38])\), not in Sourced group \((r(97) = -.057, p = .58, 95\% \text{ CI } [-.25, .14])\). This suggests that the presence or absence of a social source made participants weight information differently to make a risky decision.

### 4.3.4 Source of Information

Participants were asked to state what they thought was the source of the provided outcomes and their probabilities. Participants’ assumptions about the source of the provided information varied depending on whether the source was present or not \((\chi^2 (4, N = 199) =11.43, p = .022, \text{Cramer’s } \phi = .24)\). As can be seen in Figure 4.7, overall, 56.9% of participants in Unsourced group and 67.0% in Sourced group thought the information about choice problems was coming from other people. Sourced group

![Social Source](image)

*Figure 4.7. The assumed social source of information as reported by participants in Sourced and Unsourced groups.*
mostly reported that the information was coming from other people who generated the information in previous trials (32.0%) as was expected per the experimental description provided to participants. Even though Unsourced group reported that they did not know (36.3%) where the information about the choice problems came from, as it was not specified for them in the experimental description, still, about the same proportion of participants in this group (28.4%) reported that the information was coming from other people from an external source, e.g., a poker website.

The result provides insight into baseline perception of unsourced information in that a social source is still assumed. Additionally, participants were asked whether they felt some additional information about the choice problems would be helpful. Over half of the participants in Sourced group (54.6%) stated that more information would have been helpful in choosing between the options as compared to Unsourced group where only one third of participants stated so (31.4 %) ($\chi^2$ (2, N = 199) = 12.24, $p = .002$, Cramer’s $\phi = .002$). This result implies that the social source might change the perception of described information about risk through both its reliability and helpfulness.

4.4 Discussion

The current experiment evaluates the idea that the reason people overweight rare event in decisions from description is because of an implied social source in non-social descriptions. More specifically, people might de-bias description, based on how individuals usually react to events in personal experience and how it is transformed to a described form – by over-estimating rare events. These results are in line with Chapter 2 and Chapter 3, which showed a smaller individual bias in risky choices from observational or described experience as compared to personal experience, confirming
the idea that a social learning strategy, such as using social source attributes to judge social information, might play a role in this risky choice from description. The reason why participants acted as if the rare outcomes had more weight than it actually did, is that people could pay extra attention to the given social information attributes, such as social source, to account for source transmission error in communication and adjust personal behavior appropriately.

Risky decisions might be specifically affected by information with an identifiable social source that might signal information value. In the current experiment, participants presented with a social source tended to choose slightly more riskily for the choice problems with rare outcomes as compared to those who did not receive information with a source. Further, the reported reliability of unsourced information was scored higher compared to socially sourced information. Participants were also more likely to ask for additional information when a source was present. Overall, these results hint at the idea that people use an (implied) social source of received information as part of their decision strategy when making risky decisions from description.

4.4.1. Role of Source in Decision-Making

The social aspect of described information has been given scant attention in decision-making research so far. The current experiment addressed the problem of the source of information that has been covered in belief and information perception research. There was no difference in risky choices between participants who chose from sourced as compared to unsourced descriptions across all choice problems. Nevertheless, there was a mild effect of social source for both rare and common problems, pulling the risky choice for common and rare choice problems in opposite directions. One of the reasons for this effect can be that social source can direct other decisions by signaling information value. Further, when information is presented with
a source, such as telling an example from personal life, it is a natural way of receiving social information, so it might lead to improved decision weights and less bias in personal decisions (Moutoussis et al., 2016; Taylor & Thompson, 1982).

The overall effect of social source presence was mild overall – the effect was driven by the choice problem with the highest expected value for the risky option in rare events. In the case of risk, a social source might lead people to compensate for the typical bias toward underweighting of rare events in experience, by choosing more riskily in rare-event choice problems (H1). Competitiveness, which would lead participants to try to maximise their outcomes by playing more riskily (Olschewski et al., 2019), however, cannot explain the results as the riskiness was observed in rare choice problems only, not across all choice problems (H2). There was also no typical “fourfold pattern” of risk preferences that implies risk-aversion for gains of moderate or high probability and risk-seeking for small probabilities (Barberis, 2013; Tversky & Kahneman, 1992). The effect of social source might be mild, but it provides some evidence for a potential adaptive social learning strategy that is used in learning from described information.

4.4.2. Expected Value Difference and Choice Problem Type

Contrary to the bulk of literature, in this experiment, no evidence was found for the overweighting of described rare events in Unsourced group, corresponding to DfD (Glöckner, Fiedler, Hochman, Ayal, & Hilbig, 2012; Glöckner, Hilbig, Henninger, & Fiedler, 2016; Hertwig & Erev, 2009; Kahneman & Tversky, 1979; McDermott et al., 2008; Wulff & Hertwig, 2018). In Unsourced group, which was equivalent to a standard DfD, people selected the risky option no more often in rare than common problems: people were not risk-seeking for the rare-event problems, the riskiness readily was overcome by a mild difference in EV. One of the reasons of the failure to replicate the
overweighting of rare events in DfD might be because of the specific choice problems used in the study. Participants were sensitive to differences in EV: when the risky option had a higher EV, people often did indeed select the riskier option. This pattern, however, was only wholly consistent for common problems; in rare problems, participants played similarly when the EV difference ranged from +2 to -1 towards a risky option, but with a decreasing preference according to the decrease in EV. Specifically, in rare Choice Problem 3 that had equal EV (EV = 0) and Choice Problem 4 that had a negative EV difference for the risky option, people showed a touch of overweighting, but the average was lower because Choice Problem 5 that had a zero outcome was strongly avoided (Keupp, Grueneisen, Ludvig, Warneken, & Melis, 2020; Pisklak, Madan, Ludvig, & Spetch, 2019). In addition, a risk-seeking pattern for the extreme outcome (Problem 1) was observed, and there was a drop in risky choice in Choice Problem 5, which needed less effort to calculate, but also had the largest positive EV difference across choice problem type (Brady & Wheeler, 1996; Kool & Botvinick, 2014; Ludvig et al., 2014). Overall, EV sensitivity was not more significant in Sourced than Unsourced group, but participants still gambled more overall in rare compared to common problems in Sourced group.

4.4.3 Social Source Attributes and Information Value

People pay particular attention to attributes that are salient in a given context. The social source can be viewed as a salient feature in an environment for attention, as is discussed in stimulus enhancement and goal emulation (Charpentier et al., 2020; Dosher & Lu, 2000; Heyes, 1994). In communication, the information receiver considers the social-source attributes such as identity, preferences, or experience, which help to better perceive information and estimate its value (Xiao et al., 2016). The specific attributes of social source, e.g., a person or a group, can modulate how
information is perceived by receivers. Thus, attention to social source attributes can enhance or downgrade information value. Further, the social source reliability of information is an important cue for a receiver that considers information from a social source – an attribute that would benefit from careful attention before using the received information (De Martino et al., 2017a; Hahn et al., 2009; Jarvstad & Hahn, 2011).

In the current experiment, as predicted (H5), Unsourced group judged the provided information as significantly more reliable than Sourced group. In Unsourced group, participants could not evaluate information by its social source’s attributes; however, they could infer those attributes based on the experimental setting. A large proportion of the participants across both groups thought that the information about choice problems was coming from researchers, the perceived attributes of which might have inadvertently increased the reliability of received information. In this way, the unsourced information could be perceived as a statement or cumulative statistics coming from an expert, such as the researcher responsible for the experiment, and thus taken with more acceptance (Bonaccio & Dalal, 2006; Harris et al., 2015). In the Sourced group, as was indicated to the participants, the most reported source of information was “data from previous experiments”, so the formal setting might not rule out the difference in the scores fully.

The result that participants in Sourced group judged information as less reliable goes in conjunction with another finding that participants were less likely to ask for extra information when the social source was absent. It might be because participants in Unsourced group did not pay attention to the source of information or, given the context, assumed that the information source is the researcher, but accepted information as it is – as a statement or testimony that can be directly used in one’s own decision-making (Madsen, 2013). In Sourced group, participants were presented with more
information that could imply the social source attributes (source’s photo and name). Sourced group rated this information with additional social source attributes as less reliable, and that in turn, perhaps drove them to desire more information about the choice problems. This is intriguing, because the only difference between the groups was the presence (or absence) of a person’s portrait, a name, and a sentence stating that the outcomes and probabilities were made by the person when sampling the choice problems for themselves.

Information without an assumed social source can be taken as a base case, potentially similar to personal information, received from trial-and-error interaction from the environment, and thus rated as more reliable. In future research, it would be beneficial to address what (if any) type of “ghost” information or “robo-advice” is perceived by people as being more reliable (Croxson, Feddersen, & Burke, 2019; Ferrucci, Nougaret, & Genovesio, 2019). This has implications for understanding when people believe delivered information as a function of the presence or absence of a clearly identifiable source (Nakatudde, 2017).

### 4.4.4 Transmission Error

According to Communication theory, a slight increase in participants preference in risky choice in rare choice problems, and in one with the highest positive EV difference, might stem from a transmission error which implies a modification of information during communication from social source to receiver (Kasperson et al., 1988; Kendal et al., 2018). Transmission error could amplify social information as suggested by the risk communication literature, which usually explores risk perception in news and social media coverage (Ambler et al., 2011). This effect can be looked at through the lens of social learning. If we assume that all descriptions about events, including symbols more generally (Francis, 2017; Tomasello, 2010), are ultimately
generated by the experiences of others who generate the descriptions, an adaptive system would need to adjust to any transmission errors in that social information, tracking information value coming from social sources (De Martino et al., 2017b; Kendal et al., 2018). If such an adaptation exists, then it might manifest as a social learning strategy. When information is unsourced, there are no social attributes or intentionality to which to adjust, and thus, unsourced information could be perceived as more reliable (Hawthorne-Madell & Goodman, 2019a). Indeed, sourced information could be perceived as biased by participants, resulting in a slight adjustment to choose more riskily in rare choice problems as compared to common ones. This potentially can be explained by the fact that in DfE, people systematically underweight rare events and, which would be in turn under-represented when the information about those rare events is conveyed to others. Under this mechanism, receivers might then overcompensate for the typical bias of rare-event underweighting in learning from experience (Hertwig et al., 2018).

The Amplification of Risk Theory suggests that outcomes and their probabilities can be systematically exaggerated by people, similar to the effect observed here (Frewer, Miles, & Marsh, 2002; Kaspersion, Kasperson, Pidgeon, & Slovic, 1988; Kasperson & Kasperson, 1996). The risk communication literature though looks mostly at negative risk consequences (e.g., health hazards), which corresponds to the domain of losses in the risky decision-making literature. In this experiment, the choice problems were only in the gain domain, but an effect could arise through a similar mechanism: participants in Sourced group were more risk-seeking for rare choice problems as compared to common choice problem, implying an amplified signal for receivers by presumed social source.
4.4.5 Limitations

The main experimental results showed that people did not distinguish between sourced vs. unsourced had small effects, and there might be several reasons for this. First, the final sample size was reduced due to the large number of exclusions, which resulted in less than necessary sample size to detect the expected medium effect size as per the pre-registration. Second, people were presented with a social source in the form of a collection of photographs that contained uneven background and which were not normalised to the same standards: some pictures were taken outside, and others were more professionally done. It would be of interest to try to use pictures of participants taken in the lab or people in a gambling environment, such as a casino (Burton, White, & McNeill, 2010), but, again, that would add another clue about where the information is coming from. Next steps could also include assessing the usefulness of social information by judging how trustworthy the social source is using survey and behavioural measures.

4.5 Conclusion

In this experiment, social learning was further examined as a potential driver for the DE gap, and, in particular, whether an implied social source might be responsible for the overweighting of rare events in DfD. Participants selected slightly more riskily when information about rare choice problems was sourced as compared to common choice problems, but no such effect was observed when participants received unsourced choice problems. Participants also rated sourced information as being less reliable than unsourced information and tended to ask for more information regarding the choice problems. These results provide some evidence for the presence of a potential adaptive social learning strategy to counteract source transmission error, when faced with
presented social information. Next chapter looks how transmission error can be viewed as subjectivity – identity – between social source and receiver.
Chapter 5: Identity Alignment

Nature is uncertain, but people adapted to extract patterns in information from the noise with the help of others (Denrell & Le Mens, 2007; Körding, 2007; Thornton & Mitchell, 2017; Toelch et al., 2009; Wilson et al., 2014; Zhu et al., 2020). To deal with the uncertainty of the world, people learn the dependencies of their own experience and compare them with the experience of others (Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Mahmoodi et al., 2018). People who possess similar identity attributes are likely to have similar goals (Fritsche, Barth, Jugert, Masson, & Reese, 2018; Walton et al., 2012). If individuals have similar or shared goals, then the information they share or behaviour they exhibit is likely to be more valuable as compared to the information received from others with conflicting identity attributes, which can imply divergent goals (Denrell & Le Mens, 2007, 2015; Markant & Gureckis, 2013). Thus, social source identity attributes can mediate value of social information and affect receiver’s decision-making.

Research on social identity highlights the readiness with which people associate themselves with each other and how this affects individual behaviour. A slight or even random similarity between two individuals can create a positive social connection known as in-group favouritism (Tajfel & Turner, 1979; Turner & Oakes, 1986a; Wilder, 1986). But despite this seemingly random associations with others, people create meaningful social connections: we are friends with others who have similar interests to us or simply reside in the same area (Cummings, 2004; Gentzkow & Shapiro, 2011; Pariser, 2011). But here stands a problem: if one learns solely from similar others, this can converge to an informational cascade, thereby halting further learning and decreasing adaptive behaviour (Bikhchandani, Hirshleifer, & Welch, 1998b; Rieucau
& Giraldeau, 2011; Sikder et al., 2020a). Thus, people are adapted to navigate the world strategically to understand from whom it is useful to learn: the similarity of a social source to the receiver can be useful in terms of information gathering because the receiver can emulate useful goals and copy actions of an akin social source. Dissimilar others, however, might also play an important role in information search, by facilitating random exploration via social learning (Backstrom & Leskovec, 2011; Granovetter, 1983; Wisdom et al., 2013; Xiaowei & Xintao, 2009). The current chapter looks at how identity alignment – between social source and receiver – affects the receiver’s perception of the social source and the information they deliver.

5.1 Identity and Information

Social sources gather and manipulate information in predictable ways that can be viewed as a transmission error (see Chapter 4, Discussion) – an individual bias based on identity. Information receivers might be particularly attentive to this bias that contributes to information filtering in a certain way (Bestelmeyer et al., 2015; Brewer, 1988). There are many identities that people associate themselves with such as ethnicity (Schultz Kleine, Kleine, & Laverie, 2006), gender (Butler, 2011; Cross et al., 2011; Fearon, 1999), sports team (Heere & James, 2007) and brand loyalty (Corry & Jørgensen, 2015; Funk & Kennedy, 2016; Giddens, 2015). These identities provide information about a person’s background, experience and preferences. Individual identity is built upon two foundations – personal and social identity. Personal identity includes the unique personal characteristics of a particular individual (Cross et al., 2011; McConnell, 2011; Strohminger et al., 2017). Social identity is an association that a person claims to various groups (Abrams & Hogg, 1988; Tajfel & Turner, 1979). Based on these two vectors of identity, there is a continuum of human behaviour with
interpersonal behaviour at one end and intergroup behaviour at the other (Tajfel & Turner, 1979). In recent years, research on identity has highlighted the prominence of groups in individual cognition and behaviour: relationships that are important to an individual tend to become incorporated into the representation of self (Brewer & Gardner, 1996; Grimalda, Buchan, & Brewer, 2018) and shape one’s sense of reality (Hardin & Higgins, 1996). Similarly, individuals within groups create reality based on shared beliefs and attitudes which modulate perception (Van Bavel & Pereira, 2018). Social sources of information can play the role of informational filters by categorising and simplifying information: specific others gather and communicate information in a predictable way (Grüter, Leadbeater, & Ratnieks, 2010; McConnell, 2011; Rendell et al., 2010). Paying attention to the identity of a social source simplifies the overwhelming information flow from the environment by directing valuable information flow from others.

Social identity is formed by people’s desire for belonging as the result of our ancient need for group-forming (Harris Bond & Leung, 2009; Oyserman & Lee, 2008; Richerson & Boyd, 2004; Toelch, Bruce, Newson, Richerson, & Reader, 2014). Social identity involves a compromise between two opposing needs: the need for assimilation and the need for differentiation, which in turn creates an in-group, out-group duality: “us vs. them” (Fearon, 1999; Turner & Oakes, 1986b). Affiliation to specific others provides basic and social needs (e.g., sharing food and avoiding risks), but also aids communication and learning that can direct goals (Frith & Frith, 2011; Heyes, 2016; Smolla et al., 2016). Furthermore, because the environment contains information that can be used to learn to adapt and advance, individuals filtering information and then communicating it to others is a useful process that helps to avoid risks and save time. This potential benefit of social information filtering raises the question of how the
source of information should be taken into account in the interpretation of delivered by them information (Hahn et al., 2018).

People need to distinguish the attributes of personal identity from the attributes of another person’s identity to effectively interact and learn from each other. In any social interaction, theory of mind is at play – the process whereby individuals apply mental states such as attitudes, beliefs and goals to other people (Baker et al., 2009; Hawthorne-Madell & Goodman, 2019b; Leslie, 1987; Wimmer & Perner, 1983). When we interact with others, we are quick to categorise them as, for example, friendly or hostile, based on superficial attributes such as dressing style, or more insightful attributes such as moral views. This automatic categorisation as well as the surrounding context of social interaction carries emotional charge (Petty & Wegener, 2010; Thomas, McGarty, & Mavor, 2009) that directs perception (Van Bavel & Pereira, 2018; Xiao et al., 2016). But this categorisation and consequent association with others can be based on minimalistic or random considerations. Walton and colleagues (2012) found that a sense of social connectedness with unfamiliar others, such as the same birth date, can lead people to acquire the motivations of these others. Indeed, one of the reasons for individuals to form groups with similar others is because they are likely to search, gather and share information that is useful to them (Campbell-Meiklejohn et al., 2010; Dunne & O’Doherty, 2012; Graham et al., 2011). To understand if a social source is useful for a receiver’s needs and goals, people need to categorise others by identity attributes, which can inform the receiver about specific preferences, habits and motivations of the social source and help ensure a useful social interaction. Social source attributes are potentially more complex than a simple in-group/out-group dichotomy.

Despite significant research directed at understanding the effects of social identity on attitude change (Greene, 2016), belief (Van Bavel & Pereira, 2018), and
learning and political behaviour (Frimer et al., 2017; Nyhan & Reifler, 2010), less attention has been given to identity alignment – not the identities per se – and how it affects the perception of a social source and the information they deliver. In the current chapter, identity alignment was defined as the presence (or absence) of a correspondence between participant preference for an identity with the identity of social source. The aim of the experiments in the current chapter is to tackle the question of alignment by comparing the difference in people’s perception of information after interacting with a social source with an aligned or misaligned (i.e., rival) identity, by looking at political identity and brand loyalty.

5.1.1 Social Alignment

People readily adjust their personal views according to the views of their associated group (Tajfel & Turner, 1979; Turner & Oakes, 1986a). The theory of uncertainty reduction suggests that by psychologically bonding to an in-group, individuals obtain a clearer picture of their role in the present environment (Hogg & Abrams, 1993; Mullin & Hogg, 1998). As the result of this self-affiliation, people define themselves with others as members of the same category, and further self-stereotype in relation to that particular category by seeing themselves as even more alike (Haslam & Reicher, 2015; Kurzban & Descoli, 2008; Martin et al., 2014; Walton & Cohen, 2011). Indeed, perceptions, beliefs and actions are often aligned in a socially identified group. This social alignment brings its own advantages, such as better communication and coordination of resources. For example, accents in speech can be viewed as an identity attribute as information receivers are highly sensitive to the variation in speech and use accents to make social judgments about the social source, such as the speaker's personality (Dailey, Giles, & Jansma, 2005). People also exhibit a social preference bias
via social group membership towards accents that are similar to personal accent (Bestelmeyer, Belin, & Ladd, 2015; Labov, 2006).

Beyond explicit group memberships, such as mother tongue or ethnicity, people also infer the structure of social influence by grouping others and themselves by what choices are made (Gershman et al., 2017). This categorisation then helps people to decide whose choices to follow in the future. If a social source makes a choice that corresponds to the preferences of the receiver (e.g., “She likes dogs – I also love dogs!”), the preferences of the two are aligned. Alignment in preferences also signals alignment in behaviour that can in turn be exploited in an information exchange (“Do you know a nice place to walk a dog?”) (Kelman, 2005). Thus, alignment is a complex mechanism spanning the personal-social continuum starting from general group associations and preferences to personal choices.

Social alignment is comprised of three feedback loop components: a gap-monitoring system that detects the level of difference between self and others, an observation–execution system that regulates alignment, and a reward system responsible for signaling that the gap is optimal and that the individual is aligned with others (Shamay-Tsoory, Saporta, Marton-Alper, & Gvirts, 2019). For example, if a person associates themselves with a liberal government party, then they are rewarded for signaling liberal values to others, as someone from whom others can learn about the preferences and goals associated with that value. Indeed, political identity is one of the strongest identities that people hold, given the number of potential in-groups (Federico & Ekstrom, 2018; Rosenmann, Reese, & Cameron, 2016). Acquiring information in a social environment is a good learning strategy, but in certain instances it can also be maladaptive (Heyes, 2017; Heyes, 2016; Rendell et al., 2010; Smolla et al., 2016).
In a social environment, such as a political debate, people are rewarded by aligning beliefs and behaviours with others, but the accuracy or impartiality of those beliefs is not necessarily rewarded (Shamay-Tsoory et al., 2019; Van Bavel & Pereira, 2018; Xiao et al., 2016). In this case, social learners can become blind to the quality of information when acquiring new likes and dislikes from others, despite individual rationality. This effect of social alignment is known as an information cascade in which people make judgments based solely on the decisions of other people, ignoring personal knowledge (Anderson & Holt, 1997; Schöbel et al., 2016; Ziegelmeyer, March, & Krügel, 2013). Information cascades happen because the associations with others (via belonging) modulate information perception and the decision-making process (see Figure 4.1, Chapter 4) resulting in the acceptance of suboptimal or erroneous judgments (Anderson & Holt, 1997; Bikhchandani, Hirshleifer, & Welch, 1998a; Huber et al., 2013; Van Bavel & Pereira, 2018; Xiao et al., 2016). This process can also be viewed as filtering of social sources in learning: it is useful to conform if the value of social information is higher than personal information.

5.1.2 Social Information Perception

Acceptance of erroneous social information still can have a significant influence on individual beliefs and even become a norm in certain circumstances (Çelen & Kariv, 2004; Huber et al., 2013; Muchnik et al., 2013; Shamay-Tsoory, 2019). When personal and social information clash, an individual experiences cognitive dissonance (Wood, 2000). Because this state is aversive, people want to adjust by accepting either the personal or the social information (Van Bavel & Pereira, 2018). In some circumstances, it pays to not be accurate, but instead to align with others in beliefs and attitudes. The trade-off between accuracy of beliefs and belonging goals is thought to stem from pressure individuals face—for conformity and epistemic closure (Bikhchandani et al.,
People readily align with specific others to save time and resources when making judgements and acquiring motivations. This readiness to learn from similar others, however, can often result in a limited or biased learning. In the current chapter, Experiment 1 looked at political identity (US partisan political parties) and Experiment 2 looked at brand loyalty (popular coffee shops) to explore the idea that people might dissociate between the social source and the information they convey by perceiving and evaluating them to learn new information. These identities were chosen because political party affiliation is well-known to be polarizing with clearly distinguished identities, rather than a spectrum. The picture is less explored for brand loyalty, but it can still be a strong identity for many people (Feinberg & Willer, 2013; Haslam & Reicher, 2015; Kuo & Hou, 2017; Sikder et al., 2020b).

The first research question addressed the problem of evaluating social source and information that they deliver. Information can be evaluated in different ways – by attitudes, belief formation, or outcome behavior. Attitudes emerge from the evaluation of cognitive and affective reactions towards a stimulus, which can also include a social source (McGuire, 2008; Van Bavel & Cunningham, 2010). Attitudes towards certain issues can heavily depend on the social group with which the person affiliates (Kaltenborn, Krange, & Tangeland, 2017; Smith & Hogg, 2008). Beliefs, in turn, are related to and can be influenced by attitudes (Feldman & Lynch, 1988). In a social setting, people can use groups to validate their own beliefs (Festinger, 1954). An individual’s degree of belief in a particular proposition or hypothesis can be represented as a subjective probability on a scale between 0 and 1 (e.g., Oaksford & Chater, 2007) or any other continuous measure.
A second question assessed how people would behave toward social sources with aligned or misaligned identifies. To assess this, the behavioural measure used in the study was sharing, which was operationalised using the Dictator game (Engel, 2011). Sharing behaviour is a measure of prosocial behaviour which can be characterised as one’s effort to increase another person's welfare (Bénabou & Tirole, 2004; DeLamater & DeLamater, 2018). People tend to give more to in-group members compared to out-group members (e.g., Ben-Ner, Kramer, & Levy, 2005; Ben-Ner, McCall, Stephane, & Wang, 2009), but not always (e.g., Lei & Vesely, 2010). Identity alignment can modulate information perception in a similar way: reflecting the general in-group/out-group trend of monetary sharing, information sharing can be perceived more positively from a social source with aligned identity, and less so with misaligned identity. Thus, when the source of information has similar identity associations, shared information is more welcomed by receivers and vice versa for social source with misaligned identity.

In two experiments, participants were asked to choose between two rival identities and then read the information provided by a social source with either aligned (i.e., corresponding) or misaligned identity. Participants were asked to rate the information on an attitude scale. The primary dependent measures in this study were attitudes, beliefs and behavior towards climate change policies. Thus, there were three hypotheses in the current study. The first hypothesis was that there is a connection in how people evaluate information and social source delivering it: people evaluate social source in a similar way to how they evaluate the information the social source delivers (H1). In this case, a social source with an aligned identity should be evaluated more positively and the information they deliver should be also judged more positively, and vice versa for a source with a misaligned identity. Alternatively, information and social
source may be only weakly linked when evaluated, so there is no evaluation “spill-over” from a social source to the information they convey (H2). In this case, social source and the information they deliver would not be evaluated similarly: e.g., social source with aligned identity would not be evaluated more positively, but it would stay neutral or go in opposite direction compared to the perception of information they deliver. The third hypothesis was concerned the Dictator game and sharing behaviour. From a behavioural perspective, participants should share more with the social source that has an aligned identity compared to a social source with a misaligned identity (H3).

5.2 Experiment 1: Political Identity

In Experiment 1, identity alignment was explored by looking at a polarised topic in the U.S. political landscape: climate change policies. The influence of identity alignment on attitude, belief, reliability of information, and social source trustworthiness as well as sharing behaviour was explored. In the current experiment, group affiliation was disentangled from identity alignment, by including both party identifications (e.g., Republicans and Democrats) in each group—either aligned or misaligned.

5.2.1 Methods

Participants

Statistical power analysis was performed with GPower 3.1 (Haslam & Reicher, 2015; McConnell, 2011) taking as reference Walton et al. (2012), which showed that the effect sizes for their main effects ranged from $d = 0.24$ for belief to $d = 0.32$ for negative attitude. We decided to be conservative about the potential effect size of the current experiments and calculated that with a target effect size of 0.24, power of 0.8, and error probability $\alpha=0.05$, the sample size should have a minimum of 178
participants in the experiment for a two-tailed between-participant design. Participant recruitment used a US-based sample on Amazon Mechanical Turk, and recruitment stopped with 30% participants in excess of the power analysis sample size calculation. Overall, 282 participants were recruited, but the participants who either failed to complete the experiment or failed the manipulation/attention checks were excluded in the analysis. Thus, the final sample consisted of 214 participants (M_{age} = 39.2 \pm 1.7; 103 females; 74 Republicans, 140 Democrats) who passed the manipulation and the attention checks. There were 98 participants in the aligned group and 116 in the misaligned group – the difference in the groups was due to differential attrition as participants assigned to different group differed in their failure rates of manipulation and attention checks. The study lasted about 10 minutes, and participants were paid a flat fee $0.50. Participants who failed attention checks received no payment, as disclosed upfront in the survey form. This study obtained ethical approval from the Humanities and Social Science Research Ethics Committee (HSSREC) of the University of Warwick. All participants provided informed consent.

*Design and Measures*

The experiment used an independent group design that included one independent and several dependent measures. The independent variable was the identity alignment status – aligned or misaligned. There were two political identities from which participants could choose (Democrat or Republican, see Appendix 4c). These questions were part of several other questions assessing demographics (e.g., average income and party affiliation) and thus the inclusion of the question was unlikely to have caused any environmental or political priming. The dependent variables measuring perception of social source and the information they delivered were (a) overall attitude, (b) positive
attitude, (c) negative attitude, (d) belief, (e) sharing behaviour, (f) trustworthiness of the source, and (g) reliability of provided information.

Procedure

Following informed consent, participants provided basic demographic information (i.e., age, gender). After that, they were asked to choose between the two presented rival identities – the Democratic Party or the Republican Party. Based on the randomly assigned group (aligned or misaligned), participants were then presented with an excerpt from a social aligned or misaligned source. In the Aligned Group, the social source had the same political identity as the participant indicated, and in the Misaligned Group, the social source had a different political identity than the participant.

The information presented to participants was taken from a BBC News article about climate change policy (Mayr, Buchner, Erdfelder, & Faul, 2007; Appendix 4a). This text was directly linked to climate change policies but had no direct relation to US climate change policies. The information consisted of two paragraphs: one was more positive, and the second was more negative. The presentation of policy statements was randomised. The information was presented with a reference to aligned or misaligned political identity using the following text: “Please read the following excerpt on climate policies by a source whose political party identification is [Democrat/Republican]”. This information was selected to make sure participants could not infer anything that would affect their perception of policies or its source. The actual source of the information was disclosed to the participants in the debrief at the end of the experiment.

After reading the information presented by a social source, participants were asked to indicate their attitudes using positive and negative adjectives about several climate change policies (see Appendix 4b). Each adjective was represented with a slider bar on a scale ranging from 1 (“not applicable”) to 100 (“very applicable”) following
Van Kleef, van den Berg, & Heerdink (2015). The positive adjectives were “positive”, “good”, and “favourable”. The negative adjectives were “negative”, “unpleasant”, and “bad”. Overall attitude was calculated by subtracting the sum of the 3 negative adjectives from the sum of the 3 positive adjectives, producing an average score that could range from -100 to +100. The positive and negative adjectives were presented in a random order.

To assess the effect of social-source alignment on participants’ belief about climate change policies, an adapted version of the survey items from Correll & Park (2005) was used. After presentation of belief statements about climate change policies, participants indicated their agreement on a 7-item Likert scale using radio buttons response ranging from “strongly disagree” to “strongly agree”.

Sharing behaviour following the reception of information from a social source was assessed using the Dictator Game (Camerer & Thaler, 1995; Dreber, Ellingsen, Johannesson, & Rand, 2013). Participants were asked to share with the social source of information (vs. amount kept). Sharing behaviour was assessed as the number of tokens participants donated to the source of information. Participants were presented with the following statement asking them to imagine a hypothetical scenario: “Suppose you are entitled to allocate US $10 between yourself and the source that provided the excerpt on climate policies (e.g. If you give US $5 to the other, you keep US $5 for yourself and if you give US $3 to the other, you keep US $7). How much would you give to this source?” Participants were asked to state how much they would contribute by indicating on a 0-10 slide bar with the initial pointer on $5. Participants were also asked to explain why they shared any amount by writing an open answer to the following question: “Please briefly explain why you decided to give this amount, if any.” The responses were coded by a single researcher blind to the experimental condition during
coding the text, by the main reason stated. The responses were categorised post-hoc into the following 9 categories: “Good to share”, “To support a good cause”, “I prefer to keep the money”, “I do not believe the source”, “I don’t like the source”, “Don’t believe sharing would do any good”, “I like the source”, “Other”, “No answer given”.

Perceived trustworthiness of the source was measured using a scale from 1-100%, and perceived reliability of the provided information was assessed also using the same 1-100% scale (see Hahn, Oaksford, & Harris, 2012; Harris, Hahn, Madsen, & Hsu, 2015).

5.2.2 Analysis

Following tests for normality (Density plot), a between-subject comparisons was performed using non-parametric tests to quantify the support for any effects. All data analysis was conducted in R (version 3.6.2). Packages ggplot2, Rmisc, stats and lsr were used for the data analysis. Effect sizes were calculated as Cohen’s $d$ from the choice proportion differences, and mean differences are presented with 95% confidence intervals. In the dataset used, statistical outliers were removed during the analysis, after the participants who failed manipulation and attention checks were excluded. The outliers were identified by boxplot function in ggstatsplot R function. The function presented values using out object of any data points which lie beyond the extremes of the whiskers that then were deleted from the dataset. Tukey’s method was used for outlier detection, which highlighted the data points below (1st Quartile) or above (3rd Quartile) the Inter-Quartile Range which was set to default.
5.2.3 Results

The data did not meet the requirements for a parametric test, so independent t-tests could not be used to test the hypotheses. Therefore, in the analyses, a Wilcoxon rank-sum test with continuity correction was used. First, the attitude of the participants towards the information provided was examined. Figure 5.1 shows how overall attitude was not significantly different between the aligned (55.5 ± 7.3) and misaligned (58.0 ± 6.5) groups, $W(214) = 4734$, $d = 0.13$, $p = .34$; $BF = 5.85$, in favour of the null. There was also no significant difference in positive attitude between the groups in judging the information about climate change policies ($W(214) = 4897$, $d = 0.11$, $p = .58$; $BF = 6.15$, in favour of the null), and no difference in negative attitude either ($W(214) = 5571.5$, $d = 0.12$, $p = .29$; $BF = 5.87$, in favour of the null).

Figure 5.1. Mean perceived attitude towards information provided by the social source. Error bars indicate 95% CI for the means.
As shown in Figure 5.2, there was a slight trend in belief about the positive effects of climate change policies – but overall misaligned group was similar compared to the aligned group ($W(214) = 4125$, $d = 0.25$, $p = .087$; $BF = 1.37$, in favour of the null). Participants in the Aligned group rated the information as more reliable compared to the Misaligned group (Fig 5.2A; $W(214) = 6226$, $d = 0.36$, $p = .005$; $BF = 3.00$, in favour of the alternative) and also rated the social source as more trustworthy (Fig 5.2C; $W(214)=6420.5$, $d = 0.43$, $p < .001$; $BF = 12.62$, in favour of the alternative). Participants in the Aligned Group shared on average slightly more ($3.21 \pm 0.7$

![Figure 5.2](image1.png)

*Figure 5.2. (A) Overall belief score on the positive impact of climate change policies. (B) Perceived reliability of the provided information. (C) Perceived trustworthiness of the social source. Dashed line represents the mean of the Misaligned group. ** $p = .005$, *** $p<.001$. Error bars indicate 95% CI for the means.*

![Figure 5.3](image2.png)

*Figure 5.3. Mean of the hypothetical shared amount in Dictator Game. Error bars indicate 95% CI for the means.*
hypothetical US dollars) with the social source as compared to the Misaligned Group (2.49 ± 0.5 hypothetical US dollars), but this difference between the groups was not statistically significant ($W(214) = 5665, d = 0.22, p = .19; BF = 1.47$, in favour of the null). Thus, the results confirm the hypothesis that people distinguish social source and information that they deliver in their evaluations (H2).

As can be seen in Figure 5.4, participants in the Aligned and Misaligned Groups provided various rationales for sharing in the Dictator Game, but there was no significant difference between the groups ($\chi^2(8) = 5.50, p = .701$), providing evidence against H3. In the Aligned Group, the most popular justification for sharing was “to support a good cause” (26%), whereas in the Misaligned Group, only 17% of participants stated so. In the Aligned Group, 18% of participants justified their sharing behaviour as “Good to share” when they shared any amount, but 23% in the Misaligned Group also used the same justification, which was the most popular answer in that group.

![Figure 5.4. Open answer justification given for sharing behaviour. The reasons participants provided about sharing was coded according to the nine different categories.](image-url)
5.2.4 Discussion

In Experiment 1, political identity was used to look at the effects of identity alignment on how people evaluate information and the social source delivering it. Overall, the results showed that even though participants evaluated the social source with misaligned identity as less trustworthy and the information they provided as less reliable, participants had no differential attitude towards the provided information and believed the information in a similar manner as participants with aligned identity. Even though neither positive or negative attitude differed between Aligned and Misaligned groups, other measures such as reliability, trustworthiness and sharing behavior were in accordance with the in-group bias (Hahn et al., 2012; Harris et al., 2015). This experiment showed the discrepancy between the perception of social source and the information they deliver. Participants were given information from a social source that was either aligned, having the same political identity as the social source, or misaligned, having a different identity than that of the social source. The participants found the social source in aligned group significantly more trustworthy and judged the information they provided as more reliable. The participants also shared slightly less with the social source in the Misaligned group, but this trend was non-significant. Interestingly, participants believed in the information slightly more in the Misaligned group compared to the Aligned group; however, these effects were also non-significant.

Another identity that plays a significant role in people’s consumer life – brand loyalty – was explored in Experiment 2 (Corry & Jørgensen, 2015; Funk & Kennedy, 2016; Giddens, 2015). No previous research has looked at whether an association with brand loyalty affects how people evaluate information and the social source delivering it.
5.3 Experiment 2: Brand Loyalty

Brand loyalty is a self-chosen identity, which can be prominent in people’s lives (Cross et al., 2011; Kelman, 2005; McConnell, 2011; Reed, Forehand, Puntoni, & Warlop, 2012). For example, people can feel very strongly when choosing a particular smartphone and spend personal time leaving comments and debating features of products online (Yeh, Wang, & Yieh, 2016) or a coffee shop (Han et al., 2018). Online brand communities, composed of people who possess a social identification with others based on their shared interest in a particular brand, can be quite extensive (Algesheimer, Dholakia, and Herrmann 2005; McAlexander, Schouten, and Koenig 2002). The current experiment was built on the results from Experiment 1, looking at the relationship in evaluation of social source and the information they deliver, by using a different type of social identity: coffee shop brand loyalty. In this experiment, the same climate change policy information was used as in Experiment 1. Experiment 2 thus aimed to replicate the results and investigate how the information is evaluated by participants when they receive information coming from a social source with an aligned or misaligned brand loyalty.

5.3.1 Methods

The methods of Experiment 2 were identical to that of Experiment 1, with several exceptions described. First, the identity that participants were asked to choose from was in the brand loyalty domain. Specifically, participants were asked to choose what coffee shop they prefer more – Starbucks or Dunkin’ Donuts (see Appendix 4d). The information presented this information was identical to Experiment 1. Similarly, participants in the current experiment were also recruited using a US-based sample on Amazon Mechanical Turk. The recruitment stopped when the sample reached 30%
participants in excess of the target sample size of 178 participants based on the power analysis, given the high exclusion rate in Experiment 1. Overall, 317 participants were recruited in the survey, but the final sample consisted of 247 participants (131 female; $M_{age} = 40.3 \pm 1.5$). There were 132 participants in the Aligned Group and 115 in the Misaligned Group. The number of participants who expressed preference for Dunkin’ Donuts was 134 and for Starbucks 113. The instructions, exclusion criteria, and procedure of Experiment 2 were identical to Experiment 1. At the beginning of the survey, participants picked a preferred coffee shop brand that indicated the participant’s identity attribute (brand loyalty). This indicated identity was used to put participants into two groups. In the current experiment, as in Experiment 1, there were two groups – aligned and misaligned – presenting information about climate change policies with a social source identity. Participants were asked to rate the information and social sources as well as to share a hypothetical amount with the social source (see above).

5.3.2 Results

As in Experiment 1, the data did not meet the requirements for a parametric test, so independent-samples t-tests could not be used to compare the dependent variables. Thus, the tests used were the two-sample Wilcoxon test on vectors of data and the Wilcoxon rank sum test with continuity correction. These results use the data from the participants that passed both exclusion criteria – the manipulation check where they correctly answered what the identity of the social source was and the attention check.

Figure 5.5 shows that participants’ overall attitude towards information did not significantly differ between the Aligned (32.0 ± 7.8) and Misaligned (38.7 ± 8.8) Groups ($W(247)=6807, d =0.14, p =.16, BF = 3.93$, in favour of the null), positive attitude ($W(247)=7139, d = 0.06, p =.42; BF = 6.51$, in favour of the null), nor did
negative attitude ($W(247) = 8656.5, d = 0.21, p = .057; BF = 2.12$, in favour of the null).

![Figure 5.5](image)

*Figure 5.5.* Mean information perception value as measured in attitude towards climate-change policies. Overall attitude was calculated as the difference between positive and negative attitude. Error bars indicate 95% CI for the means.

![Figure 5.6](image)

*Figure 5.6.* (A) Overall belief score on the positive impact of climate change policies. (B) Perceived reliability of the provided information. (C) Perceived trustworthiness of the social source (C). *$p < .05$. Error bars indicate 95% CI for the means.

Figure 5.6A shows participants’ belief in the positive effects of the climate change policies, which differed slightly between the groups. The belief was slightly
higher in the Misaligned Group as compared to the Aligned Group, but the difference was not significant ($W(247) = 6971.5$, $d = 0.08$, $p = .27$; $BF = 5.91$, in favour of the null). Also, Figure 5.6B shows that participants in the misaligned group perceived the information as less reliable ($W(247) = 8763.5$, $d = 0.32$, $p = .036$; $BF = 2.07$, in favour of the alternative), and Figure 5.6.C shows that participants in misaligned group, perceived the social source as significantly less trustworthy ($W(247) = 8793.5$, $d = 0.31$, $p = .032$; $BF = 1.99$, in favour of the alternative). These results are also in line with the idea that social source and information are rated differently by information receivers, providing evidence in favour of H2.

![Alignment](image)

*Figure. 5.7. Mean of the hypothetical shared amount in Dictator Game. Error bars indicate 95% CI for the means.*

Figure 5.7 shows that participants shared similar amounts of money with the social source across both groups ($W(247) = 8189.5$, $d = 0.15$, $p = .26$; $BF = 3.66$, in favour of the null). Both Aligned and Misaligned Groups provided similar rationales for their decision in the Dictator Game ($\chi^2(8) = 7.48$, $p = 0.49$), again disconfirming H2. Further, as can be seen in Figure 5.8, in the Aligned Group, 28% of participants justified their sharing behaviour as “to support a good cause” when they shared some amount, but only 18% in the Misaligned Group justified it this way. In the Misaligned Group, the most popular justification for sharing was that “it is good to share” – 23%
of all participants in this condition provided this answer, whereas in the Aligned Group, 18% of participants stated so.

![Alignment Graph](image)

*Figure 5.8.* The reasons participants provided about sharing was coded according to the nine different categories.

### 5.3.3 Discussion

Participants in both groups similarly believed in the information from the social source, and overall and positive attitude did not differ between the groups. Participants in the Misaligned Group, however, reported a less negative attitude towards the information than those in the Aligned Group, but perceived the social source as less trustworthy and reliable. As in Experiment 1, participants in the Misaligned Group shared slightly less in the dictator game. These results go against some of the findings from the in-group bias literature, where people have been observed to evaluate one’s own group and its members more favorably and to disregard information from people with dissimilar identity attributes (Hewstone, Rubin, & Willis, 2002). I

In this experiment, brand loyalty was used to look at how identity alignment influences evaluation of social source and the information they deliver. As in Experiment 1, all participants were divided into two groups in which identical
information was presented from a social source either with an aligned or misaligned brand loyalty. Participants in Misaligned Group judged information slightly less negatively than the Aligned Group, but both groups judged information similarly on the positive attitude and overall scale. This absence of aligned identity preference as measured in information attitude is an uncommon finding in social identity research, where the majority of studies show differences in how information is evaluated because it is coming from either similar or dissimilar others (Balliet et al., 2014; Hewtone et al., 2002). However, such an evaluation of in-groups higher than out-groups is generally not found in non-competitive environment, or when participants are asked to make the ratings on a negative scale, or to make negative rather than positive allocations to in-group and out-group members (e.g., Blanz, Mummendey, Mielke, & Klink, 1998; Hewtone et al., 2002). In this experiment, however, both positive and negative attitude scales were used, which provides a fuller picture and suggests that there was no negative perception of information based on the misaligned identity of the social source.

Sharing behaviour did not significantly differ between the aligned and misaligned groups, and both groups justified sharing behaviour in similar terms. However, participants in the Misaligned Group shared slightly less and tended to justify sharing as “It’s good to share” in contrast to the Aligned Group, who justified their sharing as “To support a good cause”, and these are in accordance with Experiment 1. These responses hint that in the Aligned Group, participants focus more on information itself, whereas in the Misaligned Group, participants focus on the social source. This suggests that attention is selective when it comes to justifying sharing information; either the social source or the information they deliver must take the stage in perception to provide a justification for a decision based on this information (Adler, 2006; Bohner
Overall, Experiment 2 confirmed the results of Experiment 1 that information and social source are evaluated differently.

**5.4 General Discussion**

The results of the experiments showed that social source and the information they deliver are not always congruent in how people evaluate them. In two experiments, how identity alignment modulates the perception of social source and the information they deliver was explored using political party affiliation and brand loyalty. Participants rated the social source with a misaligned identity less favourably in trustworthiness and reliability, but this unfavourable perception was not reflected in any other measure – not in attitudes, belief nor sharing behaviour. On the contrary, participants in the Misaligned Group rated the information delivered by the source with a misaligned identity neutrally and believed the information they delivered as much or slightly more as compared to the Aligned Group (Arora, Logg, & Larrick, 2016; Hewstone et al., 2002; Hunter et al., 2012). The results suggest that social source and the information delivered by them are evaluated differently by information receivers in communication.

The aim of the experiments was to simplify the effects of identity by distilling identity to specific identity attributes and examining how identity alignment affects the perception of the social source and the delivered information. The specific identity was not important per se – the focus was on the alignment and thus two opposite identities were put in one group. In this way, polarisation was avoided, whereby the evaluation of the differences in attributes attached to either identity can drive differences in attitudes and beliefs (e.g., Smith, Ratliff, & Nosek, 2012; Van Bavel & Pereira, 2018).
5.4.1 Misaligned Means Auxiliary

The exploration-exploitation dilemma is often studied in individual learning, but there are many instances in which people make the same trade-off for social sources – from whom to learn, how much, and when. People make assumptions about others in relation to trustworthiness, similarity, relevant expertise, or authority (Martin & Marks, 2019; Petty & Cacioppo, 1986). The environment of the current experiment was non-competitive, but still participants in Misaligned group shared less in the Dictator Game as compared to Aligned group (confirming H3). Thus, the absence of a competitive environment might not fully explain the results. The evaluation of the social source with misaligned identity was expressed in neutral attitude (not negative) and can be viewed as a function of inter-individual and inter-group cooperation (Gaertner, Mann, Dovidio, Murrell, & Pomare, 1990; Reinders Folmer, Wildschut, De Cremer, & van Lange, 2017). Further, in the experiments, the information about climate change policies presented to participants was neutral without arguing for or against these policies, so correspondence with social identity was not helpful in validating attitude norms or decreasing attitude uncertainty (Clarkson, Smith, Tormala, & Dugan, 2017).

In individual learning, if people believe that the outcome from a choice is going to be negative, they are less likely to choose that option, and thus less likely to correct any false negative beliefs (Denrell, 2007). Because people have preferences and choose behaviours that they believe will result in positive experiences, false positive beliefs are more likely to be corrected, implying that false negative beliefs are more stable. The same idea can be applied to learning from others: a dissimilar social source can provide auxiliary knowledge that would lead to alternative hypothesis generation and better decision making.
A social learning strategy based on identity can also be viewed as a form of information restriction: one has to have certain shortcuts to get useful information, and individuals that are known to deliver valuable information in general, such as a social source with an aligned identity, are also likely to be good sources of valuable information in a particular situation (Denrell & March, 2001; Pope, 2007). A social source who is similar to the receiver, trustworthy, or an expert – reliable – is safe to exploit when in social learning. A more “risky” approach to social learning, but which benefits can outweigh the risk is learning from a dissimilar or unfamiliar social source, even though they might initially be perceived as a suboptimal learning source (Daw et al., 2006; Denrell & March, 2001; Gershman, 2019).

Experiences and perceptions are based on individual (identity) filter and thus information processing is filtered by specific identity, which can be related to a social group memberships (McConnell, 2011). The neutral or even positive information perception coming from a social source with a misaligned identity can be explained by the value of learning from dissimilar others – even if the attributes of the identity suggest the information might not be reliable, a social learning strategy such as “learn from dissimilar others at least occasionally” can be efficient because dissimilar others provide alternative knowledge to consider and enhance one’s decision-making. Thus, social learning from social sources with a misaligned identity might adjust personal false negatives beliefs by providing additional, unconsidered information about the state of the world.

### 5.4.2 Identity and Alignment

People often weight the information coming from out-groups more negatively (e.g., Correll & Park, 2005) and even avoid information coming from rival political parties (Frimer et al., 2017). But people also might expect that others, irrespective of
their identity, possess valuable information. Xiao and colleagues (2016) proposed a model that shows how social identity influences the receiver potentially skewing their perception. But, because negative emotions towards a social source can be an obstacle in obtaining valuable information (Zaki et al., 2016), an adaptation that would monitor how much the information differs from what is already known, or how relevant it is in the current environment is more useful than monitoring only the similarity between the receiver and the social source. Thus, even though social sources with an aligned identity are viewed more favourably than social sources with a misaligned identity, the latter can be more informative precisely because they are more dissimilar.

The evaluation about received information can be skewed based on identity of the social source. However, the executive control can work alongside ToM to overcome the tendency to discount information from unfavourable social sources (Kim, Park, & Young, 2020). People perceive the environment through perceptual and cognitive streams, which contribute to a single evaluation of information (Campbell-Meiklejohn et al., 2010; Pessoa, 2008). The perception of a social source interacts with the perception of the information they deliver; any differences between the measures of perception could be mediated by attention – either directed to the social source or the information. Information content and information about a social source could require different types of evaluation, and thus participants could treat information and social source differently. Reliability could be applied to both the information and the social source because the reliability of information is inherent to the reliability of the social source, and thus requires mixed evaluation. Perceptually, however, attitudes and reliability might be quite different: positively perceived information can still be viewed as not reliable and vice versa.
The discrepancy between the current study and what has been found in the literature (Behrens et al., 2008; Hunter et al., 2012; Pentina, Bailey, & Zhang, 2018; Van Bavel & Pereira, 2018) might stem from the fact that in this study we did not look at the associated groups per se, but at the correspondence between the groups, that is the alignment of identities. In this way, the polarisation of views between two different identities was avoided – there was no perceived differences in the attributes that are attached to either of the identities usually driving people’s attitudes and beliefs (e.g. Smith, Ratliff, & Nosek, 2012; Van Bavel & Pereira, 2018). Because a social source is mostly judged by trustworthiness that is modulated by group identification (Balliet et al., 2014; Hahn et al., 2009; Harris et al., 2015), participants indeed judged the social source’s trustworthiness and reliability in line with previous research, highlighting the distinction between attitudes towards a social source and the information they deliver. Further, because in the current experiments, social source did not provide any opinion about the information, but simply delivered a piece of information, this alone could not provide any attitude that would be integrated in participants’ perception of the information value (Clarkson et al., 2017). The information about climate change policies presented to participants was without arguing for or against these policies, and thus the correspondence to social identity could not validate attitude norms or decrease attitude uncertainty, leaving participants’ attitude neutral to the delivered information.

5.4.3 Social Cost of Information

Sharing behaviour in Dictator game is usually used to look at fairness and norms (Engel, 2011), sharing of information can be viewed as an act of cooperation. In the current experiments, participants shared less a hypothetical amount with social sources that had a misaligned identity, but the difference between the groups was non-significant (e.g. Balliet et al., 2014; Ben-Ner et al., 2009). In both groups, participants
provided various justifications for their sharing behaviour of a hypothetical amount with the social source, but the majority explained it as “to support a good cause”, “it is good to share”, and “prefer to keep the money”. In the Aligned Group, participants may have focussed attention on the information sharing cause – why the information was shared given that identities are similar. The provided information was about climate change policies suggesting that the reason for sharing was to acknowledge the attempts to combat the climate crisis and signal its importance. In the Misaligned Group, however, participants justified their sharing behaviour that it is a good act in itself gratifying the social source for sharing potentially costly information, but with slightly less attention to its importance. Participants in the Misaligned Group could disregard the informational content more than in the Aligned Group as it might be less relevant to their identity, while still acknowledging the value of the provided information. Thus, participants in the Misaligned Group have justified their sharing as “it is good to share”, pointing at reciprocity (e.g., Mahmoodi et al., 2018; Mohtashemi & Mui, 2003).

A key point of learning is that learning from others is more efficient – “cheaper” – than personal learning. But information gathering and communication can be costly for social sources. Thus, shared information can be viewed as a resource for which a social source needs to be reciprocated by the receiver. Any individual can be a potential source of valuable information (Cummings, 2004; Heyes, 2016b; Rendell et al., 2011). When learning from others, certain attributes, such as trustworthiness, are important to consider in evaluation of the information, and these can be inferred from identity (Balliet et al., 2014; Kendal et al., 2018; Xiao et al., 2016; Harris et al., 2015). Thus, a social setting can give rise to competition, but also to reciprocity: it can be cheap to learn from others, but information can be expensive – thus, information receivers were ready to pay its price.
5.4.4 Limitations

There are several limitations to the current two experiments. Because the results regarding negative attitude and belief were marginal, it would be of interest to test several other identities to better understand the generalizability of the current results. Other identities that would be interesting to explore could be, for example, sports-team preference (i.e., Liverpool vs. Manchester United) and organisational identity related to employment (i.e. Deloitte vs. PwC). Because our hobbies and jobs are often significant parts of our lives, these might influence how we perceive the information coming from people with misaligned identities to our own. Second, the information used in the two studies was regarding climate-change policies originally taken from a UK news media source but presented to a US sample. In the UK, climate change is a comparatively neutral topic, but it is more politically salient in the US. Even though the polarization was accounted for by including participants who identified with both political parties or coffee brand shops in both groups, it would be valuable to include a more diverse set of topics to understand whether the pattern of findings changes based on the topic. People’s attitude toward (general) climate change policies, a contentious issue, were highly probably well-formed before the experiment. Future work could use information that is more abstract, where people would not have strong prior opinions, e.g., art. Additionally, it would be of interest to explore the interaction between identity and emotionally charged information that is slanted to influence attitudes based on social identity alignment.

Lastly, all the measures used were self-reports, except one – sharing behaviour in the Dictator Game, which was also a hypothetical measure. Even though self-report can provide good insight about subjective evaluation, still, it only partially implies participants’ preferences, and might not capture real-life behaviour. Thus, the study
would benefit from including real-life behavioural measures such as online exchanges (e.g., tweets, messages). In the future work, an online setting can be re-created, where people can read information from an online media source to share, comment, or like the presented information. Online communities are of particular interest given the digitalization of public discourse online. People who disagree online can be highly involved in the conversation but give little critical evaluation of the informational exchange. Thus, identity alignment is a valuable avenue to pursue in the future research.

5.4.5 Conclusion

Information bubbles are based on social ties, but to avoid getting trapped in one, people need to learn from dissimilar others. Because any social information can be valuable, it can be costly to turn away from a social source with a misaligned identity. Social sources who are dissimilar to receivers can help to generate auxiliary hypothesis by providing additional information. The experiments in the current chapter showed a trend of participants to express neutrality towards the information delivered from a social source with a misaligned identity. This neutral or less-negative modulation in information evaluation is potentially an adaptive mechanism that allows people to learn new, diverse information from others. Thus, information can be differentiated from a social source in perception to allow more nuanced learning.
Chapter 6: Conclusion

This thesis addressed the question of whether people learn differently from lived (personal) experience and vicarious (social) experience by studying how these differences manifest in risky choice. This difference was proposed as a potential explanation for the DE gap, wherein people treat the impact of rare events in risky choice differently. When people learn about risk from a piece of description, they tend to make decisions as if they overweight rare outcomes relative to their probability, whereas when people encounter the risk through personal experience, they tend to make decisions as if the rare outcomes were underweighted. This difference in risky choice has previously been attributed to several possible mechanisms, including sampling biases, recency effects, and learning strategies. In this thesis, this problem was addressed using a novel outlook: that decisions-from-experience represents personal learning and decisions-from-description represents social learning. This idea was used as a novel explanation for the DE gap and applied to the general problem of individual vs. social learning biases in risky decision-making.

An interdisciplinary understanding has brought about potentially the most useful insights in illuminating human behavior, including fusions of psychology and economics (Tversky & Kahneman, 1981), or cognition and computer science (Sutton & Barto, 1998). Application of models across fields can be incredibly beneficial for understanding the mechanisms behind overlapping phenomena (Mesoudi, 2009; Renshon & Kahneman, 2016). Such bridge-building is a common practice in cognitive science, and psychology models are infused with theories and frameworks from economics, statistics, computer science, and mathematics. Two important theoretical models can help illuminate the computational role that humans play as information
filters — filtering and recursion. Filtering, which is the primary focus of this thesis, can be represented as learning (i.e., gathering, adjusting and communicating information) and recursion can be applied in the social context of learning as representing the repeating aspect of learning processes (i.e., learning from the sampling of [infinite] others). The two models are examples taken from physics and mathematics that are intuitive enough to be useful in describing personal and social learning not only in the context of risk but in other areas of psychology, such as cognition and group interaction (Connolly & van Deventer, 2017; He et al., 2017; McConnell, 2011; Rendell et al., 2010; Thompson, 1988; Wen, Yang, Luo, Wang, & Pan, 2019).

6.1 Experiencing Self via Other

In Chapter 2, a novel paradigm of decisions-from-observation was developed, in which participants made decisions based on observing another participant’s sampling from risky options. Each participant in the pair performed the same task either from personal or observed (social) experience. The results showed that learning from observation was similar to learning from personal experience – people generally tended to underweight rare events. When observing others’ experience, however, people underweighted rare events to a lesser extent, pointing in the direction of what usually happens in decisions from description. In this sense, observation might be the first “form” of description (as abstract representation of subjective experience) on the social learning spectrum. Even though learning from observation might still resemble learning from experience in choice, it also shows the transition of information into a social, more abstract form. This shift from personal to the social level in choice can be explained by social context and communicative intent. The social context can be viewed from the lens of active and passive learning, which involves the passive reception of information
(Bruner, 1961; Markant & Gureckis, 2013). For example, in Observation, as in passive learning, participants might not be as attentive to the task because they were not directly involved in sampling. Passive learning can be also linked to psychological distance – the ability to learn about the risk without experiencing it – which can play an important role in abstracting one from direct information selection, thereby saving ones’ resources (Michael et al., 2020; Trope & Liberman, 2010a). The results of this abstract (passive) learning can contribute to more risk-seeking behaviour in personal choice, as was seen in the experiments (e.g., see Chapter 2, Figure 2.4 and Figure 2.7; Chapter 3, Figure 3.7).

The contribution of the two experiments involving decisions-from-observation (Chapter 2) and one experiment involving decisions-from-described experience (Chapter 3) was to disentangle the “visceral” from the “vicarious”, which is a potential first level of abstraction from personal to social learning. The experimental paradigm of decisions-from-observation used in Chapter 3 was created so that it minimally differs from the decisions-from-experience paradigm usually used in risky decision-making. Thus, it was possible to introduce one aspect of the socialness of information reception but preserve the commonly used paradigm involving learning from personal experience. Similarly, in choices from described experience, personal experience was added to the paradigm. By using these paradigms, the transition from asocial information to social information and vice versa was captured, and the two social modes directly compared. Even though the information received by experience and observation was identical, the marginal difference between the two showed the initial stage of information into a more abstract form of learning – social learning. The experienced likelihood of events was less than expected, representing noisy experience (e.g., see Figure 3.5), which was then
transformed to a communication in the form of described experience. Thus, decision-making from social information mirrored the bias on individual level.

### 6.2 DE Gap – a Compensating Mechanism

The findings from the current thesis suggest that under-sampling and over-reporting of rare events are related. As an additional analysis Bayesian meta-analysis (see Appendix 5) was performed using data from Chapter 2,3 and 4 using gains only, as this choice problem domain was used consistently across the thesis, but loss domain was used only in Chapter 3. The analysis did not include Chapter 5 results, because there were no personal conditions and measures differed from the rest of the chapters. The analysis showed no overall difference between making decisions for gains when learning from personal and social (another individual) learning experience. This result implies that social information in the form of observation or using the described experience of one other is very similar to personal (individual) learning. The DE gap – underweighting rare events in experience vs. overweighting in description – thus was not replicated in this thesis. This is likely because in both cases – personal and social – information was subjective, i.e., not aggregated, corrected or normalized as in classical forms of descriptions in risky decision-making research. The small non-significant difference between the conditions are likely to counterbalance the absence of agency and attentional difference in learning and consequent decision-making. This counterbalancing is best observed in Chapter 3, where the chain of actions is full – from learning by personal experience, creating descriptions of the experience and then making a choice from partner’s description as well as from objective descriptions.

In Chapter 3, the process of transforming personal experience into abstract descriptions was examined and found that people exaggerate their experience when
communicated to others. This exaggeration might be necessary to account for the absence of personal experience in others (i.e., on social level) and the need for abstraction (i.e., reduction of details/dimensions) in communication. Thus, individuals must adjust to the information about risk in social context in order to be able to learn from each other about what choices to make, and especially so about risky choices with rare outcomes. In experience, a large proportion of participants (8-55%) did not encounter rare events, but the ones who experience a rare event, compensated for the social level under-encountering of rare event by overweighting their own experience when describing it.

The finding that people when describing personal risk experience overweight it when describing it is in line with the Amplification of Risk Theory, which describes risk amplification in communication as the process through which information is intensified in a social context (Kasperson, Kasperson, Pidgeon, & Slovic, 1988). There are two potential mechanisms contributing to the observed amplification of risk in the created description: agency, emotional responses (subjective experience) and memory biases, all modulated by attention. From an emotional perspective, both large gains and large losses (i.e. high stakes) are emotionally salient leading to loss-aversion and risk-aversion (Blanchette & Richards, 2010; Johnson & Tversky, 1983; Sokol-Hessner et al., 2013). Decisions made from personal experience rely on episodic memory that includes images and associations linking experience to emotional responses that also modulate communication (Bornstein & Norman, 2017; Yonelinas & Ritchey, 2015). Slovic, Finucane, Peters, & Macgregor (2012) highlight the beneficial aspect of emotional experience in risk, specifically of association-based processing, which have enabled humans to survive. Crucially, affective reactions also play a role even in seemingly objective domains, such as decisions concerning financial investments.
This emotional response to certain outcomes can increase attention and enhance the reliance on deliberate and controlled cognitive processing (Yechiam & Hochman, 2013).

The Amplification of Risk Theory discusses how communication about risks is amplified by emotional valence, which makes specific events enhanced in communication to potentially make them more memorable to receivers. Enhanced attention and cognitive processing modulate memories for rare events, especially large losses, and contribute to the over-estimation of encountered events in sampling, resulting in amplifying risk experience when communicated. Indeed, Madan, Ludvig, & Spetch (2014) showed that extreme outcomes – the highest and the lowest in context – are overweighed in memory and suggest that this memory bias might account for at least some of the differences between description and experience. The results of this experiment also align with the findings by Lieder, Griffiths, & Hsu (2018) who found that the frequency with which an outcome can be recalled is biased by its utility – rare events might be more subjectively important than the common ones as they inherently correlate with the extremity of such events. Participants might amplify negatively framed risky events (losses) in communication to avoid them in the future or on social level. Similarly, participants may amplify positively framed risky events (gains) so that they and others may be more likely to encounter them in the future. Overall, this amplification of small probabilities in description of personal risky experience, especially losses, only partly aligns with the idea that social context makes people more risky. And, this might not because of competition, but because of the abstraction process resulting in personal distance from the risky event and associated outcomes (Trope & Liberman, 2010b).
Even though the described experience was in the format usually used in a DfD paradigm, participants did not overweight rare events as compared to experience. Indeed, participants acted with DfED as they did with DfE. As the experiments showed, choices from observation and choices from described experience both likely stand closer to experience on the learning continuum than to description. This result is somehow surprising, given the diverse social communication formats used in the observation and described experience experiments. One format was clicking on the keyboard to see outcomes to come up according to a certain probability, and the second format was the outcomes and probability written by partner. The similarity of the paradigms is in the social context – a person produced information for another person to learn. In both cases, only one person was responsible for producing this information. Thus, there might be a completely different mechanism behind description to the classical understanding of it: description might be an abstraction from personal experience modulated by the number of samples taken to produce this description. Thus, described experience was as subjective as personal experience, but it did not directly reflect experience, rather counterbalanced it on social level. These results suggest that there are compensating mechanisms inherent in communication as represented by the discrepancy between risky choices from experience and using that same experience for communication. Understanding the transformation of personal subjective experience in order to communicate to others as a social phenomenon more broadly is a fruitful avenue to pursue in the future.

6.3 Unsourced Social Information – Impossible?

When there is no clearly identifiable source, people readily assume a source of social information. In Chapter 4, an experiment using one-shot binary risky choice
problems in the form of described probabilities showed only a mild effect of social source on decision-making. Participants presented with sourced information tended to choose slightly more riskily in rare choice problems compared to those who received unsourced information. This experiment also demonstrated that unsourced information is not strictly perceived as such: 57% of participants presented with unsourced information still thought it was coming from other people. This result implies that people perceive information in the form of unsourced descriptions as social information. Interestingly, participants rated sourced information as less reliable compared to unsourced information. Furthermore, participants were more likely to ask for additional information when a social source was present. The results showed that people recognise the social aspect of described information and the consequences of this socialness on information reliability. Even though participants rated information differently depending on social source presence, in this experiment, social source played only a mild role.

People might be more vigilant about information reliability only when the source of information is present, but where there is no source, people are actually less likely to question its reliability. The information with an absent social source is likely to be viewed as a statement or a common truth, not just someone’s experience, and thus perceived as more reliable. Because the reliability of information is mediated by the reliability of social source, its presence might affect how the delivered information is rated (Hahn et al., 2009). This perception of the social source could determine the reliability of the information itself. This indeed is what was found in this experiment: participants with sourced information were presented with more information, but still rated this information as less reliable, and asked more for additional information as compared to those presented with unsourced information. This is intriguing because the
only difference between the groups was the presence of a person’s portrait, their name, and a comment that these people produced the information about choice problems by sampling them. This result can be explained by social context of learning – if all descriptions about events, including symbolic abstractions, were ultimately generated from experiences of others, an adaptive system would need to adjust for any biases inherent in this transition of information from the experience of others — who biases any acquired information during communication (Castells, 2013; Francis, 2017; Kendal et al., 2018; Tomasello, 2010).

The receiver should account for a matching transmission bias of social source. Indeed, this is what was observed in Chapter 3 on described experience. The participants in the current experiment inferred and accounted for this transmission error – the modification of information in communication – by the social source to a receiver, and, as a result, acted as though the rare events had slightly more weight than the received information would suggest. This over weighting or rare events goes in accordance with the experiment in observation of the current thesis (Chapter 2), where people also acted only slightly more riskily when observing as compared to experiencing the same risky events. Similarly, the results of Chapter 4 provide a baseline understanding of people’s perception of information when it does not have a clearly identifiable source. This increase in reliability in social source absence could modulate risky choice. Potentially, when there is information about the source, receivers’ attention is diverged to the source’s attributes, such as identity, and information is judged based on those attributes (Hartman & Weber, 2009; Van Bavel & Pereira, 2018). Tversky, Sattath, & Slovic (1988) suggested this attention-attribute explanation to account for the difference in risk preferences. The experiment in Chapter 4 contributes to understanding of how social sources affect the perception of
information and related decision-making. Most studies in risky decision-making do not specify the source of information that participants receive. As such, the effects of providing explicit sources and comparing against the typical unsourced information has not been previously investigated. Contrary to the bulk of the literature the evidence for overweighting of rare events in description was not found: people in Unsourced group, who received problems identical to the usual decisions from description, selected the risky option no more often in rare than common problems (Glöckner et al., 2012, 2016; Hertwig & Erev, 2009; Kahneman & Tversky, 1979; McDermott et al., 2008; Wulff & Hertwig, 2018). This, potentially, can be explained by the Risk Communication literature, where certain risks are exaggerated in news and social media coverage (Ambler et al., 2011). The Amplification of Risk Theory, specifically, suggests that outcomes and their probabilities are systematically exaggerated by people – similar to what was observed in the experiment on described experience in Chapter 3 (Frewer, Miles, & Marsh, 2002; Kasper, Kasper, Pidgeon, & Slovic, 1988; Kasper & Kasper, 1996).

Communication theory suggests that the increase in riskiness within the rare-event domain might stem from accounting for transmission error in the communication of information (Kasper et al., 1988; Kendal et al., 2018). Further, given the specified choice problems with mid-range payoffs, the explicit socialness of described information played only a mild role with more risky decisions in choice problems with rare events. It might suggest more attention is given to rare events in social learning because it is underweighted on individual level. Even though the effect in the experiments of the current thesis was mild, it was consistent, implying a mechanism that helps individuals to adjusts to social source of information – a social learning compensation mechanism manifesting as bias in individual learning. A further account
suggests that biases can be dependent on the number of people or iterations acting in the process of social communication – one, a group, state or traditions – the information from which might represent a subjective interpretation or common-sense knowledge, each could be perceived in amplified form irrespective of accuracy.

6.3.1 Identity Alignment as Shortcut to Reliable Information

No information can be more reliable than the one experienced by self. But, a good proxy for social information reliability plays identity. Indeed, identity plays a significant role in communication as it affects how the information is gathered and perceived (Effron, 2018; Frimer et al., 2017; Van Bavel & Pereira, 2018; Xiao et al., 2016). Even though people with similar identities might be viewed as more favourable social sources of information than out-groups, Chapter 5 shows how a social source with a misaligned identity, though perceived as less trustworthy, might be not penalised nor viewed any more negatively than information from a social source with an aligned identity (Hunter et al., 2012; Xiao et al., 2016). In two experiments in Chapter 5, the question of how the alignment of political identity and brand loyalty affects perception of a social source and their delivered information about climate change policies was investigated. Results showed that information can be judged neutrally irrespective of social-source identity. This mismatch of “raw” or personal as opposed to “processed” or social (level) information evaluation can play an adaptive role – social source identity is a shortcut by which people can judge the value of information, but this shortcut depends on context (Xiao et al., 2016). If personal identity is very similar to that of social source, then social information can learnt (almost) perfectly. For example, one can evaluate information by whether social source possesses relevant expertise in the communicated context. But expertise is only partly useful – receiver needs to understand how to apply this information to self in a given context, i.e., subjective
application of social information. From an ecological point of view, the perception of information value can serve as an adaptive function by guiding socially useful behaviour and informing personal decision-making. Even if the information is coming from an individual with a misaligned identity, it can be valuable despite a higher reliability threshold (Smith, Ratliff, & Nosek, 2012a; Van Bavel & Pereira, 2018; Xiao et al., 2016). Political identity is often more salient than brand loyalty, but both experiments showed similar patterns in information and social source perception. In this way, participants disentangled information and source by rating these two aspects independently. Perception, in this context, can be described as the process of sensory signal interpretation in the domain of causal inference (Weber, 2018), and can also be viewed as the subjective evaluation of information. This type of perception is subjective and specific to each individual. Thus, the results can be viewed from the perspective of a subjective social influence of information perception applied to informational value (Campbell-Meiklejohn et al., 2010; Clark, 2013). Because social information is (mostly) acquired in a social context, social source identity may play the role of directing the receiver, e.g., about the communication goal or group perspective towards the information (Shardanand & Maes, 1995; Van Bavel & Pereira, 2018; Wisdom et al., 2013). This result suggests that information value might not depend solely on social source. Further research can include human-computer interaction that would allow to decrease transmission error of communicated information by emulating identity of the social source and the receiver given certain identity (i.e., perception and behaviour) in a certain environment (Fridman, 2014).
6.4 Policy Implications

6.4.1 Risks of Information Filtering

Appropriately filtering information – be that on social media or news platforms or personal connections – is a challenging problem. How people filter personal and social information and how this affects choice should be addressed by policy practitioners more directly (e.g., Aral, 2018). This has been a concern for quite some time now, since the era of the Internet brought up not only information explosion (Pope, 2007), but also the problem of information distortion of reality through online social media. The proliferation of Fake News, DeepFakes, unverified news outlets, trolls, and propaganda are often masked from being perceived as such by receivers, but can have strong social effect (Marwick & Lewis, 2017). Subjective personal experience in the form of identity of social source helps receivers to navigate information flow, but necessarily skews information reception, its subsequent understanding, and communication. The result of such a filtered world would be the polarisation of knowledge, perception, and attitudes, which we are already seeing now (Flaxman et al., 2016; Lewandowsky et al., 2017; Sikder et al., 2020a). To avoid being stuck in such one-sided world, one needs to be careful about where to direct attention, what information to consume, and how to treat it. Thus, policy-makers must directly address the problem of how information is filtered and what information receivers are most likely to be attend to.

Information filtering in decision science is something that we need to understand from ethical perspective (Rosenthal, 2020). The limitations of a perspective, even of a whole organisation can lead to suboptimal social consequences. Journalists, educators, and politicians are aware of the information filtering mechanism on the professional
level but need to understand the unintentional consequences of such filtering by themselves. The biases that might lie between objectivity vs. subjectivity of personal experience including in social environment potentially would be useful to address from personal vs. social experience as was discussed in this thesis. If information played a prescriptive rather than descriptive role, what it would mean for one’s understanding of the subject in question? How does the limitations of information filtering process affect communication and policy-making practises? In answering these questions, policy practitioners might learn and communicate in a way that would decrease the probability of event occurrence with negative outcomes and increase the probability of events with positive outcomes (Rollwage et al., 2020).

6.4.2 Small Probability = Big Risk

This thesis concerns small risks defined as the probability of an event occurring between 1-10% of the time. These risks, however, can also be viewed as medium risks in absolute terms. A systematic examination of real-life extreme events with small chance of occurring (e.g., 0.1%), such as existential risks, is still in its infancy (e.g., Swol & Sniezek, 2005). Do we realise the risks of selective information consumption (Bostrom, 2011; Flaxman et al., 2016)? What does it mean to have the risk of 1 in 10 of developing a general artificial intelligence that will not be safe for humanity (Armstrong, Bostrom, & Shulman, 2016; Ord, 2020)? Can we truly grasp the risks of reaching the point of avalanche of the climate catastrophe (van der Linden, 2015)? These questions are about highly disruptive risks meaning even a small probability of escalation can result in disastrous consequences for humanity. Surprisingly little attention is given to these questions in public, academic, and political debate (Bostrom, 2013).
On the flipside, some risks that are associated with extremely positive outcomes are also not considered sufficiently. What are the chances that free online education will result in a substantial decrease of inequality? Can publicly available artificial intelligence unprecedently ease the lives of the general population? Are there any strong benefits associated with a swift transition to renewable energy sources? Even though all these questions possess inherent uncertainty (Leuker et al., 2018; Pleskac & Hertwig, 2014), understanding such questions can be extremely beneficial (Bostrom & Cirkovic, 2016). In order to harness such extremely positive outcomes, effective communication stands as the cornerstone not only for understanding of such problems, but also as a protective factor for big risks – to avoid extremely negative and attract incredibly favourable states (Ord, 2020).

6.4.3 Learning from Others – The Pitfalls and Opportunities

Being surrounded by information filters is unavoidable and overall beneficial because there is more information than we can ever individually extract from the environment. To use others as social learning agents efficiently, it is important to account for the biases we and others can have when learning and communicating information – under-experiencing rare events might be just one of them. For example, people do not find understanding of probability intuitive, so potentially, applying individual knowledge (e.g., case studies, anecdotes) rather than aggregated knowledge or probabilities, could be beneficial. Indeed, research shows that people understand frequencies better (1 in 1000 cases) than probabilities (0.001% chance) (Pachur et al., 2013). The more information gets abstracted, the more likely it would get exaggerated and, counter-intuitively, believed more. Thus, learning from direct interaction with others can be beneficial for understanding event probability occurrence. Disinformation, which is also a type of social information, also necessarily has a social
source (Marwick & Lewis, 2017). As with other forms of information, the social source typically distorts information due to emotion, attention, and memory biases, as was explored in Chapter 3, or due to motives such as cooperation or competition, and identity alignment (Marwick & Lewis, 2017). This filtering of information by social sources necessary manipulates the acquired information before providing it to others.

Even though people rarely use personal or social learning in isolation, the distinction between these two learning modes is important for several reasons. One reason is that when learning through personal experience, there is less need to verify the reliability of information because it has been acquired first-hand. Because social information is filtered by someone else, however, it is not as reliable (Jarvstad & Hahn, 2011). Second, social information comes in different formats: observation or described experience (both discussed in this thesis) that can be more or less aggregated and thus more or less easy to transfer to personal (individual) goals and decision-making. These forms include aggregated knowledge, e.g., in the form of theories, urban legends, opinions, fantasies, comments and many others. Third, social information (if not corrected or normalised) is always biased and thus requires to be unbiased. Because of this diversity, one needs to deal with the distortion of social information and measure its reliability. Therefore, complementary mechanisms that would mirror this social distortion in reciever’s perception are beneficial. Overall, policy practitioners need to consider how social information would be interpreted by individual receivers and applied in personal decision-making. Providing freely available robust tools for social source evaluation might be one of the ways to deal with this distortion in public communication.

6.5 Limitations
In the experiments, rare events consisted mostly of high outcomes in the gain domain. Even though low outcomes and the loss domain were used in some of experiments, they were not systematically assessed due to the limited number of gambles used for each task. In the thesis only one type of rare events was used – zero-outcome events in a sampling paradigm (Hertwig & Erev, 2009). Other mixed-choice problems or full-feedback paradigm (or mixing feedback between subjects) would add supplementary understanding of the social learning of risk. Additionally, the extremity of events occurrence (0.00001 chance) and outcomes (£10,000) were not investigated (see below). In the future, both gain and loss outcome domains should be explored in more detail.

Furthermore, in all experiments, the choice problems stayed static – people saw the same numbers over and over again. There is a potential problem of this representation of rare events. The outcomes rarely are exactly the same across any ecological domain, and second, participants could confuse the choice problems between each other. The assumption was that participants would not realise they were playing the same choice problem in multiple conditions. There was, however, no direct measure included to check whether this was true or not. Future experiments could potentially address this problem of rare event representation by introducing a distribution of outcomes rather than a single static value. Also, in the experiments of the current thesis, the risks were small, but tangible, with relatively low stakes (Leuker et al., 2018). Future research might need to consider open-response descriptions to make the setting more naturalistic.

All the measures used in the study were either lab-based behavioural experiments with real or self-reports. Even though experiments provide good control and insight into human behavior, this only partially generalizes to people’s real-life
behaviour, such as attentiveness to social sources and other attributes such as receiver reciprocity of information exchange (Frey et al., 2017). The latter, for example, is what found in online communities: people who disagree are highly involved in conversations online but can pay little attention to the delivered information itself. Thus, similar research questions investigated in real-life setting would be beneficial.

Some of the results presented here had no or only small effect, and there might be several reasons for this. In Chapter 2 and 3, observation and descriptions were direct – partners knew that they were working together and the information they produced will be necessarily used by another person, and thus were aware of the communicative intent of the setting. A good control would have been to have people estimate the frequency without the communicative intent. Then, the experiment might have been better able to determine whether the overreporting was a fundamental misperception or arose from a more social (communication) element. Additionally, information source provides a shortcut by which the information can be judged as useful or not for the receiver. Information theory suggests that information cannot be fully objective, so it would be useful to account for social source more explicitly, including the parameters that define a social source, rather than a photo and a name as in Chapter 4.

6.6 Future Directions

6.6.1. Network and Multi-Agent Simulations

There are certain areas that could be fruitful for understanding the importance of personal and social learning as distributed inference about risk and learning in general. For example, distributed inference through biased (bounded) information processing at the individual level yields rational belief formation at the group level that can produce a more objective understanding of the world (Krafft et al., 2016). Following
the line of the current thesis, future research could examine the network of aggregated knowledge using, for example, multi-agent modeling and implementing the principles of filtering and recursion. A good start would be to look at description as aggregated knowledge, where several participants would write one description for one other or a group of participants (Tessler et al., 2020). The experiments of such a research could include observing multiple people for producing a single choice or using word-based expressions to describe the personal experience of choice.

Personal and social learning problems could also benefit by being looked at from risky choice problems more generally as in social dilemmas. Thus, it would be beneficial to look at learning about events not in dichotomous terms such as “abstract”/”specific”, “subjective”/”objective”, “description”/”experience”, but rather as a spectrum or dimensions of learning, specifically, quantum models of cognition (e.g., Li et al., 2020). The dimensions can include how many agents (e.g., 1 or 1000) or levels of abstraction (e.g., individual distance from the event, such as personal interaction or informational cascade) and context attributes are involved in producing the estimation about an event (Camilleri & Newell, 2013; Liu, Polman, Liu, & Jiao, 2018). Such research becomes beneficial for elections, arbitrage, and blockchain technology to name a few (Bilovich et al., 2018; Lesaege & Ast, 2018; Madsen & Pilditch, 2016).

6.6.2 Ethics and Real-life Risk

Risk is a special case in learning as it makes people avoid negative payoffs and encounter more safer positive outcomes (Kahneman & Tversky, 1984). The ethical problem is that individual and social experience of risks biases perception, memory, communication and consequent exploration of outcomes. This is because learning about risks tends to be skewed towards less exploration for gains than losses. Since
communication often requires live experience and passing through personal understanding, it is inevitably biased by subjective associations and representations. This thesis primarily focused on sharing of experience and related decision-making but did not address the larger ethical concerns of information filtering. The ethics of such risk communication is concerned about the cooperation of agents in information modification and sharing tendencies for better outcomes in applied setting. The combination of ethics, communication, and risk should be explored more directly, with assumptions tested in applied settings (e.g., communication about Covid-19).

The thesis hints about the importance of information aggregation and the problem of balancing underweighting in experience and overweighting in description biases, which are especially important in education, economics, and personal life. In the context of risk, a proper assessment of how information aggregation and normalisation works over diverse population and generations is potentially a fundamental question to better understand and manage real-life risks. There is emerging literature about this problem of generic aggregation (Tessler et al., 2020) and how this would manifest in collective knowledge ("the wisdom of crowds", Mannes et al., 2014), the field of learning about risk would benefit from exploring this direction further. The overweighting or rare events in description might appear when direct social learning is (still) impossible, that is when learning is done from corrected or normalised (i.e., “objective”) information, not from people’s experiences, even aggregated. Current thesis dealt with pairs only – minimal groups – where information aggregation is minimal, but similar complementary bias such as DE gap might still be found in other social contexts. Additionally, there might be a sharp difference in how information is treated when received from one another vs. many individuals. This might be because noise in personal sampling (e.g., underweighting of rare events) might complement the
noise in one another (e.g., sustaining attention on the experiencer) mirroring personal experience, but not of experience of many individuals.

Understanding risks practically in the fields of existential risks, communication, politics, and technology in terms of how they would appear in a real-world environment and how to prevent them would be important topics to pursue. Negative outcome prevention usually benefits from being implemented sooner than later, especially as some risks are potentially existential in the timeline of our generation (Bostrom, 2013; Ord, 2020).

6.7 Concluding remarks

Learning from personal experience by trial-and-error is an essential building block of human progress, but it can only get us so far in understanding learning and decision-making in the dynamic society we live in today. Without relying on the experience and communication of others, learning cannot be fully understood, and risk can only be approximated – any experience will necessarily only represent a sample from the outcome distribution. Applying information filtering to how people gather, process and communicate information within social context is a promising framework to understand why individual biases occur and how they might be complemented. This self-other mirroring of experience provides insights for designing robust learning strategies for individuals and groups: from education and communication to machine learning and existential risks. From selective information filtering stems the subjectivity of gathered knowledge. To transcend the limits of personal knowledge and make approximations more precise, people have to exercise the necessary mechanisms – sharing experiences and learning from others.
References


https://doi.org/10.1016/j.neuron.2020.02.028

https://doi.org/10.1177/0956797616656800


https://doi.org/10.1038/nn.4022

https://doi.org/10.1017/S0140525X12000477


Ferrucci, L., Nougaret, S., & Genovesio, A. (2019). Macaque monkeys learn by observation in the ghost display condition in the object-in-place task with
differential reward to the observer. *Scientific Reports, 9*(1), 1–9. https://doi.org/10.1038/s41598-018-36803-4


similarly motivated to avoid exposure to one another’s opinions. *Journal of Experimental Social Psychology, 72*, 1–12. https://doi.org/10.1016/j.jesp.2017.04.003


https://doi.org/10.1093/qje/qjr044

http://gershmanlab.webfactional.com/pubs/HowToNeverBeWrong.pdf


https://doi.org/10.1371/journal.pone.0162246

https://doi.org/10.1111/cogs.12480


https://doi.org/10.1111/j.1756-8765.2008.00058.x


Kaltenborn, B. P., Krange, O., & Tangeland, T. (2017). Cultural resources and public trust shape attitudes toward climate change and preferred futures—A case study


https://doi.org/10.1016/j.jarmac.2017.07.008


Murdock, B. B. (1962). The serial position effect of free recall. *Journal of
Experimental Psychology, 64*(5), 482. https://doi.org/10.1037/h0045106

5138(15)00058-6/fulltext


campaign leaflets misused statistics. Retrieved August 24, 2017, from LSE
Brexit website: http://blogs.lse.ac.uk/brexit/2017/01/18/unsourced-and-
incomplete-how-referendum-campaign-leaflets-misused-statistics/

labels are perceived differently. *Addiction, 115*(9), 1762–1767.
https://doi.org/10.1111/add.14954

Newell, B. R., Rakow, T., Yechiam, E., & Sambur, M. (2016). Rare disaster
information can increase risk-taking. *Nature Climate Change, 6*(2), 158–161.
https://doi.org/10.1038/nclimate2822

*Proceedings of the Seventeenth International Conference on Machine Learning,
1*(2). https://doi.org/10.2460/ajvr.67.2.323

https://doi.org/10.1016/j.cognition.2011.02.004

Niedenthal, P. M., Barsalou, L. W., Winkielman, P., Krauth-Gruber, S., & Ric, F.


https://doi.org/10.1038/nrn3776

https://doi.org/10.1177/0146167217741314

https://doi.org/10.31234/osf.io/ue7dx

https://doi.org/10.1017/S0140525X19001584


https://doi.org/10.1371/journal.pone.0146536


https://doi.org/10.1126/science.275.5306.1593


https://doi.org/10.1016/j.tics.2019.01.002


resources can explain patterns of social and individual learning in nature. *Proceedings of the Royal Society B: Biological Sciences, 282*(1815), 20151405. https://doi.org/10.1098/rspb.2015.1405


Appendix

Appendix 1: Participant Description

Each participant in a pair is either Participant A or B. Below is the description sheet for Participant A. Participants start with reporting Choice problem 1 and then exchange the sheets for every next choice problem until all set of nine choice problems is experienced and reported.

<table>
<thead>
<tr>
<th>Participant A</th>
<th>LEFT Door</th>
<th>RIGHT Door</th>
</tr>
</thead>
<tbody>
<tr>
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<td>% chance of receiving</td>
<td>% chance of receiving</td>
</tr>
<tr>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
</tr>
<tr>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
</tr>
</tbody>
</table>

<table>
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<th>RIGHT Door</th>
</tr>
</thead>
<tbody>
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<td>Choice Problem 2</td>
<td>% chance of receiving</td>
<td>% chance of receiving</td>
</tr>
<tr>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
</tr>
<tr>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
</tr>
<tr>
<td>Participant A</td>
<td>% chance of receiving</td>
<td>points</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------</td>
<td>--------</td>
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<tr>
<td>Choice Problem 3</td>
<td>LEFT Door</td>
<td>% chance of receiving</td>
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<tr>
<td></td>
<td>RIGHT Door</td>
<td>% chance of receiving</td>
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<tr>
<td></td>
<td>% chance of receiving</td>
<td>points</td>
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</table>

<table>
<thead>
<tr>
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<th>points</th>
<th>% chance of receiving</th>
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<td>% chance of receiving</td>
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<td>RIGHT Door</td>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
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<tr>
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<th>% chance of receiving</th>
<th>points</th>
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<td>RIGHT Door</td>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
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<tr>
<td></td>
<td>% chance of receiving</td>
<td>points</td>
<td>% chance of receiving</td>
<td>points</td>
</tr>
<tr>
<td>Participant</td>
<td>Choice</td>
<td>Problem 6</td>
<td>LEFT Door</td>
<td>RIGHT Door</td>
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<tr>
<td>-------------</td>
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<td>-----------</td>
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<td>-----------</td>
</tr>
<tr>
<td>B</td>
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<td></td>
<td>% chance of receiving</td>
<td>points</td>
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<tr>
<td></td>
<td></td>
<td></td>
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<td>points</td>
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<td>% chance of receiving</td>
<td>points</td>
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<td>% chance of receiving</td>
<td>points</td>
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<td></td>
<td></td>
<td>% chance of receiving</td>
<td>points</td>
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<td></td>
<td>% chance of receiving</td>
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<th>Choice</th>
<th>Problem 8</th>
<th>LEFT Door</th>
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<td>B</td>
<td></td>
<td></td>
<td>% chance of receiving</td>
<td>points</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>% chance of receiving</td>
<td>points</td>
</tr>
<tr>
<td></td>
<td>Participant A</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>---------------</td>
<td>--------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Choice</td>
<td>LEFT Door</td>
<td>RIGHT Door</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Problem 9</td>
<td>%</td>
<td>chance of receiving</td>
<td>points</td>
<td>%</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>chance of receiving</td>
<td>points</td>
<td>%</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>chance of receiving</td>
<td>points</td>
<td>%</td>
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## Appendix 2: Supplementary post-hoc analysis in Chapter 4

The post-hoc analysis by each problem type between the groups (a) and comparing problems across groups (b). Refer to Figure 2 in the main text for the graphs and description.

<table>
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<tr>
<th>Problem</th>
<th>EV</th>
<th>Unsourced (N=102)</th>
<th>Sourced (N = 97)</th>
<th>Pearson Chi-Squared</th>
<th>df</th>
<th>Cramer's Phi</th>
<th>Asymptotic Significance (2-sided)</th>
<th>Pearson Chi-Squared</th>
<th>df</th>
<th>Cramer's Phi</th>
<th>Asymptotic Significance (2-sided)</th>
<th>MEAN</th>
<th>Adj. Residual z-score (above/below group mean)</th>
<th>Chi-Square *** (Transformed scores: z-score*z-score)</th>
<th>p=0.01 (Adjusted control a Type 2 Error rate)</th>
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<td>1</td>
<td>2</td>
<td>57</td>
<td>73</td>
<td>8.24</td>
<td>1</td>
<td>0.2</td>
<td>0.004**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>2</td>
<td>1</td>
<td>58</td>
<td>59</td>
<td>0.322</td>
<td>1</td>
<td>0.04</td>
<td>0.57</td>
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<td></td>
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<td>3</td>
<td>0</td>
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<td>55</td>
<td>0.284</td>
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<td>0.04</td>
<td>0.594</td>
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<td>4</td>
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<td>52</td>
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<td>0.08</td>
<td>0.288</td>
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<td>11</td>
<td>14</td>
<td>0.603</td>
<td>1</td>
<td>0.06</td>
<td>0.438</td>
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<td>6</td>
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<td>86</td>
<td>80</td>
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<td>0.019</td>
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<tr>
<td></td>
<td>0</td>
<td>39</td>
<td>38.24%</td>
<td>32</td>
<td>32.99%</td>
<td>0.596</td>
<td>1</td>
<td>-0.05</td>
<td>0.44</td>
<td>-1.17</td>
<td>1.37</td>
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<tr>
<td>9</td>
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<td>11</td>
<td>10.78%</td>
<td>8</td>
<td>8.25%</td>
<td>0.371</td>
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<td>-0.04</td>
<td>0.543</td>
<td>-9.61</td>
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<tr>
<td>10*</td>
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<td>2</td>
<td>1.96%</td>
<td>2</td>
<td>2.06%</td>
<td>0.003*</td>
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<td>0</td>
<td>0.96*</td>
<td>-12.04</td>
<td>144.96</td>
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<td></td>
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</tr>
</tbody>
</table>

*Less than 5 counts within each group (for Problem 10)

**Bonferroni’s adjusted p=0.005. Only Problem 1 is significant.

***As described by García-Pérez & Núñez-Antó (2003).
Appendix 3: Photos used to identify a social source in Chapter 4

Edward  Chloe  Lisa

Scott  Katie  Sofia

Millie  Jacob  Oscar

Jessica  Rebecca  Jay
Appendix 4a: Text presented to participants in Chapter 5

The following text was presented to participant as information delivered by the source. These are excerpt from BBC News (Mayr et al., 2007):

**Onshore wind.** Onshore wind is our cheapest clean energy source and government surveys show it’s liked by most people. In 2015, ministers decided to virtually block new onshore wind power after it was said it was unpopular. It was said local people should have a veto over wind turbines.

**Roads.** People were urged to cycle to improve health and reduce pollution – yet local councils can’t afford to fill potholes. Meanwhile, billions are being spent on new trunk roads. The government is accused of favouring big infrastructure over small with policies such as an expansion of aviation. Roads and runways are needed to meet future demand.

**The City.** The global stand was taken by warning firms that fossil fuel assets may lose value as we tackle climate change. Some financial institutions have started to take notice, but environmentalists complain that many are pursuing business as usual.

**The science.** It has been shown to consistently over-achieve on climate science. Despite spending cuts, it continues to supply a disproportionate number of lead scientists for influential UN reports warning of the urgency of climate change.
Appendix 4b: Climate change policy attitude scale

(Experiment 1 and Experiment 2 of Chapter 5)

To assess the effect of social source alignment on participants belief about climate change policies, the adapted version of the climate change policy attitude survey items from Correll & Park (2005) was used. The survey items were as follows:

1. Climate change policies will deliver benefits by reducing human impact on environment.
2. I doubt that climate change policies will deliver substantial benefits for the issues it is trying to address.
3. Climate change policies will have very little effect on reducing environmental impact.
4. Climate change policies will deliver little benefit for me personally.
5. On a personal level, climate change policies deliver more cost than benefit.
6. It would be more beneficial if Climate change policies are implemented.
Appendix 4c: Identities Used in Experiment 1 of Chapter 5: Political Identity Study

In the experiment, only two – the most popular – US political parties were presented to participants. The following political party descriptions were provided to participants:

*Below there is a description of the two major political parties in the U.S. Please read it carefully.*

**The Democratic Party**

The Democratic Party is one of the two major contemporary political parties in the United States. The Democratic Party's philosophy of modern liberalism advocates social and economic equality, along with the welfare state. It seeks to provide government regulation in the economy. Policies such as environmental protection, support for organized labor and labor unions, the introduction of social programs, affordable college tuition, universal health care, equal opportunity, and consumer protection form the core of the party's economic policy. *(Source: Wikipedia)*
After reviewing the political parties descriptions, participants were asked the following question: *What is your political party identification?* (Choices provided: The Democratic Party, the Republican Party)
Appendix 4d: Identities Used in Experiment 1 of Chapter 2: Brand Loyalty Study

In the experiment, brand loyalty was applied by using the largest coffee-shops in the USA by the number of locations according to Allegra Strategies report 3. Participants were presented with the following coffee shop descriptions:

_Below there is a description of two of the major coffee chains in the U.S. Please read it carefully._

**Starbucks**

MISSION
To inspire and nurture the human spirit – one person, one cup and one neighbourhood at a time.

VALUES
With our partners, our coffee and our customers at our core, we live these values: Creating a culture of warmth and belonging, where everyone is welcome. Acting with courage, challenging the status quo and finding new ways to grow our company and each other. Delivering our very best in all we do, holding ourselves accountable for results.

Source: [Starbucks Website](https://www.starbucks.com)

---


The choice of the coffee shops was made by searching the most popular coffeeshops by location. List of coffeehouse chains used: Brizek, M. G. (2012). Coffee wars: The big three: Starbucks, McDonald’s and Dunkin’Donuts. _Journal of Case Research in Business & Economics_, 5, 1-12
After viewing the two coffee shop descriptions, participants were asked the following question: *Which one of the two coffee shop brands do you prefer more?* (Choices provided: Starbucks; Dunkin’ Donuts)
Appendix 5: Meta-Analysis of Chapter 2,3 and 4 (Gains only)

The used model was Robust Bayesian Meta-Analysis (RoBMA; the link to the R package: https://fbartos.github.io/RoBMA/).

Figure 1. Estimated mean and heterogeneity parameters. The arrows in the figure represent the point probability mass at $\mu = 0$ and $\tau = 0$, corresponding to the null hypotheses of the absence of effect and heterogeneity.

Figure 2. Meta-analytic forest shows no difference between social and personal experience in risky decision making for gains.
### Estimates:

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
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<tr>
<td>mu</td>
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### Models

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<th>Post. prob.</th>
<th>Inclusion BF</th>
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<tr>
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<td>0.151</td>
</tr>
<tr>
<td>Heterogeneity</td>
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### Estimates

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