DECIDING WHEN TO SEEK AND SHARE INFORMATION

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Declaration

I, Valentina Vellani, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

[redacted]

Abstract

People constantly need to decide when to seek and share information. This thesis investigates which factors shape the decision to seek information and to share it with others.

People prefer to seek positive information and this preference is coded in mesolimbic areas. In Chapter 2, I directly investigated the causal role of dopamine in shaping valenced information-seeking and found that L-DOPA administration increases seeking of negative information.

Previous studies suggest that other variables such as uncertainty and instrumental value of information also shape information-seeking. In Chapter 3, I investigated how the variables that are found to be important for seeking information are integrated to make a sharing decision. I found that people prefer to share information that is positive, useful and when uncertainty is high, suggesting that people rely on their own information-seeking preferences to solve information-sharing problems.

So far, I focused how people decide to share accurate information. In Chapter 4, I tested how people share accurate and inaccurate information when perceived accuracy is enhance via repetition. I found that people were more likely to share statements they had previously been exposed to. This relationship was mediated by perceived accuracy, that is, people were more likely to share repeated information because they perceived it as more accurate.

Millions of pieces of information are sought and shared every day. Understanding how people make these decisions can improve the efficacy of

knowledge distribution. The studies presented in this thesis provide new insight on the variables that shape information seeking and sharing.

Impact statement

The findings of the studies presented in the current thesis offer a theoretical advance and provide practical insights about how people decide to seek and share information. In particular, results described in Chapter 2 provide strong evidence that dopamine plays a crucial role in valence-dependent information-seeking. Because information-seeking is integral to decision-making, understanding its biological basis is critical to better understand impairments in this domain. Our results show that L-DOPA increases information-seeking about potential losses but not about potential gains. These results suggest that patients with deficiency to the dopamine system may exhibit abnormal patterns of information-seeking, which may provide a marker of their condition. The findings also suggest that information-seeking behaviour may be altered by drugs targeting dopaminergic function. Patients who are administered these drugs, such as, Parkinson's patients, may therefore overexpose themselves to negative information, which may induce negative affect.

In Chapter 3, I expanded the current literature on information-seeking and sharing by suggesting that people apply the same rules to decide when to share information as they do to decide when to seek information. Importantly, they apply those rules from the point of view of the recipient, not their own. In particular, participants shared information more when it could be used by the recipient to gain rewards and avoid losses, when it was good news rather than bad, and when the receiver was under high uncertainty. These results suggest that in order to decide which information to provide to the receivers, people used their own information preferences on what they would want to know.

Moreover, each individual tend to overweight one motive over the others. The importance people assign to these motives may explain why different people make different sharing decisions. A vast number of pieces of information are available every day, understanding how people make sharing decisions can improve the efficacy of knowledge distribution.

In Chapter 4, I found that even a single exposure to information increases its sharing. Specifically, the effect of repetition on sharing decisions is mediated by perceived accuracy of information. Our findings provide novel insight on how misinformation spread both online and offline. This is of interest as misinformation can negatively impact people's lives in domains ranging from public health to politics. Our results help explaining why fake news spread so easily among the population. Fake-news are often constructed to be appealing to the reader and consequently they are more likely to be repeated by many sources. Our results suggest that repeated exposure to false information will create a vicious circle in which fake-news will be perceived as more true and therefore shared more.

Overall, results described in this thesis provide new theoretical insights on how people seek and share information and help explain real life phenomena such as fake-news sharing.

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NOTES TO EXAMINERS

The findings from Chapters 2 have been published in a peer-reviewed article: Vellani, V., de Vries, L. P., Gaule, A., & Sharot, T. (2020). A selective effect of dopamine on information-seeking. *Elife*, *9*, e59152.

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CHAPTER 1:

GENERAL INTRODUCTION

OVERVIEW

This thesis investigates how people decide when to seek information and when to share it with others.

In Chapter 2, I focus on the biological basis of information-seeking. Previous studies showed that information-seeking and reward-seeking share neural systems, suggesting that the opportunity to gain knowledge is itself rewarding. As previous studies showed that the opportunity to gain information about favourable outcomes is encoded in regions rich in dopaminergic neurons, I hypothesize that dopamine administration would alter valence-dependent information-seeking.

In Chapter 3, I investigate how people solve complex information-sharing problems. Previous studies suggested that people prefer to seek information that is more likely to convey good news, that is instrumental and when uncertainty is high. In this study, I investigate whether people incorporate these three variables into an information-sharing decision.

So far, I investigated how people share accurate information. In Chapter 4, I investigate how enhancing accuracy perception via repetition affects sharing of accurate and inaccurate information. Previous studies suggest that repeated information is perceived as more accurate. I hypothesize that repeated statements will be shared more because people will believe they are more accurate.

The following sections summarize theories and empirical studies relevant to the study of how people decide when to seek and share information.

HOW PEOPLE DECIDE WHEN TO SEEK INFORMATION

Gathering information is a fundamental part of human nature and is integral to learning, social engagement and decision-making (Kidd and Hayden, 2015; Loewenstein, 1994; Sakaki et al., 2018; Gottlieb et al., 2013). Because people are exposed to a huge amount of information they need to decide when to seek it. Different factors play a role in determining when people will seek information. The following sections will explore some of the motives that have been found to impact information-seeking decisions (Sharot & Sustain, 2020; Kelly & Sharot, 2021; Dezza et al., 2022).

Studies investigating information-seeking motives showed that people seek information that is useful to obtain rewards and avoid harms (Stigler, 1961; Hirshleifer & Ryley, 1979; Kelly & Sharot, 2021; Kobayashi & Hsu, 2019; Wilson et al., 2014; Golman et al., 2021; Dezza et al., 2022). For example, you are more likely to read a cookbook if they need to cook dinner. Such instrumental utility can be quantified and measured. For instance, Kobayashi and Hsu (2019) asked participants to decide whether to accept or reject a lottery with two monetary outcomes (one positive and one negative) whose probability was hidden. Then they were presented with two probability distributions, one showing the positive outcome being more likely, and the other one showing the negative outcome being more likely. Participant could then pay to receive information about the true outcome and change their original choice. In this study, the greater the difference in the expected utility between the decision with and without information, the greater the instrumental utility of information. Results revealed that people preferred to seek information when instrumental utility of information was high.

However, often people seek information that has no instrumental benefit and avoid useful information. This suggest that instrumental value of information is not the only motive that drives information-seeking. A vast literature suggest that valence of information is crucial when determining whether to seek information. Specifically, people prefer to seek information that it is likely to convey good news than bad news (Charpentier et al., 2018). For example, people may be more willing to open an editor's email if they expect that their paper has been accepted for publication. Charpentier et al. (2018) showed that people are willing to pay to gain positive information and to avoid negative information, even when information cannot be used to alter rewards outcomes. Overall, these studies suggest that people are motivated to seek information that can generate positive beliefs, and to avoid information that can generate negative beliefs (Sharot & Sunstein, 2020; Loewenstein, 1987; Caplin & Leahy, 2001; Karlsson et al., 2009; Golman et al., 2017). This tendency can be maladaptive when people decide to avoid potentially useful negative information. For example, people might avoid collecting the results of their medical tests (Lerman et al., 1998).

Studies on non-human primates suggested that signals in dopaminergic midbrain neurons named information prediction errors (IPEs) code the opportunity to gain information (Bromberg-Martin & Hikosaka, 2009; Bromberg-Martin & Hikosaka, 2011). In humans, IPEs are valence-dependent, that is, they are stronger for opportunity to gain positive than negative information (Charpentier et al., 2018). The opportunity to gain positive information, but not negative information, is coded in mesolimbic reward areas (Charpentier et al., 2018). Differently, the orbitofrontal cortex (OFC) codes for the opportunity to obtain information regardless of its valence (Charpentier et al., 2018).

However, people also engage in information-seeking when information cannot improve their mood nor has no instrumental value. Another relevant factor that drives information-seeking is uncertainty reduction. That is, people seek information that can help reduce uncertainty (Wilson et al., 2014; Oudeyer et al., 2016; Oudeyer & Smith, 2016; Cogliati Dezza et al., 2017; Gershman, 2018; Schwartenbeck et al., 2019; Dezza et al., 2022). In a study by Cogliati Dezza et al. (2021), participants were asked to pick one out of three decks of cards while varying their knowledge about the options. Participants were more willing to seek information when uncertainty about the options was high. The drive for uncertainty reduction seems to rely on brain areas which include the dorsal anterior cingulate cortex (dACC) (Cogliati Dezza et al., 2020; Kaanders et al., 2021), the rostrolateral prefrontal cortex (flPFC) (Ligneul et al., 2018; Tomov et al., 2020) and the parietal cortex (Van Lieshout et al., 2018; Kaanders et al., 2021).

Recent findings suggest that instrumentality, valence and uncertainty of information jointly affect information-seeking behaviours (Sharot & Sunstein, 2020; Kelly & Sharot, 2021; Dezza et al., 2022). These information-seeking motives are integrated to compute information value. Kelly and Sharot (2021) suggested that people pose different weight on each of these variables, and the weights assigned to each variable generate individual differences in information-seeking behaviour. In this study, participants were asked whether they would want to receive information about how their friends and family rated them on different attributes. Then for each attribute, participants rated (1) whether it would be useful to receive such information, (2) how they would feel if they would receive that information, (3) how they would feel if they would not receive that information and (4) how often do they thing about the attribute. The first and the last question provided a proxy respectively for instrumental and cognitive utility. The difference between the second and third rating provided a proxy for hedonic utility. Results suggested that information-seeking decisions are best explained by a model that considers all three factors. Specifically, participants preferred to seek information that they believed to be useful, had a positive impact on their mood and about attributes they thought frequently about. These information-seeking preferences seems stable across domains, as the same motives have been found to predict information-seeking in different domains, including finance and health. Moreover, individuals differences in the weights assigned to cognitive utility were associated to mental health, suggesting that information-seeking patterns are strongly associated to individuals' wellbeing. Specifically, people that preferred to seek information they think about more frequently reported better mental health. Interestingly, within individuals, the weights assigned to each factor remained relatively stable, suggesting that information-seeking preferences are stable. Further studies suggest that subjective expectations about the impact of information on individuals' emotions, uncertainty and outcome predict seeking behaviour better than a model including objective measures of these three motives (Dezza et al., 2022).

The studies mentioned in this section provide insights into how people decide when to seek information. As information affect our mood, beliefs and subsequently, our behaviour, understanding how people make information-seeking choices is of the highest interest. Previous correlational studies suggested that the opportunity to gain information about favourable outcomes is encoded in regions rich in dopaminergic neurons. However, no study causally tested whether dopamine mediates valenced information-seeking. In Chapter 2, I will directly test this by administering L-DOPA or placebo to participants and comparing their performance in an information-seeking task.

HOW PEOPLE DECIDE WHEN TO SHARE INFORMATION

Sharing knowledge, whether online or offline is crucial for the survival of our species. Every day people share millions of pieces of information. Similarly to seeking information, sharing information with others is rewarding. For example, sharing information about ourselves is associated with increased activation in the mesolimbic reward system (Tamir & Mitchell, 2012). As information can impact our mood, beliefs and consequently, our action, it is crucial to understand which variables are considered when deciding whether to share information. Different factors have been found to impact the decision to share information with others.

Similarly to what has been found for information-seeking, people prefer to share with others positive information (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987; Dibble and Levine, 2010, 2013; Weenig et al., 2014; Tesser & Rosen, 1975). This phenomenon is known as the MUM ("keeping Mum about Undesirable Messages to the recipient") effect. Specifically, the effect is driven both by the willing to share good information and by the reluctance to share negative information (Diddle & Levine, 2010). The effect holds strong even when the sharer does not know the receiver. For example, Dibble & Levine (2013) found that people prefer to share good over bad news regardless of whether the recipient was a friend or a stranger. A study analyzing published journal articles showed that articles characterized by positive content were more likely to be viral in a three-month period (Berger & Milkman, 2012). However, it has been also suggested that people are more likely to share information that evoke high arousal (Gross & Levenson, 1995; Berger, 2011), regardless of its valence.

When deciding whether to share information, people also seem to take into consideration instrumental utility of information. Specifically, people prefer to share with others information that is useful (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001). For example, people are more likely to share articles that are characterized by high-information utility compared low-information utility (Bobkowski, 2015). Moreover, people also prefer to share urban legends that would make them change their behaviour (Heath et al., 2001). Instrumental utility seems also to drive sharing of information online. Bergen & Milkman (2012) found that practically useful journal articles are more likely to become viral.

Overall, these studies suggest that when informing others, people prefer to share information that can guide action (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001) and that is positive (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987;Dibble and Levine, 2010, 2013; Weenig et al., 2014). However, these variables have been studied either in isolation or in a situation where they are confounded. Moreover, it is unknown whether people take into consideration the receiver' uncertainty when deciding whether to share information with them. In Chapter 3, I will investigate how people weight different motives when solving difficult information-sharing problems to computationally disentangle the importance of these variables.

HOW INFORMATION ACCURACY AFFECTS SHARING

Results from Chapter 3 suggest that the same variables that guide information-seeking also guide information-sharing. Specifically, people prefer to seek and share information that is (i) positive, (ii) useful and (ii) when uncertainty is high. So far, I investigated how people decide to share accurate information. In Chapter 4, I will investigate how enhancing perceived accuracy via repetition shapes the decision to share accurate and inaccurate information. A vast literature suggest that repetition increases belief in accuracy. This phenomenon has been named the "Illusory truth effect" (Arkes et al., 1989; Murray et al., 2020; Fazio et al,. 2019) and describes how repeated exposure to statements increases their perceived accuracy (Arkes et al., 1991; Bacon, 1979; Begg et al., 1992; Hasher et al., 1977; Hawkins & Hoch, 1992; Law et al., 1998; Johar & Roggeveen, 2007; Pennyccok et al., 2018; for a review Dechene et al., 2010). The Illusory truth effect occurs even after only one repetition and it has been demonstrated in many domains, ranging from advertisement (Hawkins & Hoch, 1992; Law et al., 1998; Roggeveen & Johar, 2002, 2007) to opinions (Arkes et al., 1989). The effect holds even when the delay between repetitions is as long as weeks (Bacon, 1979; Gigerenzer, 1984; Hasher et al., 1977). Interestingly, repetition increases accuracy ratings even if information comes from a non-credible source (Begg et al., 1992) and when information is inconsistent with the subject's political belief (Pennycook et al., 2018).

If repeated exposure to information increases its accuracy perception, it is possible that it would also increase sharing behaviour (for similar prediction see Van Bavel at al., 2021). According to the model hypothesized by Van Bavel et al. (2021), sharing of misinformation, might expose other people to misinformation, increasing their likelihood of perceiving it as accurate and further sharing it with others.

Engagement with fake-news online has sharply increased in recent years. As an example, misleading information about COVID-19 proliferated both online and offline with 1.1 million articles, containing misinformation about COVID-19, shared on social media (Evanega et al., 2020). Fake-news spreading has concerning consequences ranging from vaccines hesitancy to violent extremism (Rapp & Salovich, 2018; Tsfati et al., 2020; Barreto et al., 2021). For example, fake-news on how to treat COVID-19 can lead to delays in properly treating patients. Thus, it is crucial to identify the factors that facilitate fake-news sharing in order to contrast their spreading.

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SUMMARY

Information-seeking is a crucial aspect of people's everyday life. As information can impact our beliefs, mood and behaviour, it is crucial to understand which variables affect the decision to seek information. It has been suggested that people prefer to seek information that is likely to convey positive news (Kelly & Sharot, 2021; Sharot & Sunstein, 2020; Charpentier et al.,2018; Dezza et al., 2022) and correlational studies suggest that this preference is coded in dopaminergic areas in the brain (Charpentier et al., 2018). In Chapter 2, I will directly test for the causal role of dopamine administration in altering valenced information-seeking by administering either L-DOPA or placebo to participants completing an information-seeking task.

People also prefer to seek information that can be useful to obtain gains and avoid punishments (Stigler, 1961; Hirshleifer & Ryley, 1979; Kelly & Sharot, 2021; Kobayashi & Hsu, 2019; Dezza et al., 2022) and when uncertainty is high (Kelly & Sharot, 2021; Wilson et al., 2014; Oudeyer et al., 2016; Cogliati Dezza et al., 2017; Gershman, 2018; Schwartenbeck et al., 2019; Dezza et al., 2022). The same variables that have been found to predict information-seeking also seem to shape the decision to share information. Specifically, people prefer to share information that covey good news (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987;Dibble and Levine, 2010, 2013; Weenig et al., 2014; Tesser & Rosen, 1975) and that can guide action (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001). While previous studies investigated these variables in isolation, in real-life, they often compete to drive sharing decisions. Moreover, it is currently unknown how the receiver's

uncertainty shapes the decision to share information. In Chapter 3, I will design an information-sharing task in which valence of information, its instrumental value and uncertainty simultaneously vary in order to investigate how these variables are computationally integrated to decide when to share information.

So far, I focused on sharing of accurate information. As misinformation can negatively impact people's lives in domains ranging from public health to politics, it is crucial to investigate the mechanisms that facilitate sharing of inaccurate information. In Chapter 4 I will investigate sharing decision while experimentally manipulating accuracy perception by showing information repeatedly (Arkes et al., 1989; Murray et al., 2020; Fazio et al., 2019).

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CHAPTER 2:

A SELECTIVE EFFECT OF DOPAMINE ON INFORMATION-SEEKING

ABSTRACT

Humans are motivated to seek information from their environment. How the brain motivates this behaviour is unknown. One speculation is that the brain employs neuromodulatory systems implicated in primary reward-seeking, in particular dopamine, to instruct information-seeking. However, there has been no causal test for the role of dopamine in information-seeking. Here, I show that administration of a drug that enhances dopamine function (dihydroxy-Lphenylalanine; L-DOPA) reduces the impact of valence on information-seeking. Specifically, while participants under Placebo sought more information about potential gains than losses, under L-DOPA this difference was not observed. The results provide new insight into the neurobiology of information-seeking and generates the prediction that abnormal dopaminergic function.

INTRODUCTION

Curiosity, commonly defined as the desire for knowledge, is a fundamental part of human nature (Kidd and Hayden, 2015; Loewenstein, 1994). In humans, it manifests as information-seeking behaviours such as asking questions, reading, conducting experiments, and online searches. Such behaviour is integral to learning, social engagement, and decision-making (Kidd and Hayden, 2015; Loewenstein, 1994; Sakaki et al., 2018). Despite information-seeking being central to behavior, I know remarkably little about the biological mechanisms that control it.

It has been suggested that information-seeking relies on the same neural system as reward-seeking (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Charpentier et al., 2018; Ligneul et al., 2018; Kobayashi and Hsu, 2019; Kang et al., 2009; Smith et al., 2016; Tricomi and Fiez, 2012; Jessup and O'Doherty, 2014; Gruber et al., 2014; van Lieshout et al., 2018), implying that the opportunity to gain knowledge has intrinsic value (Grant et al., 1998). This assumption is supported by correlational studies showing that the opportunity to gain information is encoded in regions rich in dopaminergic neurons (e.g. Ventral Tegmental Area, Substantia Nigra) and their targets (e.g. Nucleus Accumbens, Orbital Frontal Cortex) (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Charpentier et al., 2018; Ligneul et al., 2018; Kobayashi and Hsu, 2019; Kang et al., 2009; Smith et al., 2016; Tricomi and Fiez, 2012; Jessup and O'Doherty, 2014; Gruber et al., 2014; van Lieshout et al., 2018). For example, information prediction error signals have been identified in dopamine-rich brain regions

(Bromberg-Martin and Hikosaka, 2009), which analogous to reward prediction errors (Schultz et al., 1997) are theorized to provide reinforcement for seeking-information. These signals have been observed even when information is non-instrumental (Bromberg-Martin and Hikosaka, 2009) (i.e. cannot be used to gain future rewards or avoid future harm), consistent with the idea that the brain treats the opportunity to gain knowledge as a higher order reward (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Grant et al., 1998). Such coding may be adaptive because information could turn out to be useful in the future even if it appears useless at present (Eliaz and Schotter, 2007).

Thus, one hypothesis is that dopamine boosts information-seeking. However, another possibility is that dopamine selectively affects the impact of valence on information-seeking. In particular, it has been shown that individuals seek information more when information is about future gains than losses (Charpentier et al., 2018; Thornton, 2008; Persoskie et al., 2014; Dwyer et al., 2015; Caplin and Leahy, 2001; Ko˝szegi, 2010; Golman et al., 2017). For example, investors monitor their portfolio more frequently when they expect their worth has gone up rather than down (Karlsson et al., 2009); some people refuse to receive results of medical tests for fear of bad news (Hertwig and Engel, 2016); and monkeys prefer to know in advance the size of rewards they are about to receive particularly when they expect large rewards (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015). In humans, dopaminergic midbrain regions have been shown to code for the opportunity to receive information in a valence-dependent manner (Charpentier et al., 2018), suggesting that the intrinsic utility of knowledge is modulated by valence.

To test the above competing hypotheses, I enhanced dopamine function in humans by administrating L-DOPA and asked them to perform an information-seeking task (Charpentier et al., 2018). I compared their performance to participants who received Placebo to examine whether and how dopamine alters non-instrumental information-seeking.

RESULTS

Two hundred and forty-eight participants performed an information-seeking task adapted from our previous publication (Charpentier et al., 2018), of which 16 participants did not complete the task in full; therefore, data of 232 subjects was analysed. The study was a double-blind pharmacological intervention where one group of participants received Placebo (n = 116, females = 72, mean age = 24.36, *Table 2-1*) and the other received L-DOPA (150 mg) (n = 116, females = 71, mean age = 25.44, *Table 1-1*).

Demographics	**Placebo** mean (SD)	**L-DOPA** mean (SD)	**p-value**
Age	24.36(7.91)	25.44(7.92)	0.301
Gender	Females N=72	Females N=71	0.893
Income	4.85(2.38)	4.61(2.54)	0.462
Education Level	7.09(1.72)	7.39(1.50)	0.157

Table 2-1. Demographics. There were no differences between groups in terms of demographics. p-value is of independent sample t-test , or in the case of gender of X^2 . Education was measured on a scale ranging from 1 (no formal education) to 10 (Doctoral degree). Annual household income was measured on a scale from 1 (less than 10K) to 10 (more than 100K).

Participants began the task 40 min after receiving L-DOPA or Placebo (as in Guitart-Masip et al., 2012; Sharot et al., 2009; Sharot et al., 2012), as the half-life of L-DOPA is 90 min. They were endowed with £5 at the beginning of each of the four blocks to invest in two of five stocks in a simulated stock market. There were 50 trials per block. On each trial, participants observed the evolution of the market (i.e. whether the market was going up or down) and the exact value of the market (*Figure 2-1*). They then bid for a chance to know (or remain ignorant about) the value of their portfolio. Specifically, they indicated how much they were willing to pay to receive or avoid information about the value of their portfolio on a scale ranging from 99 p to gain knowledge through 0 p (no preference) to 99 p to remain ignorant. The more they were willing to pay, the more likely their choice was to be honoured.

Information was non-instrumental; it could not be used to increase rewards, avoid losses, or make changes to portfolio.

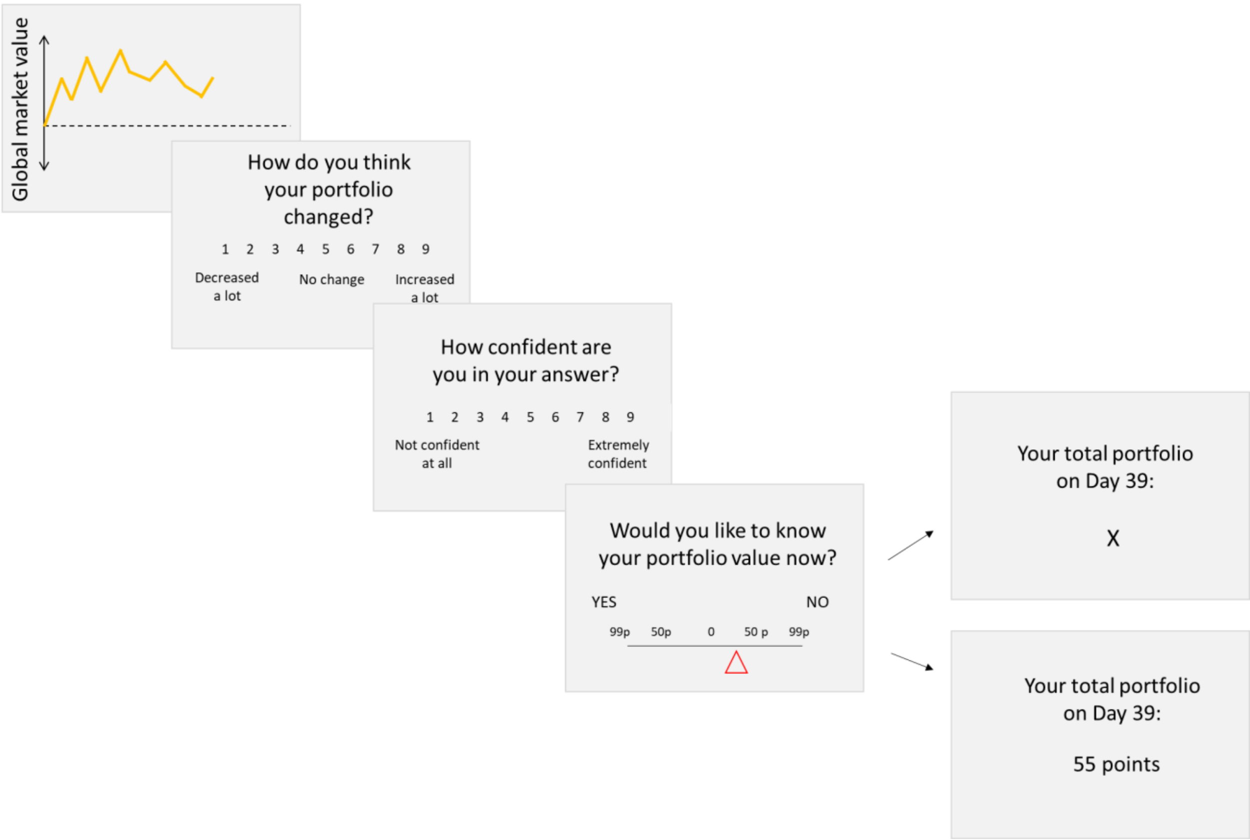

Figure 2-1. Stock market task. Participants observed the evolution of a financial market after investing in two of its five companies. They then indicated whether they believed their portfolio value likely went up or down relative to the previous trial and indicated their confidence in their answer. They then indicated how much they were willing to pay to receive or avoid information about their portfolio value. Next, their portfolio value in points was presented on screen or hidden (‘XX points’ was shown).

L-DOPA did not alter general information-seeking

L-DOPA administration did not alter general aspects of information-seeking (*Figure 2-2*). In particular, there were no difference between the Placebo and L-DOPA groups in the average number of trials in which participants selected to pay for information (Placebo = 71.16 trials, L-DOPA = 72.89 trials, t (230) = 0.226, p=0.821, independent samples t-test), pay to avoid information (Placebo = 27.79 trials, L-DOPA = 27.97 trials, t(230) = 0.036, p=0.971), or not to pay at all (i.e. entered 0 p: Placebo = 93.86 trials, L-DOPA = 92.65 trials, t(230) = 0.145 p=0.885). There was also no difference in the average amount each group paid to receive information (Placebo = 18.18 p, L-DOPA = 15.68 p, t(228) = 0.928, p=0.355) or avoid it (Placebo = 11.34 p, L-DOPA = 9.95 p, t(223) = 0.587, p=0.558). These results suggest that dopamine does not generally alter information-seeking. Finally, there was no difference across groups in the number of trials participants missed (that is trials in which they were too slow in responding: Placebo = 7.03 trials, L-DOPA = 6.50 trials, t(230) = 0.283, p=0.777), suggesting no difference in engagement with the task.

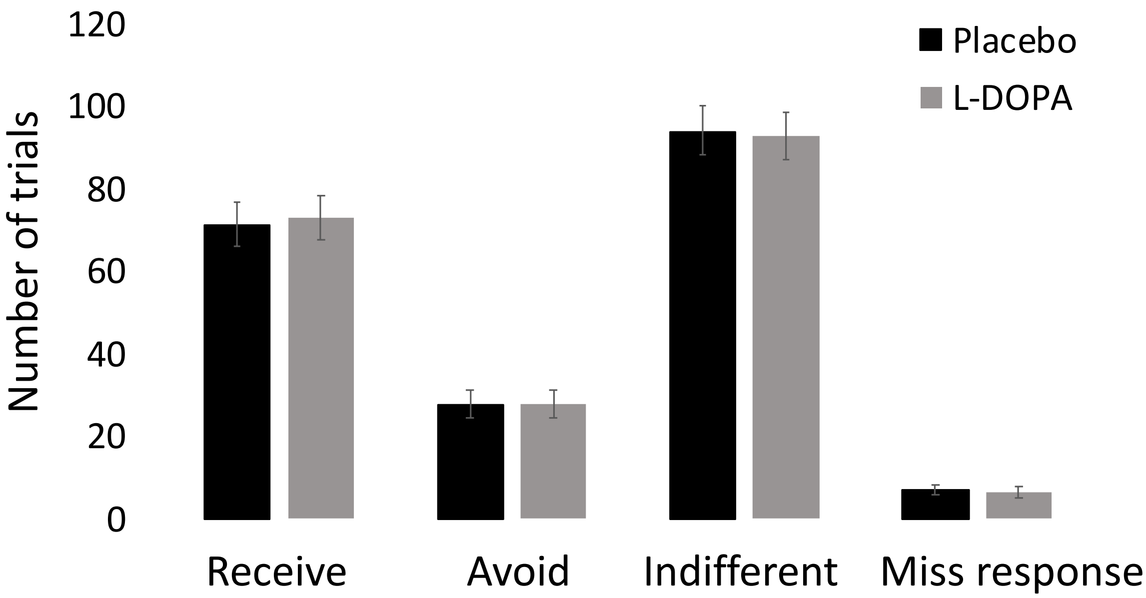

Figure 2-2. L-DOPA does not alter general aspects of information-seeking. There were no differences in general information-seeking between those who received Placebo and those who were administered L-DOPA. In particular, there were no differences in the average number of trials on which the participants decided to receive or to avoid information or were indifferent (i.e. paid 0). Furthermore, there was no difference across groups in the number of trials participants missed (that is trials in which they were too slow in responding). Error bars SEM.

L-DOPA diminished the effect of valence on information-seeking

In this task, studies from my lab had previously shown that despite participants wanting information both when the market was going down and when it was going up (Charpentier et al., 2018), information-seeking was modulated by the expected valence of the outcome (Charpentier et al., 2018). In particular, they had reported that participants were more likely to pay for information when the market was going up rather than down and more likely to pay to avoid information when the market was going down rather than up (Charpentier et al., 2018). This is because people expected to learn about gains when the market was going up and expected to learn about losses when the market was going down (Charpentier et al., 2018). The second factor I had reported to influence information-seeking was the absolute amount of change in the market. Participants were willing to pay more for information when there were big changes in the market. Here, I examine whether dopamine modulates these effects on information-seeking.

On each trial, I calculated the Willingness To Pay (WTP) for information. WTP is coded positively if participants indicated they wanted to receive information and negatively if they wanted to avoid information (Charpentier et al., 2018). I then ran a Linear Mixed Model to predict WTP on each trial from the two factors I had previously shown to impact information-seeking in this task (Charpentier et al., 2018): (i) valence (quantified as signed market change, which is the amount by which the market went up or down); (ii) absolute market change; as well as from (iii) group (L-DOPA or Placebo). All three factors were included as fixed and random effects, as were the interactions of group with each of the other two factors. Random and fixed intercepts were also included in the model.

The results revealed an interaction between group and valence on the WTP for information ($\beta = 0.15$, CI = 0.29 /- 0.01, $t(230.52) = 2.15$, $p = 0.032$) as well as a main effect of valence ($\beta = 0.20$, CI = 0.11/0.30, $t(229.60) = 4.11$, $p = 0.0001$) and a main effect of absolute market change ($\beta = 0.41$, CI = 0.25/0.58, $t(231.35) = 4.87$, $p = 0.0001$). There was no interaction between group and absolute market change (β = 0.07, CI = 0.17/0.30, t(232.42) = 0.576, p = 0.565) nor a main effect of group (β = 2.61, CI = 7.50/2.28, t(232.53) = 1.045, p = 0.297).

The interaction indicates that expected valence differentially effected the desire for information in the Placebo and L-DOPA groups. To tease apart the interaction, I next ran two mixed linear models separately for the Placebo and L-DOPA groups. WTP was entered as the dependent factor and valence and absolute market change as fixed and random factors. The model included fixed and random intercepts. This revealed a significant effect of valence in the Placebo group (main effect of signed market change: β = 0.20, CI = 0.08/0.33, t(115.25) = 3.18, p = 0.001, *Figure 2-3a*), but lack thereof in the L-DOPA group (main effect of signed market change: β = 0.05, CI = 0.005/0.11, t (115.28) = 1.78, p = 0.076, *Figure 2-3a*). Both groups showed a main effect of absolute market change (Placebo: β = 0.41, CI = 0.23/0.59, t(117.58) = 4.52, p = 0.0001; L-DOPA: β = 0.48, CI = 0.33/0.63, t (113.54) = 6.266, p = 0.0001, *Figure 2-3a*). These results suggest that L-DOPA selectively reduced the impact of the expected valence of information on the desire for knowledge.

The same results are observed also when using a simpler model with WTP as a dependent measure and only one independent factor - valence - coded in a binary fashion (1 for market up and 0 for market down) as fixed and random variable with fixed and random intercepts. I find a significant effect of valence in the Placebo group (β = 1.85, CI = 0.64/3.05, t(116.88) = 3.01, p = 0.003) with WTP for information being greater for trials in which the market went up (indicating potential gains) than down (indicating potential losses), and lack thereof in the L-DOPA group (β = 0.35, CI = 0.21/ 0.91, t(117.58) =

1.22, p = 0.224). This shows that under Placebo participants desired information more when the market was up vs down, whereas under L-DOPA the desire for information was not altered by valence.

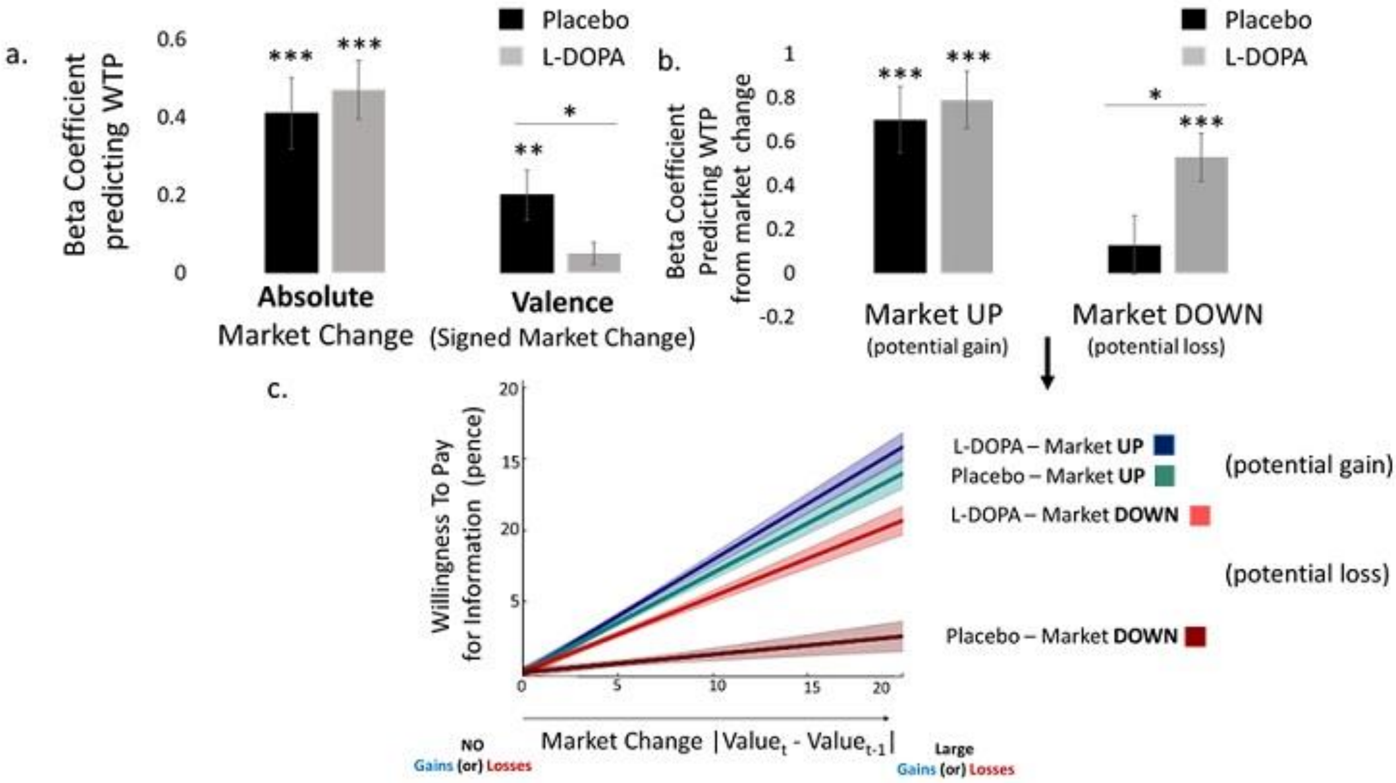

Figure 2-3. L-DOPA reduces the effect of valence on information-seeking. (a) A mixed linear model predicting Willingness To Pay (WTP) for information revealed an interaction between group (Placebo/L-DOPA) and valence (the amount by which the market went up or down), with no interaction between group and absolute market change. To tease apart the interaction, I ran linear mixed models separately for the L-DOPA and Placebo groups. Plotted are the fixed effects of those models. As observed, this revealed a significant effect of valence on information-seeking in the Placebo group but lack thereof in the L-DOPA group. Absolute change was a significant predictor in both groups. This indicates a reduction in the influence of

valence on information-seeking under L-DOPA. (b) To further characterize the effect of valence and drug on information-seeking, I run separate mixed linear models for each group and polarity predicting WTP from market change, trial number and the interaction of the two. Plotted are the fixed effects of market change for each. As can be observed under L-DOPA market change was a significant predictor of information-seeking about potential losses and gains - the greater the expected gain/loss the more participants were willing to pay for information. In contrast, under Placebo market change was a significant predictor of information-seeking about potential gains, but not losses. These results show that L-DOPA selectively alters information-seeking about losses. (c) Plotted is the effect of market change on WTP for information controlling for any effects of trial number. As can be observed the slopes are significantly positive for all groups/conditions except for the Placebo group in the loss domain. Clouds are based on Standard Errors of the fixed effect. Error bars SEM, * $p < 0.01$, *** $p < 0.001$.

L-DOPA selectively alters information-seeking about potential losses.

Our results indicate that L-DOPA selectively reduces the impact of valence on information-seeking. Next, I ask if this effect is due to L-DOPA altering information-seeking about potential losses, about potential gains, or both. Moreover, I ask whether the effect of L-DOPA emerged over the course of the experiment or whether it was apparent from the very beginning.

To that end, I ran two separate mixed effect linear model predicting the WTP for information – one for trials in which the market went up (potential gain trials) and one for which the market went down (potential loss trials). The independent factors included (i) market change, (ii) trial number, and (iii) group

(L-DOPA/Placebo). As each model now includes only one polarity - either market going up or down - signed market change and absolute market change are perfectly correlated. Thus, only one factor 'market change' is added. In the loss domain, the greater the 'market change' the greater the expected losses. In the gain domain, the greater the 'market change' the greater the expected gains. All three factors and their interactions were included as fixed and random effects. Random and fixed intercepts were also included in the model. The results revealed an interaction between market change and group in the loss domain ($\beta = 0.40$, CI = 0.07/0.74, $t(751.900) = 2.35$, $p = 0.018$), but not in the gain domain ($\beta = 0.10$, CI = 0.29/0.50, $t(490.600) = 0.505$, $p = 0.614$) where instead there was a main effect of market change ($\beta = 0.70$, CI = 0.42/.98, $t(495.800) = 4.896$, $p = 0.0001$). No other effects were significant.

To characterize the interaction of interest (between market change and group) in the loss domain and lack thereof in the gain domain, I ran four linear mixed models - one for each group and valence polarity. WTP was the dependent factor, and the independent factors were (i) market change and (ii) trial number. Both factors and their interactions were included as fixed and random effects. Random and fixed intercepts were also included in the model. This revealed that under L-DOPA participants were willing to pay more for information the greater the gains (effect of market change: $\beta = 0.79$, CI = 0.53/1.05, $t(313.300) = 5.98$, $p = 0.0001$; *Figure 2-3b*) and the greater the losses (effect of market change: $\beta = 0.53$, CI = 0.33/0.74, $t(484.700) = 5.033$, $p = 0.0001$; *Figure 2-3b*). In contrast, under Placebo participants were willing to pay more for information the greater the gains (effect of market change: $\beta = 0.69$, CI = 0.40/0.99, $t(219.92) = 4.64$, $p = 0.0001$, *Figure 2-3b*) but did not show this effect for losses (effect of market change: β = 0.12, CI = 0.13/0.39, t(335.800) = 0.956, p = 0.33, *Figure 2-3b*). For L-DOPA in the gain domain, there was an additional interaction between trial and market change (β = 0.002, CI = 0.004 /- 0.006, t(382.20) = 2.74, p = 0.006). No other effects were significant.

The results show that under L-DOPA, participants' desire for information increased as the expected magnitude of the outcome increased - participants were willing to pay more for information as potential gains and losses increased (*Figure 2-3c*). In contrast, under Placebo, participants' desire for information increased as potentials gains increased but remained constant and relatively low for potential losses (*Figure 2-3c*).

The effect of L-DOPA on information-seeking for losses is not explained by changes in expectations.

I next ask whether the selective effect of L-DOPA on information-seeking about losses can be explained by a selective effect of L-DOPA on expectations about losses. To test participants' expectations regarding their outcomes, I asked participants whether they believed their stocks went up or down after observing the global market change. This was done by having participants rate their expectations on a scale ranging from 1 (decreased a lot) to 9 (increased a lot). I then entered these ratings into Linear Mixed Model predicting expectation ratings. The independent factors were: (i) valence (signed market change), (ii) absolute market change, and (iii) group (L-DOPA or Placebo). All three factors were included as fixed and random effects as were the interactions of group with each of the other two factors. Random and fixed intercepts were also included in the model. There was no main effect of group ($\beta = 0.06$, CI = 0.05/0.17, $t(257.400) = 1.01$, $p = 0.310$), nor an interaction between group and valence ($\beta = 0.01$, CI = 0.03/0.02, $t(232.900) = 0.63$, $p = 0.529$) nor an interaction between group and absolute market change ($\beta = 0.00$, CI = 0.01/0.01, $t(242.900) = 0.266$, $p = 0.790$). There was a main effect of absolute market change ($\beta = 0.01$, CI = 0.02 /- 0.0001, $t(241.000) = 2.28$, $p = 0.023$) and of valence ($\beta = 0.21$, CI = 0.19/0.22, $t(233.000) = 23.264$, $p = 0.0001$). The latter confirms that participants' expectations about their outcomes were linked to the observed trends in the market.

These results suggest that L-DOPA did not affect participants' expectations. To further examine whether there may be an effect of L-DOPA on expectations that altered over time, I added to the model above trial number as a fixed and random factor as well as all the two- and three-way interactions of trial number with the other factors. Once again, this neither revealed an effect of group on expectations ($\beta = 0.05$, CI = 0.49/0.60, $t(312.800) = 0.186$ $p = 0.852$) nor were any of the interactions between group and any of the other factors significant (all Ps > 0.329). These results suggest that L-DOPA selectively altered the effect of valence on information-seeking without altering outcome expectations.

DISCUSSION

Humans and non-human animals seek information even when information cannot be used to alter outcomes (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Charpentier et al., 2018). This observation led to the notion that knowledge may have evolved to carry intrinsic value (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Grant et al., 1998). Indeed, it has been shown that the opportunity to receive non-instrumental information is encoded by the same neural system as for primary rewards (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Charpentier et al., 2018; Ligneul et al., 2018; Kang et al., 2009; Gruber et al., 2014; van Lieshout et al., 2018). As this system includes regions rich in dopamine, the findings triggered the hypothesis that dopamine plays a critical role in non-instrumental information-seeking (Bromberg-Martin and Hikosaka, 2009; Bromberg-Martin and Hikosaka, 2011; Blanchard et al., 2015; Charpentier et al., 2018). By manipulating the dopamine levels in humans, I were able to directly test this hypothesis.

Our results show that L-DOPA has a selective effect on non-instrumental information-seeking. Administration of L-DOPA dampened the effect of valence on non-instrumental information-seeking, altering non-instrumental information-seeking about potential losses without impacting non-instrumental information-seeking about potential gains. Specifically, while participants under Placebo sought information more about potential gains than losses (an effect observed in the past [Charpentier et al., 2018]), under L-

DOPA this difference was not observed. Moreover, under L-DOPA, participants' WTP for information increased as potential gains and losses increased. In stark contrast, under Placebo, participants' WTP for information increased as potential gains increased but remained constant and relatively low as potential losses increased.

An intriguing question concerns the mechanism by which L-DOPA alters information-seeking about potential losses. The effect could not be explained by changes to participants' mood, as there were no differences in participants' self-reported subjective state under Placebo and L-DOPA (see *Table 2-2*). Neither could it be explained by reduced attention and/or engagement, as participants under L-DOPA did not miss more trials than those under Placebo. L-DOPA also did not alter expectations of outcomes. Thus, modulation of outcome expectations (that is how much is expected to be lost/gained) cannot explain the results. Moreover, as the task did not involve learning (past outcomes had no impact on future outcomes, see *supplementary results*), L-DOPA did not affect learning about potentials outcome gains and losses.

Subjective State Questionnaire	*Before the task*			*After the task*		
	Placebo mean (SD)	**L-DOPA** mean (SD)	**p-value**	**Placebo** mean (SD)	**L-DOPA** mean (SD)	**p-value**
Alert to drowsy	2.68(1.19)	2.62(1.08)	0.687	3.60(1.41)	3.85(1.57)	0.208
Calm to excited	2.33(1.11)	2.29(1.03)	0.808	2.34(1.09)	2.27(1.22)	0.632
Strong to feeble	2.68(1.01)	2.63(1.01)	0.699	2.97(1.13)	3.15(1.35)	0.264
Muzzy to clear headed	4.47(1.26)	4.48(1.11)	0.956	3.70(1.23)	3.41(1.39)	0.099
Coordinated to clumsy	2.28(1.14)	2.22(1.06)	0.722	2.80(1.16)	3.02(1.31)	0.187
Lethargic to energetic	3.89(1.14)	3.94(1.18)	0.736	3.20(1.24)	3.00(1.43)	0.263
Contented to discontented	2.18(1.01)	2.12(0.83)	0.620	2.58(1.16)	2.65(1.19)	0.644
Troubled to tranquil	4.83(1.02)	4.66(1.02)	0.201	4.52(1.13)	4.55(1.13)	0.858
Slow to quick witted	4.32(1.11)	4.28(1.04)	0.761	3.63(1.30)	3.31(1.30)	0.069
Tense to relaxed	4.64(1.11)	4.67(0.98)	0.803	4.47(1.14)	4.42(1.23)	0.733
Attentive to dreamy	2.78(1.26)	2.73(1.10)	0.740	3.47(1.34)	3.42(1.38)	0.804
Incompetent to proficient	4.56(0.98)	4.70(0.86)	0.260	4.14(1.16)	4.02(1.26)	0.450
Happy to sad	2.43(1.06)	2.34(0.84)	0.453	2.62(1.12)	2.57(0.95)	0.712
Antagonistic to friendly	5.08(0.97)	5.07(0.81)	0.942	4.65(0.95)	4.60(1.04)	0.703
Interested to bored	2.35(1.21)	2.28(1.02)	0.639	3.52(1.45)	3.63(1.50)	0.587
Withdrawn to sociable	4.34(1.17)	4.36(1.18)	0.868	3.90(1..)17	3.83(1.39)	0.672

Table 2-2 Subjective State Questionnaire. Subjective State Questionnaire (Joint Formulary Committee, 2009) revealed no differences in subjective state between groups. p-Value relates to independent sample t-test.

One possibility is that L-DOPA altered expectations not about outcomes per-se, but about the affective impact of negative information. A negative cue (e.g. watching the financial market fall) triggers expectations not only about the material outcome (the amount one has likely lost) but also about how bad it would be to receive information about that loss (Bromberg-Martin and Sharot, 2020). L-DOPA may have triggered less pessimistic expectations regarding the latter, altering the value of information about losses, which could have changed information-seeking in the loss domain. To illustrate this point, imagine two participants who accurately expect to lose £100 when they observe the market falling. One participant predicts that learning about the loss will have little negative impact, whereas the other predicts a large negative impact. Dopamine dips could signal both elements separately when observing the cue. As L-DOPA is thought to interfere with such dips (Ungless et al., 2004; Satoh et al., 2003), it could result in less pessimistic expectations about the value of bad news and thus more information-seeking. This possibility can be investigated in the future by recording participant's actual and predicted expectations regarding the affective impact of information.

It is important to keep in mind that our task exclusively examined non-instrumental information about gains and losses. As dopamine is known to play an important role in reward-guided learning and decision-making, it is possible that dopamine plays a more general role in information-seeking when information has instrumental value and/or for non-valenced information. Future studies are needed to investigate the role of dopamine in those situations.

Because information-seeking is integral to decision-making (Kidd and Hayden, 2015; Loewenstein, 1994), understanding its biological basis is important for understanding impairments in these domains. Our results suggest that patients with deficiency to the dopamine system may exhibit abnormal patterns of information-seeking, which may provide a marker of their condition. For example, patients with low levels of dopamine function, such as patients with Parkinson’s disease, may be less likely to seek information regarding negative events. The findings also generate predictions of how prescription drugs targeting dopamine function may alter patients’ information-seeking behavior. For example, patients taking L-DOPA may increase self-exposure to negative information, which may induce negative affect.

MATERIALS AND METHODS

Participants

Two hundred and forty-eight subjects were recruited via the University College London psychology online system and assigned randomly to receive Placebo (123) or L-DOPA (125). Sample size was calculated based on our previous studies (Sharot et al., 2009; Sharot et al., 2012) looking at dopamine effects on decision-making. All participants filled in the informed consent and a screening form for significant medical conditions, medications, and illicit drugs. All subjects were paid for their participation. The study was double-blind and approved by the UCL ethics committee (Project ID Number: 8127/001). Data from five subjects was lost due to technical error, and 11 subjects did not complete the task due to either feeling nausea (five subjects), power outage (one subject) or lack of interest/motivation (five subjects). Thus, I obtained full data sets from 232 participants (Placebo group: $n = 116$, females = 72, mean age = 24.36, $SD = 7.918$; L-DOPA group: $n = 116$, females = 71, mean age = 25.44, $SD = 7.926$). Education level was measured on a scale from 1 (no formal educatio) to 10 (Doctoral Degree). Income was measured on a scale from 1 (annual household income £10,000 or less), to 9 (annual household income over £100000). There were no significant differences between the groups in terms of age ($t(230) = 1.036$, $p = 0.301$), income ($t(228) = 0.737$, $p = 0.462$), gender ($X2\ (1) = 0.018$, $p = 0.893$), and education level ($t(230) = 1.420$, $p = 0.157$).

Procedure and task

Participants were administered either Placebo or L-DOPA (150 mg of levodopa, 37.5 mg of carbidopa, and 200 mg of entacapone) upon arrival to the lab in a double-blind fashion. They then completed a brief questionnaire - the Subjective State Questionnaire (SSQ) (Joint Formulary Committee, 2009). They began the task 40 min after the administration of L-DOPA/Placebo (LDOPA half-life is 90 min and peaks at 60 min). The task took about 60 min to complete after which they completed the SSQ (Joint Formulary Committee, 2009) again. There was no differences between the Placebo and L-DOPA groups across SSQ (Joint Formulary Committee, 2009) items either before or after the task (see *Table 2-2*).

The task, known as the Stock Market Task, was adapted from our previous study (Charpentier et al., 2018). This task is composed of four blocks of 50 trials each. At the beginning of each block, each participant received 50 points, worth £5, which they had to invest in 2 of 5 five fictitious companies which compose a 'global market'. On each trial, participants first observed changes in market value (a dynamic increase or decrease in the curve lasting 2.3 s). The market value fluctuations reflected changes in the overall market; therefore, it partially indicated changes in the participant's own portfolio value. Unbeknown to the participants, on each trial, there was a 65% probability that their actual portfolio value would change consistent with the market trend. After observing the global market change, participants were asked to predict how their portfolio value likely changed relative to the previous trial from 1 (decreased a lot) to 9 (increased a lot) and their confidence in their answer from 1 (not confident at all) to 9 (extremely confident). They had up to 8 s to perform each rating. Sixty-four subjects (34 subjects received Placebo and 30 L-DOPA) were asked to state their expectation and confidence on their answer only on blocks 3 and 4, while all other subjects were asked to respond on every trial.

Participants were then given the chance to discover their portfolio value on that trial. Subjects had up to 8 s to state how much they were willing to pay to either receive or avoid information about their portfolio value. They could state their decision using a scale ranging from 99 p to avoid information ('NO'), through 0, to 99 p to receive information ('YES') (p indicated pence). Position of 'YES' and 'NO' (left/right) were counterbalanced across participants. They were informed that the more they paid the greater the probability that their wish would be honoured. When 0 p was selected, information was delivered 50% of the time. If they selected an amount between 1 p and 20 p, their request was honoured on 55% of the trials, between 21 p and 40 p - 65%, and so on up to 95%. Participants were not aware of these exact mathematical relationships. After that, the current value of their portfolio was shown on screen or hidden (that is 'XX points' was shown) for 3 s. In this study, information was not instrumental, in the sense that it could not be used to change the portfolio.

At the end of the task, one trial was randomly selected and participants received the value of their portfolio on that trial (e.g, portfolio value of 60 points=£6). If on that trial they decided to pay a certain amount to receive or avoid information and their wish was honoured (e.g. they paid 40 p to receive information and they received it), then that amount was deducted from the portfolio value (e.g. £6-£0.40 = £5.60).

Data analysis

First, I investigated the effect of dopamine manipulation on general aspects of information-seeking by comparing the number of trials in which subjects decided to pay to receive information, avoid information, or pay nothing, the average amount they paid to receive information, the average amount they paid to avoid information and number of missed trials between the L-DOPA and the Placebo groups with an independent samples t-test.

Then, I computed willingness to pay (WTP) on every trial with amount paid to avoid information scored negatively, and amount paid to receive information positively (zero is simply coded as zero). For each trial, a Linear Mixed Model was run to predict WTP from the two factors I had previously shown to impact information-seeking in this task (Charpentier et al., 2018) (i) valence (quantified as signed market change, which is the amount by which the market went up or down); (ii) absolute market change; as well as from (iii) group (L-DOPA or Placebo). All three factors were included as fixed and random effects, as were the interactions of group with each of the other two factors. Random and fixed intercepts were also included in the model. All linear mixed models were run in R using the lmer function (lme4 package) using maximum likelihood estimation method, the BOBYQA (Bound Optimization BY Quadratic Approximation) optimizer and a maximum number of iterations of 100,000.

As the model revealed a group by valence interaction, I next ran two mixed linear models separately for the Placebo and L-DOPA groups to tease apart that interaction. WTP was entered as the dependent factor and valence and absolute market change as fixed and random factors. The model included fixed and random intercepts. I also ran simpler models for each group separately, with WTP as a dependent measure and valence, coded in a binary fashion (market up/down), as fixed and random variable with fixed and random intercepts.

As the above analysis revealed a significant effect of valence in the Placebo group but not the L-DOPA group, I asked if the effect is due to L-DOPA altering information-seeking about potential losses, about potential gains, or both. Moreover, I ask whether the effect of L-DOPA emerged over the course of the experiment or whether it was apparent from the very beginning. Thus, I ran two separate mixed effect linear model predicting the WTP for information – one for trials in which the market went up (potential gain trials) and one for which the market went down (potential loss trials). The independent factors included (i) market change, (ii) trial number (iii), and group (L-DOPA/ Placebo). As each model now includes only one polarity - either market going up or down - signed market change and absolute market change are perfectly correlated. Thus, only one factor 'market change' is added. In the loss domain, the greater the 'market change' the greater the expected losses. In the gain domain, the greater the 'market change' the greater the expected gains. All three factors and their interactions were included as fixed and random effects. Random and fixed intercepts were also included in the model. I followed up with four linear mixed models - one for each group and valence polarity. WTP was the dependent factor and the independent factors were (i) market change (ii) and trial number.

Both factors and their interactions were included as fixed and random effects. Random and fixed intercepts were also included in the model. Finally, I examined whether participants' expectations are affected by L-DOPA. To this aim, I run a Linear Mixed Model predicting expectations with the following independent factors: (i) valence (signed market change), (ii) absolute market change, and (iii) group (L-DOPA or Placebo). All three factors were included as fixed and random effects as were the interactions of group with each of the other two factors. Random and fixed intercepts were also included in the model. To further examine whether there may be an effect of L-DOPA on expectations that alters over time, I added to the model above trial number as a fixed and random factor as well as all the two- and three-way interactions of trial number with the other factors.

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SUPPLEMENTARY MATERIAL

As described in the method section, our task was not designed to be a learning task. Rather, the task was a non-instrumental task where subjects could not influence outcomes. Neither were they incentivized to generate accurate expectations regarding outcomes. Nor did past outcomes have any bearing on present outcomes. The likelihood that outcomes (that is change to portfolio value) will follow the same trend as the market was 65% and 35% that it would be *random.* Thus, the most accurate way to make a prediction is simply to rely on the market change on the present trial regardless of previous outcomes. Indeed, I have previously shown that participants are unaffected by trial history when making predictions on present trials in this task.

Nevertheless, I tested whether there were any effects on past trials on expectations on present trials regrading portfolio outcomes. In particular, I run a mixed linear model predicting participants' expectation rating on trial t (note that the rating is always about change in portfolio on that trial relative to previous trial) from past outcome ($portfolio_{t-1}$). Results showed that past outcomes did not predicted participants' expectations (L-DOPA group: β = 0.0001, CI = -0.003/0.002, t(519.000) = 0.464, p = 0.643; Placebo group: β = 0.0009, CI = -0.001/0.003, t(213.500) = 0.621, p = 0.535). I also tested whether current expectations were related to the difference between outcome on last trial ($portfolio_{t-1}$ minus $portfolio_{t-2}$) and expectation rating on last trial In this analysis, I only included trials in which portfolio value was observed on the last trial. They were not (L-DOPA: β = -0.001, CI = -0.01/0.008, t(120.787) = 0.315, p = 0.753; Placebo: β = 0.001, CI = -0.009/0.12, t(108.300) = 0.304, p = 0.762). As participants often did not observe the portfolio value on trial t-2 I ran the analysis again this time instead of inserting $portfolio_{t-2}$ in the equation above I inserted the portfolio value last observed before t-1. Again, this did not predict subjects' expectations (L-DOPA: β = -0.001, CI = -0.008/0.006, t(112.877) = 0.330, p = 0.742; Placebo: β = -0.0007, CI = -0.006/0.005, t(102.700) = 0.253, p = 0.800). I then examined whether wiliness to pay for information on the current trial was influenced by previous outcomes by running all these models again, this time predicting WTP for information. As expected, none showed a significant effect (all P > 0.240). This analysis confirms that subjects did not treat this task as an outcome learning task.

Indifferent trials

To examine if L-DOPA and valence altered the number of trials in which participants decided to pay 0p ('indifferent trials') I conducted a repeated measures ANOVA with group (L-DOPA/placebo) as a between subject variable and valence (market up/down) as a within subject variable. There was not an effect of valence (F(1,230) = 3.025, p = 0.083) nor an effect of group (F(1,230) = 0.021, p = 0.885) or an interaction (F(1,230) = 0.080, p = 0.778). There were no differences between groups regarding the number of indifferent trails when the market went down (t(230) = 0.175 p = 0.861) or up (t(230) = 0.112 p = 0.911). Note, that indifferent trails are included in all the analysis in the main text.

CHAPTER 3:

HOW PEOPLE DECIDE WHEN TO INFORM OTHERS

ABSTRACT

Human knowledge is distributed over many individuals. As such, humans are tasked with informing one another for the betterment of all. But as information can alter people’s action, affect and cognition in both positive and negative ways, deciding whether to share information can be a particularly difficult problem to solve. Here, I examine how people integrate potentially conflicting consequences of knowledge, to decide whether to inform others. I show that participants (N = 247) use their own information-seeking preferences to solve complex information-sharing decisions. In particular, when deciding whether to inform others, participants consider the usefulness of information in directing action, its valence and the receiver’s uncertainty level. I demonstrate that participants integrate these assessments into a calculation of the value of information that explains information sharing or its avoidance. A K-means clustering analysis revealed that participants cluster into groups according to the different weights they assign to these different factors. While some people predominantly shared information when it was useful in selecting action, others predominantly shared information when it was positive, while others predominantly shared information when the receiver was under high uncertainty. Within individuals the relative influence of each of these factors was stable across information-seeking and information-sharing decisions. These results suggest that people put themselves in a receiver position to determine whether to inform others and can help predict when people will share information.

INTRODUCTION

From financial advisors to doctors and parents – humans are endowed with the task of informing others to aid their decision-making. How do people decide whether to share relevant information? This is a difficult problem to solve, because information can serve several, sometimes competing, goals. Imagine, for example, a teacher who must decide whether to provide a student with negative feedback. The negative feedback may hurt the students' motivation but may be necessary to improve their skills. Thus, the teacher will need to arbitrate between the impact on the student's emotional state and future performance to select a plan of action. The teacher's decision may depend on how much they value (or believe the student values) these different outcomes. Here, I investigate how people solve such complex problems. I hypothesize that people rely on their own *information-seeking* preferences to solve *information-sharing* problems, integrating their preferences over different outcomes into a calculation that leads to information sharing or its avoidance.

I have recently proposed a theory which characterizes three key motives for information-*seeking* (Sharot & Sunstein, 2020). According to this theory, when deciding whether to seek information, people first estimate what the information will reveal and then estimate the expected impact of that information on their affect (i.e., how the information will make them feel), cognition (how the information will improve their models of the world) and action (how the information will be useful for obtaining rewards). In particular, all else being equal, people will be more likely to seek information (i) when they expect knowledge to make them feel better (Cogliati Dezza et al., 2022; Charpentier et al., 2018; Golman et al., 2017; Hertwig & Engel, 2016; Karlsson et al., 2009; Kelly & Sharot, 2021; Kobayashi et al., 2019; Lerman et al., 1998; Stigler, 1061; van Lieshout et al., 2020), (ii) when uncertainty is high (Chater & Lowenstein, 2016; Cogliati Dezza et al., 2021; Gottlieb et al., 2013; Jezzini et al., 2021; Kidd & Hayden, 2015; Kobayashi et al., 2019; Schwartenbeck et al., 2019; van Lieshout et al., 2020 Golman et al., 2021), and (iii) when it can aid in selecting action that will help gain rewards and avoid harm (Cogliati Dezza et al., 2022; Kobayashi & Hsu, 2019; Stigler, 1961; Wilson et al., 2014).

Different people assign different weights to each of these factors when deciding whether to seek information (Cogliati Dezza et al., 2022; Kelly & Sharot, 2021). These are integrated into a computation of the value of information, which result in individual differences in information-seeking behavior (Cogliati Dezza et al., 2022; Kelly & Sharot, 2021). For example, an individual who puts most weight on how information may impact their affective state may decide to skip a medical screening while another who puts most weigh on whether information is useful in avoiding harm may attend them religiously.

While there are clues in the literature that when informing others people also prefer to *share* information that is positive (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987;Dibble and Levine, 2010, 2013; Weenig et al., 2014; Tesser & Rosen, 1975) and that can guide action (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001), studies have yet to computationally disentangle the importance of these (sometimes) competing motives. Rather, motives have either been studied in isolation or in a situation where they are confounded. Moreover, whether people consider the receiver's level of uncertainty in making sharing decisions is unknown. In real-life, conflicting outcomes of knowledge for the receiver are often present. Thus, characterizing information-sharing in such situations is crucial for understanding how people decide whether to inform others.

Here, I *simultaneously* varied the instrumental utility of information that could be shared, the level of uncertainty of the receiver, and the valence of information. I then examine how these considerations are integrated into a sharing decision and whether sharers weigh these factors as they do when they themselves make information-seeking decisions.

RESULTS

Participants (N = 125) performed an information-sharing task ('sharers', *Figure 3-1*), or an information-seeking task (N = 122 'recipients', *Figure 3-1*) or both (N = 55 out of the numbers above). In both tasks I manipulated (i) the valence of information for the recipient, (ii) the level of uncertainty of the recipient and (iii) the instrumental utility of information for the recipient.

In the information-seeking task recipients were told they own stocks in a financial market I created. On each trial they were showed an algorithm's prediction of the current value of their stocks. A positive number indicated the algorithm predicted a current net gain, thus inducing positive expectations, and a negative number indicated a prediction of a current net loss, thus inducing negative expectations. They were also shown the algorithm's accuracy, which ranged from 0% to 99%. The high the number the more often the algorithm is accurate, thus there is high certainty regarding the value of the stocks.

After observing the algorithm's prediction and accuracy level the recipients were asked to indicate if they would like to open an envelope which contained the actual current value of their stocks on a scale from 1 (not at all) to 6 (very much) (information-seeking decision). If they indicated they wanted to open the envelope they were then likely to be shown the current value of their stocks (information). If they indicated they did not want to open the envelope they were then likely to observe 'XX' (no-information).

Recipients played 2 blocks of 40 trials each. In one block participants could decide whether to add 10 stocks, give away 10 stocks or leave the number of stocks as is after receiving information (financial decision). This is the block where information is instrumental (that is, it can be used to make better decisions to gain more money and avoid losing money). In the other block a computer randomly made the decision for them. In this block information is not instrumental as it cannot be used by the participants to make portfolio decisions.

In the information-sharing task on each trial sharers observed an algorithm's prediction about the stocks value of the "recipient" that may be playing a similar task tomorrow and the algorithms' prediction accuracy. They then observed an open envelope with the value of the "recipient"'s stocks on that trial. In other words, the sharer was completely certain of the value of the "recipient's" stock, but they were aware the receipt was under uncertainty.

Moreover, they knew the “recipient’s” level of uncertainty as they were informed of the algorithms’ accuracy, which the “recipient” observed. They then indicated on a scale from 1 (not at all) to 6 (very much) whether they wanted to share the information in the envelope with tomorrow’s “recipient” so that the “recipient” could observe the value of their stocks on that trial (information-sharing decision). Participants were told that if they indicated they wanted to open the envelope for the “recipient”, the “recipient” was likely to observe the value of their stocks and vice versa. In the instrumental block sharers were told the “recipient” could decide whether to add or give away stocks (other player’s financial decision) after observing the information. In the non-instrumental block of trials participants were told the “recipient” could not use the information shared with them.

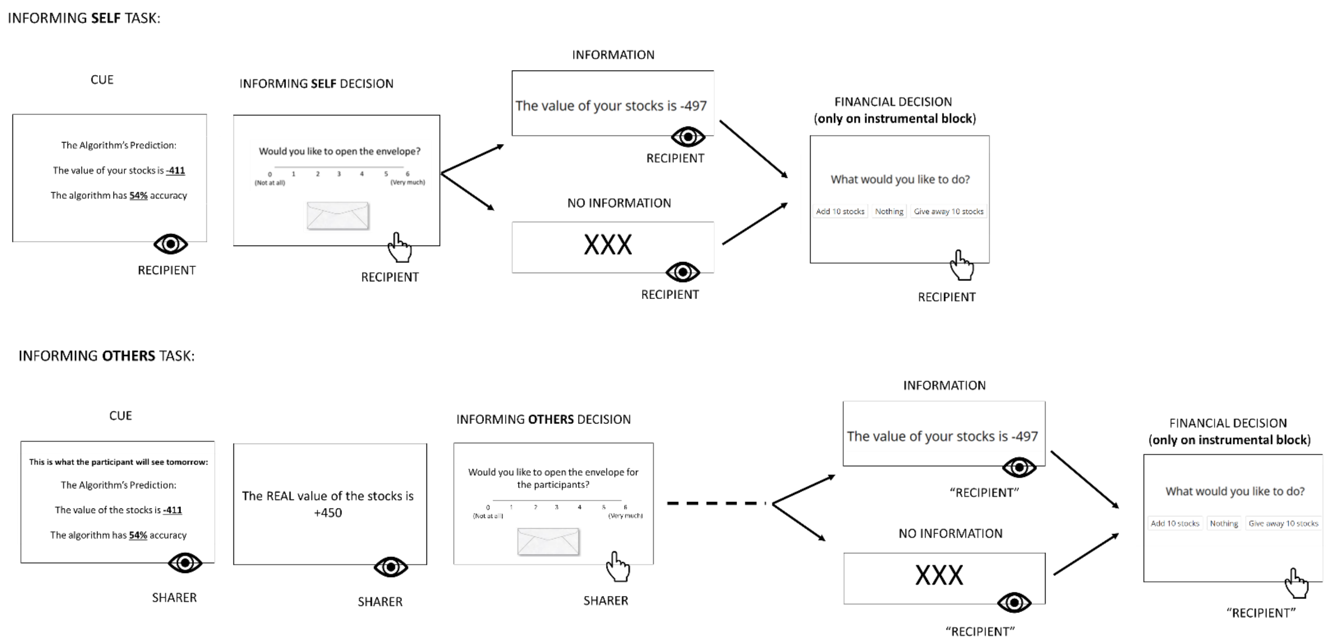


Figure 3-1 Task (a) In the information seeking task recipients were given stocks in a financial market I created. On each trial they observed an algorithm's prediction of the current value of their stocks and the prediction accuracy of the algorithm (cue). They then indicated on a scale from 0 (not at all) to 6 (very much) whether they wanted to open an envelope to observe the current value of their stocks (informing self). If they indicated they wanted to open the envelope they were likely to then observe the current value of their stocks (information). If they indicated they did not want to open the envelope they were then more likely to observe 'XX' (no-information). On the instrumental block recipients could then decide whether to add 10 stocks, give away 10 stocks or leave the number of stocks as is (financial decision). On the non-instrumental block a computer randomly made the decision for them. (b) In the information sharing task on each trial sharers first observed an algorithm's prediction about the value of stocks of a "recipient" that may be playing a similar task tomorrow and the prediction accuracy of the algorithm (cue). They were aware that the "recipient" will be observing this same cue tomorrow. Then they observed the actual value of the stocks. Next, they indicated whether they wanted to open the envelope for tomorrow's "recipient" so that the "recipient" could observe the value of their stocks on that trial (informing others). Sharers were told that if they indicated they wanted to open the envelope for the "recipient", the "recipient" was then more likely to observe the value of their stocks (information). If they indicated they did not want to open the envelope for the "recipient", the "recipient" was then more likely to observe 'XX' (no-information). On the instrumental block of trials sharers were told the "recipient" could then decide whether to add or give away stocks ("recipient's financial decision). In the non-instrumental block sharers were told the "recipient" was not able to make that decision. In reality, there were no participants playing the next day. Thus, parts of the trial marked as "recipient" in the sharing task represent only what the participants believed would happen the next day. There were 2 blocks, each composed of 40 trials.

Participants consider the impact of information on affect, action and uncertainty when deciding whether to inform others.

I first tested whether participants consider the valence of information, the receiver's uncertainty and the instrumentality of information when making information-sharing decisions as they do for information-seeking decisions. Two separate Linear Mixed-Effects Models were run to predict (a) information-sharing and (b) information-seeking on each trial from three factors: (i) level of *un*certainty (equal to 100 minus the algorithms' accuracy), (ii) instrumentality (coded as 1 if information could be used to alter the portfolio and 0 otherwise) and (iii) valence of information (based on the algorithm's prediction in the information-seeking task and on the actual stock value in the information-sharing task). Predictors were included as fixed and random effects. Random and fixed intercepts were also included.

$$\text{Information Decision} = \beta 0 + \beta 1{*}\text{Uncertainty} + \beta 2{*}\text{Instrumentality} + \beta 3{*}\text{Valence}$$

Results reveal that participants prefer to share and seek information when (i) the receiver's uncertainty was high (Sharing: $\beta = 0.49$, $SE = 0.24$, $t(125.11) = 2.059$, $p = 0.041$; Seeking: $\beta = 0.71$, $SE = 0.18$, $t(121.96) = 3.93$, $p < 0.001$); (ii) when information was instrumental to the receiver (Sharing: $\beta = 0.77$, $SE = 0.15$, $t(125.02) = 5.280$, $p < 0.001$; Seeking: $\beta = 1.46$, $SE = 0.18$, $t(121.99) = 8.043$, $p < 0.001$), and (iii) when the information would likely convey good news – that is when the expected/true value of the stocks was high

(Sharing: β = 0.42, SE = 0.09, t(125.11) = 4.194, p < 0.001; Seeking: t β = 0.40, SE = 0.09, t(121.63) = 4.50, p < 0.001,).

I then compared this three-factors model which included instrumentality, valence and uncertainty to models including only one or two of the variables. The full model fitted the data better both when information others (*Figure 3-2a*) and when informing the self (*Figure 3-2b*) as observed by lower AIC score. The same results are obtained when calculating the BIC scores (*Table 3-1*).

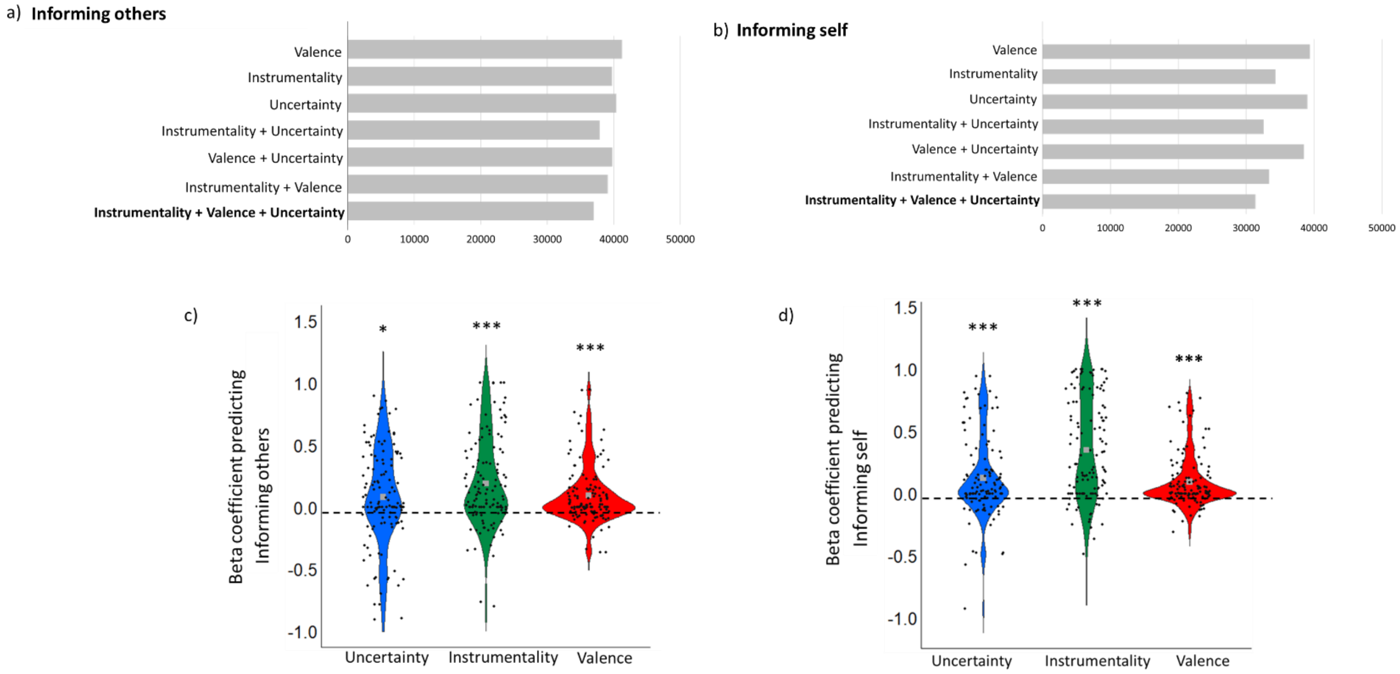


Figure 3-2 (a-b) Information-sharing decisions (a) and information-seeking decisions (b), are best explained by a model that includes the instrumentality of information, its valence and the uncertainty of the receiver, as observed by lower AIC score. For both seeking and sharing information, the model including the three factors fit the data better than models including only one or two. (c-d) Plotted on the y axis are the beta coefficients from two Linear Regressions predicting information sharing (c) and seeking (d). Participants seek and share information more when (i) the receivers' uncertainty is high (in the case of seeking the receiver is the 'self') (uncertainty is defined as 100 minus the algorithm's prediction accuracy); (ii) when information is useful (defined as 1 if receiver can use information to alter stocks and 0 otherwise) and (iii) when information is more positive (valence is defined as the algorithm's prediction in the case of seeking and the actual value in the case of sharing). Black dots represent beta estimates for each participant obtained by fitting the model to each subject individually. Grey squares represent the mean. * $p < 0.05$, *** $p < 0.001$.

Informing Self	BIC	Informing Others	BIC
Intrumentality+Valence+Uncertainty	**31468.8**	**Intrumentality+Valence+Uncertainty**	**37107.8**
Valence	39422.9	Valence	41290.2
Instrumentality	34354.7	Instrumentality	39777.1
Uncertainty	39042.8	Uncertainty	40413.5
Intrumentality+Uncertainty	32612.8	Intrumentality+Uncertainty	37937.6
Valence+Uncertainty	38603.8	Valence+Uncertainty	39860.8
Intrumentality+Valence	33461.3	Intrumentality+Valence	39148.9

Table 3-1 Information-sharing and information-seeking are best explained by a model that includes the instrumentality of information, its valence and the uncertainty of the receiver, as observed by lower BIC score. For both seeking and

sharing information, the model including the three factors fit the data better than models including only one or two.

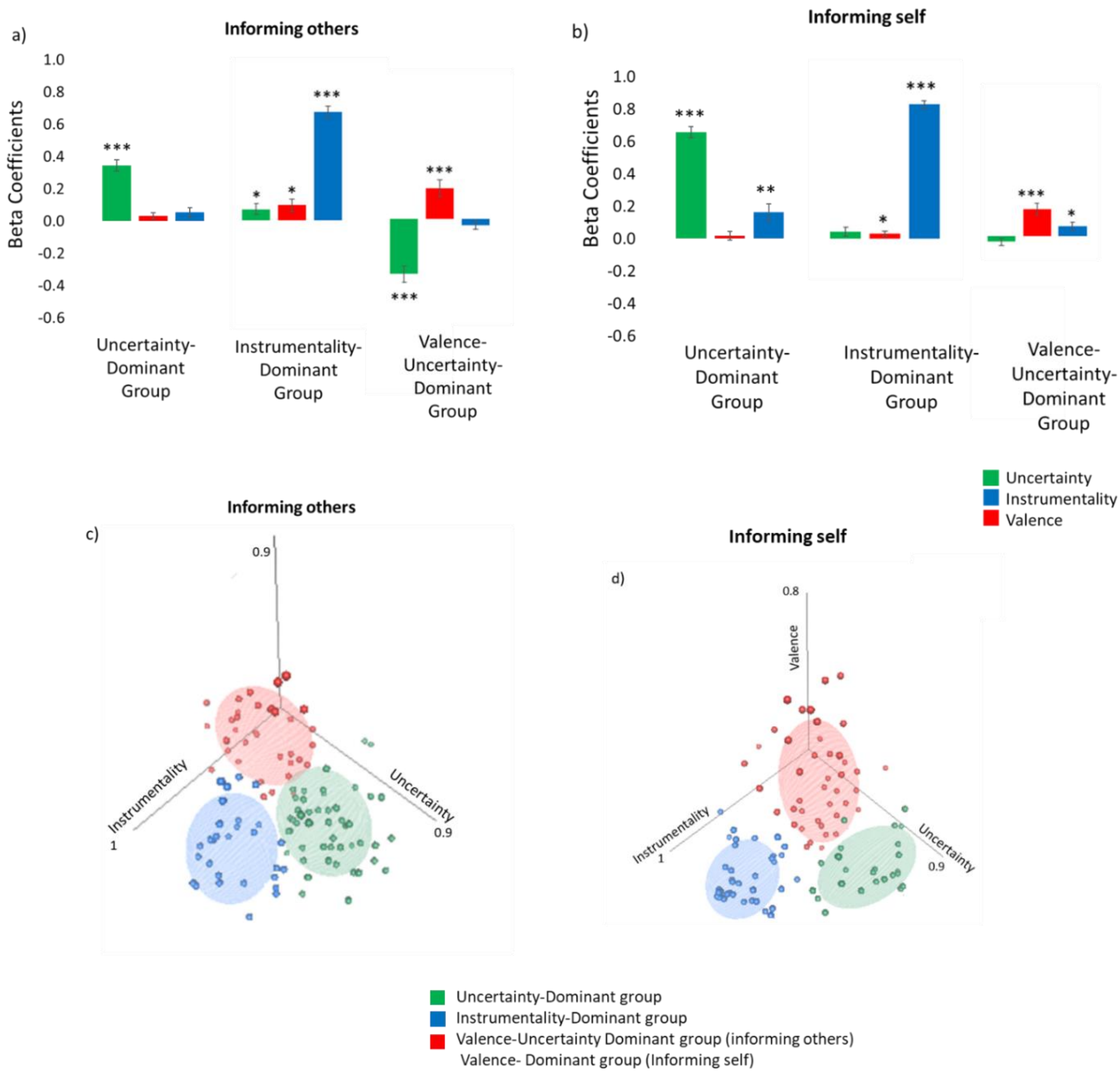
The same results are obtained when Linear Regression models are fitted to each participant individually and then betas across participants are compared to zero (*Uncertainty:* Seek: $M = 0.13$, $t(121) = 4.244$, $p < 0.001$, *Figure 3-2d*; Share: $M = 0.08$, $t(124) = 2.360$, $p = 0.02$, *Figure 3-2c*; *Valence:* Seek: $M = 0.09$, $t(121) = 4.904$, $p < 0.001$, *Figure 3-2d*; Share: $M=0.095$, $t(124) = 4.606$, $p < 0.001$, *Figure 3-2c*; *Instrumentality:* Seek: $M = 0.35$, $t(121) = 9.669$, $p < 0.001$, *Figure 3-2d*; Share: $M = 0.19$, $t(124) = 5.92$, $p < 0.001$, *Figure 3-2c*).

Individual differences in sharing decisions.

The results thus far suggest that when deciding whether to inform others, people consider the receiver's uncertainty, the instrumental utility of information and its valence. However, it is likely that different people put different weights on these different factors. Indeed, when it comes to information-seeking it has been shown that most individuals weigh one of these factors over and above the rest (Kelly and Sharot, 2021). As a result, information-seeking decisions are vastly different across individuals. Here, I tested whether similar individual differences are observed when informing others. To that end, I performed a K-means cluster analysis separately for information seeking decisions and information sharing decisions. The number of clusters (K=3) was based on our past study (Kelly and Sharot, 2021).

Cluster analysis on information-seeking decisions revealed that participants were clustered into the following three groups (*Figure 3-3b&d*); The first cluster, which I will call the "Uncertainty-Dominant Group", included 24 participants who assigned a large positive weight to uncertainty ($\beta = 0.66$, $t(23) = 19.153$, $p < 0.001$), a moderate positive weight to instrumentality ($\beta = 0.16$, $t(23) = 3.162$, $p = 0.004$) and no significant weight to valence ($\beta = 0.02$, $t(23) = 0.664$, $p = 0.513$) when seeking information. The second cluster, which I will call the "Instrumentality-Dominant Group", included 43 participants who assigned a large positive weight to instrumentality ($\beta = 0.82$, $t(42) = 33.736$, $p < 0.001$) and a moderate positive weight to valence ($\beta = 0.03$, $t(42) = 2.160$, $p = 0.036$) and no significant weight to uncertainty ($\beta = 0.04$, $t(42) = 1.424$, $p = 0.162$) when seeking information. The third cluster, which I will call the "Valence-Dominant Group", included 55 participants who assigned a large positive weight to valence ($\beta = 0.18$, $t(54) = 4.970$, $p < 0.001$), a moderate positive weight to instrumentality ($\beta = 0.06$, $t(54) = 2.474$, $p = 0.017$) and no significant weight on uncertainty ($\beta = -0.04$, $t(54) = 1.547$, $p = 0.128$) when seeking information.

The analysis on sharing decisions revealed a similar pattern by which participants wee clustered into the following three groups (*Figure 3-3a&c*); The first cluster, which I will call the "Uncertainty-Dominant Group", included 58 participants who assigned a large positive weight to uncertainty ($\beta = 0.34$, $t(57) = 9.804$, $p < 0.001$), no significant weight to instrumentality ($\beta = 0.05$, $t(57) = 1.758$, $p = 0.08$) nor to valence ($\beta = 0.03$, $t(57) = 1.657$, $p = 0.103$) when sharing information. The second cluster, which I will call the "Instrumentality-Dominant Group", included 32 participants who assigned a large positive weight to instrumentality (β = 0.69, t(31) = 19.392, p < 0.001), a moderate weight to valence (β = 0.096, t(31) = 2.598, p = 0.013) and uncertainty (β =



0.07, t(31) = 2.190, p = 0.036) when sharing information. The third cluster, which I will call the “Valence-Uncertainty-Dominant Group”, included 35 participants who assigned a large positive weight to valence (β = 0.197, t(34) = 3.712, p = 0.001) and no significant weight to instrumentality (β = -0.037, t(34) = 1.364, p = 0.182) when sharing information.

Figure 3-3 **Participants cluster into three groups, characterized by the weight they assign to the valence of information, its instrumentality and the receiver's uncertainty, when deciding to inform the self and others.** I calculated the weights each participant assigned to each of the three factors (instrumentality, valence and uncertainty) when seeking and sharing information. The obtained betas were submitted into a cluster analysis to identify groups of participants that have similar combination of weights when seeking or sharing information. (a-b) Plotted are the average beta coefficients assigned to each factor, averaged across participants in each cluster. As can be seen the Instrumentality-Dominant group put the most weight on instrumental value of information, the Valence-Dominant group put the most weight on valence, the Uncertainty-Dominant group put the most weight on uncertainty and the Valence-Uncertainty-Dominant group put the most weight on uncertainty and valence. (c-d) The weights individual participants assigned to each of the three motives are plotted with participants colored according to their assigned cluster. Ellipsoid highlights 50% of data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Error bars represents SEM.

In contrast to the equivalent information-seeking group, this group showed a large negative weight to uncertainty ($\beta = -0.35$, $t(34) = 7.075$, $p < 0.001$). In other words, these participants preferred to share *positive and certain* information, that is, they preferred to share information when the receiver was more certain that stocks' value was positive.

Individual differences are stable across information-seeking and information-sharing decisions.

I next examined whether within each individual the weight participant's assign to the different outcomes of information when deciding whether to inform others is correlated with the weight they assign to these factors when deciding whether to inform the self (i.e., information-sharing). Fifty-five of the participants in the study completed both the information-seeking and information-sharing task in random order. Examining the weight each participant assigned to instrumentality in both tasks revealed that participants who assigned greater weight to a particular factor when seeking information themselves also assigned a greater weight to that factor when deciding whether to share information (Uncertainty: $r = 0.688$, $p < 0.001$, *Figure 3-4a*; Valence: $r = 0.503$, $p < 0.00$, *Figure 3-4b*; and a trend for Instrumentality $r = 0.226$, $p = 0.097$, *Figure 3-4c*).

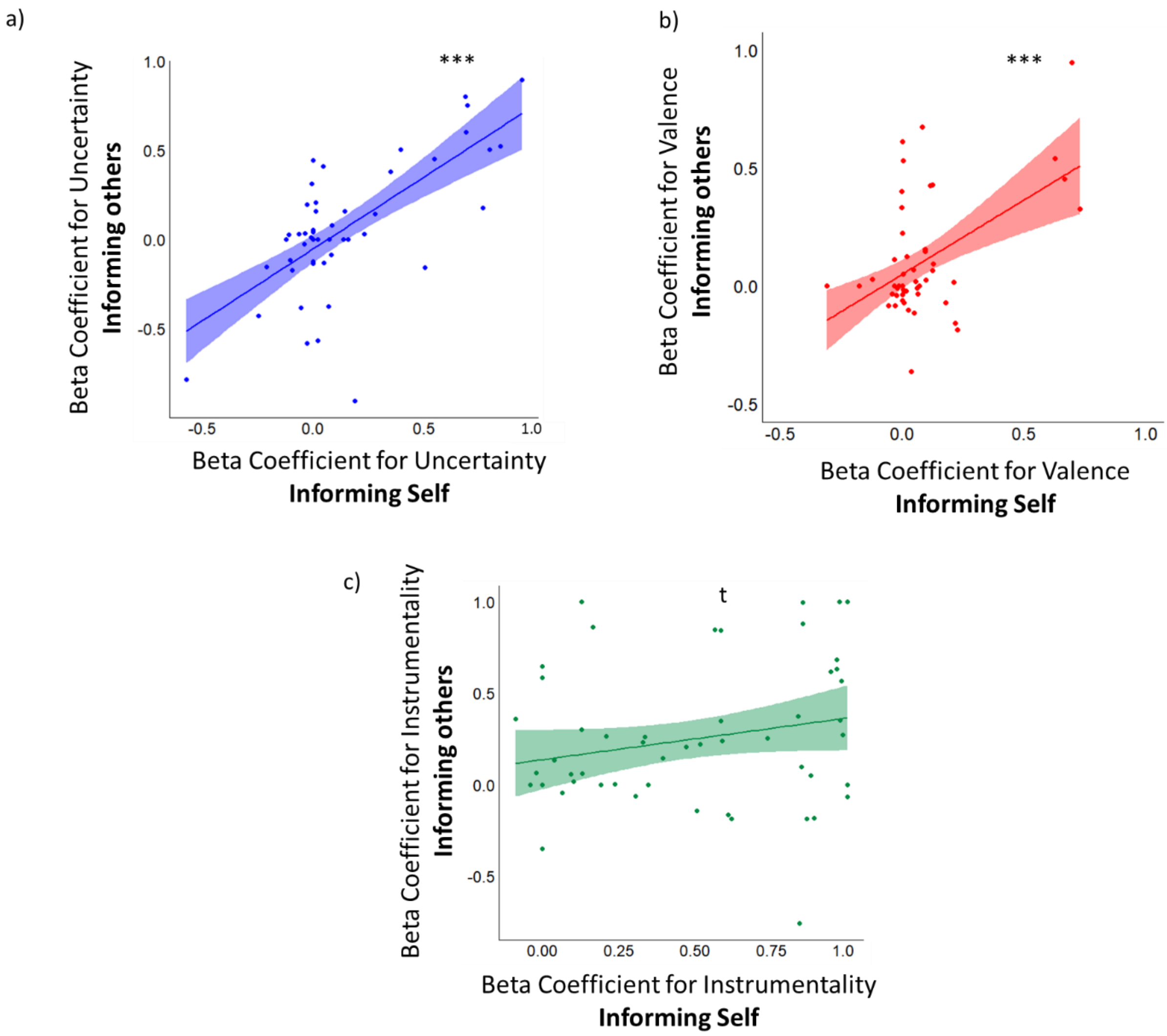


Figure 3-4 Preferences are stable across information-seeking and information-sharing. Plotted are the correlation between the beta coefficient obtained when predicting information-seeking (x-axis) and information-sharing (y-axis) for (a) uncertainty, (b) valence, and (c) instrumentality. (a) Participants who preferred to seek information under high uncertainty also prefer to share information when the receiver was under high uncertainty. (b) Participants who preferred to seek positive information also preferred to share positive information. (c) Participants who preferred to seek useful information also preferred to share useful information (trend level). Lines represent regression lines. Smooth areas represents the confidence interval. t = p < 0.1, *** = p < 0.001.

DISCUSSION

Our results show that people use their own information-preferences to solve complex information-sharing decisions. In particular, when deciding whether to inform others participants assigned similar weights to the usefulness of information, its valence and the level of uncertainty as they do when deciding whether to seek information for themselves. These results suggest that people likely put themselves in the receiver's position to determine whether to inform others.

Specifically, I found that participants shared information more when (i) the recipient could use it to gain rewards and avoid losses (i.e., when it had instrumental utility), (ii) when it was good news for the recipient rather than bad news and (iii) when the recipient was under high uncertainty. Sharers used the same rules to decide when to share information as they did to decide when to seek information. Importantly, the results suggest that they implement those rules from the point of view of the recipient, not their own. They seemed to consider the *recipient*s' level of uncertainty, whether the *recipient* can use the information and how the information would make the *recipient* feel. They clearly did not consider their own point of view when sharing, as they were always completely certain of the content of the information and could not use information in any way to better their material outcome.

Previous studies on information-*seeking* indicate large individual difference in what people what to know (Cogliati Dezza et al., 2022; Kelly & Sharot, 2021; Sunstein, 2019). I have previously shown that these differences can be accounted for by the different weights people assign to different motives for seeking information (Kelly & Sharot, 2021; Cogliati Dezza et al., 2022). People tend to overweight one motive over the rest. Here, I replicated this result for information-seeking, and more importantly show similar individual differences for sharing preferences. In particular, a cluster analysis revealed that participants could be classified into three groups – one group cared mostly about instrumentality when deciding whether to share information, another mostly about the receiver's uncertainty and a third preferred to share information that was positive, for which the receiver was relatively certain about. The different weights people assign to these factors may help explain why different people will make vastly different decisions on whether to inform others. For example, following the Robb Elementary School shooting in Texas, some parents throughout the US decided to inform their children of the shooting, perhaps because they felt such information may be useful, while others decided not to inform their children, perhaps to avoid inducing anxiety.

I find that such individual differences are constant across information-sharing and information-seeking decisions. In particular, the weight assigned to each factor when seeking information was correlated to that assigned to each factor when sharing information. That is, the more people care about valence, instrumental value and uncertainty when seeking information, the more they care about these factors when informing others. These results suggest that information seeking and sharing may rely on similar cognitive and neural mechanisms.

Thanks to advances in technology, massive amounts of information are now easily accessible. This includes personalized information that can provides clues about a person’s future health and finance. It is important to understand how people decide when to share such information. Here, I show that people consider the valence of information, its instrumental utility and the receiver’s uncertainty. People combine these estimates into a calculation of the value of information that can guide information-sharing choices. Our findings can help predict which information will be shared and help in framing critical information (such about health and safety) to increase the likelihood that it will be shared by others.

MATERIALS AND METHODS

Participants

Participants were recruited via Prolific Academic (https://www.prolific.co/) and were paid £7.50 per hour for their participation. The study was approved by the departmental ethics committee at UCL. All tasks were created using Gorilla Experiment Builder (www.gorilla.sc; Anwyl-Irvine et al., 2020). Sample size was determined based on our previous study on information-seeking (Kelly and Sharot, 2021).

124 participants performed an information-seeking task of which one participant was excluded for failing all catch trials (see procedure for more details) and one because of an error in data storing. Final sample was composed of 122 participants (55 males, 63 females, 4 other, mean age = 31.42 years ±9.7 (SD), age range: 18 to 60 years). 128 participants performed an information-sharing task of which two participants were excluded for failing all catch trials and one for completing the task twice. Final sample was composed of 125 participants (54 males, 71 females, mean age = 32.28 years ±9.09 (SD), age range: 18 to 60 years). Out of all participants, 56 participants participated in both the seeking and sharing task. One participant completed the information-sharing task twice so their data was not included, therefore data from 55 participants was analysed.

Procedure and task

Information-seeking task

Following instructions, participants answered six comprehension questions before the first block and one question before the second block. Participants who responded incorrectly twice on at least one question were not permitted to go on to complete the task. After reading the instructions, participants completed two example trials before starting the actual task.

In the information-seeking task (*Figure 3-1a*) recipients were told they owned 100 stocks in a financial market I created. On each trial recipients were presented with an algorithm's prediction of the value of their stocks and the algorithm's average prediction accuracy (the algorithms could be different on each trial). These cues were presented for 5s. Predictions regarding the stocks' value ranged from -400 to -500 and from +400 to +500. A positive stock value meant recipients were earning money, a negative value meant they were losing money. The algorithm's prediction accuracy ranged from 0 to 99%. High numbers suggest the algorithm is often correct and vice versa. For example, an accuracy of 50% indicates the predicted stock's value was the true value 50% of the time, and 50% of the time prediction was randomly selected from all possible stock's values.

Recipients then indicated whether they wanted to open an envelope containing information about the true value of their stocks (information-seeking decision). They did so using a seven points Likert scale ranging from 0 "Not at all" to 6 "Very much". Recipients were told that the closer their answer was to "Very much", more likely I were to open the envelop and reveal the value of their stocks, and vice versa. If they selected 0, 1, 2, 3, 4, 5, 6 then information was delivered with a probability of 5%, 20%, 35%, 50%, 65%, 80%, 95%, respectively. Recipients were not aware of these mathematical conversions. Next, either the value of their stocks (information) was presented on screen for 4s or hidden (‘XX’ was shown).

The task was composed of two blocks. In the instrumental block recipients were informed that on each trial they would be able to decide whether to add 10 stocks to their portfolio, give away 10 stocks or leave the number of their stocks as is (financial decision). In the non-instrumental block recipient were informed that the computer would randomly make this decision for them.

Recipients were informed that they would start the task with 250K bonus points which were worth between £1 and £5 together. At the end of the task the Gorilla program randomly selected one trial and the value of their stocks on that trial was multiplied by the number of stocks they had. The resulting sum was added to their initial bonus. For example, if on the selected trial they had 200 stocks worth -450 points, 90K points would be subtracted from their initial bonus of 250K.

Order of blocks were counterbalanced across individuals. Each block was composed of 44 trials plus 4 catch trials. Catch trials were added to check participants’ engagement and attention. In those trials, instead of indicating how much they wanted to share/seek information, participants were instructed to select a specific rating (for example: *Select 1*). Participant who failed all catch trials in one of the blocks were excluded from the analysis.

In addition, to check whether participants were encoding the information provided in the cues, on four trials (memory check trials) in each block I asked participants to recollect whether the algorithm predicted the stocks to be positive or negative and/or I asked them what was the prediction accuracy of the algorithm. Those trials were excluded from the analysis, therefore 40 trials for each block were analysed. Results indicated good attention and memory - on average 87.5% of participants provided the correct response.

Information-sharing task

The information-sharing task (*Figure 3-1b*) was nearly identical to the information-seeking task described above. The difference was that in the sharing task participants (sharers) did not own stocks. Rather, they were told "recipients", who may play the task tomorrow, will own stocks in the market. On each trial they were presented with the algorithm's predictions regarding the stocks of those "recipients" and the prediction accuracy of that algorithm (cue). They were aware the "recipient" tomorrow would also observe these cues. Then they received an open envelope containing the actual value of the "recipients'" stocks. They were then asked to indicate whether they wanted to share the envelope's content with tomorrow's "recipients" so that they could observe the value of their stocks on that trial (information-sharing decision) on a 7 Likert scale ranging from 0 "Not at all" to 6 "Very much". In the instrumental block sharers were informed that tomorrow's "recipients" would be able to use the information provided to decide whether to add or give away stocks (other's financial decision). Sharers were told that the closer their answer was to “Very much”, the greater the probability that I will open the envelope and reveal the value of the stocks, and vice versa. In the non-instrumental block sharers were informed tomorrow’s “recipients” could not use the information shared with them. The order of blocks were counterbalances across. Results indicated good attention and memory - on average 89.1% of participants provided the correct response to the memory questions. Out of the final sample, 55 participants performed both the information-seeking and sharing task. Order of the tasks was counterbalanced.

Data Analysis

Model estimation

Before running the Linear Mixed-Effects Models, valence and uncertainty were rescaled to values between 0 and 1. Two separate Linear Mixed Effects Models were run to predict information sharing and seeking on each trial from level of uncertainty (calculated by subtracting the algorithm’s accuracy percentage from 100), valence of information (valence was defined according to the algorithm’ prediction of value in the information-seeking task, and as the actual value of the stocks in the information-sharing task) and instrumentality (whether the information could be used to make decisions to alter the portfolio or not) both as fixed and random factors. The model also included random and fixed intercept and subject as the grouping factor. Below a formula summarizing the variables modeled:

Information Seeking/Informing = β0 + β1*Uncertainty + β2*Instrumentality + β3*Valence

I compared the full model with models including only one or two variables. Best winning model was determined using the AIC, where smaller values indicate a better fit. All linear mixed models were run in R using the lmer function (lme4 package) using maximum likelihood estimation method, the BOBYQA (Bound Optimization BY Quadratic Approximation) optimizer and a maximum number of iterations of 100,000.

In addition, to obtain individual weights for each subject, Linear Models were run for each individual predicting information seeking or sharing from uncertainty, valence and instrumentality of information. All variables were z-scored to obtain standardized betas. Betas across participants were compared to zero using a One-Sample t-test.

Cluster analysis

From the previous analysis I obtained three beta coefficients per participant indicating the weight they assign to instrumentality, valence and uncertainty when deciding whether to seek and share information. Those betas were submitted into a cluster analysis using an unsupervised machine learning approach known as k-means cluster analysis (Forgy, 1965). The analysis groups individuals whose data are most similar by attempting to reduce the within-cluster sum of squares (i.e. variance) of the deviation of each point from the centroid. This was done using SPSS. The number of clusters

(N= 3) was based on our previous study of information-seeking (Kelly and Sharot, 2021). I characterized the defining features of each cluster by calculating the average value across participants in each cluster of each beta coefficient. All betas were compared to zero (One sample T-test, two sides).

For participants who completed both the information sharing and seeking task the weight each participant assigned to uncertainty, valence and instrumentality when seeking information was correlated with the weight they assigned when sharing information.

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CHAPTER 4:

THE ILLUSORY TRUTH EFFECT LEADS TO THE SPREAD OF MISINFORMATION

ABSTRACT

Misinformation can negatively impact people's lives in domains ranging from health to politics. An important research goal is to understand how misinformation spreads in order to curb it. Here, I test whether and how a single repetition of false information fuels its spread. Over two experiments (N = 260) participants indicated which statements they would like to share with other participants on social media. Half of the statements were repeated and half were new. The results reveal that participants were more likely to share statements they had previously been exposed to. Importantly, the relationship between repetition and sharing was mediated by perceived accuracy. That is, repetition of false information biased people's judgement of accuracy and as a result fuelled the spread of misinformation. The effect was observed in the domain of health (Exp 1) and general knowledge (Exp 2), suggesting it is domain general.

INTRODUCTION

Engagement with misleading information online has doubled in recent years. Fake news about COVID-19, for example, proliferated over the last year with 1.1 million articles containing misinformation about COVID-19 shared on social media (Evanega et al., 2020). Such growth has concerning consequences including the increase of vaccines hesitancy, polarization, violent extremism and racism (Rapp & Salovich, 2018; Tsfati et al., 2020; Barreto et al., 2021; Swire-Thompson & Lazer, 2019; Newman et al., 2022). For instance, misleading information on how to treat COVID-19 can lead to delays in properly treating patients. To halt the spread of misinformation it is crucial to identify the mechanisms facilitating its spread. Here, I ask whether and how a single previous exposure to misinformation alters the likelihood that it will be shared.

A vast literature suggests that repeated statements are perceived as more accurate (Arkes et al., 1991, 1989; Bacon, 1979; Begg et al., 1992; Hasher et al., 1977; Hawkins & Hoch, 1992; Law et al., 1998, 1997; Roggeveen & Johar, 2002; Johar & Roggeveen, 2007; Begg at al., 1985; Begg & Armourm, 1991; Brown & Nix, 1996; Doland, 1999; Gigerenzer, 1994; Hawkins, 2001; Law & Hawkins, 1997; Schwart, 1982; Fazio et al., 2015, 2019; Swire et al., 2017; for a review Dechêne et al., 2010) even when statements are from non-credible sources (Begg et al., 1992; Fazio et al., 2019; Murray et al., 2020; Pennycook et al., 2018). This phenomenon is known as “The Illusory Truth Effect” (Arkes et al., 1989; Murray et al., 2020; Fazio et al., 2019) and has been shown in domains ranging from marketing (Hawkins & Hoch, 1992;

Law et al., 1998; Roggeveen & Johar, 2002; Johar & Roggeveen, 2007) to news (Murray et al., 2020; Pennycook et al., 2018). A single previous exposure to fake news headlines can increase perceived accuracy even when the information is inconsistent with the participant's ideology (Pennycook et al., 2018; Murray et al., 2020).

I pose that if (i) people prefer to share true information and (ii) repetition increases perceived accuracy, then repeated information will be shared more than new information because people will believe it is accurate (for similar prediction see Van Bavel et al., 2021).To test this, I run an information-sharing task in which participants indicated whether they would like to share health-related statements (Exp 1) and general knowledge statements (Exp 2) with other participants on social media. Half of the statements were repeated, and half were new. In addition, participants indicated whether they perceived each statement as true of false. This allowed us to test whether repetition increases belief in accuracy, even when statements are false, leading to increased sharing of misleading information.

RESULTS

Task. Exp 1.

To investigate whether, and why, repeated information is shared more than new information, 160 participants performed an information-sharing task (*Figure 4-1*). On one block of trials, they indicated whether they would like to share health-related statements (e.g., ‘For better health, one needs to remove sugar entirely from one’s diet’) with participants who may be playing a similar task on the following day. Half of the statements were true and half were false.

Half of the statements (randomly assigned) were previously presented to the participants and half were new. On another block of trials, participants rated whether they believed each statement was true or false (accuracy judgment). The order of the sharing block and the accuracy judgment block was counterbalanced across individuals.

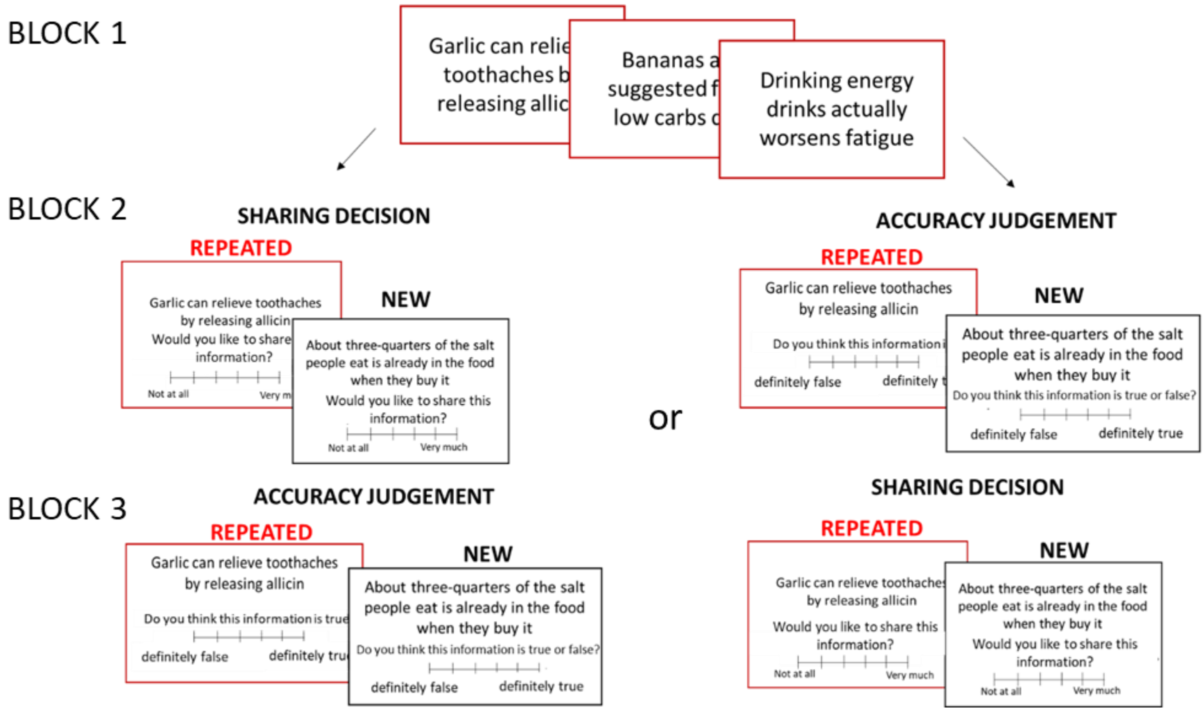

Figure 4-1 Task. In the first block, participants observed 30 health-related statements randomly selected from a list of 60. On the second or third block (counterbalanced) participants observed each of the 60 statements and indicated whether they would have liked to share the information with participants who may be playing a similar task on the following day. They replied on a continuous scale ranging from 1 “Not at all” to 100 “Very much”. In the second or third block (counterbalanced), participants indicated whether they believed each statement was true or false using a continuous scale ranging from 1 “Definitely False” to 100 “Definitely True”. Red color is used for illustrative purposes only.

Repeated information is perceived as more true

I first tested for the “Illusory truth effect” - that is whether participants are more likely to perceive repeated information as true. To that end, I submitted accuracy ratings to a 2x2 Repeated Measures Anova with ground truth (true /false) and repetition (repeated/new) as within subject variables and perceived accuracy as the dependent variable. In accordance with the literature on the “Illusory truth effect”, I found a main effect of repetition: repeated statements ($M = 60.51$, $SD = 10.04$) were rated as more true than new statements ($M = 56.77$, $SD = 8.91$; $F(1,159) = 39.92$, $p < 0.001$, $\eta^2 = 0.201$, *Figure 4-2*). This was found for both true (Repeated: $M = 76.98$, $SD = 8.96$, New: $M = 73.80$, $SD = 9.14$, $t(159) = 5.419$, $p < 0.001$) and false statements (Repeated: $M = 44.00$, $SD = 14.52$, New: $M = 39.62$ $SD = 12.36$, $t(159) = 4.482$, $p < 0.001$). Moreover, I found a main effect of ground truth: true information ($M = 75.46$, $SD = 8.25$) was judged as more true than false information ($M = 41.82$, $SD = 12.06$; $F(1,159) = 1222.202$, $p < 0.001$, $\eta^2 = 0.885$, *Figure 4-2*). No significant interaction between repetition and ground truth was found ($F(1,159) = 1.244$, $p = 0.266$, $\eta^2 = 0.008$).

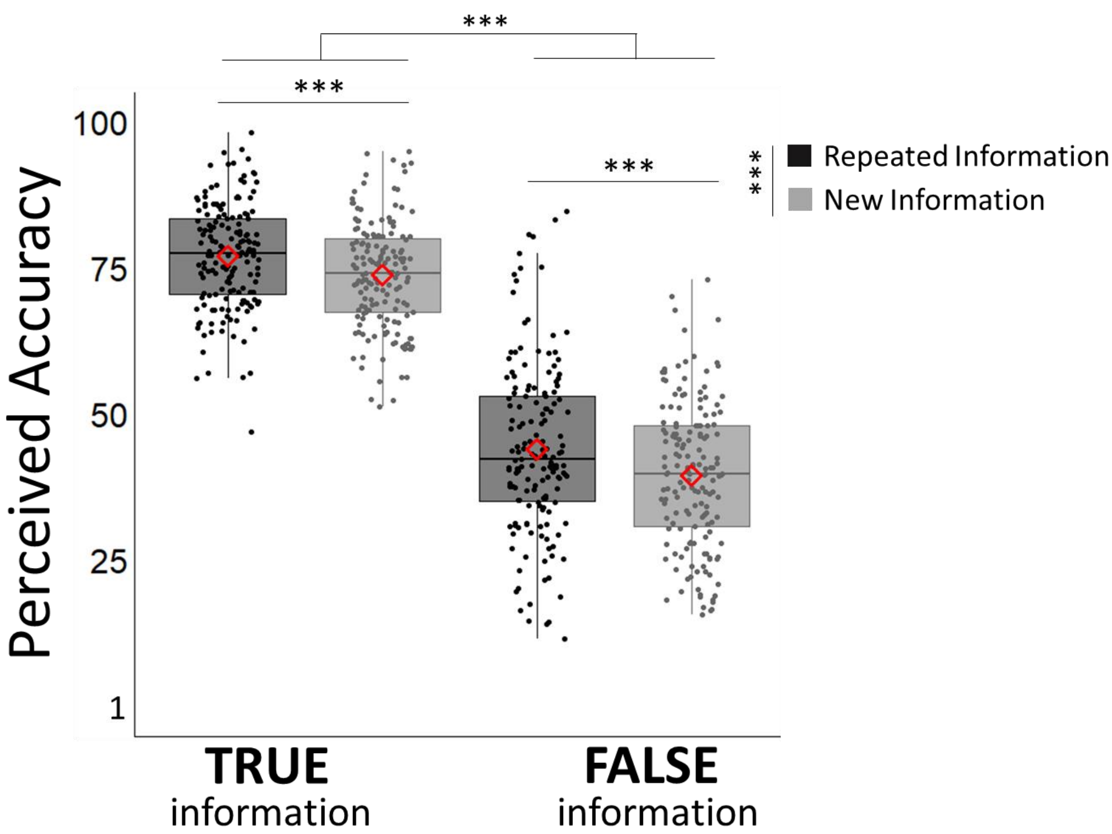

Figure 4-2 Repeated information is perceived as more accurate than new information. Horizontal lines indicate median values, boxes indicte 25–75% interquartile range, diamonds indicate mean value and whiskers indicate 1.5 × interquartile range; individual scores are shown separately as dots. ** p = 0.001, *** p < 0.001.

Repeated information is shared more than new information

Next, I tested whether repeated statements were shared more than new statements. To that end I performed a 2x2 Repeated Measures ANOVA with ground truth (true/false) and repetition (repeated/new) as within subject variables and sharing decision as the dependent variable. I found a main effect of repetition: people shared repeated statements (M = 41.03, SD = 20.16) more than new statement (M = 38.81, SD = 18.45; $F(1,159) = 12.066$, $p = 0.001$, $\eta^2 = 0.071$; *Figure 4-3*). This was observed both for true (Repeated: M = 53.92, SD = 23.90, New: M = 51.88, SD = 22.34, $t(159) = 2.437$, $p = 0.016$) and false statements (Repeated: M = 27.78, SD = 19.27, New: M = 25.78 SD = 17.38, $t(159) = 2.478$, $p = 0.014$). There was also a main effect of ground truth; people share true statements (M = 53.02, SD = 22.58) more than false statements (M = 26.83, SD = 17.78; $F(1,159) = 475.925$, $p < 0.001$, $\eta^2 = 0.750$; *Figure 4-3*). No significant interaction between repetition and ground truth was found ($F(1,159) = 0.001$, $p = 0.972$, $\eta^2 < 0.000$).

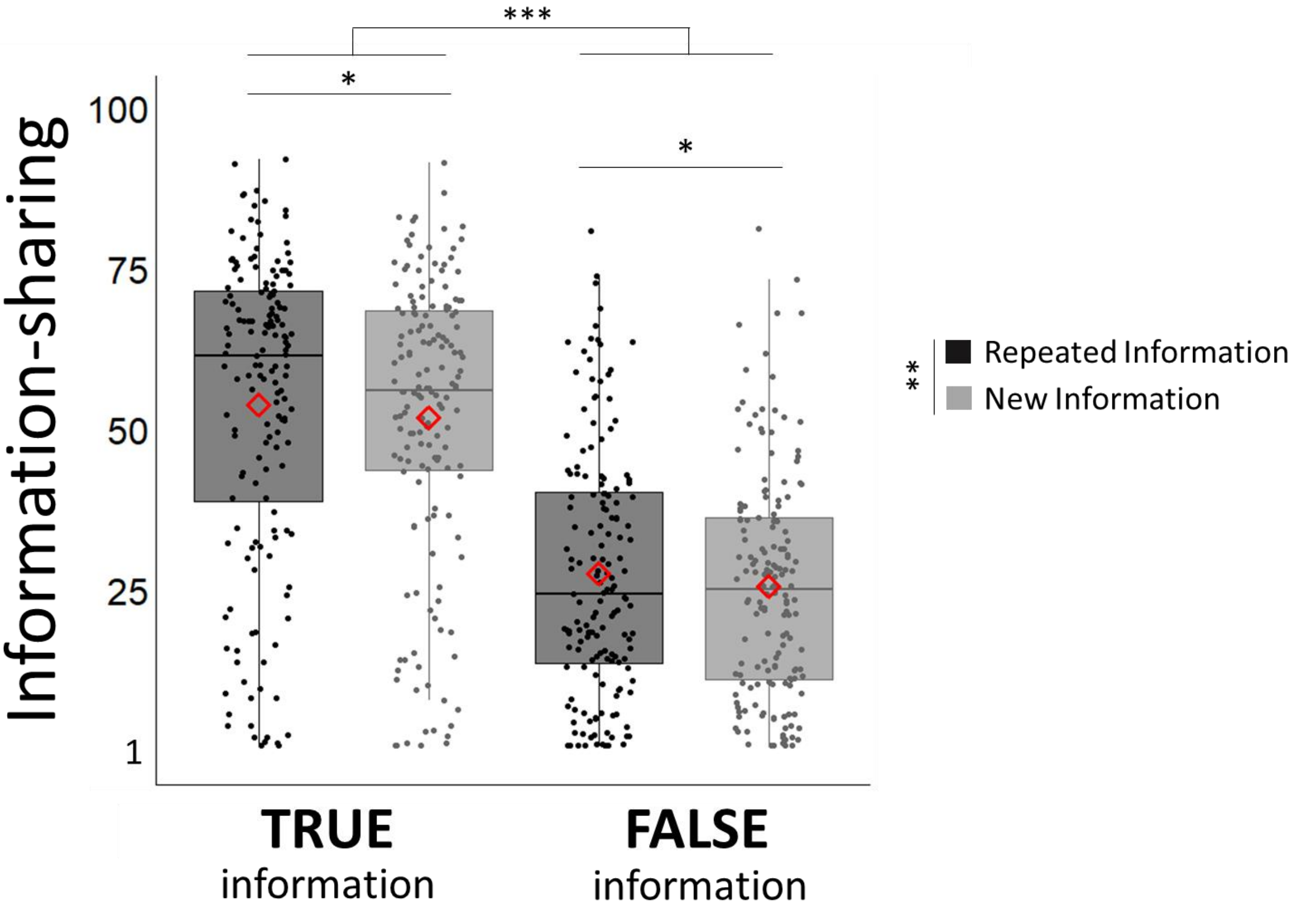

Figure 4-3 People are more likely to share information they have been previously exposed to and are also more likely to share true information. Horizontal lines indicate median values, boxes indicate 25–75% interquartile range, diamonds indicate mean values, scores and whiskers indicate 1.5 × interquartile range; individual scores are shown separately as dots. ** p = 0.001, *** p < 0.001.

The effect of repetition on sharing is fully mediated by perceived accuracy

So far, I found that repeated information is more likely to be shared by participants than new information. A possible underlying mechanism is that repetition boosts perceived accuracy, which in turn leads to greater sharing.

To test this possibility, I performed a mediation analysis for each participant and tested the obtained estimates against zero. I found that repetition was related to greater sharing (Total effect = 2.23, SD = 8.71, $t(158) = 3.235$, $p = 0.001$, *Figure 4-4*) The effect of repeated exposure on information-sharing was fully mediated by perceived accuracy (Index of indirect effect = 2.45, SD = 6.42, $t(158) = 4.814$, $p < 0.001$). Specifically, repetition of information was associated with higher perceived accuracy ($\beta = 3.71$, SD = 9.02, $t(158) = 5.188$, $p < 0.001$) and perceived accuracy was associated with greater sharing ($\beta = 0.62$, SD = 0.32, $t(158) = 24.25$, $p < 0.001$). After accounting for perceived accuracy the relation between repetition and sharing was not significant ($\beta = -0.22$, SD = 5.64, $t(158) = 0.485$, $p = 0.629$).

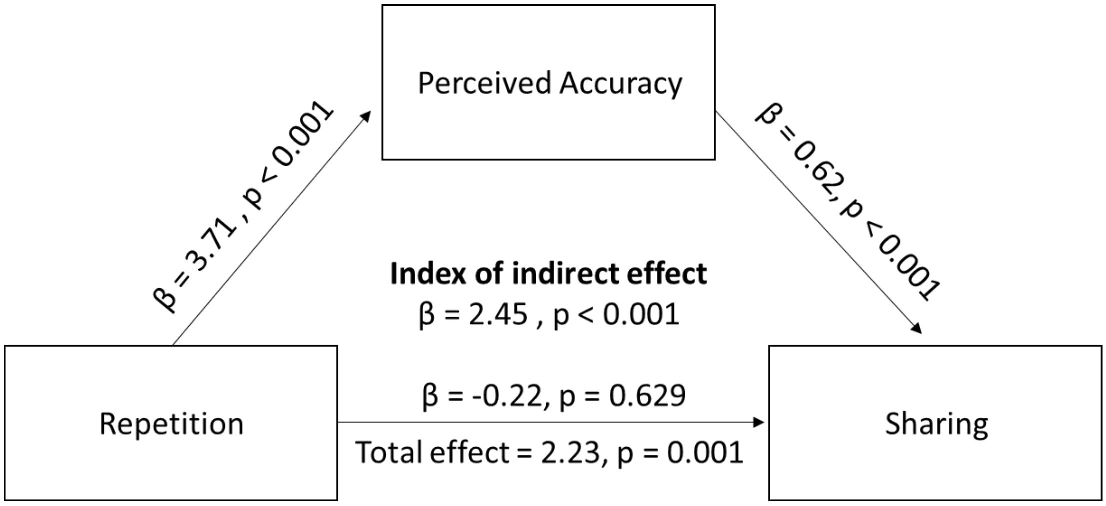

Figure 4-4 The effect of repetition on sharing is fully mediated by perceived accuracy. Repeated information is perceived as more accurate, which increases sharing of that information. The figure represents the mediation model and the Beta Coefficients obtained. *** $p < 0.001$.

Exp 2: Results are domain general

So far, I found that repetition leads to increased information sharing of health-related information. Next, I examined whether the results would generalize to information related to different domains. To that end, 100 participants completed the same task as in Exp 1 except that the information was 'general knowledge' (e.g., 'The Cyclops is the legendary one-eyed giant in Greek mythology'). There were two other differences between Exp 2 and Exp 1: (i) instead of being told that they would be deciding which information to share with participants that may be performing the task the next day, participants' were told that they were managing a social media page and they had to decide which information they would like to post. (ii) I used a 6-point Likert scale for all ratings.

The analysis was exactly as in Exp 1. Replicating previous results, I found that repeated statements ($M = 3.97$, $SD = 0.57$) were rated as more true than new statements ($M = 3.75$, $SD = 0.37$; $F(1,99) = 15.949$ $p < 0.001$, $\eta^2 = 0.139$). This was observed for both true (Repeated: $M = 4.59$, $SD = 0.58$, New: $M = 4.40$, $SD = 0.46$, $t(99) = 2.842$, $p = 0.005$) and false statements (Repeated: $M = 3.34$, $SD = 0.72$, New: $M = 3.11$ $SD = 0.52$, $t(99) = 3.498$, $p = 0.001$). Moreover, true information ($M = 4.49$, $SD = 0.40$) was judged as more truer than false information ($M = 3.22$, $SD = 0.53$; $F(1,99) = 541.264$, $p < 0.001$, $\eta^2 = 0.845$). The interaction between repetition and ground truth was not significant ($F(1,99) = 0.301$, $p = 0.585$, $\eta^2 = 0.003$; *Figure 4-5a*)

As previously found, people shared repeated statements ($M = 2.43$, $SD = 0.95$) more than new statements ($M = 2.30$, $SD = 0.86$; $F(1,99) = 10.886$, $p = 0.001$, $\eta^2 = 0.099$). This was observed for both true (Repeated: $M = 2.77$, $SD = 1.16$, New: $M = 2.62$, $SD = 1.06$, $t(99) = 3.139$, $p = 0.002$) and false statements (Repeated: $M = 2.10$, $SD = 0.87$, New: $M = 1.97$ $SD = 0.78$, $t(99) = 2.233$, $p = 0.028$).They also shared true statements ($M = 2.70$, $SD = 1.08$) more than false statements ($M = 2.03$, $SD = 0.78$; $F(1,99) = 94.482$, $p < 0.001$, $\eta^2 = 0.488$). A significant interaction between ground truth and repetition was not observed ($F(1,99) = 0.337$, $p = 0.563$, $\eta^2 = 0.003$; *Figure 4-5b*)

As in Exp 1, repetition was related to greater sharing (Total effect = 0.16, $SD = 0.47$, $t(86) = 3.078$, $p = 0.003$, *Figure 4-5c*). This relation was partially mediated by perceived accuracy (Index of indirect effect = 0.12, SD =

0.37, $t(92) = 3.070$, $p = 0.003$**)**. Specifically, repetition was related to higher perceived accuracy ($\beta = 0.23$, SD =0.57, $t(92) = 3.820$, $p < 0.001$) which in turn was associated with greater sharing ($\beta = 0.46$, SD =0.36, $t(92) = 12.393$, $p < 0.001$). Once again after accounting for perceived accuracy the relation between repetition and sharing was not significant ($\beta = 0.16$, SD = 1.47, $t(92) = 1.056$, $p = 0.294$).

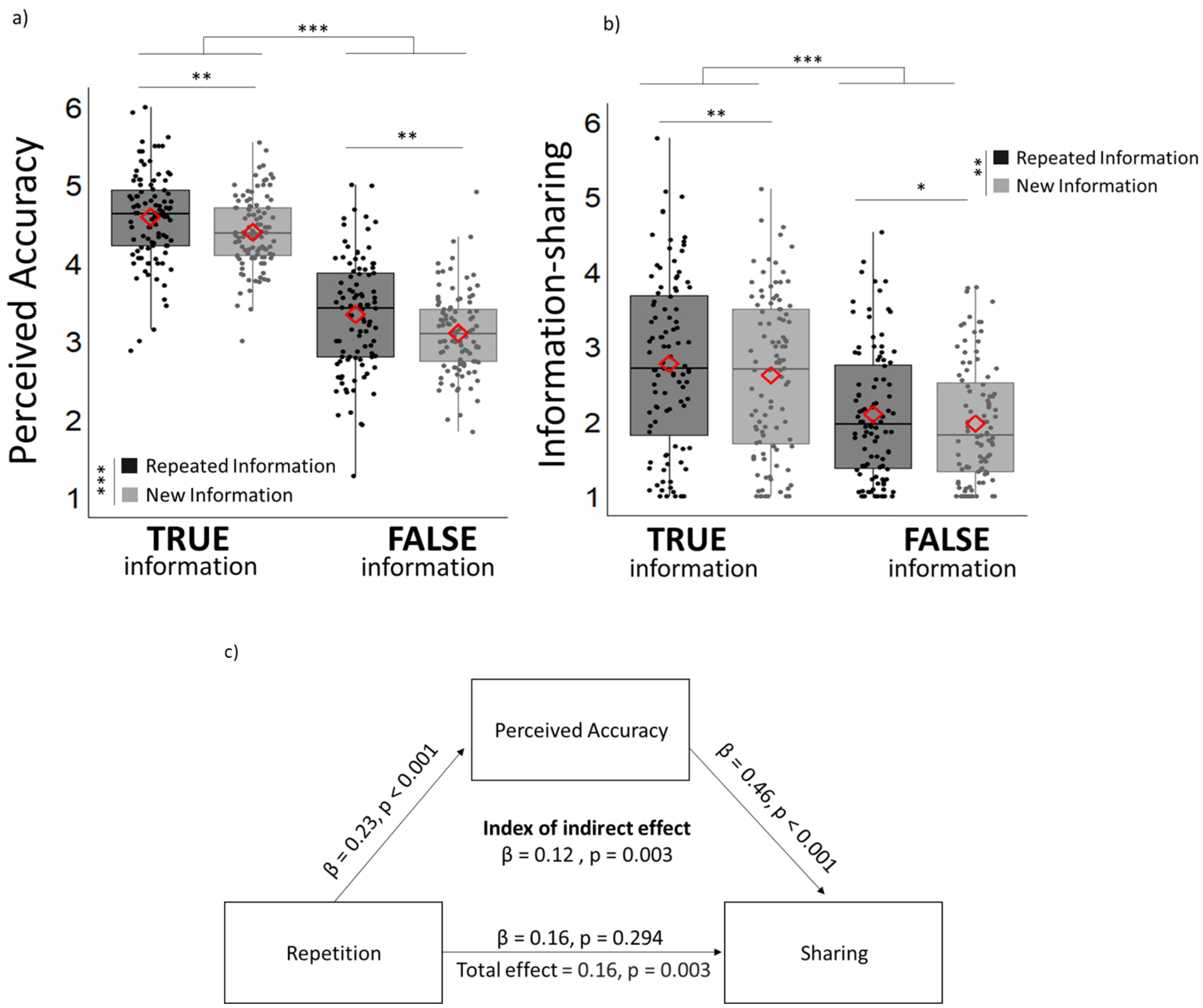

Figure 4-5. Results are domain general. (a) Repeated information is perceived as more accurate than new information. (b) People share repeated information more than new. Horizontal lines indicate median values, boxes indicate 25–75% interquartile range, diamonds indicate mean values, the horizontal dotted line indicate 0 change in anxiety scores and whiskers indicate 1.5 × interquartile range; individual scores are shown separately as dots. (c) Perceived accuracy fully mediates the relationship between repetition and information-sharing. The figure represents the mediation model and the Beta Coefficients obtained. ** p = 0.001, *** p < 0.001.

DISCUSSION

Here, I provide evidence for a mechanism which facilitate the spread of misinformation. In particular, I demonstrate that the well-known ‘illusory truth effect’ fuels the spread of false information. It has been suggested that a single exposure to repeated information boosts its accuracy perception (for a review Dechêne et al., 2010) – here I show that by doing so it also boosts the spread of said information.

Specifically, our data reveal that people are more likely to share information they have been previously exposed to. I show that the relationship between repetition and sharing is mediated by perceived accuracy. That is, repeated information seems to be shared more because people judge repeated information as more accurate. Our results help explain why fake news spread so easily among the population. Fake-new is often constructed to be appealing to the reader and consequently is more likely to be repeated by different sources. Results of our study suggest that repeated exposure to fake news will create a vicious circle in which fake-news will be perceived as true and therefore shared more. These results stress the importance of quickly tagging fake news as such. If repeated exposure biases people to share news more, the longer information circulates, the higher the probability that it will be considered as true and further shared with others.

Importantly, repetition increased sharing intentions in different domains. I show that the results replicate for health-related information as well as ‘general knowledge’, suggesting that the effect of repetition on information-sharing is domain general.

In sum, I show that even a single previous exposure to information will increase the likelihood of sharing by enhancing perceived accuracy. This will create a viscous cycle of exposure – increase belief – sharing – exposure - increase belief - which in turn can influence actions. For example, misinformation about COVID-19 vaccines can increases vaccine hesitancy and as a result reduce the likelihood of vaccine uptake.

MATERIALS AND METHODS

Participants

Participants were recruited via Prolific Academic (https://www.prolific.co/) and were paid £7.50 per hour for their participation. The task was created using Gorilla Experiment Builder (www.gorilla.sc; Anwyl-Irvine et al., 2020) and the JsPsych library (de Leeuw, J. R., 2015). The sample size for was determined based on previous studies on the truth effect (Dechêne et al., 2010). The study was approved by the departmental ethics committee at UCL. 162 subjects participated in Exp 1. Data from one subject was eliminated as they completed one phase of the experiment twice and data from one subject failed to save correctly. Thus, data from 160 participants was analyzed in Exp 1 (44 males, 115 females, 1 prefer not to say/other; mean age = 35.26 years ± 11.05 (SD)). 102 subjects participated in Exp 2. Data from two subjects was eliminated as they completed one phase of the experiment. Thus, data from 100 subject was analyzed (53 males, 45 females, 2 other; mean age = 32.81 years ± 8.99 (SD)).

Procedure and task – Exp 1

In block 1, participants observed 30 health-related statements in random order, each for 6 seconds. Statements were randomly selected for each participant from a list of 60 (see supplement material for all statements). Half of the statements were true and half were false.

In either the second or third block (counterbalanced across participants) participants observed 60 statements (half were new, half repeated) one at a time, in a random order. For each, they indicated whether they wanted to share the statement with participants who might play a similar task the following day. They did so using a continuous scale ranging from 1 “Not at all” to 100 “Very much”.

In either the second block or third block (counter balanced across participants), participants indicated whether they thought each statement was true or false on a continuous scale ranging from 1 “Definitely False” to 100 “Definitely True” (Accuracy Judgment Block). Sentences were presented in a random order. In Exp 1, 77 participants completed the Accuracy Judgment Block first, and 83 completed the Information-Sharing Block first.

Attention Check: In block 1 4 attention check were included. In 2 of these trials participants observed a statement (which was not drawn from the 60 statements list) and subsequently were presented with a list of 3 statements which included the one they previously saw. Their task was to indicate the previously seen statement. In the other 2 trials, after the presentation of the statement (which was not drawn from the 60 statements list), participants were asked to answer a question about the statement they had just seen.

In block 2 and 3, 6 attention check trials were inserted. 4 of these trials were identical to check trials in block 1. In the other 2 trials, instead of indicating their sharing decision or accuracy judgment, subjects were instructed to select a specific rating (for example: *Select Definitely False*). In Exp 1, selecting 1 to 10 was considered correct on this attention check. Participants answered correctly on 89.22% of the attention checks in Exp 1. Between block 1 and the block 2, participants filled questions about their social-media use. After completing the study, participants filled the BES (Basic Empathy Scale).

Procedure and task – Exp 2

The task was identical to the task used in Exp 1, with three exceptions

(i) Information was ‘general knowledge’.

(ii) Participants indicated their answers on a 6-point Likert scale.

(iii) The sharing scenario was hypothetical. Participants were asked to imagine they had a Twitter account about in ‘general knowledge’. In the information-sharing block, they indicated whether they wanted to share the statement on their hypothetical Twitter account.

57 participants completed the Accuracy Judgment Block first, and 43 completed the Information-Sharing Block first. Participants answered correctly on 80.75% of the attention checks.

Data Analysis

For each subject I computed the average rating on the sharing scale and the average rating on the perceived accuracy scale, separately for repeated and new statements, and for true and false statements. A Repeated Measures ANOVA with conducted with repetition (new/ repeated) and ground truth (true/ false) as within subject variables, and perceived accuracy as the dependent variable. The same ANOVA was conducted for sharing ratings.

I then performed a mediation analysis for each participant, using the R package Process 4.0 with 10000 permutations, to test whether perceived accuracy mediated the effect of repetition on sharing decision. Significance of the mediation was determined by the Index of indirect effect. I could not estimate the mediation model for 1 subject in Exp 1 and 7 in Exp 2 due to non-sufficient variability in responses (that is subjects either made the exact same sharing response on all trials and/or used only two numbers on the accuracy scale). Therefore, the mediation model was estimated for 159 participants in Exp 1 and for 93 in Exp. The total effect cannot be estimated when subjects used only two numbers on the sharing scale , this was true for 6 subjects in Exp 2. Estimates were compared to 0 across participants using a T-test.

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SUPPLEMENTARY MATERIALS

Experimental Stimuli

Exp 1

1. Sugar-sweetened beverages decrease risk of heart disease
2. Adults should eat no more than 6g of salt a day
3. Art can improve your enjoyment of life and your health
4. Avocados are different than most fruits because they are loaded with healthy fats instead of carbs
5. Caffeine consumption reduces bone growth in kids.
6. Being optimist has strong links with longevity
7. Bottled water is better for one's health than tap water
8. Spicy food helps weight loss by encouraging thermogenesis, the process of creating heat from burning fat
9. Eating a lot of carrots gives you great night vision.
10. Drinking hot drinks is more effective for cooling off than drinking cold drinks
11. Drinking more alcohol can cure an ongoing hangover
12. Eating at night may cause trouble sleeping
13. Humans can't grow new brain cells.
14. Eating too many carrots can lead to a condition called carotenemia which is an orange skin discoloration
15. Electronic screens emit blue light, which suppresses the sleep-inducing hormone melatonin
16. Everyone needs about 8 hours of sleep every day
17. For better health, one needs to remove sugar entirely from one's diet
18. Garlic can relieve toothaches by releasing allicin
19. Ginger has potent anti-inflammatory and antioxidant effects
20. Maintaining good relationships can reduce harmful levels of stress

21. It takes 7 years for gum to digest if you swallow it.
22. You lose 90% of your body heat through your head.
23. People who have close friends and family are healthier and live much longer
24. Bananas are among the world's best sources of potassium
25. Speaking positive affirmations out loud can boost self-esteem and keep us motivated
26. Sugary drinks are among the most fattening items you can put into your body
27. To avoid cramps and drowning, one needs to wait an hour after eating to swim
28. Washing your hands is an excellent way to stave off infection and food poisoning
29. Being cold can give you a cold.
30. Going out with wet hair gets you sick
31. Eating food within five seconds of dropping it on the floor is safe
32. Bananas are suggested for a low carbs diet
33. Microwave ovens is bad for your health
34. Canned foods have little nutritional value
35. Gluten should be removed from our diet
36. Chocolate is an aphrodisiac
37. Crusts are the most nutritious part of the bread in terms of the quantity of antioxidants
38. Cracking joints causes arthritis
39. Eating sugar is associated to poor focus in kids
40. During the weekend, you can catch up on sleep you have missed during the weekdays, preventing negative health outcomes
41. Eating enough protein is particularly important for weight loss and for maintaining good health overall
42. Eating fiber-based food is recommended for maintaining good gut health
43. Eating slowly gives your brain the chance to get the signal that you're full
44. Eating sugar is the direct cause of diabetes in the population
45. Eating yogurt helps put the digestive system back in order thanks to its probiotics

46. Eggs increase the risk for heart disease and atherosclerosis

47. Fatty fish is extremely beneficial to health due to the concentration of omega-3 fatty acids

48. Juice cleanses enhances the body's ability to cleanse itself

49. Nuts and seed are very low in proteins and fibers

50. Laughing is good for the heart and can increase blood flow by 20%

51. Mindful breathing can keep you present and help you centre your attention

52. People who consume extra virgin olive oil have a much lower risk of dying from heart attacks

53. Pickle juice alleviates muscle cramps

54. Poor sleep can reduce your physical and mental performance

55. Refined carbs consumption is discouraged because of its low concentration in fiber

56. Sunlight is a source of vitamin D, which helps our brains release mood-boosting endorphins and serotonin

57. Tomatoes are usually categorized as a vegetable, although they are technically a fruit

58. Using deodorant with aluminium-based compounds can cause diseases

59. Walking for 20-30 minutes a day, five days a week can improve your immune system

60. Yoga helps bone health and boosts the immune system

Exp 2

1. The thigh bone is the largest bone in the human body

2. Mexico is the world’s largest producer of silver

3. The largest dam in the world is in Pakistan

4. The Cyclops is the legendary one-eyed giant in Greek mythology

5. Marconi is the inventor of the wireless radio

6. The largest planet in the solar system is Jupiter

7. Volleyball was originally called mintonette

8. Walruses use their tusks primarily for mating

9. Greenland is a part of the Kingdom of Denmark
10. The stationary ball in lawn bowls is called a jack
11. Domesticated goats are descended from the pasang
12. Kava is a beverage made from the root of the pepper plant
13. Lake Baikal is the world's largest freshwater lake by volume
14. Female turkeys generally weigh half as much as males
15. The lima bean is also known as the sieva bean
16. Halvah is a confection made of sesame seeds
17. Normal color vision is known as trichromacy
18. The stones used in curling are concave on the bottom
19. The tool that plots position relative to the poles is a compass
20. The ship that carried the Pilgrims to America is the Mayflower
21. The world famous magician and escape artist was Houdini
22. Molten rock that runs down the side of a volcano is lava
23. The men who flew the first airplane were the Wright brothers
24. The liquid portion of whole blood is plasma
25. A rider on horseback hits a ball with his mallet in polo
26. Severe headaches accompanied by nausea are migraines
27. The ocean between Africa and Australia is the Indian Ocean
28. The Italian city known for its canals is Venice
29. A giant ocean wave caused by an earthquake is a tsunami
30. The outer layer of cheese is known as the rind
31. New Delhi, India, is the world’s most populous city
32. The capital of Russia is Saint Petersburg
33. The Indian Ocean is the smallest ocean on Earth
34. The planet Venus is larger than the planet Earth
35. The Atlantic Ocean is the largest ocean on Earth
36. Bell is the inventor of the wireless radio
37. The capital of New York is New York City

38. The Chicago Marathon is the world’s oldest annual marathon
39. Kvass is an alcoholic beverage fermented from honey
40. The monetary unit in Afghanistan is the rupee
41. Europe has the highest average elevation of the continents
42. Spain produces most of the world's almonds
43. Competitive badminton is usually played outdoors
44. Dough is boiled in the process of making croissants
45. The highest waterfall in the world is in Argentina
46. Biking is the first event in a triathlon
47. The mouth of a sea urchin is on its top
48. Candlepins is the most widely played variation of bowling
49. Tennis has been traced back to the baths of Rome
50. Endothermic reactions release chemical energy
51. The thick layer of fat on a whale is its peduncle
52. Michelangelo painted the ceiling of Saint Peter's Basilica
53. Plants make their food during chemosynthesis
54. Abraham Lincoln was assassinated by Ray
55. The name for the collar bone is the scapula
56. The sport associated with Wimbledon is field hockey
57. The villainous captain in the story 'Peter Pan' is Captain Smee
58. The name of Tarzan's girlfriend is Marian
59. The short pleated skirt worn by Scottish men is a sari
60. Old Faithful is located in Yosemite Park

CHAPTER 5:

GENERAL DISCUSSION

SUMMARY OF EMPIRICAL FINDINGS, LIMITATIONS AND FUTURE DIRECTIONS

CHAPTER 2: A SELECTIVE EFFECT OF DOPAMINE ON INFORMATION-SEEKING

Summary

Previous studies suggest that mesolimbic areas code the opportunity to gain information in a valence dependant manner (Charpentier et al., 21018). To test for the causal role of dopamine in valenced information-seeking, in this study, participants were administered with either L-DOPA or placebo and completed an information-seeking task. I found that dopamine altered valence-dependent information-seeking by reducing the effect of valence on seeking behaviour. Specifically, while participants under placebo sought more positive than negative information, I did not observe the same in participants who were administer with LDOPA. Instead, these subjects exhibited increased information-seeking about undesirable information as compared to controls. Moreover, dopamine administration did not alter general patterns of information-seeking. Together, these results suggest that dopamine reduces the impact of valence on information-seeking.

Limitations and future directions

In this study information was non instrumental, that is, it could not be used to change the outcome of the task. Future research could investigate how dopamine administration affects information-seeking when information can be used to obtain rewards or avoid harms.

Results of the current study suggest that people with impaired dopamine function (such as Parkinson's disease patients) may exhibit abnormal patterns of information-seeking behaviour. For example, they could be less likely to engage in information-seeking about negative events. Future studies could investigate whether this clinical population shows altered information-seeking behaviour and if this is the case, how abnormal information-seeking patterns affect their mood.

CHAPTER 3: HOW PEOPLE DECIDE WHEN TO INFORM OTHERS

Summary

As information can serve different, sometimes competing goals, deciding whether to seek and share information can be a difficult problem to solve. Previous studies suggested that people prefer to gather information that is likely to be positive (Kelly & Sharot, 2021; Sharot & Sunstein, 2020; Charpentier et al.,2018; Dezza et al., 2022), that is useful (Kelly & Sharot, 2021; Stigler, 1961; Hirshleifer & Ryley, 1979; Kobayashi & Hsu, 2019; Dezza et al., 2022;) and when uncertainty is high (Kelly & Sharot, 2021; Wilson et al., 2014; Oudeyer et al., 2016; Cogliati Dezza et al., 2017; Gershman, 2018; Schwartenbeck et al., 2019; Dezza et al., 2022). Some studies also suggest that people also prefer to share information that is positive (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987; Dibble and Levine, 2010, 2013; Weenig et al., 2014; Tesser & Rosen, 1975) and useful (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001). However, no studies disentangled the weight assigned to these variables. Moreover, how the receiver's uncertainty

affect the decision to share information is unknown. This study investigated how people integrate several, sometimes competing, goals to decide when to share information with others. I showed that people prefer to share information that is positive, useful and when the receiver's uncertainty is high. These results suggest that in order to decide when to share information, people used their own information preferences on what they would want to know. Results also revealed that people tend to overweight one factor over the others. The different weights people assign to each factor may explain why different people make such different sharing decisions. The importance assigned to each factor seem to be constant across information-sharing and information-seeking decisions. Overall, results of this study suggest that the same mechanism could be responsible for seeking and sharing information.

Limitations and future directions

In this study subjects participated in a financial task in which they could seek information for themselves and to share it with others. Participants were told that information would be shared with individuals who would do a similar task on a following day. The ecological validity of such design is limited as individuals provide their sharing decisions in an experimentally controlled environment (the financial decision-making task I created). Future studies could investigate information-seeking and sharing behaviours in a more naturalistic environment, for example on social-media.

Previous studies suggested that individual differences in the weight assigned to each motive when seeking information provide insights about their mental health (Kelly & Sharot, 2021). Future studies could investigate whether this is also the case for information-sharing. That is, whether individual differences in sharing behaviour are associated to psychopathology.

Results of the studies reported in Chapter 3 suggest that a common mechanism could determine both sharing and seeking behaviour. Future neuroimaging studies could investigate whether the motives that drive sharing and seeking information are characterized by the same neural signatures.

CHAPTER 4: THE ILLUSORY TRUTH EFFECT LEADS TO THE SPREAD OF MISINFORMATION

Summary

Previous studies suggested that a single exposure to information increases its perceived accuracy (Arkes et al., 1991 & 1989; Bacon, 1979; Begg et al., 1992; Hasher et al., 1977; Hawkins & Hoch, 1992; Law et al., 1998; Johar & Roggeveen, 2007; Murray et al., 2020; Fazio et al,. 2019; Pennycook et al., 2018; for a review Dechene et al., 2010). In this study, I tested whether repetition also leads to increased sharing intentions. To do so, participants completed an information-sharing task in which they first observed a list of statements. Then they were asked to decide whether to share the statements with other participants and whether they perceived them as true or false. Participants saw half of the statements in the first phase of the experiment, while half of the statements were new. I found that people were more likely to share information they have been previously been exposed to even when it was false. This relationship was fully mediated by perceived accuracy. That is, repeated information was shared more because it was

considered more accurate. This study shed new light on the mechanism underlying the information spreading.

Limitations and future directions

In this study I found that even a single exposure to information increases its sharing. In their everyday life, people are often exposed to the same piece of information multiple times. Future studies could investigate whether increasing the number of repetitions would further enhance sharing intentions. As previous studies showed that the more repetitions, the greater the perceived accuracy of information (Hassan & Barber, 2021; DiFonzo et al., 2016), I would hypothesize that a higher number of repetitions would also lead to an increase in participants' sharing intentions.

It would be interesting to investigate whether the effect of repetition on sharing is long-lasting. To this aim, subjects that completed the task a few months ago could be recruited. Participants would be asked to declare their sharing intentions of new statements and of statements that they had already seen when they completed the task the first time. Sharing intentions of new statements would then be compared to sharing intentions of the statements shown in the first experiment. If the effect of repetition is long-lasting, I would hypothesize to observe higher sharing intentions for statements that participants had previously seen.

Another follow up study could investigate whether the repetition effect is related to low or high-level features of information. Low-level features of information are the visual features that characterize the exact words used to convey a message, while high-level features represent the meaning of the message. For example, the sentences “The house at the end of the street is very nice” and “The mansion situated at the end of the boulevard is gorgeous” do not have the same low-level feature but they have the same high-level features as they convey the same meaning. If the effect of repetition on sharing is related to low-level features, then I would hypothesize that changing the wording used to convey the information would cancel the effect of repetition on sharing. Alternatively, if the effect is due to high-level features of information, changing the wording should not cause a change in the observed effect. Disentangling whether the effect of repetition on sharing intentions is related to perceptual or semantic features of information is crucial to better understand the impact of this effect on misinformation sharing.

SYNTHESIS

The aim of the current thesis is to explore the neural and cognitive mechanisms that underlie people's decision to seek and share information. Seeking information is integral to learning, decision-making and social interactions (Kidd and Hayden, 2015; Loewenstein, 1994; Sakaki et al., 2018; Gottlieb et al., 2013). Similarly, the ability to share information with other individuals is also of the highest importance for the survival of our species. For example, being able to inform others about the location of food increases the likelihood of survival of a community.

Previous studies investigated which variables are important to determine information-seeking. Valence of information is found to predict seeking behaviour with people preferring to seek positive over negative information (Kelly & Sharot, 2021; Sharot & Sunstein, 2020; Charpentier et al.,2018; Dezza et al., 2022). Previous correlational research suggest that the opportunity to gain positive information is coded in mesolimbic dopaminergic areas (Charpentier et al., 2018). In the second Chapter of this thesis, to causally test for the role of dopamine valenced information-seeking, participants were either administered L-DOPA or placebo and completed an information-seeking task. I found that under L-DOPA, participants were less impacted by valence of information when deciding whether to seek information. Specifically, under placebo, participants preferred to seek positive information, while under L-DOPA participants sought equally positive and negative information. In particular, dopamine increased seeking of information that conveyed negative outcomes. This study demonstrates that dopamine reduces the impact of valence on information-seeking. Results of this study also suggest that clinical populations characterized by abnormal dopaminergic function (Parkinson’s disease and schizophrenia patients) may exhibit an altered pattern of information-seeking which, in turn, could influence their mood. Moreover, dopaminergic drugs are commonly used to treat symptoms of several disorders, including Parkinson’s and schizophrenia, potentially altering information-seeking patterns. As information acquired from the environment can influence our mood, beliefs, and actions, it is crucial to understand how dopamine administration impacts information-seeking

Other studies suggested that uncertainty associated with information and its instrumental value also predict information-seeking. Specifically, people prefer to seek information that can be used to gain rewards or avoid harms (Stigler, 1961; Hirshleifer & Ryley, 1979; Kelly & Sharot, 2021; Kobayashi & Hsu, 2019; Dezza et al., 2022) and when uncertainty is high (Kelly & Sharot, 2021; Wilson et al., 2014; Oudeyer et al., 2016; Cogliati Dezza et al., 2017; Gershman, 2018; Schwartenbeck et al., 2019; Dezza et al., 2022).

Previous studies suggest that some variables that are important to determine information-seeking also predict information-sharing. Specifically, people prefer to share information that coveys good news (Tesser et al., 1971, 1972, 1973; Rosen et al., 1973; Dibble, 2014; Uysal et al., 2007: Bisel et al., 2011; Bond and Anderson, 1987; Dibble and Levine, 2010, 2013; Weenig et al., 2014; Tesser & Rosen, 1975) and that is useful (Berger & Milkman, 2012; Bobkowski, 2015; Heath et al., 2001). However, no study investigated how these variables are computationally integrated to form a sharing decision. Moreover, how the receiver’s uncertainty affect sharing is unknown. In Chapter 3, I investigated how uncertainty, valence and instrumentality of information are weighted to solve complex information-sharing problems. I found that people's sharing behaviours align with the receiver preferences. That is, people prefer to share information when the receiver is most unsure about it, when information is likely to convey good news and when it can be used by the receiver to alter outcomes. These results suggest that people used their own information preferences on what they would want to know to decide which information to provide to the receivers. Results also show individual differences in sharing behaviour, with people overweighting one factors over the others. Within individuals, the relative influence of the motives was stable across seeking and sharing decisions.

So far, I showed that people integrate uncertainty associated to information, its valence and instrumental value to decide whether to share it. In Chapter 3, I investigated how people decide to share accurate information. As misinformation sharing has consequences ranging from vaccine hesitancy to racism, it is crucial to determine the mechanisms that facilitate inaccurate information spreading. In Chapter 4, I enhanced accuracy perception by repeating information presented to participants and ask them to decide whether to share such information. A vast literature suggest that repetition of information plays an important role in accuracy judgment. Specifically, repeated exposure to information, even when false, increase its truth perception, an effect that has been named "Illusory truth effect" (Murray et al., 2020; Fazio et al,. 2019; Arkes et al., 1991 & 1989; Bacon, 1979; Begg et al., 1992; Hasher et al., 1977; Hawkins & Hoch, 1992; Law et al., 1998; Johar & Roggeveen, 2007; Pennycook et al., 2018; for a review Dechene et al., 2010). If repetition increases perceived accuracy of information, it is possible that it would also increase its sharing. In Chapter 4, I tested this hypothesis and I found that even a single previous exposure to information led to increased information-sharing. Importantly, the effect of repetition on sharing intentions holds strong even when information is false. I also found that this relationship was fully mediated by accuracy judgments. That is, people preferred to share information they have been previously exposed to because they perceived it as more true. Crucially, the effect of repeated exposure on sharing intentions replicates for both health-related information and "general knowledge" suggesting that the effect is domain general. Results obtained in this study provide a possible explanation to fake-news spreading. As fake-news are purposely constructed to be easily spread, it is likely that I are overexposed to fake-news. Repeated exposure to fake-news would, in turn, make us more likely to perceived information as true and therefore to share it, creating a dangerous circle of misinformation sharing. These results highlight the importance of quickly identifying fake-news with the aim to minimize repeated exposure among the population.

Overall Conclusions

Taken together the findings reported in this thesis provide new insights into how people decide when to share and seek information. Chapter 2 and 3 provide a more complete understanding of biological and cognitive factors shaping information-seeking and sharing behaviours. Specifically, they indicate that (i) dopamine administration boosts seeking of negative information, and that (ii) people use the same rules to decide when to share information with others as they do to decide to seek information for themselves. Specifically, people use their own information preferences to solve complex decision-sharing problems. As information affects our mood, beliefs and actions, it is crucial to understand how people decide which information to seek for themselves and to share with others.

Studies presented in this thesis also provide new insights about the mechanisms underlying misinformation sharing. Specifically, Chapter 4 suggests that (iii) even a single previous exposure to information (even when false) boosts its sharing because it increases its perceived accuracy. Fake-news sharing is a global issue that has consequences in many fields ranging from politics to health. It is crucial to understand how misinformation spread in order to develop tools to prevent it. Overall, the studies presented in this thesis suggest mechanisms underlying information-seeking and sharing and aim to pave the way for future research in this field.

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