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THE ROLE OF FUTURE-ORIENTED AFFECT IN DECISION-MAKING

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Abstract

A significant aspect of human cognition involves planning for the future. To do so, we need to anticipate how different decisions will make us feel — *anticipated affect* — and balance it with the emotions that future events trigger in us in the present — *anticipatory affect.* This future-oriented affect can have a profound impact on the way we make decisions. The current thesis aimed to gain a deeper understanding of how these two types of future-oriented affect influence our decision-making processes and how this may relate to their interplay with attention. Using psychophysiology, computational modeling, and brain imaging methods across three experimental studies, we show that anticipatory affect draws attention and modulates decision-making behavior, and that top-down attentional goals modulate neural activity when anticipating future emotions.

In *Study 1,* we show that the affect gap, a systematic difference in decision behavior under risk when choosing between affect-rich compared to affect-poor outcomes, may be driven by differences in affective arousal across affect-rich and affect-poor choices. In *Study 2*, we tested an alternative explanation for what could be driving the affect gap, namely that increased affective arousal leads to reduced cognitive resources, thus resulting in simplified decision behaviors; however, we did not find support for this hypothesis. In *Study 3*, we investigated how attentional deployment, an emotion regulation strategy by which one focuses attention away or towards a given aspect of a stimulus, modulated neural activity during affective forecasting — the process of anticipating future emotions. We show that focusing on the positive part of a bivalent (i.e., simultaneously positive and negative) outcome selectively engages reward-related brain processes, while focusing on the negative recruits regions related to aversion.

Results across the three studies highlight the important effects future-oriented affect has on decision-making processes and its interaction with attention. Affective information about the future can put a person into approach or avoidance states, resulting in simplified decision-making strategies that rely less on cognitive evaluations and more on affective evaluations of the events. Affect both draws attention through its salience, but can also be modulated by attention-based emotion regulation strategies. This research highlights the need for appropriate risk communication, especially in emotionally charged decision contexts.

Use of AI disclaimer

During the preparation of this thesis, the author used GPT-3.5 from OpenAI (2023), for proofreading purposes and to ensure linguistic precision, good style, and readability. After using these tools, the author reviewed and edited the text as needed, and takes full responsibility for the content and wording of the thesis.

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List of Abbreviations

BF	Bayes' Factor
BIC	Bayes' Information Criterion
CV	Coefficient of Variation
ECG	Electrocardiogram
EDA	Electrodermal Activity
EV	Expected Value
fMRI	functional Magnetic Resonance Imaging
HF-HRV	High-Frequency Heart Rate Variability
HRV	Heart Rate Variability
ITI	Intertrial Interval
NA	Negative Affect
PA	Positive Affect
PCC	Posterior Cingulate Cortex
RMSSD	Root Mean Square of Successive Differences
SCRs	Skin Conductance Responses
SMH	Somatic Marker Hypothesis
VA	Valence
vmPFC	Ventromedial Prefrontal Cortex
WTP	Willingness-to-pay
FWE	Family-wise error
GLM	General Linear Model
SFG	Superior Frontal Gyrus
ISPA	Intersubject Pattern Analysis

1. Introduction

> "*We used to believe that we were thinking beings who just happen to feel. We now know that we are feeling beings who think.*"
> — Antonio Damasio

Decision-making has long been the subject of intense scrutiny across various disciplines, ranging from psychology and neuroscience to economics and computer science, with traditional models often emphasizing rationality and logical reasoning as the primary drivers of choice. However, a wave of research has increasingly recognized the profound influence of emotions in shaping our decisions and challenging the notion of a purely cognitive decision-making process (Volz & Hertwig, 2016). Future-oriented cognition is inherent to decision-making, as we need to make choices that will influence our future experiences. Thus, the aim of the current thesis was to study the role of future-oriented affect in decision-making.

Info box one provides a distinction between affect and emotions. In the thesis, the term *emotion* will be used when referring to affective states of a short duration and particular quality (e.g., sadness, fear, etc.). In contrast, *affect* is used as a broader term to capture affective states along a valence and arousal continuum. Furthermore, when citing literature, terms from that literature are employed.

INFO BOX 1: Differentiating affect and emotions

The differentiation of affect and emotion has not always been clear and the confusion between the two has led to some scientific errors. In her book "How Emotions are Made: The Secret Life of the Brain" Dr. Lisa Feldman Barrett describes **affect** as a "basic sense of feeling which ranges from unpleasant to pleasant (*valence*) and from idle to activated (*arousal*)". Importantly, affect is something we experience at all times because we experience interoception at all times. **Emotions** on the other hand are a more complex and are not occurring continuously. The dictionary of the american psychological association defines emotion as "a complex reaction pattern, involving experiential, behavioral, and physiological elements, by which an individual attempts to deal with a personally significant matter or event. The specific quality of the emotion (e.g., fear, shame) is determined by the specific significance of the event."

There are two types of future-oriented affect: 1) anticipatory affect describes affective states that we feel in the present in response to an upcoming decision or future event, such as worry or hope, and 2) anticipated affect are the emotions we predict we will feel in response to a decision outcome or future event, such as regret or joy. A key function of emotions is to put people into a state of readiness to approach or avoid events (Van Boven & Ashworth, 2007). Future-oriented emotions are especially important for this function, as they provide a basis for valuing future outcomes and events. Using a wide range of methodologies, including computational modeling, psychophysiology, and brain imaging, our results show that future-oriented affect systematically influences our decision processes. Through three experimental studies, we also explore the interaction between affect and attention, which can bi-directionally impact each other and influence decision-making. The first two studies investigate the affect gap, a robust finding in the literature that people systematically change their decision behavior under risk when prospects elicit high compared to low anticipatory affect (Pachur et al., 2014). In the third study, we launched an investigation into anticipated affect, specifically, we studied the neural correlates of attentional deployment in affective forecasting with bivalent complex gains and losses. To break that down, attentional deployment is an emotion regulation strategy in which people direct attention towards or away from certain aspects of a stimulus (Mauss et al., 2007). We implemented it as a voluntary regulatory goal by instructing participants to focus on either the positive or negative part of a bivalent outcome (i.e., an outcome that produces mixed emotions), while engaging in affective forecasting, the process by which we try to anticipate our emotions in response to a decision outcome or future event.

The following sections of the introduction will detail relevant concepts and highlight the literature that inspired the current work. The first section will delineate and define anticipatory and anticipated affect. This is followed by a discussion of how attention and affect interact, as well as their influence on decision-making. The third section will describe the

literature on the role of affect in decision-making under risk. Subsequently, research on affective forecasting, its neural correlates, and effects on decision behavior is discussed. Finally, the introduction will wrap up with a discussion on the aims and research questions of this thesis and how the three studies inform them.

1.1 Future-oriented affect: anticipatory and anticipated emotions

Individuals spend a considerable amount of time thinking about the future. A detailed investigation into future thought suggests that we think about the future roughly every 16 minutes and spend twice the amount of time thinking about the future than we do thinking about the past (D'Argembeau et al., 2011). Future-oriented cognition, or our ability to mentally time travel, occupies a prevalent space in our mental lives because it serves a number of important functions, including decision-making, action planning, and emotion regulation (Barsics et al., 2016; D'Argembeau et al., 2011). While not all future-oriented thought is affective in nature, D'Argembeau and colleagues' diary study (2011) suggests that a majority of future thoughts are affective (~60% of future thoughts).

The literature differentiates two types of future-oriented emotions: anticipatory emotions and anticipated emotions. Anticipatory emotions are ones that we experience in the present in response to a potential decision outcome or future event. Anticipated emotions are ones that we anticipate we will feel when a decision outcome or future event comes to pass. Let's take the example of a dinner with friends: we may anticipate that we will feel joy as a consequence of spending time with close ones, at the same time, we may, in the present, worry about not being able to find parking close to the restaurant. Barsics and colleagues (2016) launched a detailed investigation into the frequency, function, and characteristics of emotional future thoughts, differentiating between anticipatory and anticipated emotions. Their investigation highlights the importance of future-oriented affect for goal-directed behavior. In fact, 60% of emotional future thoughts were related to planning, decision-making, and intention

formation, with the other 40% serving the function of emotion regulation. Importantly, their study and other work emphasize that anticipatory and anticipated affect are distinct concepts that are driven by different mechanisms and can independently motivate goal-directed behavior (Baumgartner et al., 2008; Schlösser et al., 2013; Xu & Guo, 2019).

1.1.1. What do anticipatory and anticipated affect have in common?

Both anticipated and anticipatory affect are useful to predict behavior (Xu & Guo, 2018; Schlösser et al., 2011). For both anticipatory and anticipated affect, positively valenced thoughts tend to take the form of visual imagery, whereas negatively valenced thoughts are dominated by inner dialogue (Barsics et al., 2015). Both anticipatory and anticipated emotions are significantly related to mood states preceding and following the occurrence of an emotional thought. Finally, negative affect seems to lead to stronger behavioral intentions than positive affect for both anticipatory and anticipated affect (Baumgartner et al., 2008).

1.1.2. How do anticipatory and anticipated affect differ*?*

The range of anticipatory emotions is smaller than that of anticipated emotions, as they are limited to emotions that are related to the prospects of future events, while anticipated emotions can be any emotion that one anticipates feeling (Baumgartner et al., 2008). It has also been suggested that anticipatory emotions better predict behavioral expectations (i.e., the subjective probability that a behavior will be performed; Carrera et al., 2012). Anticipated emotions, on the other hand, better predict behavioral intention (i.e., the amount of effort individuals are willing to invest to attain a goal; Barsics et al., 2015; Baumgartner et al., 2008). Finally, anticipated emotions tend to be experienced as more intense than anticipatory emotions (Clayton McClure et al., 2024; Ernst et al., 2018).

1.1.3. Conclusion

Future-oriented affect serves a multitude of functions, including goal-directed behavior, decision-making, action planning, motivation, and emotion regulation. They have been

leveraged in intervention and shown to have an effect on behavioral intention and expectation, as well as actual behavior. For example, future-oriented emotions are thought to mediate the positive effect of episodic future thinking on the reduction of delay discounting rates (Ballance et al., 2022; Wang et al., 2022) and have been shown to positively contribute to self-control behaviors (Kruschwitz et al., 2024). In sum, future-oriented affect can serve as a basis for valuing decision outcomes or future events and thus helps place us into approach and avoidance states.

1.2. Affect and attention: bi-directional influences

Our capacity to take in sensory information is limited. Attention is the process by which we select and maintain information for further processing. Affect and attention are linked as they both deal with information-processing priorities and impact on each other in a bi-directional fashion. Attention can be exogenous, or bottom-up, whereby salient stimuli grab attention automatically. From this perspective, affective stimuli are highly salient and thus attract attention (LeDoux, 1996; Lundqvist & and Ohman, 2005; Öhman, 2002). It is suggested that the pre-attentive detection of affect has a motivational influence by rapidly signaling the presence or absence of a threat and thus cueing the relevant cognitive strategies to elicit the perceived needed response (LeBlanc et al., 2015). However, attention can also be endogenous, top-up, or goal-directed. Here, emotion can also impact attention in a top-down fashion. For example, anxious individuals are primed to attend to and appraise information as negative (Clark, 2001). On the other hand, attention has also been demonstrated to impact on emotion. Stimuli that are attended to tend to be perceived as more vivid and distinct; consequently, this intensifies the emotion towards this stimulus (Mrkva et al., 2020).

1.2.1. Affect, attention, and decision-making

The consequences of attention and affect on decision-making are not always easily distinguished. Specifically, it is suggested that attention can affect decision-making by

increasing emotion towards choice outcomes (Mrkva et al., 2020). For example, in the affect gap literature, computational modeling and process-tracing methods (Pachur et al., 2014, 2018) have highlighted that when choice outcomes elicit high anticipatory affect, individuals pay less attention to probability information, prioritizing outcome information. By virtue of affect's attention-capturing effect (Lundqvist & Ohman, 2005; Ngai & Jin, 2025; Öhman, 2002), it is thus assumed that affect and attention interact to impact subsequent cognitive processes. This, in turn, influences the information that is encoded and retrieved from memory and the decisions made.

1.3. Affect and decision-making under risk

Early decision-making under risk research originated from economic ideas of rationality, which did not include emotions as a possible driver of choice behavior. For example, Expected Utility Theory (Von Neumann & Morgenstern, 1947) suggests that decisions are made by weighting the utility of each possible outcome with its probability and choosing the option with the highest expected utility. Such models describe compensatory decision-making strategies, which assume that each piece of information is weighed to come to an optimal choice. These models are quite effective at describing decision behavior under relatively affect-poor conditions, such as when choosing between moderate monetary gambles. However, when choices involve prospects that elicit comparatively more anticipatory affect, these models no longer accurately describe decision behavior (Pachur & Galesic, 2013; Pachur et al., 2014).

The affect gap details this phenomenon, and several robust findings have been highlighted. For one, people are more likely to use a non-compensatory decision strategy in affect-rich choices (i.e., a decision strategy which does not consider all pieces of information equally) (Pachur et al., 2014; Pachur & Galesic, 2013; Popovic et al., 2019). This manifests as probability neglect (Sunstein, 2002), i.e., people tend to pay less attention to probability

information. Furthermore, people tend to be more risk averse when deciding between affect-rich prospects and are less likely to maximize expected value (expected value is the weighting of an outcome with its probability, e.g., the expected value (EV) of a gamble that has a 30% chance of resulting in a loss of 20€ has an expected value of: 20x0.3= 6) (Frank & Pachur, in press). This affect gap is a robust phenomenon and has been shown to persist when making decisions from experience (Lejarraga et al., 2016), across different age groups (Frank & Pachur, in press), and when deciding for other people (Popovic et al., 2019).

The exact mechanisms by which affect impacts on decision-making are still debated. Some theories center around the fact that emotion serves as information and can substitute for numerical information (Wang et al., 2022). The risk-as-feelings hypothesis, for instance, assumes that risk is assessed on two levels: a cognitive evaluation of risk and the emotional reaction to it (Loewenstein et al., 2001). Authors argue that in many instances, people will rely on the emotional reaction to risk, which can explain why people deviate from expected value maximization, especially when affect is highly salient. A hypothesis that centers on this idea biologically is the somatic marker hypothesis (SMH) (Bechara & Damasio, 2005). The SMH posits that visceral changes (e.g., heart rate, sweating) serve as somatic markers which represent emotion-related signals providing a signal to the organism about the perceived aversiveness or attractiveness of an outcome and thus bias choice.

Other perspectives have emphasized the role of affect in shifting cognitive processes. For instance, some authors propose that affect impacts on decision-making by reducing the availability of processing resources (Channon & Baker, 1994; Eysenck, 1998; Kensinger & Corkin, 2003). More recently, Plass and Kalyuga (2019) outlined four ways in which emotion impacts on cognitive load: 1) as a source of extraneous cognitive load (e.g., extra processing by thinking about one's emotional state or processing information that is not task relevant), 2) emotional stress reduces the amount of working memory that is available, 3) emotions impacts

on memory processes, and 4) emotion as intrinsic cognitive load (e.g., when decisions require emotion regulation). Trémolière and colleagues (2016) launched a detailed investigation on the interaction of emotion and cognitive load on analytical thinking and found that across a series of tasks, emotion disrupted task processes due to the allocation of cognitive resources toward emotion processing at the expense of other activities.

The current thesis investigates two hypotheses, building on this literature, across two studies. The first study investigated psychophysiological markers of affect during decision-making in the affect gap. This allows us to study whether differences in affective arousal are driving changes in decision behavior in affect-rich compared to affect-poor choice, lending evidence to affect-as-information frameworks. The second study investigated how taxing cognitive resources would impact the affect gap. This allows us to investigate whether higher affective arousal in affect-rich choices is driven by a reduction in cognitive resources.

From the body of work examined above, it is interesting to note that, in part due to the anticipatory affect associated with different outcomes, decision-making is not domain-general. Many models of decision-making have, by and large, been based on simple monetary gains and losses, and the validity of these models in other decision domains, such as medical decision-making, is not always clear. This is especially true in medical decisions, since medical decisions are rarely devoid of affect and occur in a particular social setting where one relies on doctors to inform and guide our choices. As such, it is crucial to get a deeper understanding of how future-oriented emotions impact decision-making when dealing with complex decisions. For this reason, we next turned to investigating the relationship between endogenous attention and anticipated affect with complex medical gains and losses.

1.4. Anticipating the future: Affective forecasting and its neural signatures

Affective forecasting involves the anticipation of our emotions in response to future outcomes and events. As such, it involves anticipated emotions. As previously highlighted,

anticipated emotions are experienced as more intense than anticipatory ones and have better predictive validity for behavioral intention (Baumgartner et al., 2008; Gillman et al., 2022; Wang et al., 2022). Nonetheless, research on affective forecasting has uncovered some systematic biases in our forecasts, demonstrating that we are not the most accurate forecasters. This is especially true for outcomes that involve bivalent (mixed) outcomes (Gilbert & Wilson, 2009). Affective forecasting, as a future-oriented cognition, is an inherently cognitive process because it involves mechanisms such as prediction and simulation. For this reason, the third experiment investigated the neural correlates of attentional deployment and affective forecasting in the context of bivalent medical outcomes. The next sections will highlight the behavioral literature on affective forecasting in medical decision-making and the neural correlates of affect and affective forecasting.

1.4.1. Affective forecasting in medical contexts

Research on affective forecasting in medical contexts has highlighted that patients do indeed use their affective forecasts to make decisions (Hoerger et al., 2016; Perry et al., 2020) and that these forecasts are often biased. For instance, several forecasting biases have been uncovered, including focalism, a bias that occurs because people are too narrowly focused on what is lost (or changed) without considering other factors. Info-box two provides an overview of further common forecasting biases that may impact decisions. A recent meta-analysis (Bosch et al., 2021) of affective forecasting in medical contexts has concluded that people tend to overestimate their quality of life when they are expecting health improvements and underestimate their quality of life when they are expecting health deterioration. Importantly, this suggests patients may selectively attend to the positive or negative anticipated emotions depending on their expectations. Crucially, this highlights the interaction between attention and affect. This makes it essential to understand the processes that underlie affective forecasting to

better understand how we can build decision aids and interventions that will support people in making their medical decisions.

	INFO BOX 2: Affective forecasting biases
Focalism	Being too focused on one factor (e.g., a loss or a change) at the expense of others
Impact bias	Overestimating the intensity and duration of future emotions
Immune neglect	Not considering the psychological coping mechanisms that will help us cope with negative emotions

1.4.2. Neural correlates of affective forecasting

Reflective of early models of decision-making which considered emotions to be an "irrational" and biasing influence on judgment and decision-making, early neurocognitive models also highlighted dual systems in the brain by which newer frontal brain regions were responsible for reasoning and cognitive processes and the older structures such as the limbic system were responsible for emotional processing (LeBlanc et al., 2015). It was assumed that cognitive and emotional functions were primarily processed separately, and emotional systems interfere with frontal cognitive processing (e.g., McClure et al., 2004, 2007; Turner et al., 2019). However, a wealth of literature has challenged this notion and has shown that brain networks do not differ as much as suggested. Structures from the limbic system are also important to cognitive processes, and the frontal regions also play an active role in emotional processing (Damasio, 1994; LeBlanc et al., 2015). Affective forecasting is a good example of this, as future prospection about emotional outcomes requires both cognitive and emotional processing and highlights the interaction of these different neural signals. The anticipation of future emotional events, for instance, includes a variety of brain regions, including emotion processing regions (amygdala, insula, and ventromedial prefrontal cortex), sensory processing

regions (lateral temporal and parietal cortices), and lateral prefrontal regions commonly associated with top-down cognitive control processes (D'Argembeau et al., 2008; Sharot et al., 2007).

Research on affective forecasting with univalent stimuli (exclusively negative or positively valenced stimuli) has highlighted that affective forecasting involves the ventromedial prefrontal cortex (vmPFC) (Bray et al., 2010; D'Argembeau et al., 2008; Knutson & Greer, 2008; Sharot et al., 2007), ventral striatum (nucleus accumbens) (Greenberg et al., 2015; Knutson & Greer, 2008), insular cortices (Greenberg et al., 2015; Knutson & Greer, 2008), amygdala (Sharot et al., 2007), and the posterior cingulate cortex (PCC) (D'Argembeau et al., 2008; Sharot et al., 2007). Kruschwitz and colleagues (2018) were the first to investigate how neural correlates are modulated when anticipating bivalent stimuli. They showed that when anticipating a bivalent outcome, neural systems for reward and punishment co-activated. Importantly, in a second study in which they instructed participants to attend to either the positive part of the outcome (monetary gain) or the negative part of the outcome (aversive sound), i.e., attentional deployment, neural systems shifted towards reward processing and punishment processing, respectively. Additionally, the anticipation of the positive part of the outcome recruited vmPFC and PCC, regions implicated with coding subjective reward value and self-referential processing (Kruschwitz et al., 2018). We build on this work by investigating the neural correlates of attentional deployment in affective forecasting with complex medical gains and losses.

1.5. Aims and research overview

Building on the literature described above, the current thesis includes three experiments that investigate future-oriented affect and decision-making. In the first two studies, we expand on the literature on the affect gap. The first experiment launched a more detailed investigation into the affective dynamics of the affect gap. To date, the results described in the affect gap

have been attributed to anticipatory affect through post-hoc affect ratings (e.g., Pachur & Galesic, 2013; Pachur et al., 2014; Lejarraga et al., 2016; Popovic et al., 2019). We build on this work by measuring psychophysiological markers of affective arousal (i.e., electrodermal activity) and emotion regulation (i.e., vagally mediated HRV indices) during the decision-making process. Following up on this study, we launched a behavioral experiment in which we introduced a time pressure manipulation to a commonly used paradigm to investigate the affect gap, which includes a risky choice task in which participants have to make binary choices between affect-rich and affect-poor lotteries. The goal of this second experiment was to investigate whether anticipatory affect exerts its effect on decision behavior under risk by limiting the amount of cognitive resources available.

In the third study, we shift focus to anticipated emotions in an affectively complex medical decision context. We follow up on previous investigations of the neural correlates underlying affective forecasting by investigating its neural correlates in the context of complex gains and losses and how activity is modulated by voluntary emotion regulation through attentional deployment (i.e., intentionally focusing on a given aspect of an outcome/situation).

From a methodological point of view, this thesis investigates future-oriented affect's implications in decision-making using a multitude of approaches, allowing us to inform our understanding of its processes from a behavioral, cognitive, and biological perspective. In the first two studies, we used behavioral and computational modeling approaches to understand changes in decision behavior and decision strategies used when anticipatory affect is high compared to low. In the first study, we additionally use psychophysiological methods to track objective measures of affect, allowing us to investigate to what extent decisions under risk with varying affective investment are informed by embodied affective states. Finally, we use functional magnetic resonance imaging (fMRI) to investigate anticipated affect. The aims and methods used across studies are summarized in Table 1.

Table 1.

Aims and methods of each experimental study in the thesis

Study	Aims	Methods
Study 1: "Investigating the affect in the affect gap"	The aim is to understand whether the affect gap is due to differences in affective arousal when choosing between affect-rich and affect-poor prospects	- Psychohphysiology: electrodermal activity - Computational modeling: maximum likelihood estimation of decision strategies - Behavioral: risky choice task
Study 2: "Does time pressure alter the affect gap in risky choice?"	To investigate whether the affect gap may be explained by differences in cognitive resource allocation in affect-rich choice	- Behavioral: risky choice tasks - Computational modeling: maximum likelihood estimation of decision strategies
Study 3: "An fMRI investigation of attentional deployment in affective forecasting with complex gains and losses"	To study how attentional deployment modulates neural correlates of anticipated emotions in complex medical decisions	- Brain imaging: fMRI

1.6. References

Ballance, B. C., Tuen, Y. J., Petrucci, A. S., Orwig, W., Safi, O. K., Madan, C. R., & Palombo, D. J. (2022). Imagining emotional events benefits future-oriented decisions. *Quarterly Journal of Experimental Psychology*, *75*(12), 2332-2348. https://doi.org/10.1177/17470218221086637

Barsics, C., Van Der Linden, M., & D'Argembeau, A. (2016). Frequency, characteristics, and perceived functions of emotional future thinking in daily life. *Quarterly Journal of Experimental Psychology*, *69*(2), 217–233. https://doi.org/10.1080/17470218.2015.1051560

Baumgartner, H., Pieters, R., & Bagozzi, R. P. (2008). Future-oriented emotions: Conceptualization and behavioral effects. *European Journal of Social Psychology*, *38*(4), 685–696. https://doi.org/10.1002/ejsp.467

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010

Bosch, G. J. V. D., Roos, R. A. N., Otten, R., Bockting, C., & Smulders, Y. M. (2021). Are patients accurate forecasters of their emotional response to medical conditions? A scoping review on affective forecasting. *BMJ Open*, *11*(12), e053370. https://doi.org/10.1136/bmjopen-2021-053370

Bray, S., Shimojo, S., & O'Doherty, J. P. (2010). Human medial orbitofrontal cortex is recruited during experience of imagined and real rewards. *Journal of Neurophysiology*, *103*(5), 2506–2512. https://doi.org/10.1152/jn.01030.2009

Channon, S., & Baker, J. (1994). Reasoning strategies in depression: Effects of depressed mood on a syllogism task. *Personality and Individual Differences*, *17*(5), 707–711. https://doi.org/10.1016/0191-8869(94)90148-1

Clark, D. M. (2001). A cognitive perspective on social phobia. In W. R. Crozier & L. E. Alden (Eds.), International handbook of social anxiety: Concepts, research and interventions relating to the self and shyness (pp. 405–430). John Wiley & Sons Ltd.

Clayton McClure, J. H., Riggs, K. J., Dewhurst, S. A., & Anderson, R. J. (2024). Differentiating anticipated and anticipatory emotions and their sensitivity to depressive symptoms. *Emotion*. https://doi.org/10.1037/emo0001371

Damasio, A. R. (1994). *Descartes' Error: Emotion, Reason, and the Human Brain*. New York: G.P. Putnam.

D'Argembeau, A., Renaud, O., & Van Der Linden, M. (2011). Frequency, characteristics and functions of future-oriented thoughts in daily life. *Applied Cognitive Psychology*, *25*(1), 96–103. https://doi.org/10.1002/acp.1647

D'Argembeau, A., Xue, G., Lu, Z.-L., Van Der Linden, M., & Bechara, A. (2008). Neural correlates of envisioning emotional events in the near and far future. *NeuroImage*, *40*(1), 398–407. https://doi.org/10.1016/j.neuroimage.2007.11.025

Eysenck, N. D. M. W. (1998). Working memory capacity in high trait-anxious and repressor groups. *Cognition and Emotion*, *12*(5), 697–713. https://doi.org/10.1080/026999398379501

Frank, C., & Pachur, T. (2025). The affect gap in risky choice is similar for younger and older adults. *Psychology and Aging*. https://doi.org/10.1037/pag0000889

Gilbert, D. T., & Wilson, T. D. (2009). Why the brain talks to itself: Sources of error in emotional prediction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1521), 1335–1341. https://doi.org/10.1098/rstb.2008.0305

Gillman, A. S., Iles, I. A., Klein, W. M. P., Biesecker, B. B., Lewis, K. L., Biesecker, L. G., & Ferrer, R. A. (2022). The role of future-oriented affect in engagement with genomic

testing results. *Journal of Behavioral Medicine*, *45*(1), 103–114. https://doi.org/10.1007/s10865-021-00253-7

Hoerger, M., Scherer, L. D., & Fagerlin, A. (2016). Affective forecasting and medication decision making in breast-cancer prevention. *Health Psychology*, *35*(6), 594–603. https://doi.org/10.1037/hea0000324

Kensinger, E. A., & Corkin, S. (2003). Effect of negative emotional content on working memory and long-term memory. *Emotion*, *3*(4), 378–393. https://doi.org/10.1037/1528-3542.3.4.378

Knutson, B., & Greer, S. M. (2008). Anticipatory affect: Neural correlates and consequences for choice. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1511), 3771–3786. https://doi.org/10.1098/rstb.2008.0155

Kruschwitz, J. D., Goschke, T., Ahmed Mohamed Ali, E., Kraehe, A.-C., Korb, F. M., & Walter, H. (2024). The role of anticipated emotions in self-control: Linking self-control and the anticipatory ability to engage emotions associated with upcoming events. *Frontiers in Psychology*, *14*, 1152155. https://doi.org/10.3389/fpsyg.2023.1152155

Kruschwitz, J. D., Waller, L., List, D., Wisniewski, D., Ludwig, V. U., Korb, F., Wolfensteller, U., Goschke, T., & Walter, H. (2018). Anticipating the good and the bad: A study on the neural correlates of bivalent emotion anticipation and their malleability via attentional deployment. *NeuroImage*, *183*, 553–564. https://doi.org/10.1016/j.neuroimage.2018.08.048

LeBlanc, V. R., McConnell, M. M., & Monteiro, S. D. (2015). Predictable chaos: A review of the effects of emotions on attention, memory and decision making. *Advances in Health Sciences Education*, *20*(1), 265–282. https://doi.org/10.1007/s10459-014-9516-6

LeDoux, J. E. (1996). *The Emotional Brain: The Mysterious Underpinnings of Emotional Life*. Simon and Schuster.

Lejarraga, T., Pachur, T., Frey, R., & Hertwig, R. (2016). Decisions from experience: From monetary to medical gambles. *Journal of Behavioral Decision Making*, *29*(1), 67–77. https://doi.org/10.1002/bdm.1877

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Lundqvist, D., & and Ohman, A. (2005). Emotion regulates attention: The relation between facial configurations, facial emotion, and visual attention. *Visual Cognition*, *12*(1), 51–84. https://doi.org/10.1080/13506280444000085

Mauss, I. B., Bunge, S. A., & Gross, J. J. (2007). Automatic emotion regulation. *Social and Personality Psychology Compass*, *1*(1), 146–167. https://doi.org/10.1111/j.1751-9004.2007.00005.x

McClure, S. M., Ericson, K. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2007). Time discounting for primary rewards. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *27*(21), 5796–5804. https://doi.org/10.1523/JNEUROSCI.4246-06.2007

McClure, S. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science*, *306*(5695), 503–507. https://doi.org/10.1126/science.1100907

Mrkva, K., Ramos, J., & Van Boven, L. (2020). Attention influences emotion, judgment, and decision making to explain mental simulation. *Psychology of Consciousness: Theory, Research, and Practice*, *7*(4), 404–422. https://doi.org/10.1037/cns0000221

Ngai, H. H. T., & Jin, J. (2025). Emotion-guided attention impacts deliberate multi-evidence emotion-related perceptual decision-making. *Psychophysiology*, *62*(5), e70059. https://doi.org/10.1111/psyp.70059

Öhman, A. (2002). Automaticity and the amygdala: Nonconscious responses to emotional faces. *Current Directions in Psychological Science*, *11*(2), 62–66. https://doi.org/10.1111/1467-8721.00169

Pachur, T., & Galesic, M. (2013). Strategy selection in risky choice: The Impact of numeracy, affect, and cross-cultural differences. *Journal of Behavioral Decision Making*, *26*(3), 260–271. https://doi.org/10.1002/bdm.1757

Pachur, T., Hertwig, R., & Wolkewitz, R. (2014). The affect gap in risky choice: Affect-rich outcomes attenuate attention to probability information. *Decision*, *1*(1), 64–78. https://doi.org/10.1037/dec0000006

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., & Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, *147*(2), 147–169. https://doi.org/10.1037/xge0000406

Perry, L. M., Hoerger, M., Korotkin, B. D., & Duberstein, P. R. (2020). Perceived importance of affective forecasting in cancer treatment decision making. *Journal of Psychosocial Oncology*, *38*(6), 687–701. https://doi.org/10.1080/07347332.2020.1768198

Plass, J. L., & Kalyuga, S. (2019). Four ways of considering emotion in cognitive load theory. *Educational Psychology Review*, *31*(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Popovic, N. F., Pachur, T., & Gaissmaier, W. (2019). The gap between medical and monetary choices under risk persists in decisions for others. *Journal of Behavioral Decision Making*, *32*(4), 388–402. https://doi.org/10.1002/bdm.2121

Schlösser, T., Dunning, D., & Fetchenhauer, D. (2013). What a feeling: The role of immediate and anticipated emotions in risky decisions. *Journal of Behavioral Decision Making*, *26*(1), 13–30. https://doi.org/10.1002/bdm.757

Sharot, T., Riccardi, A. M., Raio, C. M., & Phelps, E. A. (2007). Neural mechanisms mediating optimism bias. *Nature*, *450*(7166), 102–105. https://doi.org/10.1038/nature06280

Sunstein, C. R. (2002). Probability Neglect: Emotions, Worst Cases, and Law Essay. *Yale Law Journal*, *112*(1), 61–108.

Trémolière, B., Gagnon, M.-È., & Blanchette, I. (2016). Cognitive load mediates the effect of emotion on analytical thinking. *Experimental Psychology*, *63*(6), 343–350. https://doi.org/10.1027/1618-3169/a000333

Turner, B. M., Rodriguez, C. A., Liu, Q., Molloy, M. F., Hoogendijk, M., & McClure, S. M. (2019). On the neural and mechanistic bases of self-control. *Cerebral Cortex (New York, N.Y.: 1991)*, *29*(2), 732–750. https://doi.org/10.1093/cercor/bhx355

Van Boven, L., & Ashworth, L. (2007). Looking forward, looking back: Anticipation is more evocative than retrospection. *Journal of Experimental Psychology: General*, *136*(2), 289–300. https://doi.org/10.1037/0096-3445.136.2.289

Volz, K. G., & Hertwig, R. (2016). Emotions and decisions: Beyond conceptual vagueness and the rationality muddle. *Perspectives on Psychological Science*, *11*(1), 101–116. https://doi.org/10.1177/1745691615619608

Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior, 2nd rev. Ed* (pp. xviii, 641). Princeton University Press.

Wang, X. T. (XiaoTian), Wang, P., Lu, J., Zhou, J., Li, G., & Garelik, S. (2022). Episodic future thinking and anticipatory emotions: Effects on delay discounting and

preventive behaviors during COVID-19. *Applied Psychology: Health and Well-Being*, *14*(3), 842–861. https://doi.org/10.1111/aphw.12350

Xu, Z., & Guo, H. (2019). Advantages of anticipated emotions over anticipatory emotions and cognitions in health decisions: A meta-analysis. *Health Communication*, *34*(7), 774–781. https://doi.org/10.1080/10410236.2018.1434738

2. Study 1: Investigating the Affect in the Affect Gap

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Abstract

The “affect gap” refers to the systematic differences in decision behavior when individuals evaluate affect-rich (e.g., medication side effects) vs. affect-poor (e.g., monetary losses) outcomes under risk. While prior work has attributed this to affective engagement, little research has examined the affective responses during the decision process itself. We addressed this gap by measuring physiological markers of anticipatory affect and emotion regulation, specifically skin conductance responses (SCRs) and heart rate variability (HRV), respectively, while participants made risky decisions involving either affect-rich or affect-poor outcomes. We further investigated how decision perspective (personal vs. interpersonal) modulated the affect gap, as a test of its sensitivity to different levels of affective engagement. Finally, we investigated whether anticipatory affect induced subsequent carry-over effects on mood. SCR amplitudes were significantly higher during affect-rich choices, compared to affect-poor ones, suggesting heightened anticipatory arousal in affect-rich decisions. However, HRV measures were unrelated to decision-making behavior, suggesting that emotion regulation, as operationalized in this study, did not modify the affect gap. Finally, there was no carry-over effect of anticipatory arousal on subsequent mood. These findings offer the first direct physiological evidence of anticipatory affect in the affect gap, suggesting that emotional arousal underlies the shift in decision behavior under affect-rich risk.

Keywords: affect gap, anticipatory affect, electrodermal activity, decisions under risk

2.1. Introduction

Decisions under risk involve the evaluation of uncertain outcomes, often balancing potential gains and losses against their probability of occurring. Traditional economic theories describe these decisions using compensatory decision-making strategies (Bernoulli, 1954; Von Neumann & Morgenstern, 1947). Compensatory strategies generally weigh all pieces of information to come to an optimal decision. These models assume a rational and emotion-free computation of risk. However, when outcomes evoke anticipatory affect, such as when evaluating medication side effects, decision behavior often deviates from compensatory decision strategies, revealing what has been dubbed the "affect gap" (Pachur et al., 2014).

The affect gap captures a robust phenomenon: when choosing between affect-rich outcomes (e.g., harmful side effects) versus affect-poor ones (e.g., monetary losses), people tend to rely on simpler, non-compensatory decision strategies, display greater risk aversion, and reduced expected value maximization (Frank & Pachur, in press; Lejarraga et al., 2016; Suter et al., 2016). While this pattern is well documented, its affective underpinning remains insufficiently understood. Previous studies have inferred affective engagement from outcome ratings, not from real-time affective states during decision-making. As a result, it remains unclear whether the affect gap reflects anticipatory affect during choice or a purely cognitive evaluation of affective information. For instance, anticipating positive or negative future events (such as a decision outcome) is not necessarily associated with an emotional response in the present (Baumgartner et al., 2008). This may be related to the fact that anticipation can occur at different levels of abstraction, from highly detailed visualization of an outcome (episodic future thought) to semantic information and integrating conceptual autobiographical knowledge (Barsics et al., 2016).

The current study fills this gap by measuring psychophysiological correlates of affect during decision-making in the affect gap. Electrodermal activity (EDA), and in particular skin

conductance response (SCR) amplitudes, provides an index of affective arousal and has been linked to emotional reactivity in decision-making contexts (Boucsein, 2012; Figner & Murphy, 2011; Molins et al., 2021). For instance, previous research has shown that EDA responses are larger for losses than wins (Wu et al., 2016) and that EDA increases with increasing bet sizes and can be used to index objective risk (Holper et al., 2014; Studer & Clark, 2011; Wu et al., 2016). Based on this literature, we hypothesized that anticipatory SCR amplitudes should be larger in response to affect-rich compared to affect-poor outcomes.

To the extent that anticipatory affect impacts decision behavior, it follows that better emotion regulators should show fewer fluctuations in decision behavior across affect-rich and affect-poor choices. To investigate this, we derived participants' resting and task-related heart rate variability (HRV) as a measure of emotion regulation and inhibitory capacity (Appelhans & Luecken, 2006; Thayer & Lane, 2000, 2009; Balzarotti et al., 2017). Previous findings show that individuals with higher resting HRV show more context-appropriate emotional reactions, compared to individuals with lower HRV (Ruiz-Padial et al., 2003). Furthermore, longitudinal data suggest that resting HRV, as an index of cardiac vagal modulation, was predictive of emotion regulation and daily affect during the COVID-19 breakout (Makovac et al., 2021). Investigations of HRV in risky choice have shown that higher resting HRV can protect against decision biases. For example, Sütterlin and colleagues (2011) show that individuals with higher resting HRV show reduced susceptibility to framing effects in a risky choice task. Additionally, phasic increases in task-related HRV facilitate emotion regulation (Butler et al., 2006; Lane et al., 2013). Thus, we hypothesized that higher resting HRV and increased task-related HRV during decision-making would result in participants being less susceptible to changing their decision behavior in response to affect-rich prospects.

To get an idea of the sensitivity of the affect gap to different levels of affective engagement, we furthermore modulated decision perspective within-subjects. Participants had

to make decisions with affect-rich and -poor prospects for themselves and for an unfamiliar peer. Emotion theories of interpersonal decision making have highlighted that differences between personal and interpersonal choices can be attributed to the fact that we have weaker emotional responses when prospects do not concern ourselves (Loewenstein et al., 2001). In a between-subjects investigation Popovic and colleagues (2019) showed that the affect gap is maintained when making interpersonal decisions, but they also highlighted that the affective evaluation of choice outcomes was lower for others than for themselves. Thus, we used a within-subjects decision perspective condition to study the affect gap's sensitivity to different levels of affective engagement toward the outcomes. We hypothesized that SCR amplitudes and affect ratings would be lower in interpersonal compared to personal choices.

Finally, prior work has demonstrated that anticipatory affect can have an effect on subsequent mood states (Barsics et al., 2016). As risky choice paradigms often include repeated choices that repeatedly engage anticipatory affect, we wanted to assess whether this would have a downstream effect on subsequent state affect. As such, we included a self-report positive and negative affect scale at baseline and after each of the decision blocks in the risky choice task. We hypothesized that, to the extent that anticipatory affect impacts subsequent state affect, this effect should be stronger for affect-rich choices than affect-poor ones.

In sum, the current investigation seeks to elucidate whether the affect gap is driven by anticipatory affect as indexed by skin conductance response amplitudes. We further investigate whether better emotion regulation capacity, as indexed by HRV, buffers against fluctuations in decision behavior across affect-rich and -poor choices. Finally, we also investigate the sensitivity of the affect gap by including interpersonal choices and study the downstream effects of anticipatory affect on participants' mood states.

2.2. Method

2.2.1. Participants

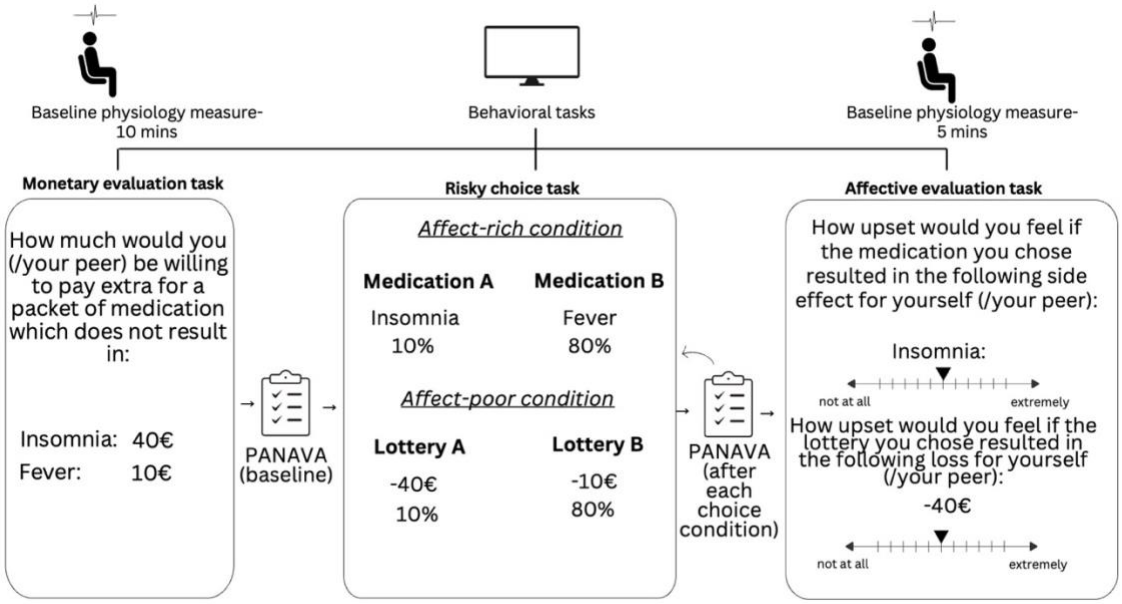
A total of 60 participants were recruited for the study (M_{age}=26.23 [SD=5.72, range:18-43], N_{women}= 34, N_{men}=24, $N_{unspecified}$=2). Recommendations for sample size in psychophysiological research suggest to include 20-40 participants per group in between-subjects investigations (Christopoulos et al., 2019), with within-subjects investigations typically requiring fewer participants. Nonetheless, since we have two within-subjects conditions, we aimed to match what would be considered an adequate sample size for group comparisons. Additionally, from a behavioral perspective, the affect gap has been evidenced in samples of diverse sizes ranging from n = 40 (Pachur et al., 2014) to n = 1047 (Pachur & Galesic, 2013). The sample consists of students from the University of Luxembourg. Participants could complete the study in English, German, or French. 57 participants were included for the data analysis as a technical error prevented two participants from completing the entirety of the study, and another participant provided the same willingness-to-pay (WTP) for every side effect (more details under *monetary evaluation task*). This study is in line with the principles of the Declaration of Helsinki, and ethical approval was granted by the institutional ethics board of the University of Luxembourg (ERP 22-018A AffGap).

2.2.2. Experimental Design

We employed a two (affect condition: rich vs. poor) by two (decision perspective: personal vs. interpersonal) within-subjects design. The current investigation was part of a larger project, which, in addition to the behavioral tasks, comprises an interoceptive task as well as a series of questionnaires, not reported here. These additional measures were collected in an exploratory manner to inform future investigations. Participants' psychophysiological responses were recorded throughout the experiment. The conditions were counterbalanced across participants. Figure 1 depicts the procedure and tasks used in the study.

Figure 1

Procedure and experimental design



2.2.3. Equipment

Electrodermal activity and HR were recorded using Biopac's MP150 recorder, software (AcqKnowledge 5.0.5; Almond, 2017), and amplifiers (ECG100C, GSR100C, RSP100C). Physiological measures were sampled at 1000 samples per second. The risky choice task was coded in PsychoPy 2022.1.4 (Peirce et al., 2019), using Python 3.1.3 and displayed on a DELL monitor and computer with Windows 10 operating system.

2.2.4. Behavioral tasks

Monetary evaluation task. Participants were first presented with the twelve side effects they would encounter during the task (Insomnia, Depression, Dizziness, Speech Disorder, Trembling, Hallucinations, Fever, Fatigue, Memory loss, Diarrhea, Flatulence, Itching) and were asked to rank the side effects by their preceived severity, once from their own perspective and once from the perspective of a peer. We defined "peer" as someone of their own cohort, but that they do not know well. These rankings were meant to help them

perform the monetary evaluation task, in which participants were given the following description:

> "*Imagine that you were suffering from a severe but treatable illness. There are two equally effective medications available to treat this illness. One always results in a side effect, while the other never results in a side effect. For every side effect indicated, please provide the amount of money in euros you would be willing to pay extra for a packet of medication which does not produce the side effect*."

In the interpersonal condition, participants were asked to indicate how much they thought their peer would be willing to pay extra for the packet of medication that does not result in the side effects.

Risky choice task. Next, participants started the choice task. It consisted of two factors (each with two conditions) carried out over four blocks of twenty trials. The two factors were affect condition and decision perspective. In the affect-rich condition, participants had to decide between two medications with a given chance of resulting in a side effect, either for themselves or for a peer. In the affect-poor condition, participants had to decide between two loss lotteries in which there was a given chance to lose an indicated amount of money. Participants made choices for themselves (personal decisions) and for a peer (interpersonal decisions). Importantly, the affect-poor choice problems were structurally equivalent to the affect-rich ones by replacing the side effects with the monetary equivalents (WTP) provided in the monetary evaluation task (see Figure 1 for an example). A trial occurred as follows: Fixation cross (8s), Stimulus presentation (10s), response (no fixed duration). Before starting with the choice task and after each condition (i.e., decision block of 20 trials), participants filled out the 10-point PANAVA scale to assess self-reported affect at baseline and after each condition.

Affective evaluation task. In the affective evaluation task participants were presented with every possible choice outcome from the choice task (i.e., side effects and monetary losses)

and were asked to rate how upset they would feel if they were to experience this outcome on a scale from 1 (not at all upset) to 10 (extremely upset) in the personal condition, and how upset they would feel if their choice resulted in their peer experiencing a given outcome on the same scale in the interpersonal condition.

2.2.5. Procedure

Participants attended a single experimental laboratory session of about two and a half hours. Upon arrival, participants were first asked to read and sign the consent form. Once informed consent was obtained, participants were prepared for the physiological recordings by fixing surface electrodes to their bodies. For the ECG, three electrodes were attached to the torso in Einthoven's Lead-II formation. Two EDA electrodes were attached to the hypothenar eminence of the non-dominant hand. A respiration belt was fastened around participants' chests. When the signal was deemed to be acceptable, participants engaged in a rest period for a baseline recording of physiological measures. For this 10-minute rest period, participants were instructed to sit with their feet on the ground, knees at a 90° angle, with their hands lying palm facing up on their thighs, and keeping their eyes closed. Following this rest period, participants were asked to perform the behavioral tasks described above. After completion of these tasks, there was a second baseline measure of five minutes.

2.2.6. Statistical analysis

All behavioral analyses were carried out in R Studio (2022.07.2 + 576, R Core Team, 2021). For the mixed effects models, we used the lme4 package (Bates et al., 2015). Predictors of the mixed models were tested by leaving them out of the model and comparing the full and reduced models using a likelihood ratio test. If the likelihood ratio test was significant, we concluded that the predictor significantly contributes to the model.

HRV. Heart rate variability (HRV) was computed through Kubios (version 2.1.; Tarvainen et al., 2014), using the last five minutes of the 10-minute rest period at the onset of

the study. We further used the last five-minute segments of each condition of the choice task, as well as the second baseline, to obtain a measure of task-related and recovery HRV. HRV analyses were performed on vagally mediated HRV indices, specifically, the root mean square of successive differences (RMSSD) and the high frequency band in the frequency-domain analysis, as specifically cardiac vagal tone is thought to reflect self-regulation processes and has shown longitudinal predictiveness of emotion regulation (Laborde et al., 2017; Thayer & Lane, 2009; Makovac et al., 2021). Furthermore, a review supports the use of HRV as an objective marker of emotion regulation (Balzarotti et al., 2017).

EDA. 53 participants were included in this analysis, as we had six non-responders (i.e., individuals who showed very low or unmeasurable EDA activity) in our sample. Preprocessing of EDA included visually inspecting the raw data for artefacts; in cases where artefacts were found, that segment was cut. Raw data was then resampled to 62.5Hz, and median smoothing matching the downsampled frequency was used. Lastly, a 1 Hz FIR filter was passed over the data. Skin conductance responses (SCR) were computed in *AcqKnowledge* (version 5.0.5) using the event-related EDA routine. An SCR was deemed to be event-related if it occurred within 10 seconds after stimulus onset and had an amplitude of at least 0.03μS. SCR amplitudes used in the analysis were participants' averaged amplitude across all event-related SCRs in a condition.

Strategy classification. We used the maximum likelihood approach from Pachur and Galesic (2013) to classify participants according to one of three strategies: 1) expected value (EV) strategy, 2) affect heuristic (Finucane et al., 2000), 3) guessing/using another strategy. The strategy that resulted in the best (i.e., lowest) goodness of fit parameter (Equation 1) was assigned to the participant. Choices were modeled separately for each condition.

$$G_{i,j}^2 = -2 \sum_{j=1}^{N} \ln [f_j(y)] \qquad \text{Eq. 1}$$

$F_j(y)$ represents the probability with which a strategy predicts an individual's choice y at lottery j. If a choice matched the prediction of the strategy, then $fj(y)=1 - \varepsilon_{j,k}$; otherwise $f_j(y)= \varepsilon$, where ε represents the application error across all choice problems. For the guessing strategy, we assumed $\varepsilon=0.5$. We calculated the Bayes Factor according to equation 2 as a measure of classification confidence. The BIC was computed according to equation 3.

$$BF = \exp\left(-\frac{1}{2}\Delta BIC\right) \quad \text{Eq. 2}$$

$$\text{BIC} = G^2 + 1*\log(n_{trials}) \quad \text{Eq.3}$$

EV maximization. We investigated whether people are equally likely to choose the option with the better EV across conditions, using a logistic mixed-effects model. We modeled whether participants chose the option with the better EV, using affect condition and decision perspective as fixed effects. We further included a measure of whether the option with the better EV was also the more risky option as a fixed covariate (more details in *risk attitude*). We included random intercepts over participants and choice problems.

Risk attitude. To investigate whether risk-taking differs across conditions, we calculated the coefficient of variation (CV) for each lottery (Pachur et al., 2017; Weber et al., 2004). If participants selected the option with the higher CV, then they picked the riskier gamble. We then used a mixed effects logistic regression with affect condition and decision perspective as fixed effects and random intercepts across subjects. We further included a control variable as a fixed effect term that indicated whether the risky option was also the one with the better EV on a given trial (0-if no, 1- if yes).

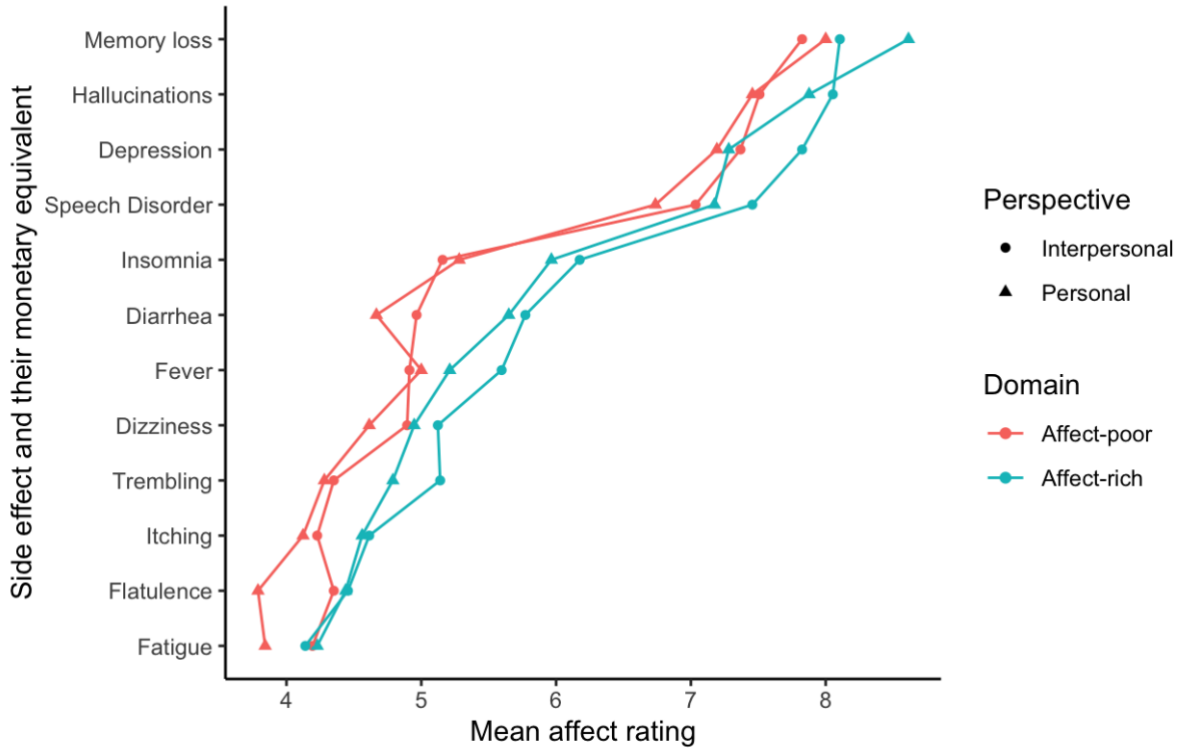
Affect ratings. To check for differences in affect ratings across conditions, we used a linear mixed model with affect rating as the outcome, affect condition, and decision perspective as fixed effects, and random intercepts across subjects and stimuli.

2.3. Results

2.3.1. Affective evaluation task

Figure 2.

Average affect ratings for side effects and their monetary equivalents



There was a significant effect of affect-condition on the affect evaluations ($\chi^2(1) = 43.007$, $p < 0.001$). As can be seen in Figure 2, the affect ratings are consistently higher for the side effects than their monetary equivalents. There was a significant effect of decision perspective ($\chi^2(1) = 4.13$, $p = 0.042$). Contrary to our expectations, the affect ratings were higher for outcomes that affect a peer than for outcomes that affect oneself.

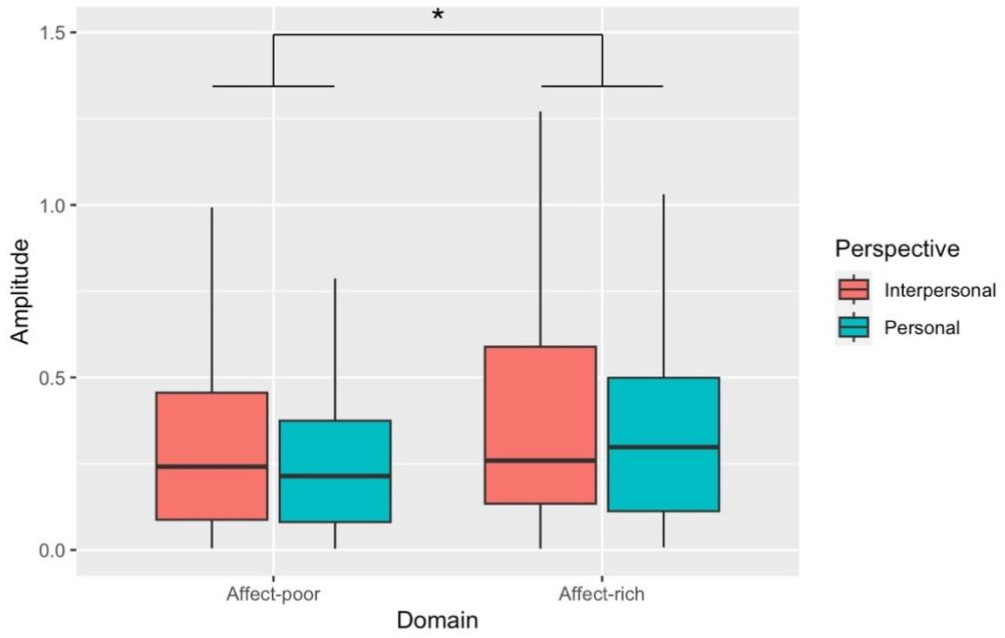
2.3.2. EDA

Amplitude data for skin conductance responses were square-root transformed due to skew (Braithwaite et al., 2013). We tested whether the averaged amplitudes for each condition significantly differed from each other and found a significant difference across affect-conditions ($\chi^2(1) = 4.15$, $p < 0.05$) but not decision perspective ($\chi^2(1) = 0.35$, $p = 0.55$). As

can be seen in Figure 3 and in line with our hypothesis, SCR amplitudes in the affect-rich condition were higher than in the affect-poor condition.

Figure 3.

Skin conductance response amplitudes across conditions



2.3.3. HRV

We investigated whether HRV at rest, as a measure of emotion regulation, would play a role in strategy selection, expecting lower resting HRV to increase the likelihood of using the affect heuristic, but found no effect ($\chi^2(1) = 2.49$, $p = 0.114$). We further investigated whether task-related HRV would help explain strategy selection. Contrary to our expectation that greater phasic increases in HRV would lead to decreased likelihood in changing strategies across conditions, we found no effect for either HRV index (RMSSD: $\chi^2(1) = 3.11$, $p = 0.78$, HF HRV: $\chi^2(1) = 0.94$, $p = 0.33$).

2.3.4. Monetary evaluation task

Willingness-to-pay (WTP) amounts were log transformed as they were positively skewed. Participants expected their peers to be willing to pay more money for a packet of medication without side effects than they reported for themselves ($\chi^2(1) = 15.773$, $p < 0.001$).

2.3.5. Self-reported affect

Using a repeated-measures ANOVA we found that there was no difference in negative affect (NA), positive affect (PA) or valence (VA) from baseline or between the conditions (NA: $F(3.31, 192) = 2.18$, $p = 0.255$; PA: $F(3.24,188) = 1.82$, $p = 0.42$; VA: $F(3.45,200) = 1.73$, $p = 0.465$).

2.3.6. Risky choice task

EV maximization

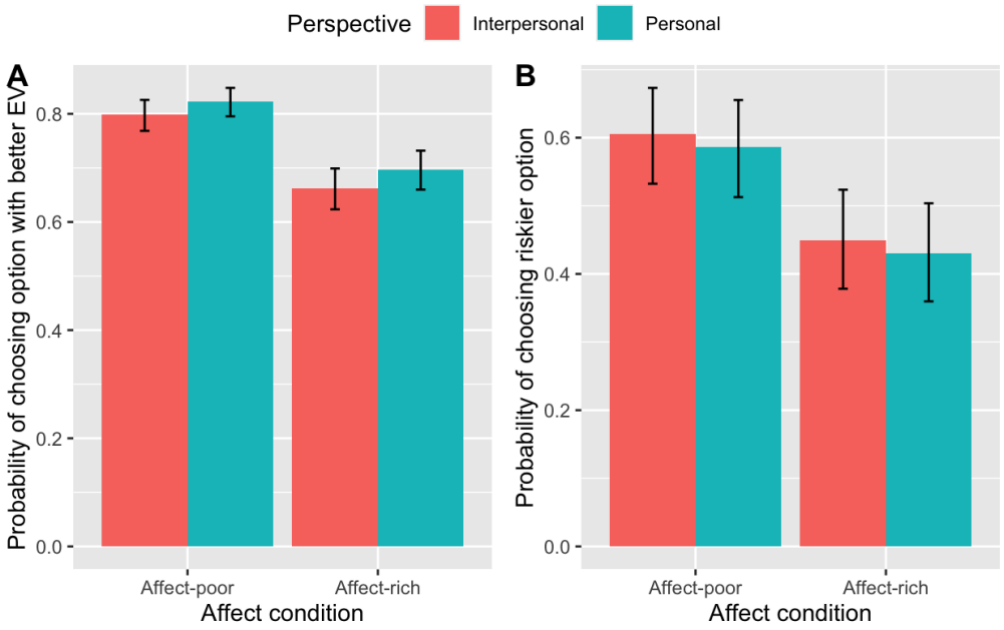
In line with previous studies on the affect gap, Figure 4 (panel A) shows that participants were less likely to pick the option with the better EV in the affect-rich compared to affect-poor choices ($\chi^2(1) = 103.4$, $p < 0.001$). Interestingly, people were also less likely to choose the better EV for peers than for themselves ($\chi^2(1) = 5.33$, $p < 0.05$).

Risk attitude

With regards to risk attitude across the conditions, Figure 4 (panel B) shows that participants were more likely to make risky choices in the affect-poor compared to the affect-rich condition ($\chi^2(1) = 77.25$, $p < 0.001$). There was no significant difference in risk-taking across decision perspectives ($\chi^2(1) = 1.23$, $p = 0.27$).

Figure 4.

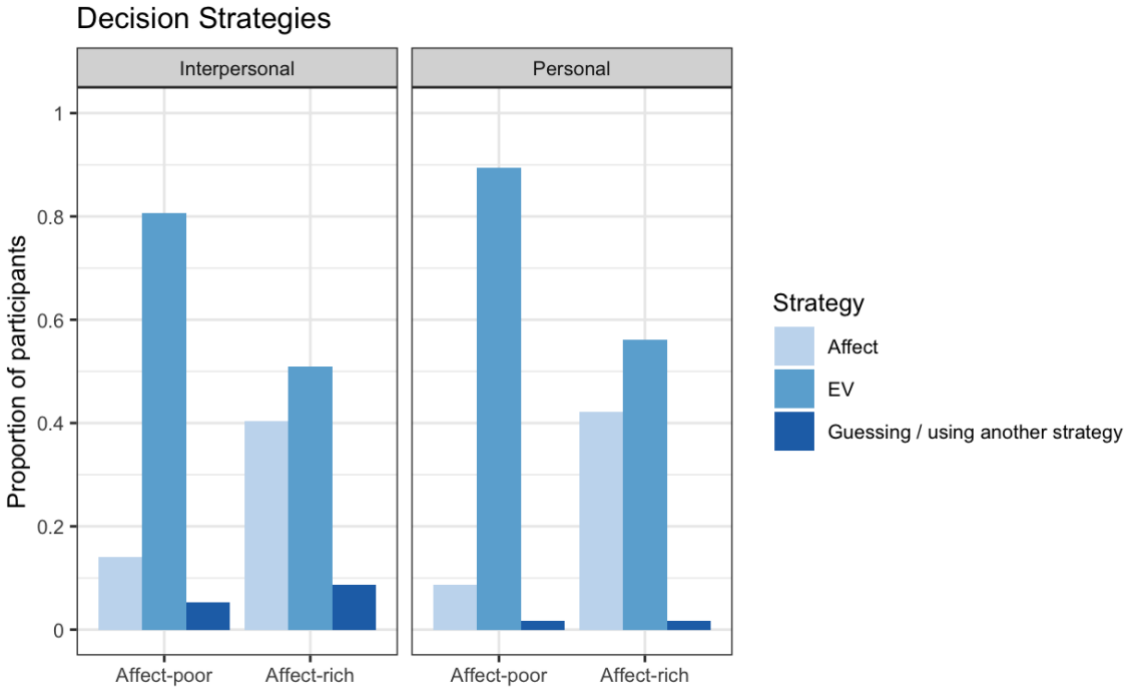
Predicted probabilities of EV maximization and picking the risky option across conditions



Strategy classification

Figure 5.

Proportion of participants using affect heuristic, EV strategy, or other strategy across conditions



In line with with previous research, Figure 5 highlights results from the log-linear analysis for decision strategies and conditions, which retained a final model that includes affect condition and strategy but not decision perspective and shows that participants are more likely to use the affect heuristic in the affect-rich choices ($\beta = 2.035$, $p < .001$). Table 2 indicates the classification confidence for each condition based on Lee and Wagenmakers (2013) benchmarks.

Table 2.

Median Bayes' Factor for each condition as a measure of classification confidence

Condition	Bayes Factor	Classification confidence
Affect-rich - Personal	5.18	Moderate
Affect-rich - Interpersonal	5.18	Moderate
Affect-poor - Personal	65.83	Very strong
Affect-poor - Interpersonal	42.9	Very strong

2.4. Discussion

This study provides the first direct psychophysiological evidence that anticipatory affect contributes to the affect gap. Elevated SCR amplitudes during affect-rich choice indicate that affective arousal is at play. This supports models such as the somatic marker hypothesis (Damasio, 1996) and risk-as-feelings hypothesis (Loewenstein et al., 2001), which posit that emotions guide attention and decision behavior under uncertainty. Anticipatory affect allows us to analyze risks rapidly, but may introduce decision biases. This is highlighted by our replication of the affect gap. In affect-rich choice individuals are more likely to use a non-compensatory decision strategy, are more risk averse, and less likely to pick the choice option with the better expected value. The idea that affect serves as information is central to many theories of decision-making (Bechara & Damasio, 2005; Carpenter & Niedenthal, 2018;

Loewenstein et al., 2001; Storbeck & Clore, 2008), and essentially converges on the idea that affect can help guide behavior by providing approach and avoidance motivation towards choice options. As such, it has been shown that anticipatory affect can help cope with uncertainty by substituting for more numerical information, such as the probabilities of expected outcomes (Wang et al., 2022). In sum, our finding indicates that in affect-rich choices, people use increased affective arousal as a source of information about the decision outcomes, resulting in reduced attention paid to other sources of information, such as probabilities.

This result echoes findings from the literature on probabilistic inference. Wichary and colleagues (2016) showed that with greater emotional stress, as indexed by EDA and self-report measures, individuals turn to easier non-compensatory decision strategies, which manifests behaviorally as a reduction in information search and increased attention paid to the most important cue. Importantly, these findings, along with our own, suggest an interaction between affective arousal and attention processes. Our result indicating increased use of non-compensatory decision strategies in affect-rich choices (i.e., showing probability neglect), in combination with the finding of increased affective arousal in the same condition, supports the attention narrowing hypothesis (Easterbrook, 1959), which posits that negative affect results in the narrowing of attention on the most relevant feature of a choice option at the expense of other pieces of information. Overall, the findings are in line with theories on emotion in decision-making and highlight that affective arousal can lead to changes in decision behavior, often reflected by the use of noncompensatory decision-making strategies.

While we did find support for differences in affective arousal across affect conditions, we did not find HRV as a measure of emotion regulation to be predictive of decision behavior in the affect gap. We do not know how intensely anticipatory affect is experienced or how long-lasting it is. Thus, it may simply be the case that individuals did not engage in emotion regulation during their choices. This would also be supported by the fact that we did not find a

downstream effect of anticipatory arousal on the subsequent affective state of the participant. After each choice block, there was no change from baseline in either state positive affect, negative affect, or valence. Thus, anticipatory arousal may be quite fleeting and thus not engage emotion regulation processes. Alternatively, individuals might engage in emotion regulation strategies not captured by HRV as a proxy.

Finally, we also investigated the sensitivity of the affect gap to different levels of affective engagement. To test this, we introduced a within-subjects interpersonal decisions condition, in which participants had to make choices for an unfamiliar peer. In line with Loewenstein and colleagues' (2001) risk-as-feelings hypothesis, we hypothesized that affective engagement would be lower when deciding for others and that, in consequence, affect ratings and SCR amplitudes should be lower for interpersonal compared to personal choices. Contrary to this hypothesis and previous work (Popovic et al., 2019), participants actually reported feeling more upset when a choice results in a bad outcome for their peers than for themselves. The increased distress ratings when negative outcomes occur to peers rather than themselves may indicate that people felt social emotions such as accountability or guilt (DeSteno, 2009; Eriksen et al., 2020; Leonhardt et al., 2011; Sun et al., 2021). For example, one study showed that interpersonal decision makers (compared with people deciding for themselves) felt significantly more guilt when an undesirable outcome, such as a lottery loss, occurred (Wagner et al., 2012). Additionally, making a poor choice, especially on behalf of another person, can threaten a decision-maker's sense of competence (Polman & Wu, 2020). Thus, participants may have felt more responsible when making choices for others, which could result in picking gambles that may be statistically worse but carry a lesser degree of perceived blame. If participants feel particularly responsible, then they may also show greater discomfort with uncertainty when deciding for others and thus may have focused on safer but sub-optimal choices on a handful of trials.

An alternate explanation could be that individuals distort probabilities when deciding for others, and as such, avoid gambles with better expected values if they also carry a significant risk of an adverse effect. Given that participants showed increased distress ratings on the evaluation of outcomes for peers, and did not show a difference in SCR amplitudes, it is not surprising that the affect gap emerges similarly when deciding for others than when deciding for themselves. The lack of differences in decision behavior with regards to risk taking and decision strategy is in line with previous research demonstrating that preferences are stable when decisions resemble each other or the information available is the same (this was the case for us as the choices only differed in the WTP provided as monetary equivalents for the side effects) (Schwarz, 2007; Schwarz & Bohner, 2001). Additionally, recent research also found that a majority of participants tend to use a "golden rule" by which people choose the same way for others as they would for themselves (Ifcher & Zarghamee, 2020). The only difference in interpersonal decision making we found was that participants were less likely to pick the option with better EV for their peer than for themselves. These results can be interpreted in line with the idea that participants may have acted on moral and social considerations. For instance, participants may have felt an obligation to protect others from potential losses and may thus have prioritized choosing a less significant potential loss in some trials, even if the expected value may have been better for the other alternative.

2.4.1. Limitations and future work

This study has several limitations. To construct the monetary lotteries, we used the willingness-to-pay reported by the participants to ensure comparability between affect-rich and affect-poor choice problems. Since monetary choices include numbers and medical ones do not, the EV is a more latent construct in the medical choices; thus, results may also be attributable to format effects. Previous research, however, has demonstrated that the effect persists even when side effects are presented with their monetary equivalents (Suter et al.,

2016) and when results are independent of WTP (Lejarraga et al., 2016), suggesting that they cannot simply be due to format. Additionally, while we observed skin conductance responses in the choice blocks, they were not elicited on every trial. We accounted for the number of SCRs a person had in a given condition in the mixed model, such that the results should not be due to differences in the number of SCRs. However, this still calls for further research to validate that differences in affective arousal across conditions are not a spurious result. Future work should expand on the current research by employing additional measures of affect, such as electromyograms, to track the muscular activity of the eyes and mouth. This could lend further evidence of differences in objective measures of affect in the affect gap. Future research could also have participants rate the level of experienced affect after each trial, instead of each decision block, allowing to probe for the subjective experience of affect across conditions.

2.4.2. Conclusion

Our findings reveal that anticipatory affect, as indexed by EDA, underpins behavioral differences in affect-rich decision-making under risk. These effects are robust across interpersonal and personal decision contexts. Anticipatory affect does not seem to carry over to participants' mood, and results are not mediated by psychophysiological markers of emotion regulation (i.e., HRV). We conclude that increased affective arousal in affect-rich choices serves as input to decision-making processes, impacting attentional processes and biasing decisions to avoid outcomes that produce strong negative affective arousal.

2.5. References

Almond, A. (2017). Acqknowledge (Software). In *The International Encyclopedia of Communication Research Methods* (pp. 1–2). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118901731.iecrm0001

Appelhans, B. M., & Luecken, L. J. (2006). Heart rate variability as an index of regulated emotional responding. *Review of General Psychology*, *10*(3), 229–240. https://doi.org/10.1037/1089-2680.10.3.229

Barsics, C., Van Der Linden, M., & D'Argembeau, A. (2016). Frequency, characteristics, and perceived functions of emotional future thinking in daily life. *Quarterly Journal of Experimental Psychology*, *69*(2), 217–233. https://doi.org/10.1080/17470218.2015.1051560

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

Baumgartner, H., Pieters, R., & Bagozzi, R. P. (2008). Future-oriented emotions: Conceptualization and behavioral effects. *European Journal of Social Psychology*, *38*(4), 685–696. https://doi.org/10.1002/ejsp.467

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010

Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. *Econometrica*, *22*(1), 23–36. https://doi.org/10.2307/1909829

Boucsein, W. (2012). *Electrodermal Activity*. Springer US. https://doi.org/10.1007/978-1-4614-1126-0

Braithwaite, J. J., Watson, D. G., Jones, R., & Rowe, M. (2013). A guide for analysing electrodermal activity (EDA) & skin conductance responses (SCRs) for psychological experiments. *Psychophysiology*, *49*(1), 1017-1034.

Butler, E. A., Wilhelm, F. H., & Gross, J. J. (2006). Respiratory sinus arrhythmia, emotion, and emotion regulation during social interaction. *Psychophysiology*, *43*(6), 612–622. https://doi.org/10.1111/j.1469-8986.2006.00467.x

Carpenter, S. M., & Niedenthal, P. M. (2018). Emotional processes in risky and multiattribute health decisions. *Psychology & Health*, *33*(1), 58–76. https://doi.org/10.1080/08870446.2017.1314478

Damasio, A. (1996). *The somatic marker hypothesis and the possible functions of the prefrontal cortex*. *351*(1346), 1413–1420.

DeSteno, D. (2009). Social emotions and intertemporal choice: "Hot" mechanisms for building social and economic capital. *Current Directions in Psychological Science*, *18*(5), 280–284. https://doi.org/10.1111/j.1467-8721.2009.01652.x

Easterbrook, J. A. (1959). The effect of emotion on cue utilization and the organization of behavior. *Psychological Review*, *66*(3), 183–201. https://doi.org/10.1037/h0047707

Eriksen, K. W., Kvaløy, O., & Luzuriaga, M. (2020). Risk-taking on behalf of others. *Journal of Behavioral and Experimental Finance*, *26*(C). https://econpapers.repec.org/article/eeebeexfi/v_3a26_3ay_3a2020_3ai_3ac_3as2214635502030023x.htm

Figner, B., & Murphy, R. O. (2011). Using skin conductance in judgment and decision making research. In *A Handbook of Process Tracing Methods for Decision Research: A Critical Review and User's Guide*. Psychology Press.

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, *13*(1), 1–17.

https://doi.org/10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S

Frank, C., & Pachur, T. (in press). The affect gap in risky choice is similar for younger and older adults. *Psychology and Aging.*

Holper, L., Wolf, M., & Tobler, P. N. (2014). Comparison of functional near-infrared spectroscopy and electrodermal activity in assessing objective versus subjective risk during risky financial decisions. *NeuroImage*, *84*, 833–842. https://doi.org/10.1016/j.neuroimage.2013.09.047

Ifcher, J., & Zarghamee, H. (2020). Behavioral economic phenomena in decision-making for others. *Journal of Economic Psychology*, *77*, 102180. https://doi.org/10.1016/j.joep.2019.06.003

Lane, R. D., Weidenbacher, H., Smith, R., Fort, C., Thayer, J. F., & Allen, J. J. B. (2013). Subgenual anterior cingulate cortex activity covariation with cardiac vagal control is altered in depression. *Journal of Affective Disorders*, *150*(2), 565–570. https://doi.org/10.1016/j.jad.2013.02.005

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press.

Lejarraga, T., Pachur, T., Frey, R., & Hertwig, R. (2016). Decisions from experience: From monetary to medical gambles. *Journal of Behavioral Decision Making*, *29*(1), 67–77. https://doi.org/10.1002/bdm.1877

Leonhardt, J. M., Keller, L. R., & Pechmann, C. (2011). Avoiding the risk of responsibility by seeking uncertainty: Responsibility aversion and preference for indirect agency when choosing for others. *Journal of Consumer Psychology*, *21*(4), 405–413. https://doi.org/10.1016/j.jcps.2011.01.001

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Molins, F., Ayuso, C., & Serrano, M. Á. (2021). Emotional stress & decision-making: An emotional stressor significantly reduces loss aversion. *Stress*, *24*(6), 780–786. https://doi.org/10.1080/10253890.2021.1919617

Pachur, T., & Galesic, M. (2013). Strategy selection in risky choice: The impact of numeracy, affect, and cross-cultural differences. *Journal of Behavioral Decision Making*, *26*(3), 260–271. https://doi.org/10.1002/bdm.1757

Pachur, T., Hertwig, R., & Wolkewitz, R. (2014). The affect gap in risky choice: Affect-rich outcomes attenuate attention to probability information. *Decision*, *1*(1), 64–78. https://doi.org/10.1037/dec0000006

Pachur, T., Mata, R., & Hertwig, R. (2017). Who Dares, Who Errs? Disentangling Cognitive and Motivational Roots of Age Differences in Decisions Under Risk. *Psychological Science*, *28*(4), 504–518. https://doi.org/10.1177/0956797616687729

Pachur, T., Suter, R. S., & Hertwig, R. (2017). How the twain can meet: Prospect theory and models of heuristics in risky choice. *Cognitive Psychology*, *93*, 44–73. https://doi.org/10.1016/j.cogpsych.2017.01.001

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, *51*(1), 195–203. https://doi.org/10.3758/s13428-018-01193-y

Polman, E., & Wu, K. (2020). Decision making for others involving risk: A review and meta-analysis. *Journal of Economic Psychology*, *77*, 102184. https://doi.org/10.1016/j.joep.2019.06.007

Popovic, N. F., Pachur, T., & Gaissmaier, W. (2019). The gap between medical and monetary choices under risk persists in decisions for others. *Journal of Behavioral Decision Making*, *32*(4), 388–402. https://doi.org/10.1002/bdm.2121

R Core Team. (2021). *R: A language and environment for statistical computing.* [Computer software]. https://www.R-project.org/

Ruiz-Padial, E., Sollers, J. J., Vila, J., & Thayer, J. F. (2003). The rhythm of the heart in the blink of an eye: Emotion-modulated startle magnitude covaries with heart rate variability. *Psychophysiology*, *40*(2), 306–313. https://doi.org/10.1111/1469-8986.00032

Schwarz, N. (2007). Attitude construction: Evaluation in context. *Social Cognition*, *25*(5), 638–656. https://doi.org/10.1521/soco.2007.25.5.638

Schwarz, N., & Bohner, G. (2001). The construction of attitudes. In *Blackwell handbook of social psychology: Intraindividual processes* (pp. 436–457). Blackwell Publishers.

Storbeck, J., & Clore, G. L. (2008). Affective arousal as information: How affective arousal influences judgments, learning, and memory. *Social and Personality Psychology Compass*, *2*(5), 1824–1843. https://doi.org/10.1111/j.1751-9004.2008.00138.x

Studer, B., & Clark, L. (2011). Place your bets: Psychophysiological correlates of decision-making under risk. *Cognitive, Affective, & Behavioral Neuroscience*, *11*(2), 144–158. https://doi.org/10.3758/s13415-011-0025-2

Sun, Q., Polman, E., & Zhang, H. (2021). On prospect theory, making choices for others, and the affective psychology of risk. *Journal of Experimental Social Psychology*, *96*, 104177. https://doi.org/10.1016/j.jesp.2021.104177

Suter, R. S., Pachur, T., & Hertwig, R. (2016). How affect shapes risky choice: Distorted probability weighting versus probability neglect. *Journal of Behavioral Decision Making*, *29*(4), 437–449. https://doi.org/10.1002/bdm.1888

Sütterlin, S., Herbert, C., Schmitt, M., Kübler, A., & Vögele, C. (2011). Frames, decisions, and cardiac–autonomic control. *Social Neuroscience*, *6*(2), 169–177. https://doi.org/10.1080/17470919.2010.495883

Tarvainen, M. P., Niskanen, J.-P., Lipponen, J. A., Ranta-Aho, P. O., & Karjalainen, P. A. (2014). Kubios HRV--heart rate variability analysis software. *Computer Methods and Programs in Biomedicine*, *113*(1), 210–220. https://doi.org/10.1016/j.cmpb.2013.07.024

Thayer, J. F., & Lane, R. D. (2000). A model of neurovisceral integration in emotion regulation and dysregulation. *Journal of Affective Disorders*, *61*(3), 201–216. https://doi.org/10.1016/S0165-0327(00)00338-4

Thayer, J. F., & Lane, R. D. (2009). Claude Bernard and the heart–brain connection: Further elaboration of a model of neurovisceral integration. *Neuroscience & Biobehavioral Reviews*, *33*(2), 81–88. https://doi.org/10.1016/j.neubiorev.2008.08.004

Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior, 2nd rev. Ed* (pp. xviii, 641). Princeton University Press.

Wagner, U., Handke, L., Dörfel, D., & Walter, H. (2012). An experimental decision-making paradigm to distinguish guilt and regret and their self-regulating function via loss averse choice behavior. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00431

Wang, X. T. (XiaoTian), Wang, P., Lu, J., Zhou, J., Li, G., & Garelik, S. (2022). Episodic future thinking and anticipatory emotions: Effects on delay discounting and

preventive behaviors during COVID-19. *Applied Psychology: Health and Well-Being*, *14*(3), 842–861. https://doi.org/10.1111/aphw.12350

Weber, E. U., Shafir, S., & Blais, A.-R. (2004). Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psychological Review*, *111*(2), 430–445. https://doi.org/10.1037/0033-295X.111.2.430

Wichary, S., Mata, R., & Rieskamp, J. (2016). Probabilistic inferences under emotional stress: How arousal affects decision processes. *Journal of Behavioral Decision Making*, *29*(5), 525–538. https://doi.org/10.1002/bdm.1896

Wu, Y., Van Dijk, E., Aitken, M., & Clark, L. (2016). Missed losses loom larger than missed gains: Electrodermal reactivity to decision choices and outcomes in a gambling task. *Cognitive, Affective, & Behavioral Neuroscience*, *16*(2), 353–361. https://doi.org/10.3758/s13415-015-0395-y

3. Study 2: Does Time Pressure Alter the Affect Gap in Risky Choice?

Published

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Abstract

People often exhibit systematic differences in their risky choices when decisions elicit high anticipatory affect, compared to choices that are relatively affect-poor—typically showing lower decision quality and greater risk aversion. This *affect gap* can be modeled by assuming that people use a compensatory strategy (i.e., a strategy that weighs outcomes against their probability of occurring) for affect-poor choices, but a simple non-compensatory strategy that considers outcome but ignores probability information in affect-rich choices. The reasons for these differences in strategy selection, however, are not yet understood. To examine whether the affect gap may reflect that in affect-rich choices, cognitive resources are more strongly taxed (leading to a simplification of the underlying decision strategy), we investigated whether the affect gap is impacted by a time pressure manipulation. Participants were asked to choose between affect-rich prospects (medical lotteries) and economically equivalent but relatively affect-poor prospects (monetary lotteries), either without a time constraint or under time pressure. The results indicated that the affect gap manifested similarly under time pressure as without time pressure. Specifically, differences between affect-rich and affect-poor choices in strategy selection did not differ between time pressure conditions, and differences in decision quality and risk aversion were even slightly attenuated under time pressure. The findings suggest that the differences in decision behavior between affect-rich and affect-poor choices are not driven by cognitive constraints. We discuss the potential psychological mechanisms involved in the affect gap.

Keywords: risky choice, affect gap, time pressure

3.1. Introduction

Anticipatory affect plays a key role in our ability to make decisions (e.g., Bechara & Damasio, 2005; Loewenstein et al., 2001). It allows a person to simulate the consequences of different choice outcomes, and thereby helps to guide behavior based on "gut feeling" responses (Bechara & Damasio, 2005). Anticipatory affect has also been shown to influence decision-making under risk (e.g., Lejarraga et al., 2016; Pachur et al., 2014; Pachur & Galesic, 2013; Popovic et al., 2019; Rottenstreich & Hsee, 2001; Suter et al., 2016). Affect-rich choices have often been studied using medical lotteries, such as choosing between different medications that may elicit a side effect with a given probability (see Pachur et al., 2014; see Rottenstreich & Hsee, 2001, for other types of outcomes). The affect-rich choices are compared to choices in problems that are economically and structurally matched to the medical choice problems but trigger less affect, that is, affect-poor choices (Pachur et al., 2014; Popovic et al., 2019; Suter et al., 2016). Studies have consistently found an *affect gap*, in that there are differences in decision behavior in affect-rich choice problems compared to relatively affect-poor choice problems. For instance, participants show lower decision quality (in terms of selecting the option with the higher expected value, a frequently used proxy measure for decision quality; e.g., Pachur et al., 2017; Zilker et al., 2020; Zilker, 2024) and higher risk aversion in affect-rich choice problems (with negative outcomes) than in matched affect-poor choice problems (e.g., Frank & Pachur, in press).

Several studies have suggested that the affect gap reflects a systematic difference in strategy selection between affect-rich and affect-poor choices. In compensatory decision strategies, all pieces of information are weighted against each other to optimize one's choice, such that, for instance, a large loss can be balanced out if it only occurs with a low probability. In non-compensatory decision strategies, by contrast, only some of the available information about an option is considered, and if an option has a large possible loss, this cannot be balanced

out by the outcome occurring with only a low probability. Importantly, because they consider only part of the available information and forego information integration, non-compensatory strategies are typically less cognitively demanding than compensatory ones (Gigerenzer & Goldstein, 1996; Payne et al., 1993; Shah & Oppenheimer, 2008; but see Fechner et al., 2018). In line with the notion of probability neglect in decisions that trigger intense affect (Sunstein, 2002), the studies on the affect gap have provided robust evidence that relative to affect-poor choices, in affect-rich choices individuals are more likely to use a non-compensatory decision strategy that ignores the probability of the outcomes (Pachur et al., 2014; Popovic et al., 2019; Suter et al., 2016). This is also supported by process data, showing that people make faster choices and inspect less information about the options in affect-rich than in affect-poor choices (Lejarraga et al., 2016; Pachur et al., 2014; Popovic et al., 2019).

Although the affect gap has been established as a robust phenomenon, it is still unclear what drives the greater reliance on a simpler, non-compensatory strategy in affect-rich choices. One possibility is that high anticipatory affect produces cognitive constraints, leading people to simplify the decision process. Affect has been observed to negatively impact cognition in a variety of ways, including reasoning, working memory, and central executive capacity (Kensinger & Corkin, 2003; Oaksford et al., 1996; Trémolière et al., 2016). Plass and Kalyuga (2019) found that affect increases cognitive load by triggering additional processing—including both task-relevant (i.e., the processing of emotion takes up space in working memory) and task-irrelevant processing (i.e., shifting attention away from relevant information).

In light of these findings, decision makers may rely on non-compensatory decision strategies in affect-rich choices to adapt to the possibly reduced availability of cognitive resources. Importantly, in previous strategy classification analyses, a marked proportion of participants used a compensatory strategy even in affect-rich choice (e.g., up to 30% in Pachur

et al., 2014). As such, one way of testing whether increased use of non-compensatory strategy in affect-rich choice is due to cognitive constraints is to introduce further constraints. The present study sought to test this possibility by examining whether adding a further constraint, time pressure, amplifies the difference in decision behavior in affect-rich choice. Time pressure is assumed to constrain decision-making by increasing stress, thereby reducing available cognitive resources (Maule & Hockey, 1993; Na, 2021; Payne et al., 1988, 1996; Rieskamp & Hoffrage, 2008; Sweller, 1994; Wickens, 1992; Wright, 1974). Comparing four types of cognitive load manipulations, Deck et al. (2021) found that time pressure produced comparable decreases in task performance as a variety of dual-task manipulations (simultaneous number memorization task, visual pattern task, and an auditory recall task). In the decision-making literature, several studies have observed that time pressure increases people's reliance on non-compensatory strategies (e.g., Oh et al., 2016; Payne et al., 1988; Rieskamp & Hoffrage, 2008), reduces attention to probability information, and increases attention to negative outcomes (e.g., Huber & Kunz, 2007; Young et al., 2012). Given that the affect gap seems to be due to a greater reliance on a strategy that neglects probability information and focuses on outcome information (Pachur et al., 2014), time pressure might lead to a further amplification of the affect gap. Alternatively, if the use of a non-compensatory strategy in affect-rich choice is not primarily driven by increased cognitive constraints, then time pressure could either not alter the affect gap or even reduce it, by increasing the use of a non-compensatory strategy in affect-poor choice under time pressure.[1]

In our study, we used a risky choice paradigm (adapted from Pachur & Galesic, 2013, Pachur et al., 2014) that contrasts affect-rich choice (between medical lotteries) and affect-poor choice (between monetary lotteries) and included a between-subjects time pressure manipulation. In one condition, participants made their decisions without time constraints. In

[1] We are grateful to an anonymous reviewer for highlighting this possibility.

the other condition, participants were instructed to make a choice as fast as possible—a common procedure to induce time pressure (e.g., Glöckner & Hodges, 2011; Wu et al., 2022).[2] Using a strategy classification approach, we classified participants as following a compensatory *expected value* (EV) strategy, which predicts that participants would choose the option with the better EV (i.e., the multiplication of a possible loss/gain with its probability of occurring) or the non-compensatory *affect heuristic* (Finucane et al., 2000), which predicts that participants would choose the option whose worst outcome is associated with the least bad self-reported affect rating, regardless of the outcome's probability of occurring. We expected (i) to replicate the affect-gap, such that in the affect-rich condition there is lower decision quality, higher risk aversion, and more pronounced reliance on the non-compensatory affect heuristic than in the affect-poor condition; and (ii) that, to the extent that the affect gap is driven by cognitive constraints in affect-rich choices, these patterns should be more pronounced under time pressure.

3.2. Method

3.2.1. Participants

We recruited 162 participants from a Bachelor level introductory course on Psychology, at UCLouvain, Belgium. A sample of 153 participants was included in the data analysis (75 female [78 male], average age: 19.16 years, age range: 18-34 years). The sample size was based on Popovic et al. (2019), who also adapted the risky choice paradigm to include a between-subjects factor. Nine participants were excluded from the analysis due to technical issues during data collection (they could not complete the entire experimental session). The study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by

[2] We used this implementation of time pressure (rather than giving people a fixed short time limit) as it reduces the possibility that participants will make a random choice (guess) in order to fit the time limit. Additionally, this manipulation is less artificial and previous literature showed that time pressure effects on strategy selection do not differ across different implementations of time pressure (Glöckner & Hodges, 2011).

the institutional ethics review committee of the Psychological Sciences Institute of UCLouvain (IPSY; #2022-31).

3.2.2. Design

Our experimental paradigm consisted of three tasks: 1) a monetary evaluation task, 2) a risky choice task, and 3) an affective evaluation task. The experiment involved a 2 (time pressure: time pressure vs. no time pressure) by 2 (anticipatory affect: rich [medical] vs. poor [monetary]) mixed design. Time pressure during the risky choice task was manipulated between-subjects, and anticipatory affect was manipulated within-subjects. Participants were randomly assigned to time pressure (n = 80) and no time pressure groups (n = 73). All participants completed all three tasks, with the instructions for the risky choice task differing across time pressure groups. The experiment was programmed in PsychoPy 2021.2.3 (Peirce et al., 2019).

Monetary evaluation task. At the onset of the study, participants were asked to imagine that they had a severe but treatable illness (see Figure 6A for an example). They were told that there are two equally effective medications to treat this illness. One of the medications always leads to a side effect lasting for about a week, while the other never leads to any side effect. For each of 12 side effects (memory loss, depression, hallucinations, speech disorder, insomnia, dizziness, itching, diarrhea, fever, trembling, flatulence, and fatigue; taken from Suter et al., 2016) they would encounter in the study, participants were asked to indicate how much money they would be willing to pay (WTP) extra for the package of medication that did not result in that side effect.

Risky choice task. Next, participants were presented with a risky choice task (see Figure 6B for an example). Both affect conditions (affect-rich vs. affect-poor; presented as separate blocks) involved 30 structurally equivalent choice problems, resulting in 60 trials overall. To ensure structural equivalence between affect-rich and affect-poor choice problems, the affect-

poor choice problems were constructed by replacing the side effects in the medical lotteries (i.e., the affect-rich condition) with each participant's indicated monetary equivalents (WTP) in the monetary evaluation task. Figure 6 shows an example of this: if a participant indicated in the monetary evaluation task that they would be willing to pay 40€ more for a packet of medication that would not result in insomnia, then the affect-rich option, in which medication A would entail a 10% probability of experiencing insomnia, would have an equivalent affect-poor option in which a person has a 10% of losing 40€. The choice problems were taken from Popovic et al. (2019) and Suter et al. (2016) and involved a wide range of probabilities, ranging from 0.3% to 100%. They were created such that the occurrence of choice problems with a dominant option (i.e., where an option's outcome was both less aversive and less probable) would be minimized.[3] The order in which the affect-rich and affect-poor conditions were presented was counterbalanced across participants. They then received an introduction to the task and worked on a practice phase where they completed five trials of each condition. The time pressure group was instructed to give their responses in the risky choice tasks as fast as possible, while the no time pressure group was instructed to take their time making the choices. In each trial of the affect-rich condition, people choose between two medications, each resulting in a side effect with a given probability. In the affect-poor condition, participants chose between two monetary loss lotteries. Between trials, there was a 1−2s jittered intertrial interval.

As we were also interested in measuring participants' perceived stress across the experiment, participants were asked to rate how stressed they currently felt on a scale from 1 (= not at all) to 5 (= extremely) at three time points: right before the risky choice task (baseline) and right after completing the affect-rich choice task and after the affect-poor risky choice task.

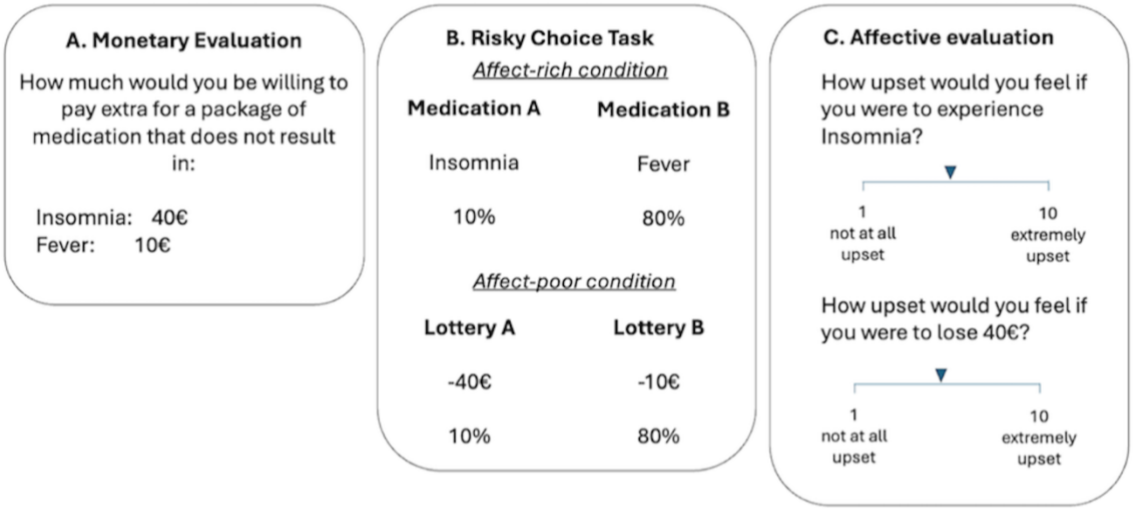
[3] Nonetheless, due to the variability in the WTP amounts across participants, in our study there was a dominant option (i.e., one where one of the options is superior both in terms of outcome and probability) in 15% of trials across all participants. Sensitivity analyses excluding these trials were conducted and any differences in results are reported. Detailed information on the sensitivity analyses can be found in the Supplemental Material.

After each part of the risky choice task (i.e., affect-rich vs. affect-poor), participants could take a self-timed break. The stress ratings allowed us to explore whether the time pressure manipulation had a general effect on the perceived stress and whether there were differences in perceived stress after performing the affect-rich and affect-poor choice problems.

Affective evaluation task. In the third and final task (see Figure 6C), participants were presented with each of the possible outcomes from the risky choice task, from both the affect-rich and the affect-poor conditions, and asked to indicate how upset they would feel if they were to experience the outcome (on a 10-point Likert scale: 1 = not at all upset, 10 = extremely upset)

Figure 6.

Graphical illustration of the tasks



Note. In panel A participants are first asked to provide their willingness-to-pay (WTP) to avoid each side effect, which provides the monetary equivalents for the monetary lotteries in the risky choice task. In panel B we see an example of a choice problem in the affect-rich (medical) and affect-poor (monetary) condition. In Panel C. we see how people had to give an affect rating for each outcome encountered in the risky choice task.

3.2.3. Statistical Analyses

All analyses were implemented in R 4.2.2 (R Core Team, 2021), and mixed-effects models were implemented using the lme4 package (Bates et al., 2015). In the mixed-effects

models, the predictors were tested by leaving out one predictor at a time and comparing the full and reduced models using a χ^2-test. The results of these model comparisons for each predictor are reported. Tables S1, S2, and S3 in the supplementary materials report the descriptive statistics for all relevant variables in the analyses. Study materials, anonymized dataset, and R scripts are openly available on the Open Science Framework (OSF) platform at https://osf.io/r2emf/ (DOI 10.17605/OSF.IO/R2EMF).

Decision quality. As a proxy of decision quality, we first determined the proportion of trials in which each participant selected the option with better EV.[4] To determine whether time pressure affected the probability of picking the option with the better EV, we ran a mixed-effects logistic regression predicting whether a person chose the option with the more favorable EV on a given trial, with time pressure, affect, and their interaction as fixed effects. Random effects included random intercepts for participants and choice problems. Additionally, because EV maximization and risk attitude can be empirically confounded, we included a binary fixed effects covariate indicating whether the option with higher EV was also the more risky option, as indexed by whether the option had the higher coefficient of variation (CV) (more details under risk attitude). Note that the differences in EV and CV across choice problems were only weakly correlated across the stimulus set ($r = 0.09$).

Risk attitude. We analyzed the risk attitude implied by participants' choices in the affect-rich and affect-poor conditions. To this end, we calculated the CV for each lottery and determined whether participants picked the more risky option (i.e., the option with the higher coefficient of variation; Pachur et al., 2017; Weber et al., 2004). To test whether the probability of choosing the more risky option differed between affect and time pressure conditions, we used mixed-effects logistic regression. The dependent variable was binary, indicating whether

[4] This does not imply that the decision maker necessarily perceives the option with higher EV as the most attractive option. Nevertheless, the proportion of choices of the option with the higher EV is commonly considered a proxy for decision quality (e.g., Pachur et al., 2017; Zilker et al., 2020; Zilker, 2024) and indicates how frequently the option is chosen that will lead to the higher payoff in the long run.

a person picked the more risky option on a given trial or not. We included affect, time pressure, and their interaction as fixed effects. Furthermore, to control for potential confounds between risk attitude and EV maximization, we included as a fixed-effect covariate a variable indicating whether the more risky option was also the one with the better EV. As random effects, we included random intercepts for participants and choice problems.

Strategy classification. Following Pachur and Galesic (2013), we used a maximum likelihood approach for strategy classification. We modeled participants' choices using two strategies: the compensatory expected value (EV) strategy and the non-compensatory affect heuristic (Finucane et al., 2000). The choices for each affect and time pressure condition were modeled separately. We then classified participants as following the EV strategy, the affect heuristic, or other strategy/guessing (cf. Pachur & Galesic, 2013). To do so, we calculated the goodness-of-fit index G^2 for each participant i and strategy k across N choice problems:

$$G^2_{i,j} = -2 \sum_{j=1}^{N} \ln [f_j(y)] \quad \text{(Eq. 1)}$$

A lower G^2 indicates a better model fit. The probability with which a strategy predicts an individual's choices y at lottery problem j is represented by $f_j(y)$. If a choice matches the prediction of the strategy, then $f_j(y) = 1\text{-}\varepsilon_{i,k}$; if the choice does not match the strategy's prediction, then $f_j(y) = \varepsilon_{i,k}$, where ε (which was estimated from the data) represents a given participant's i strategy application error ($0 \leq \varepsilon \leq .5$) for strategy k across all choice problems. Participants were then classified as following the strategy with the best goodness of fit. If for a participant the G^2 of the best strategy was not better than the value of G^2 under random choice (i.e., assuming $f_j(y) = .5$) the participant was classified as guessing (or using another strategy). As a measure of classification confidence, we calculated the Bayes Factor (BF) based on the differences of the Bayesian Information Criterion (BIC) of the best and second-best performing strategy (Eq. 2):

$$BF = \exp\left(-\frac{1}{2}\Delta BIC\right) \quad \text{(Eq. 2)}$$

The BIC for best and second-best performing strategy was calculated as follows: BIC = G^2 + 1*log(n_{trials}). We report the median (across participants) BF for each condition.

Affect ratings. Participants provided a rating of negative affect for each of the possible outcomes of the risky choice task. To examine whether there was a difference in affective ratings between the side effects and the corresponding monetary losses, we used a mixed-effects linear regression with type of outcome (side effect vs. monetary loss) as a fixed effect and random intercepts for participants and stimuli.

Response times. To check the effectiveness of the time pressure manipulation, we compared response times across time pressure conditions. Response times that were 3 SD from the mean were considered outliers and excluded. We also excluded response times under 100ms, as this constitutes the assumed minimum perceptual threshold to give a response (Whelan, 2008). This resulted in the exclusion of 1.77% of trials across all participants. For the statistical analyses, response times were log-transformed and analyzed with linear mixed-effects model with affect condition, time pressure, and their interaction as fixed effects, and random intercepts for participants.

3.3. Results

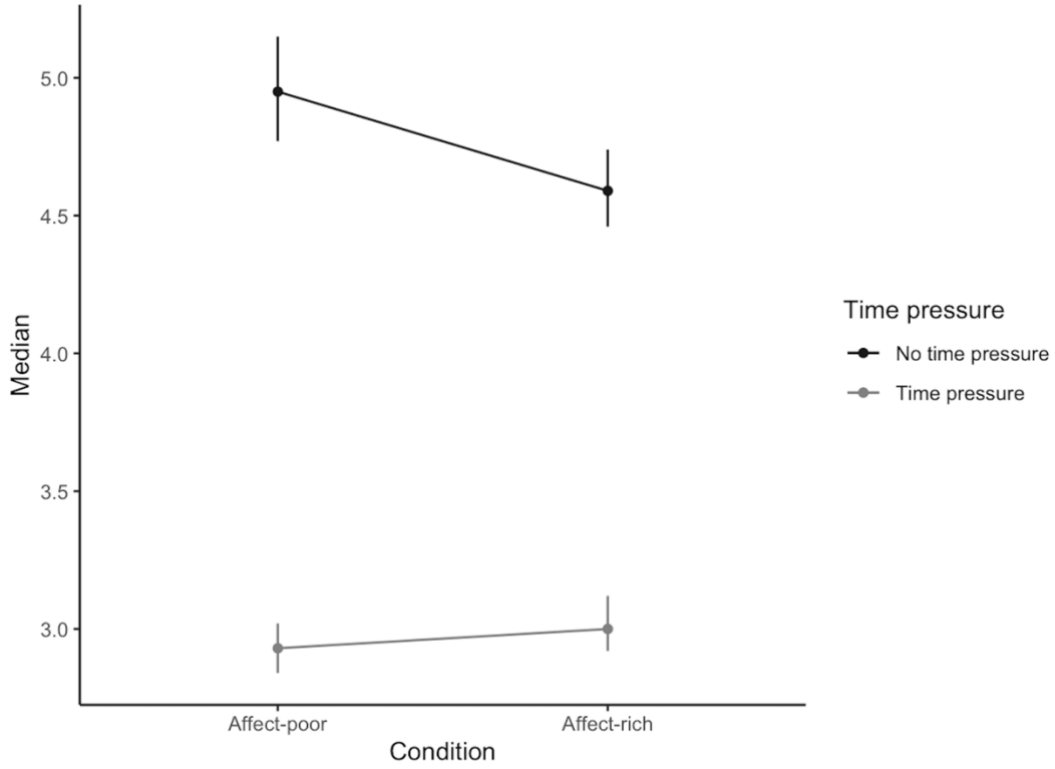
Response times of participants' choices were considerably faster in the time pressure (*Mdn* = 2.97 seconds, *IQR* = 2.4) than in the no time pressure (*Mdn* = 4.76 seconds, *IQR* = 4.67) conditions. This was corroborated statistically by a main effect of time pressure on the log-transformed response times (χ^2 = 64.08, $p < 0.001$), suggesting that the time pressure manipulation was successful. Additionally, there was an interaction between affect and time pressure (χ^2 = 33.58, $p < 0.001$). Specifically, as can be seen in Figure 7, in the condition without time pressure, response times were faster for the affect-rich choices than for the affect-poor choices, whereas in the condition with time pressure, response times for the affect-poor

and affect-rich choices did not differ. Sensitivity analyses showed that these patterns were robust when including the outliers.

Responses on the stress item were analyzed using an ANOVA and pairwise comparisons between conditions with Bonferroni correction for multiple comparisons. There was a significant interaction between time pressure and affect condition, $F(1.78, 268.9) = 6.49$, $p = 0.003$. Figure S1 in the supplementary materials suggests that the interaction is driven by a reduction in stress from baseline to the risky choice task in the condition without time pressure (baseline: $M = 2.16$, $SD = 1.12$, affect-poor: $M = 1.85$, $SD = 0.98$, affect-rich; $M = 1.88$, $SD = 1.01$), whereas there was no such reduction in stress in the time pressure condition (baseline: $M = 1.98$, $SD = 0.98$, affect-poor: $M = 2.00$, $SD = 0.99$, affect-rich: $M = 2.05$, $SD = 1.03$). Importantly, however, post-hoc tests correcting for multiple comparisons did not indicate that for any of the three stress measurement points (baseline, after affect-rich choice task, after affect-poor choice task) there were significant differences between the conditions. Note, however, that the stress ratings were collected either before or between rather than during the risky choice tasks, so they do not necessarily reflect the level of stress experienced when participants made their choices.

Figure 7.

Median response times across conditions



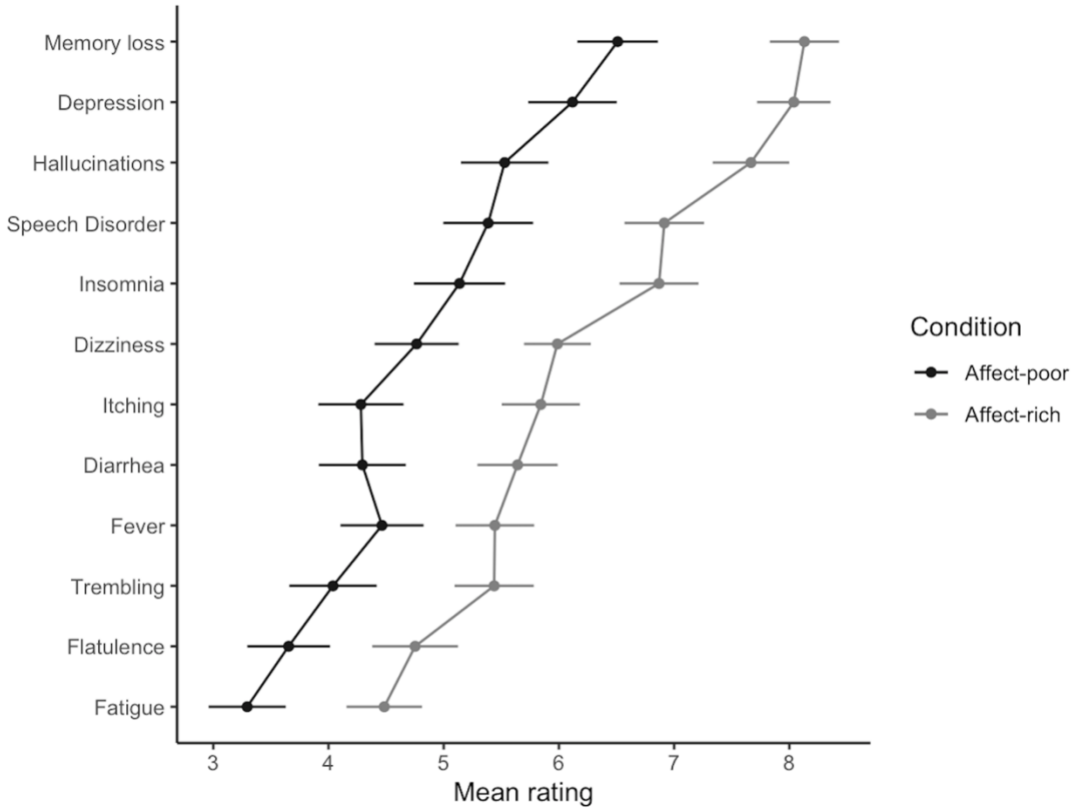
Note. Error bars represent the bootstrapped 95% confidence interval about the median.

3.3.1. Affective Evaluation Task

As shown in Figure 8, the affect ratings were higher for the side effects than for the monetary losses, $\chi^2 = 547.11$, $p < 0.001$. This confirms that the medical outcomes were relatively more affect-rich than the monetary outcomes.

Figure 8.

Affective evaluation of the side effects and their monetary equivalents



Note. Shown are the mean affect ratings of each side effect and its monetary equivalent with error bars representing the 95% confidence intervals about the mean.

3.3.2. Monetary Evaluation Task

The monetary equivalents of the side effects ranged between 0−2000€ (*Mdn* = 15€, *M* = 25.11€). The medians and the lower and upper quantiles of the monetary equivalents for each side effect are displayed in Figure S2 in the supplementary materials.

3.3.3. Risky Choice Task

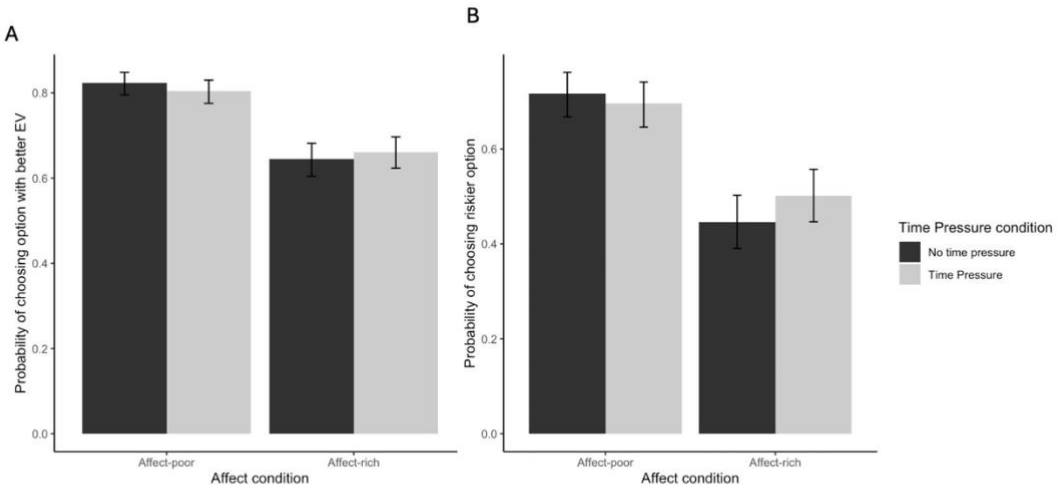
Decision quality. Controlling for risk aversion, participants chose the option with the higher EV more often in the affect-poor (No time pressure: *M* = 82.3%, *SE* = 9.2%; Time pressure: *M* = 80.4%, *SE* = 8.8%) than the affect-rich condition (No time pressure: *M* = 64.4%, *SE* = 8.6%; Time pressure: *M* = 66.1%, *SE* = 8.4%). As shown in Figure 9A, however, there was a significant interaction between affect and time pressure on this proxy measure of decision

quality, $\chi^2(1) = 4.13$, $p < 0.05$. The affect gap was attenuated in the time pressure condition (vs. no time pressure), as evidenced by an increased probability of choosing the option with the better EV in the affect-rich condition, but a decreased probability in the affect-poor condition. However, in analyses in which the trials in which there was a dominant choice option were excluded, the interaction was no longer significant; instead, there was only a main effect of affect, whereby participants chose the option with better EV more often in affect-poor than in affect-rich choices (please refer to Table S4 and S5 in the supplementary materials for result comparisons of sensitivity analyses).

Risk attitude. Controlling for decision quality across affect conditions (specifically whether the more risky option was also the option with the better EV), there was a significant interaction between time pressure and affect on predicting the probability of choosing the more risky option, $\chi^2(1) = 10.58$, $p < 0.001$. Specifically, as shown in Figure 9B, the difference between the affect-rich and affect-poor conditions in risk aversion was somewhat reduced in the time pressure condition relative to the condition without time pressure. Rather than increasing the affect gap, time pressure thus seemed to reduce the gap slightly.

Figure 9.

Decision quality and risk attitude across conditions



Note. Panel A shows the probability that participants chose the option with the better EV across conditions (decision quality); Panel B shows the probability with which participants chose the more risky option across conditions (risk attitude). Error bars represent the 95% confidence interval.

Strategy classification. Figure 10 shows the proportion of participants classified as using the EV strategy or the affect heuristic, or as guessing (or using another strategy). As can be seen, whereas for the affect-poor choices the majority of participants were classified as using the EV strategy (i.e., *time pressure*: 81.25%; *no time pressure*: 89.04%), for the affect-rich choices the majority of participants were classified as using the affect heuristic (i.e., *time pressure*: 61.25%; *no time pressure*: 61.64%), replicating previous findings (e.g., Pachur & Galesic, 2013; Popovic et al., 2019). This affect gap in strategy selection was corroborated by a three-way log-linear analysis conducted with JASP (JASP Team, 2024), using time pressure, affect, and strategy as factors. The final model retained affect and strategy, whose interaction was significant ($\beta = 0.511$, $p < 0.001$). Most importantly, note that the differences in strategy selection between the affect-rich and the affect-poor conditions were unaffected by the time

pressure manipulation. Time pressure thus did not alter the affect gap in terms of strategy selection. Table 3 reports the median Bayesian Information Criterion (BIC) and median Bayes Factor (BF) for each condition, supporting the conclusions from the log-linear analysis.

A mixed ANOVA showed that the estimated strategy application error (ε) for the best-fitting strategy was higher in the affect-rich (*Mdn* = 0.233 [*IQR* = 0.13]) than in the affect-poor condition (*Mdn* = 0.167 [*IQR* = 0.133]; $F(1, 140) = 50.818$, $p < 0.001$), but that there was no difference between time pressure conditions ($F(1, 140) = 0.567$, $p = 0.453$). Only very few participants were classified as guessing (affect-poor: $n = 7$ [4.57%], affect-rich: $n = 4$ [2.61%]).

Table 3.

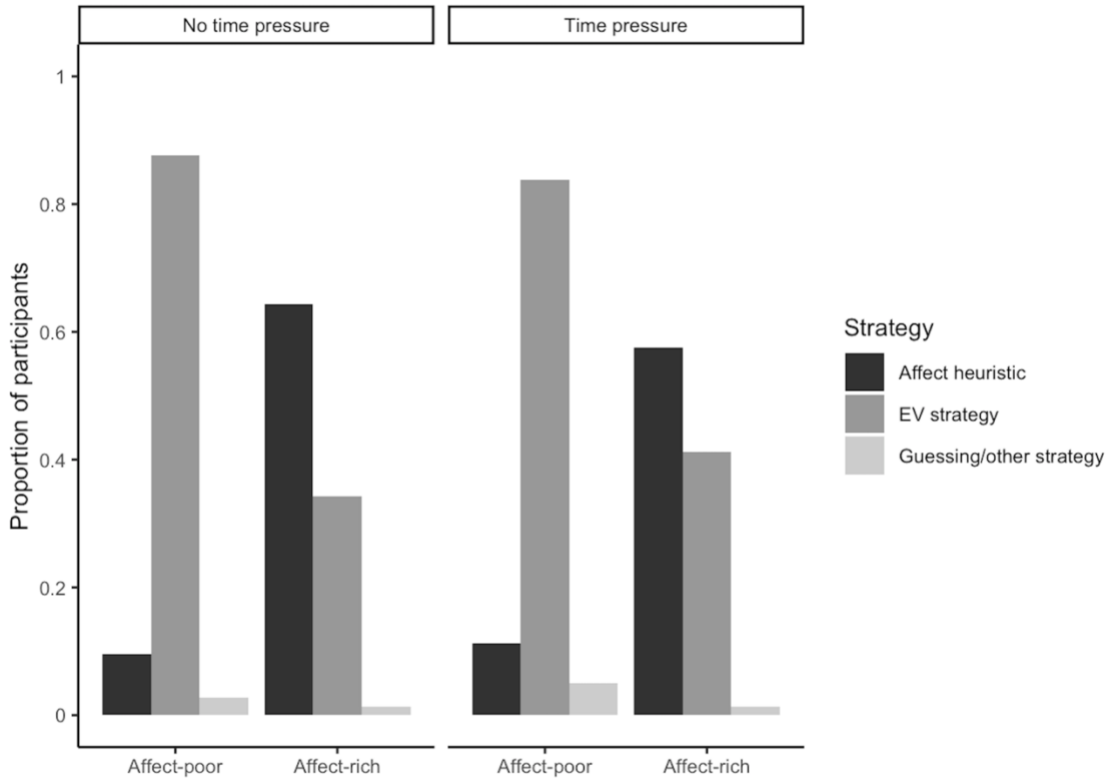
Median Bayesian Information Criterion (BIC) and Bayes' Factor (BF) for decision strategies across conditions

Strategy	No time pressure				Time pressure			
	Affect-poor		Affect-rich		Affect-poor		Affect-rich	
	BIC	BF	BIC	BF	BIC	BF	BIC	BF
EV strategy	26.96	2110	38.19	10.15	30.43	696	38.19	10.15
Affect heuristic	33.43	27.49	38.19	22.9	35.99	3	34.71	16.36

Note. While lower BIC values indicate better model performance, a greater value for the Bayes' Factor represents greater classification confidence. Values between 3-10 are generally considered to provide moderate evidence, 10-30 strong evidence, 30-100 very strong evidence, and anything above 100 as extreme evidence (Lee & Wagenmakers, 2013).

Figure 10.

Classification of strategy use across conditions



3.4. Discussion

The affect gap refers to differences in decision behavior between affect-rich and affect-poor choices. Specifically, relative to affect-poor choices, in affect-rich choices, participants maximize EV less and show higher risk aversion; the affect gap seems to reflect a greater reliance on a simpler heuristic decision-making strategy that neglects probability information for affect-rich choices (Lejarraga et al., 2016; Pachur et al., 2014; Pachur & Galesic, 2013; Popovic et al., 2019; Suter et al., 2016). In this article, we examined a possible explanation for the affect gap, according to which high anticipatory affect may constrain cognitive resources available to the decision maker. To test this possibility, we collected affect-rich and affect-poor choices both with and without time pressure. We predicted that if the affect gap reflects a response to added cognitive constraints in affect-rich choices, the aforementioned differences

in decision behavior under affect-rich choice would be increased under time pressure. Our results replicated the affect gap and showed that participants showed less EV maximization and were more risk-averse in the affect-rich than in the affect-poor condition; we also found them to be more likely to select the non-compensatory affect heuristic in the former than in the latter. Importantly, however, contrary to our cognitive constraint hypothesis, the difference between the affect-rich and affect-poor conditions in the proportion of participants classified as using the non-compensatory affect heuristic was not impacted by time pressure. Although under time pressure, participants responded equally fast for affect-rich and affect-poor choices, the affect gap emerged similarly. This suggests that the affect gap is not driven by a reduction in available cognitive resources in affect-rich choice.

What else could be driving the affect gap, if not cognitive constraints? One possibility is that the gap reflects a motivational shift in strategy selection that results from people aiming more strongly to minimize "regret" in the affect-rich than in the affect-poor choices. High anticipatory affect may lead participants to prioritize avoiding regret over increasing the chance of not experiencing a side effect. Regret minimization could also help explain the seemingly deliberate avoidance of probability information (cf. Fuławka et al., 2024), evidenced by the increased use of the non-compensatory affect heuristic in the affect-rich choices. Anxiety and the minimization of disappointment and regret have all been linked to avoidance of potentially useful information (see Golman et al., 2017). Alternatively, as affective information tends to be salient to decision makers, the difference between affect-rich and affect-poor choices may simply reflect the attention drawn by the affect-rich outcome at the expense of attention paid to the probability information. Needless to say, these considerations are speculative and post-hoc and should be investigated more specifically in future research.

In contrast to previous results on the effects of time pressure on affect-poor choices (i.e., monetary lotteries; Oh et al., 2016; Payne et al., 1988; Rieskamp & Hoffrage, 2008), we

did not find a difference in strategy selection between time pressure conditions for the affect-poor choices. This could be due to the type of time pressure manipulation we used, which consisted of a self-paced approach instructing participants to decide as fast as they could. This procedure might have allowed participants to adaptively respond to time pressure, such as through an acceleration of information processing (e.g., Maule & Hockey, 1993). Such an adaptation may also explain why the time pressure group did not report feeling more stressed than the no time pressure group, despite their response times in the risky choice task being substantially shorter. Time pressure has also been shown to impact decision behavior differently on simple decision tasks (such as the binary choices we used) versus complex decision tasks, in that rather complicated decision processes can be maintained under time stress if the choice task is relatively simple (Zakay, 1993). We employed the current implementation of time pressure because under stricter time pressure manipulations, individuals might simply become more error-prone (Olschewski & Rieskamp, 2021).

Interestingly, time pressure had an impact on the affect gap in terms of EV maximization and risk aversion; however, rather than amplify differences in decision behavior under affect-rich choice, time pressure decreased the affect gap (somewhat). With regard to risk aversion, this was due to slightly lower risk aversion under time pressure (vs. no time pressure) in the affect-rich condition. With regard to EV maximization, there was a slight increase in EV maximization for affect-rich choice under time pressure (vs. no time pressure), and a decrease for affect-poor choice. One possible explanation for this finding is that in at least some trials in the affect-rich condition, participants might have responded to the time pressure by comparing the options on the (numerical) probabilities rather than the (nonnumerical) outcomes, choosing the option with the less likely side effect. Similarly, in the affect-poor condition, participants may have responded to the time pressure by focusing on some trials on outcome over probability information. Importantly, however, the interaction

effect for EV maximization did not hold when analyses were repeated while excluding trials that contained a dominant option, whereas the finding that participants were less likely to choose the option with better EV in affect-rich compared to affect-poor choices, regardless of time pressure, was maintained.

Our results have implications for considerations of how to overcome the affect gap, that is, to reduce the neglect of probability information to make a decision (cf. Fuławka et al., 2024). Recall that to make the best choice when choosing between medical treatments, it is crucial to also take into account the probability of different possible outcomes. How can we ensure that people also attend to the probabilities of affect-rich outcomes and thus reduce the affect gap? Our results indicate that simply giving people ample time to decide is not effective in reducing the affect gap. Expanding on regret minimization as one of the alternative explanations we have discussed, previous literature on regulatory focus (Higgins, 1998) suggests that prevention-focused individuals are more likely to engage in regret minimization, while promotion-focused individuals are more likely to engage in utility maximization (Lim & Hahn, 2020). Interventions that encourage a promotion focus—for instance, by reframing choices in a way that increases the salience of promotion-focused regret (i.e., regret centered on missing out on a positive outcome, such as a high chance of not experiencing any loss) (Leder et al., 2013) — may help to reduce the affect gap.

A limitation of our study is that we only considered choice problems with negative outcomes. It therefore remains to be investigated how anticipatory affect and time pressure might interact in choice problems with positive outcomes. In addition, we used participants' self-reported WTP amounts of the side effects to calculate the expected value in the affect-rich condition. Since these monetary equivalents are noisy and contain a degree of uncertainty and because the EV may be a distant latent signal in the medical choices, the differences between affect-rich and affect-poor choices may also be attributable to format effects. While we cannot

fully exclude this possibility, it is important to note that previous research has shown that the WTP provided by participants are reliable over time (Pachur & Galesic, 2013) and that the affect gap also emerges when in the affect-rich task the side effects are presented alongside their WTPs, thus facilitating numerical computations (Suter et al., 2016). Finally, we used EV maximization as a proxy of decision quality, which might be debatable given that decision makers are usually not risk neutral. Nevertheless, EV maximization reflects the degree to which the decision maker chooses the option with the highest returns in the long run, and therefore reflects an important property of choice behavior.

3.4.1. Conclusion

In conclusion, the findings of the current study suggest that the affect gap is not driven by increased cognitive constraints under affect-rich choice. In fact, with regards to decision quality and risk attitude the affect gap seemed to be slightly reduced under time pressure, rather than amplified. Instead of a reduction in cognitive resources, the selection of a non-compensatory strategy for affect-rich choices that ignores probability information may be driven by motivational factors, such as the goal to minimize regret.

3.5. References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010

Deck, C., Jahedi, S., & Sheremeta, R. (2021). On the consistency of cognitive load. *European Economic Review*, *134*, 103695. https://doi.org/10.1016/j.euroecorev.2021.103695

Fechner, H. B., Schooler, L. J., & Pachur, T. (2018). Cognitive costs of decision-making strategies: A resource demand decomposition analysis with a cognitive architecture. *Cognition*, *170*, 102–122. https://doi.org/10.1016/j.cognition.2017.09.003

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, *13*(1), 1–17. https://doi.org/10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S

Frank, C., & Pachur, T. (in press). The affect gap in risky choice is similar for younger and older adults. *Psychology and Aging.*

Fuławka, K., Hertwig, R., & Pachur, T. (2024). COVID-19 vaccine refusal is driven by deliberate ignorance and cognitive distortions. *npj Vaccines*, *9*, Article 167. https://doi.org/10.1038/s41541-024-00951-8

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650

Glöckner, A., & Hodges, S. D. (2011). Parallel constraint satisfaction in memory-based decisions. *Experimental Psychology*, *58*(3), 180–195. https://doi.org/10.1027/1618-3169/a000084

Golman, R., Hagmann, D., & Loewenstein, G. (2017). Information avoidance. *Journal of Economic Literature*, *55*(1), 96–135. https://doi.org/10.1257/jel.20151245

Higgins, E. T. (1998). Promotion and prevention: Regulatory focus as a motivational principle. In M. P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Vol. 30, pp. 1–46). Academic Press. https://doi.org/10.1016/S0065-2601(08)60381-0

Huber, O., & Kunz, U. (2007). Time pressure in risky decision-making: Effect on risk defusing. *Psychology Science, 49*(4), 415-426.

JASP Team. (2024). *JASP* [Computer software]. https://jasp-stats.org/

Kensinger, E. A., & Corkin, S. (2003). Effect of negative emotional content on working memory and long-term memory. *Emotion*, *3*(4), 378–393. https://doi.org/10.1037/1528-3542.3.4.378

Leder, S., Florack, A., & Keller, J. (2013). Thoughts about possible failure: Regulatory focus and the anticipation of regret. *Social Cognition*, *31*(3), 349–373. https://doi.org/10.1521/soco.2013.31.3.349

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian cognitive modeling: A practical course*. Cambridge University Press. https://doi.org/10.1017/CBO9781139087759

Lejarraga, T., Pachur, T., Frey, R., & Hertwig, R. (2016). Decisions from experience: From monetary to medical gambles. *Journal of Behavioral Decision Making*, *29*(1), 67–77. https://doi.org/10.1002/bdm.1877

Lim, J., & Hahn, M. (2020). Regulatory focus and decision rules: Are prevention-focused consumers regret minimizers? *Journal of Business Research*, *120*, 343–350. https://doi.org/10.1016/j.jbusres.2019.11.066

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Maule, A. J., & Hockey, G. R. J. (1993). State, stress, and time pressure. In O. Svenson & A. J. Maule (Eds.), *Time pressure and stress in human judgment and decision making* (pp. 83–101). Springer US. https://doi.org/10.1007/978-1-4757-6846-6_6

Na, K. (2021). The effects of cognitive load on query reformulation: Mental demand, temporal demand and frustration. *Aslib Journal of Information Management*, *73*(3), 436–453. https://doi.org/10.1108/AJIM-07-2020-0206

Oaksford, M., Morris, F., Grainger, B., & Williams, J. M. G. (1996). Mood, reasoning, and central executive processes. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(2), 476–492. https://doi.org/10.1037/0278-7393.22.2.476

Oh, H., Beck, J. M., Zhu, P., Sommer, M. A., Ferrari, S., & Egner, T. (2016). Satisficing in split-second decision making is characterized by strategic cue discounting. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *42*(12), 1937–1956. https://doi.org/10.1037/xlm0000284

Olschewski, S., & Rieskamp, J. (2021). Distinguishing three effects of time pressure on risk taking: Choice consistency, risk preference, and strategy selection. *Journal of Behavioral Decision Making*, *34*(4), 541–554. https://doi.org/10.1002/bdm.2228

Pachur, T., & Galesic, M. (2013). Strategy selection in risky choice: The impact of numeracy, affect, and cross-cultural differences. *Journal of Behavioral Decision Making*, *26*(3), 260–271. https://doi.org/10.1002/bdm.1757

Pachur, T., Mata, R., & Hertwig, R. (2017). Who dares, who errs? Disentangling cognitive and motivational roots of age differences in decisions under risk. *Psychological Science*, *28*(4), 504–518. https://doi.org/10.1177/0956797616687729

Pachur, T., Hertwig, R., & Wolkewitz, R. (2014). The affect gap in risky choice: Affect-rich outcomes attenuate attention to probability information. *Decision*, *1*(1), 64–78. https://doi.org/10.1037/dec0000006

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.

Payne, J. W., Bettman, J. R., & Luce, M. F. (1996). When time is money: Decision behavior under opportunity-cost time pressure. *Organizational Behavior and Human Decision Processes*, *66*(2), 131–152. https://doi.org/10.1006/obhd.1996.0044

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, *51*(1), 195–203. https://doi.org/10.3758/s13428-018-01193-y

Plass, J. L., & Kalyuga, S. (2019). Four ways of considering emotion in cognitive load theory. *Educational Psychology Review*, *31*(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Popovic, N. F., Pachur, T., & Gaissmaier, W. (2019). The gap between medical and monetary choices under risk persists in decisions for others. *Journal of Behavioral Decision Making*, *32*(4), 388–402. https://doi.org/10.1002/bdm.2121

R Core Team. (2021). *R: A language and envrionment for statistical computing.* [Computer software]. https://www.R-project.org/

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. https://doi.org/10.1016/j.actpsy.2007.05.004

Rottenstreich, Y., & Hsee, C. K. (2001). Money, kisses, and electric shocks: On the affective psychology of risk. *Psychological Science*, *12*(3), 6.

Shah, A. K., & Oppenheimer, D. M. (2008). Heuristics made easy: An effort-reduction framework. *Psychological Bulletin*, *134*(2), 207–222. https://doi.org/10.1037/0033-2909.134.2.207

Sunstein, C. R. (2002). Probability neglect: Emotions, worst cases, and law. *Yale Law Journal*, *112*(1), 61–108.

Suter, R. S., Pachur, T., & Hertwig, R. (2016). How affect shapes risky choice: Distorted probability weighting versus probability neglect. *Journal of Behavioral Decision Making*, *29*(4), 437–449. https://doi.org/10.1002/bdm.1888

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*, *4*(4), 295–312. https://doi.org/10.1016/0959-4752(94)90003-5

Trémolière, B., Gagnon, M.-È., & Blanchette, I. (2016). Cognitive load mediates the effect of emotion on analytical thinking. *Experimental Psychology*, *63*(6), 343–350. https://doi.org/10.1027/1618-3169/a000333

Weber, E. U., Shafir, S., & Blais, A.-R. (2004). Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psychological Review*, *111*(2), 430–445. https://doi.org/10.1037/0033-295X.111.2.430

Whelan, R. (2008). Effective analysis of reaction time data. *The Psychological Record*, *58*(3), 475–482. https://doi.org/10.1007/BF03395630

Wickens, C. D. (1992). *Engineering psychology and human performance* (2nd ed). Harper Collins Publishers. http://www.gbv.de/dms/bowker/toc/9780673461612.pdf

Wright, P. (1974). The harassed decision maker: Time pressures, distractions, and the use of evidence. *Journal of Applied Psychology*, *59*(5), 555–561. https://doi.org/10.1037/h0037186

Wu, C. M., Schulz, E., Pleskac, T. J., & Speekenbrink, M. (2022). Time pressure changes how people explore and respond to uncertainty. *Scientific Reports*, *12*(1), 4122. https://doi.org/10.1038/s41598-022-07901-1

Young, D. L., Goodie, A. S., Hall, D. B., & Wu, E. (2012). Decision making under time pressure, modeled in a prospect theory framework. *Organizational Behavior and Human Decision Processes*, *118*(2), 179–188. https://doi.org/10.1016/j.obhdp.2012.03.005

Zakay, D. (1993). The impact of time perception processes on decision making under time stress. In O. Svenson & A. J. Maule (Eds.), *Time pressure and stress in human judgment and decision making* (pp. 83–101). Springer US. https://doi.org/10.1007/978-1-4757-6846-6_6

Zilker, V. (2024). Attentional dynamics of evidence accumulation explain why more numerate people make better decisions under risk. *Scientific Reports*, *14*(1), 18788. https://doi.org/10.1038/s41598-024-68969-5

Zilker, V., Hertwig, R., & Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity. *Journal of Experimental Psychology: General*, *149*(9), 1644–1683. https://doi.org/10.1037/xge0000741

4. Study 3: An fMRI investigation of attentional deployment in affective forecasting with complex gains and losses

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Abstract

Predicting the emotional impact of future events is paramount to cognition and guides decision-making through a process known as affective forecasting. Yet, when outcomes are emotionally bivalent (i.e., positively and negatively valenced), for example, medical treatments involving both remission and adverse side effects, such forecasts are prone to inaccuracies. Here, we used functional MRI to investigate the neural mechanisms of affective forecasting in scenarios involving emotionally complex trade-offs, and how these are shaped by attentional deployment – an emotion regulation process by which we direct attention toward or away from given aspects of an outcome. In the current study, participants imagined undergoing a medical treatment offering relief from chronic pain but causing other side effects, while instructed to forecast their emotions while attending either to the positive (remission) or negative (side effect) component of the outcome. Univariate results demonstrate that attentional deployment modulates neural activity related to forecasting emotions. While negative affective forecasting recruits the insula and frontal pole, positive affective forecasting recruits the superior frontal gyrus and frontal pole. Multivariate results highlight that a broad network including sensory, valuation, emotion, and memory circuits differentially contributes to positive and negative affective forecasting. Results highlight that attentional deployment during affective forecasting results in distinct recruitment of brain regions related to positive and negative affective processing, and centers the frontal pole as a key region in maintaining the emotion regulation goal.

Keywords. Affective forecasting, attentional deployment, fMRI

4.1. Introduction

Affective forecasting, the ability to predict our future emotional reactions to events, is central to how humans plan and make decisions. Yet, despite its importance, previous research shows that we are not always accurate forecasters, particularly when choice outcomes evoke bivalent (i.e., mixed valence) or conflicting emotions (Gilbert & Wilson, 2009). fMRI studies on the anticipation of emotional events have highlighted the involvement of emotion processing regions such as the ventromedial prefrontal cortex (vmPFC) (Bray et al., 2010; D'Argembeau et al., 2008; Knutson & Greer, 2008; Sharot et al., 2007), amygdala (Sharot et al., 2007), and insula (Greenberg et al., 2015; Knutson & Greer, 2008), as well as reward-processing related regions for the anticipation of positive events, such as the ventral striatum (Greenberg et al., 2015; Knutson & Greer, 2008), and self-referential processing, such as the posterior cingulate cortex (PCC) (D'Argembeau et al., 2008; Sharot et al., 2007). However, these studies have only used univalent stimuli to elicit a singular emotional experience.

Our study advances this body of work by investigating the neural underpinnings of affective forecasting when individuals anticipate events that elicit mixed emotions, such as the experience of a treatment that may alleviate a disease but also cause adverse side effects. Specifically, we examined how attentional deployment, the strategic focusing on certain aspects of a future event, influences neural activity during affective forecasting with bivalent stimuli. Attentional deployment is an emotion regulation strategy (Gross, 1998; Mauss et al., 2007) by which people focus their attention on certain aspects of a situation to influence their emotional response. For instance, a PhD candidate with an upcoming defense may choose to focus their attention on the anticipated joy of finishing the PhD, rather than the anticipated anxiety of having to present in front of a jury.

Mis-predicting our emotions can have consequences for our actions, and these may be especially important for medical choices, in which we have important trade-offs to consider. For example, Hoerger and colleagues (2016) have shown that affective forecasting uniquely contributes to medical decision-making for the use of chemopreventive medications for women at risk of breast cancer. They find that there is a negative forecasting bias for preventive medications, as women are worried that their health-related stress will increase if they take the medication. In line with this finding, a recent meta-analysis on affective forecasting in medical decision-making has shown that patient tend to overestimate their quality of life when they expect health improvements and underestimate their quality of life when they expect health deterioration (Bosch et al., 2021). Such results suggest that patients may selectively attend to positive (negative) anticipated emotions when expecting health improvement (deterioration). In fact, Peters and colleagues (2006) have argued that in medical decision-making, affect serves as a spotlight, resulting in more focused attention on some information than others. As such, it is important to better understand the neural mechanisms underlying attentional deployment in the context of complex emotional trade-offs that are often present in medical decision-making.

To our knowledge, only one study to date has investigated the neural mechanisms of attentional deployment in affective forecasting with bivalent stimuli. Kruschwitz and colleagues (2018) combined monetary gains (losses) with aversive (pleasant) sounds, instructing individuals to anticipate the positive (i.e., a monetary gain or a pleasant sound) or negative part of the outcome (i.e., a monetary loss or aversive sound). They found that shifting attention towards the positive outcome revealed activations in the PCC, ventral striatum, and vmPFC. In contrast, when anticipating the negative part of the outcome, the insula became active (Kruschwitz et al., 2018). Thus, focusing on the anticipation of the positive part of a bivalent outcome seems to recruit emotion processing and reward-related regions, whereas focusing on the negative part recruits emotion processing regions specific to negative affect.

We expand on this work by investigating more complex trade-off scenarios that might be encountered in medical decision-making. To this end, we developed a cue exposure paradigm in which participants would have to engage in affective forecasting in response to a hypothetical treatment, while either focusing on the positive part of the treatment (i.e., remission from illness) or the negative part of the treatment (i.e., a side effect). The paradigm was first validated behaviorally to ensure that participants are able to project themselves into these medical scenarios and engage in attentional deployment. We then implemented the paradigm in the functional Magnetic Resonance (fMRI) scanner. Based on the literature highlighted above, we anticipated that regions relevant to future prospection of emotional events would become active, including the ventromedial prefrontal cortex (vmPFC), (para)hippocampus, medial parietal regions, and lateral temporal cortex (D'Argembeau et al., 2008). Given that mental simulation tends to recruit the brain regions active during the simulated events, we also expected emotion processing regions, such as the amygdala, to become active (Holmes & Mathews, 2010). Furthermore, based on Kruschwitz and colleagues' (2018) results and other work on the neural mechanisms of attentional deployment (Li et al., 2022; Liu et al., 2020), we anticipated that directing attention toward the negative part of the bivalent outcome would engage the insula, and focusing on the positive part would engage the ventral striatum, as well as superior and medial frontal gyrus.

We used fMRI to measure brain activity while participants imagined future scenarios involving medical treatments with both positive (remission of disease) and negative (side effects) aspects. We further asked participants to rate the encountered stimuli (i.e., side effects) according to how familiar they were with them and how distressed they would feel if they had to experience them. Finally, participants rated the vividness with which they could forecast their emotions in the focus remission and focus side effects conditions. These ratings allowed us to investigate whether brain activity is modulated by familiarity with the stimuli, how much

negative affect the stimuli elicit, and the vividness with which they are able to project themselves. Regarding the modulation of activity through familiarity, we anticipated that unfamiliar side effects would result in additional engagement of hippocampal activity, as previous work has suggested the hippocampus is recruited to a greater degree for unfamiliar future events (Sasse et al., 2015). We did not have hypotheses regarding the modulation of brain activity by affect or vividness. However, previous research has highlighted that increased activity in reward-related brain regions was significantly associated with increased levels of anticipated pleasure and relief, and increased insula activity was associated with increased levels of anticipated negative affect (Kruschwitz et al., 2018). From a behavioral perspective, vividness is relevant as more vivid prospection is associated with greater affective arousal (Van Boven & Ashworth, 2007), has been shown to mediate the link between anticipatory affect and behavioral intentions (Mazzoco et al., 2019), and moderates the effectiveness of episodic future thinking on intertemporal choice (Rösch et al., 2022). Additionally, vividness of prospection has been shown to modulate neural activity (Lee et al., 2021; Aupperle et al., 2021; Saint-Laurent et al., 2015).

4.2. Behavioral validation

4.2.1. Method

To ensure that the experimental task is feasible for participants, we conducted a behavioral validation of the experimental task. In a first step, we selected the stimuli by conducting an anonymous 5-minute survey (n = 181) in which participants rated the perceived severity of 30 side effects on a scale of 1 (not at all severe) to 5 (extremely severe). Included side effects were all potential side effects of common analgesics. The nine side effects with the highest and lowest ratings were selected for a total of 18 side effects. In a second step, we invited participants for a lab experiment in which they would perform the cue exposure task,

which would be used in the MRI. The procedure for the behavioral validation is described below.

4.2.1.1. Participants

52 participants were recruited at the Belval campus of the University of Luxembourg (Age: *M* = 26.12[4.86], Female = 35, Male = 16, undisclosed = 1). Participants had to be at least 18 years old, have unimpaired or corrected vision, and not currently experiencing physical or mental disorders. Data collection took place in the CLIPS laboratory at the University of Luxembourg, and ethical approval was received from the institutional ethics board (ERP 23-090 AffMed).

4.2.1.2. Experimental task and procedure

Upon arrival in the laboratory, participants were asked to read the information notice and sign the informed consent form. Once informed consent was obtained, participants received task instructions. First, participants were given the following illness description:

> "*Imagine that you have been suffering from chronic pain for the last two years. Every day, you feel pain throughout your body. This chronic pain has had a considerable impact on your life. At times, you are unable to work, eat properly, take part in physical activity, or enjoy life. Without treatment, your condition will never improve."*

They were asked to take a moment and imagine as vividly as possible what their life would be like under these conditions. Following this, they were introduced to the cue-exposure paradigm. They were informed that there was a medication that could cure their chronic pain, but it entailed a side effect. During the task, they would be presented with side effects across two different conditions: (i) a side effect and (ii) a remission condition. In the side effect condition, participants were instructed to project as vividly as possible their emotional state in response to having to experience the side effect. In the remission condition, they were asked to

project as vividly as possible their emotional state in response to experiencing remission from their chronic pain despite the indicated side effect. Each condition consisted of three blocks with six trials each. Participants encountered 18 side effects (dry mouth, flatulence, itching, chills, loss of appetite, fatigue, constipation, irritability, weakness, memory loss, hallucinations, depression, speech disorder, shortness of breath, anxiety, hair loss, blurry sight, insomnia) that repeated across conditions. Order of conditions alternated consecutively, and the starting condition was counterbalanced across participants (i.e., if a person started with the side effect condition, the next block would be remission, followed by side effect, etc.). At the onset of each block, participants received a cue indicating which condition they were in (5s). A trial occurred as follows: 1) 1-3s intertrial interval (ITI), 2) stimulus presentation during which they had to engage in affective forecasting (10s), 3) participants gave a rating on the vividness of their projection, the level of anticipated distress, and the level of anticipated relief on a 5-point Likert scale ranging from 1 (not at all vivid/distressed/relieved) to 5 (extremely vivid/distressed/relieved). At the end of the task, participants answered four post-experimental questions: 1) Did you find it difficult to project yourself into these scenarios?, 2) Were you able to switch focus between focusing on the negative (side effect condition) and the positive (remission condition)?, 3) Did you have enough time to visualize each event?, and 4) Across the 36 trials did you project any other feelings/emotion other than distress or relief?

4.2.2. Statistical analyses

We tested whether vividness, distress, and relief ratings differed significantly across conditions using linear mixed effects models, computed in R Studio (R Core Team, 2021) using Bates and colleagues' (2015) lme4 package. We determine whether there are significant differences by testing a full model that includes condition against a null model that does not, using a likelihood ratio test.

4.2.3. Results

Vividness of projection

Average ratings of the vividness of projection were quite high for both side effect (M =4 .13, SD = 0.97) and remission (M = 4.09, SD = 0.95) condition, and did not differ significantly as tested by a linear mixed effects model with vividness rating as the outcome, condition as a fixed effect and subject ID and side effect as random effects (random intercept) ($\chi^2(1)$ = 0.8, p = 0.37).

Emotion ratings

Comparing a model that includes condition as a fixed effect to a null model without condition revealed a significant effect of condition on both anticipated distress ($\chi^2(1)$ = 108.36, $p < 0.001$) and anticipated relief ($\chi^2(1)$ = 198.3, $p < 0.001$). Random effects included random intercepts over subjects and stimuli. Specifically, the estimated beta values indicate that distress ratings are higher in the side effect compared to the remission condition (β = 0.49, se = 0.04) and relief is lower in the side effect compared to the remission condition (β = -0.66, se = 0.05).

Post-experimental questions

A large majority of participants indicated that they did not find it difficult to project their emotions (43 out of 52), were able to switch focus between side effect and remission conditions (43 out of 52), and had enough time to project their emotions (44 out of 52). The most commonly mentioned emotions other than distress or relief were sadness (mentioned 11 times) and anger (8 times), but relief and distress seemed to capture the anticipated emotions quite well.

4.2.4. Discussion

The purpose of the behavioral validation was to ensure that participants were able to engage in affective forecasting with these hypothetical medical outcomes and that they were able to selectively attend to the positive (remission) or negative (side effect) parts of the

outcome. Overall, the results of the behavioral validation were favorable. Participants were able to engage in affective forecasting, as highlighted by the high ratings of vividness of projection. They also succeeded in focusing their attention on the positive and negative sides of the outcomes, as evidenced through the significant differences in anticipated distress and relief across side effect and remission conditions. As such, we decided to move forward with the fMRI experiment.

4.3. fMRI experiment

4.3.1. Method

The study was preregistered at (https://osf.io/u9qpb).

4.3.1.1. Participants

34 participants were recruited from the UC Louvain campus in Belgium. Participants were healthy volunteers and met the following eligibility requirements: at least 18 years old, no major physical or psychological disorders (including chronic conditions), no shrapnel, electrical, or mechanical implants, and not currently pregnant. Interested participants were pre-screened for eligibility criteria and invited to participate. Imaging took place in October/November 2024 at the Ghent Institute for Functional and Metabolic Imaging on the premises of the Gent University hospital (UZ Gent), Belgium. The study was in accordance with the Declaration of Helsinki and was approved by the ethics review boards of Gent University (ONZ-2023-0663) and the University of Luxembourg (ERP 24-030 MedCast).

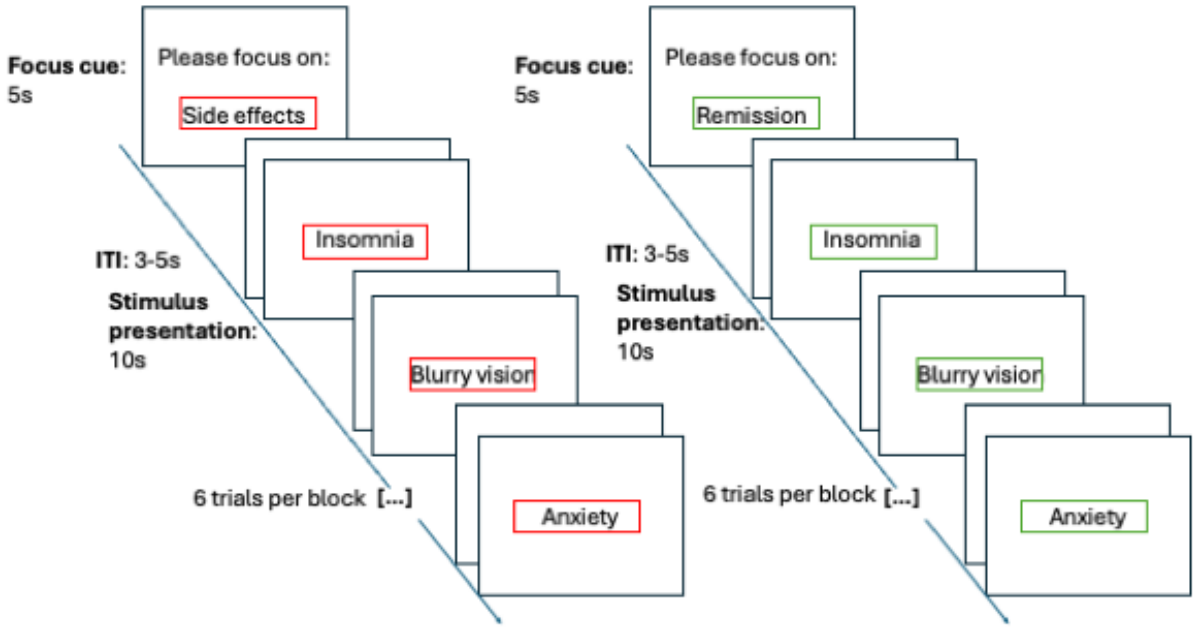
4.3.1.2. Experimental task and MRI procedure

Following informed consent and safety screening procedures, participants were introduced to the experimental task. Figure 11 describes the cue-exposure task performed in the scanner. The task did not differ from the behavioral validation, except that participants did not provide ratings after each stimulus, and the inter-trial interval was adjusted to 3- 5s for design efficiency. Additionally, due to feedback that some of the side effects were perceived as

more severe than chronic pain, we updated the stimulus list to less severely rated side effects, resulting in the following 18 side effects: Dry mouth, flatulence, itching, chills, loss of appetite, fatigue, constipation, irritability, headache, insomnia, confusion, vomitting, shortness of breath, anxiety, hair loss, blurry sight, chest pain, and fever.

Figure 11.

Cue-exposure task



Note. Depicted is the procedure for a block of the 'side effect' condition and the 'remission' condition. To help participants remember the condition throughout the blocks, stimuli are framed in red for side effect and green for remission conditions.

4.3.1.3. Post-task questionnaires

After the experimental task, participants were asked to complete three rating scales and a questionnaire. The three ratings scales asked participants to provide 1) a rating of how distressing they would find each side effect on a scale from 1 (not at all distressing) – 5 (extremely distressing), 2) how familiar (i.e., previous experience) they are with each side effect on a scale from 1 (not at all familiar) – 5 (extremely familiar), and 3) How vivid on average their projection for side effect and remission condition was on a scale from 1 (not at all vivid) – 5 (extremely vivid). Finally, participants filled out the RAND-36 questionnaire,

which measures participants' global physical and mental health, to ensure that participants do not vary considerably in their current health states. Tables S6 and S7 in the supplementary materials show the descriptives of the rating scales.

4.3.1.4. Brain imaging data acquisition

The experimental task was implemented using Python and PsychoPy on an IBM-compatible computer. Imaging was conducted on a 3T Siemens MAGNETOM Prisma scanner at the Gifmi center, UZ Gent. 176 slice T1-weighted anatomical images were obtained using an MPRAGE sequence (TE = 4.18ms, TR = 2250ms, flip angle = 9°, 1-mm slice thickness). Fieldmaps were acquired using standard Siemens magnetic field maps using a multi-echo gradient echo acquisition (TR = 588ms, TE 1 = 4.92ms, TE 2 = 7.38ms, flip angle = 60°). Finally, the fMRI scan used a z-shim gradient echo EPI sequence (TE= 31ms, TR=1070ms, flip angle = 52°, voxel size = 2.5×2.5×2.5mm^3).

4.3.1.5. Preprocessing of imaging data

Image preprocessing steps included: motion correction, distortion correction, co-registration, normalization, and spatial smoothing. All steps were implemented in the fMRI Expert Analysis Tool (version 6.0, part of the FSL package, FMRIB software library). Motion correction was implemented using FSL's MCFLIRT algorithm, which uses a linear interpolation, designating the middle volume as the initial template. All participants demonstrated less than 1.0mm of absolute or relative motion; as such, no participants were excluded. Data was then temporally high-pass filtered. Geometric distortions caused by magnetic field inhomogeneities were corrected using the acquired field maps. To do so, the first magnitude image was brain extracted using FSL's bet2 algorithm, and the edges were then further eroded using the -ero function. We then used the fsl_prepare_fieldmaps function to transform the units of the phase difference image into radians per second. FSL's BBR registration was used to co-register the anatomical and functional images using the information

from the field maps to correct for geometric distortions. Normalization into MNI space was performed using FSL's FNIRT algorithm to perform a non-linear transformation. Finally, images were spatially smoothed using a 5-mm FWHM Gaussian kernel.

4.3.2. Statistical Analyses

4.3.2.1. Whole-brain univariate analysis

To compare blood-oxygen-level-dependent (BOLD) activity during side effect and remission conditions, we implemented a general linear model in FSL with the following explanatory variables (EVs): onsets for side effect trials (EV1), onsets for remission trials (EV2), parametric modulation (PM) assessing familiarity for side effect trials (EV3), PM assessing familiarity for remission trials (EV4), PM assessing affective evaluation of side effect for side effect trials (EV5), PM assessing affective evaluation of side effect for remission trials (EV6). We included six standard motion parameters as nuisance regressors. For group-level analyses, we performed a mixed-effects analysis using FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < 0.05$ with family-wise error (FWE) correction for multiple comparisons across the whole brain.

4.3.2.2. Multivariate analysis

We further conducted an exploratory multivariate intersubject pattern analysis using a whole-brain searchlight approach (Wang et al., 2020). Beta values for EV1 (side effect trials) and EV2 (remission trials) were extracted from the univariate whole-brain GLM analysis. We then implemented a leave-one-subject-out cross-validation schema using Nilearn (Python v.3.9.20). Using a logistic regression as a classifying algorithm, all subjects but one were used as a training set, with the one left out participant left as the test set. This was repeated until we had a single-fold accuracy map for every participant. To get a final accuracy map, we used $n = 1000$ non-parametric permutations with correction for multiple comparisons at an FWE threshold of $p < 0.05$ in SnPM (v13.1.09).

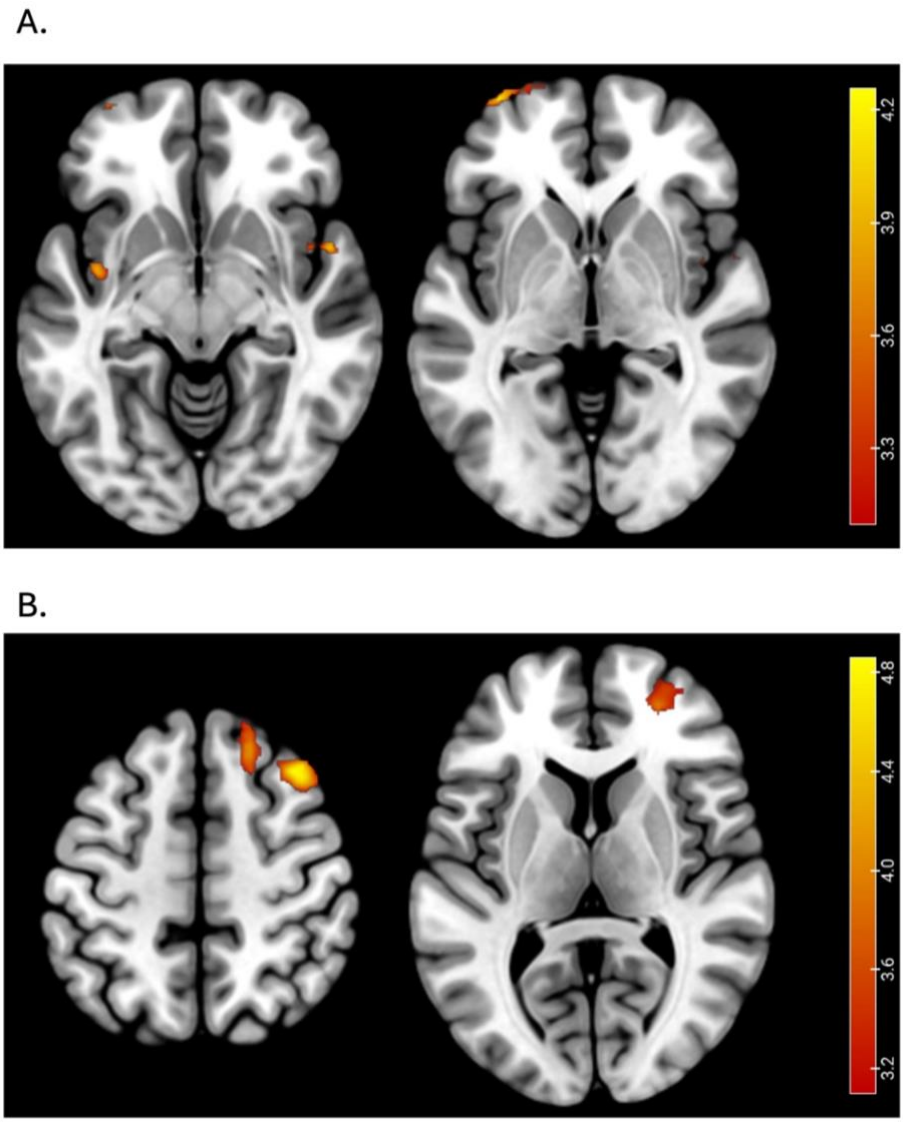
4.3.3. Results

4.3.3.1. Univariate analyses

Side effect vs. remission conditions. Activations for this contrast are shown in Figure 12A, and Table S8 with all clusters and subclusters can be found in the supplementary materials. For the "side effect minus remission" contrast, we see three clusters of activations. The first (cluster size = 209) has its peak of activation in the left frontal pole (-36 ,62, -6; z_{max} = 4.32). The second cluster of activation (cluster size = 169) peaks in the right planum polare (50, 6, -8; z_{max} = 4.09) and extends into the temporal pole. The third cluster (cluster size = 119) peaks in the left insular cortex (-40, -2-, 10; z_{max} = 4) and extends into the central opercular cortex and planum polare. The "remission minus side effect" contrast resulted in two clusters of activation, the first of which (cluster size = 492) peaks in the right middle frontal gyrus (36, 25, 52; z_{max} = 4.91) extending into the superior frontal gyrus. The second cluster (cluster size = 283) peaks in the right frontal pole (26, 50, 8; z_{max} = 3.98).

Figure 12.

Univariate whole-brain activation for side effect and remission conditions



Note. Panel A and B show activations for "side effect minus remission" and "remission minus side effect" respectively. These images were thresholded using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain.

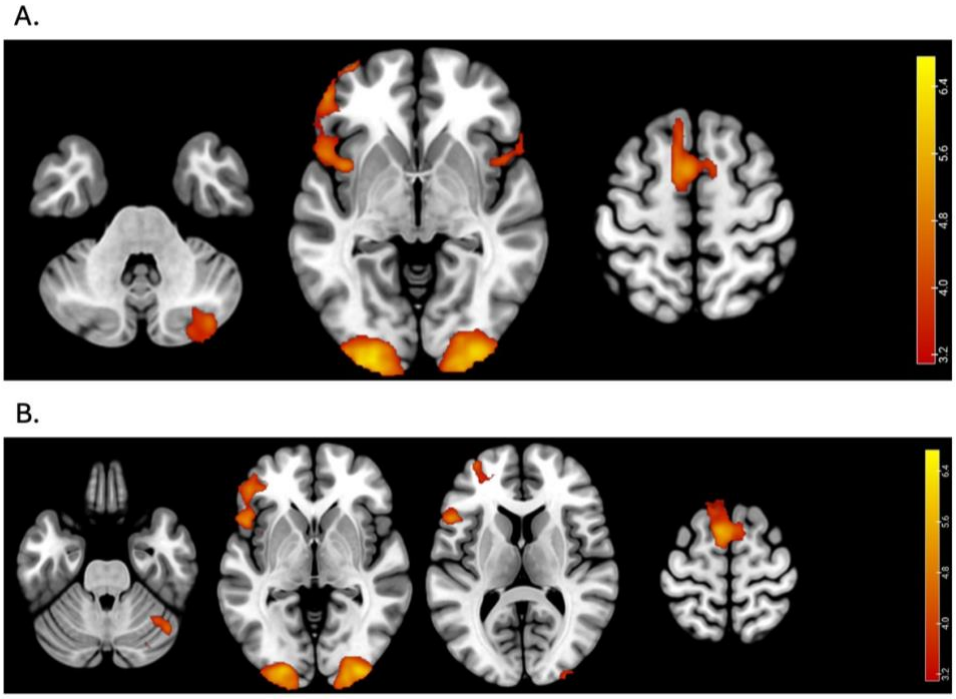
Affective forecasting vs baseline. We found six clusters for the "side effect minus baseline" contrast (see Figure 13A). The first cluster (cluster size = 2068) peaks in the insular cortex (-40, 8, -2, z_{max} = 5.26) and extends into opercular cortices, inferior frontal gyrus, and temporal pole. The second cluster (cluster size = 1742) peaks in the left occipital pole (-24, -98, -8, z_{max} = 6.28) and extends into the inferior lateral occipital cortex. The third cluster (cluster size = 1307) peaks in the left juxtapositional lobule cortex (-4, 6, 58, z_{max} = 5.37) and

extends into the superior frontal gyrus. The fourth cluster (cluster size = 1263) is centered on the right occipital pole (32, -96, - 4, z_{max} = 6.19) and extends into inferior lateral occipital cortex. Cluster five (cluster size = 399) is in the right cerebellum crus I and II (38, -80, -36, z_{max} = 4.74). Finally, the sixth cluster (cluster size = 252) peaks in the central opercular cortex and extends into the insular cortex, inferior frontal gyrus, and frontal and temporal pole (46, 10, 0, z_{max} = 4.92).

For the "remission minus baseline" contrast, we found another seven clusters (see Figure 13B). The first (cluster size = 1642) peaks in the left juxtapositional lobule (-6, 8, 64, z_{max} = 5.68) and extends into the superior frontal gyrus, paracingulate gyrus, and frontal pole. The second cluster (cluster size = 1544) is centered on the left occipital pole (-24, -96, -6, z_{max} = 6.75) and extends into the inferior lateral occipital cortex. The third cluster (cluster size = 1478) peaks in the inferior frontal gyrus (-50, 16, 0, z_{max} = 5.35) and extends into the frontal opercular cortex and frontal pole. The fourth cluster (cluster size = 1184) spans the same regions as the second cluster but in the right hemisphere and also peaks in the occipital pole (32, -94, -2, z_{max} = 6.17). Cluster five (cluster size = 583) spans the left frontal pole (-34, 58, 10, z_{max} = 4.55). The last two clusters are in the right cerebellum, one spanning Crus I (cluster size = 178, 44, -62, -28, z_{max} = 4.61), the other Crus I and II (cluster size = 150, 28, -80, -40, z_{max} = 4.56). A table of activations (Table S9) can be found in the supplementary materials.

Figure 13.

Univariate whole-brain activations for affective forecasting



Note. Panel A shows the contrast for "side effect minus baseline" and Panel B shows "remission minus Baseline". These images were thresholded using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain.

Parametric modulation of familiarity. No significant activation was observed when comparing the PM of familiarity between side effect and remission conditions.

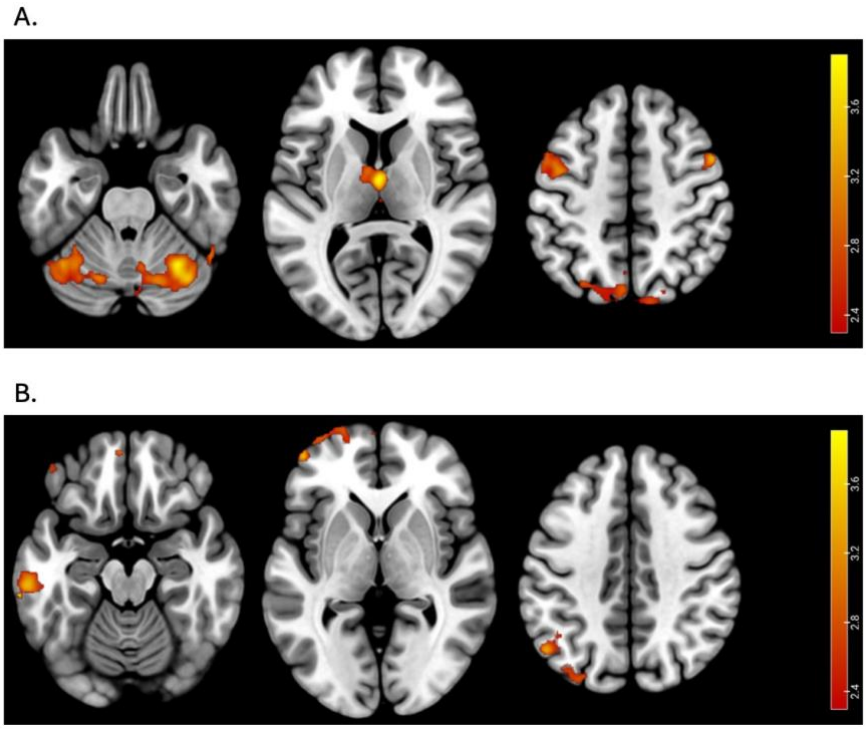
Parametric modulation of emotion. We did not find parametric modulations of emotion at a height threshold of $z > 3.1$. At a more lenient threshold of $z > 2.3$, we did find six clusters in the 'side effect minus remission' condition (see Figure 14A). The first cluster (cluster size = 1608) peaks in the right cerebellum in region VI and extends into right VII and Crus I (30, -60, -26, $z_{max} = 3.92$). The second cluster (cluster size = 1570) peaks in the left superior lateral occipital cortex and extends into the precuneus, cuneal cortex, and occipital pole (-16, -74, 58, $z_{max} = 3.39$). The third cluster (cluster size = 602) peaks in the left cerebellum in region Crus I and extends to left VI (-42, -58, -28, $z_{max} = 3.5$). Cluster four (cluster size = 552) peaks in the left middle frontal gyrus and extends into inferior frontal gyrus, precentral gyrus, and

postcentral gyrus (-40, -2, 62, z_{max} = 3.49). Cluster five (cluster size = 513) spans the left and right thalamus (0, -8, 8, z_{max} = 3.95) and extends into the caudate. Finally, cluster six (cluster size = 443) peaks in the right precentral gyrus and extends into the middle frontal gyrus, superior frontal gyrus, and precentral gyrus (50, 4, 50, z_{max} = 3.53).

We also found three significant clusters of activation in the PM for emotion in the 'remission minus baseline' contrast (see Figure 14B). The first (cluster size = 654) peaks in the left lateral occipital cortex and extends into the angular gyrus (-50, -66, 40, z_{max} = 3.39). Cluster two (cluster size = 606) peaks in the left frontal pole and extends into medial frontal cortex (-46, 52, 0, z_{max} = 3.61). Cluster three (cluster size = 509) peaks in the left middle temporal gyrus and extends into the inferior and superior temporal gyrus (-66, -32, -18, z_{max} = 4.1). A table of activations (Table S10) can be found in the supplementary materials.

Figure 14.

Results for the parametric modulation (PM) of distress



Note. Panel A shows PM for "side effect minus baseline" contrast, and Panel B shows PM for "remission minus baseline" contrast. Results were computed using FSL FLAME 1 with a

height threshold of $z > 2.3$ and a cluster probability of $p < 0.05$, FWE corrected for multiple comparisons across the whole brain.

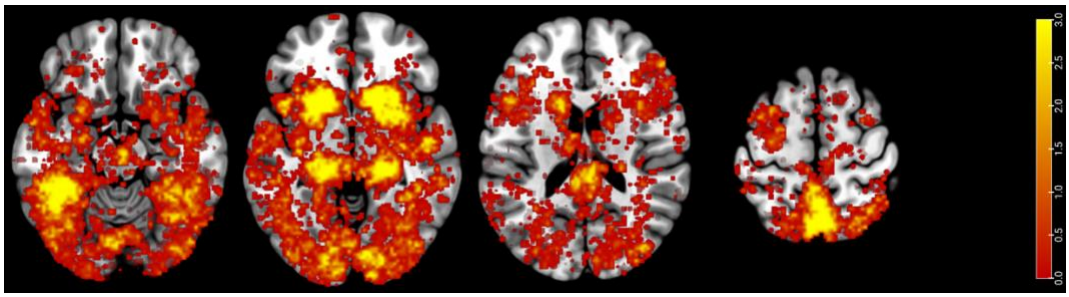
Parametric modulation of vividness. With regards to parametric modulation of the vividness of projection we found one cluster for the parametric weights of the vividness for side effects (cluster size = 121, -56, -26, 24, z_{max} = 4.18) in the 'side effect minus baseline' contrast, which peaks in the supramarginal gyrus, and extends into postcentral gyrus and Central/parietal operculum cortex.

4.3.3.2. Multivariate analysis

The intersubject pattern analysis (ISPA) uncovered a wide network of regions that are able to discriminate between side effect and remission conditions (see Figure 15). Specifically, six clusters were identified. Cluster 1 (cluster size = 1867) peaks in the right thalamus (22,-32,-4) and extends into the right hippocampus, parahippocampal gyrus, and posterior cingulate cortex. The second cluster (cluster size = 3343) peaks (2, -68, 60) in the precuneus cortex and extends into the cuneal cortex, lateral occipital cortex, and postcentral gyrus. Cluster 3 (cluster size = 1279; 3, -20, 18) spans the left putamen and caudate, as well as extending into the left accumbens and amygdala. Cluster 4 (cluster size = 3947; -40, -44, -16) peaks in the left temporal fusiform cortex, temporal occipital fusiform cortex, inferior temporal gyrus, middle temporal gyrus, and extends into the cerebellum. Cluster 5 (cluster size = 755; 26, -66, 6) peaks in the right intracalcarine cortex and extends into the occipital pole and the lingual gyrus. Finally, cluster 6 (cluster size = 1334; 12, 14, -4) peaks in the right caudate, extending into the right putamen and insular cortex as well as frontal orbital cortex.

Figure 15.

Results of the intersubject pattern analysis



Note. Depicted are the clusters of voxels that significantly decoded side effect and remission conditions across participants. They were computed using n=1000 non-parametric permutations with correction for multiple comparisons using an FWE threshold of $p < 0.05$.

4.4. Discussion

The current investigation sought to identify the neural correlates underlying affective forecasting in complex, bivalent medical decision contexts and to determine how attentional deployment influences this process. We extend prior work on affective forecasting by shifting focus from simple, often univalent stimuli (e.g., monetary gains and losses) to more ecologically valid and emotionally complex scenarios.

4.4.1. Selectively anticipating the good and the bad

The contrasts for side effect and remission conditions partially confirmed our hypotheses. Focusing on the positive part of the outcome (i.e., remission) was associated with increased activity in the superior frontal gyrus and the frontal pole. These regions are implicated in both cognitive control and emotion regulation. Notably, the frontal pole has been linked to manipulating representations held in working memory (Kroger & Kim, 2022), managing competing goals (Mansouri et al., 2017), and prospective thought (Okuda et al., 2003). Within our study, its activity may reflect the deliberate maintenance of the emotion regulation goal. Similarly, the superior frontal gyrus (SFG) has been implicated in attentional deployment towards gains in risky choices (Liu et al., 2020, 2017). Liu and colleagues (2017) investigated the role of attentional deployment on reducing regret in risky choice and showed

that the SFG activity increased when participants had to focus on collected gains as opposed to missed chances. This result was interpreted in line with the idea that negative information automatically captures attention (Kahneman & Tversky, 1979; Tom et al., 2007; Vuilleumier & Schwartz, 2001) and that focusing on gains thus requires more effort. Consequently, the prefrontal activations in our study in response to focusing on remission do not seem to reflect generic emotion processing but rather appear to reflect the strategic deployment of attention during the simulation or anticipation of positive emotional outcomes.

Consistent with earlier findings (Kruschwitz et al., 2018) and in line with our hypotheses, directing attention towards the negative part of the outcome (i.e., side effects) engaged the bilateral insula. The insula is a region that is broadly associated with interoception (Critchley et al., 2004; Fermin et al., 2022; Hassanpour et al., 2018; Zaki et al., 2012), emotional processing (Craig, 2009; Duerden et al., 2013; Zaki et al., 2012), and aversive prediction (Liljeholm et al., 2014; Sarinopoulos et al., 2006; Wicker et al., 2003; Wright et al., 2004). Its activation in our study supports the idea that paying attention to the negative part of an outcome when anticipating our future emotional state recruits circuits that simulate embodied emotional states, particularly ones related to aversion or distress. This may particularly be the case when envisioning side effects, as anticipating one's affective state in response to a side effect might entail a simulation or recall of the physical sensations associated with this side effect.

The fact that the frontal pole was active in both side effect and remission conditions further highlights that this region may serve as a valence-independent hub for the integration of emotional and goal-related information, rather than exclusively supporting positive or negative affective anticipation. This interpretation would align with recent models positioning the frontal pole as a key region for emotional set-shifting and emotion regulation (Roelofs et al., 2023).

4.4.2. Multivariate analyses highlight a distributed representational network

The intersubject pattern analysis (ISPA) revealed a broad network of regions capable of differentiating positive and negative forecasting. Consistent with previous work on future prospection of emotional events, these included the posterior cingulate cortex, hippocampus, parahippocampal cortex, and lateral temporal cortices (D'Argembeau et al., 2008; Sharot et al., 2007). These areas are thought to contribute to the construction and contextualization of emotional simulations, drawing on autobiographical memory and spatial processing resources.

Importantly, the fact that reward-sensitive (ventral striatum and orbitofrontal cortex) and emotion-processing regions (amygdala and insula) were included in this network highlights that core circuits for valuation and emotion are differentially engaged depending on the regulatory goal (i.e., focus positive or negative). This bolsters the idea that affective forecasting engages partially distinct neural representations depending on whether the focus is placed on gains or losses.

We further observed contributions from sensorimotor and cerebellar regions, which suggests that affective forecasting involves multisensory integration and embodied simulation. This is particularly intriguing in light of recent literature suggesting that the cerebellum plays a role in emotional and cognitive processing (Baumann & Mattingley, 2022; Ciapponi et al., 2023; Van Overwalle, 2024).

4.4.3. Frontal activity reflects forecasting complexity

Compared to previous research on affective forecasting using simple gains and losses, our task elicited more anterior frontal activations, including the robust engagement of the frontopolar cortex across conditions. We interpret this to be reflective of the cognitive and emotional complexity inherent to the task. Forecasting, in the context of medical trade-offs, requires the participants to handle emotionally conflicting information, sustain task-relevant attentional goals, and simulate their future affective state, all of which place demands on high-

order cognitive systems. Additionally, while care should be taken in interpreting parametric modulation results at a more lenient threshold, the parametric modulation of distress ratings in the remission condition highlighted increased frontopolar activity for increasing distress ratings, suggesting that as side effects become more aversive it becomes more effortful to maintain the focus on the positive part of the outcome. This would be in line with the negativity bias often observed in the literature, by which negative affect tends to attract attention through its motivational salience in signaling threat.

4.4.4. Limitations and future directions

Our study has some limitations. Firstly, the moderate sample size reduced our statistical power for detecting more subtle modulations of neural activity, such as parametric effects of familiarity. Furthermore, while our focus was purely on anticipation, our use of hypothetical scenarios in which participants do not experience the actual outcomes limits the interpretability of the results to real-world medical decision-making. It would be essential for future work to investigate these processes in patient populations who have to deliberate on treatment options. Furthermore, given that we used a healthy student sample, caution is warranted when generalizing to older populations who may have more experience with health problems or to individuals with chronic conditions. Additionally, we did not have hypotheses regarding the parametric modulation of distress and vividness, and as such, results should be replicated with stimulus sets that systematically vary these variables, allowing for a more fine-grained and informed investigation of these modulations. For instance, results from the parametric modulation of distress highlight a negativity bias, suggesting that maintaining focus on the positive is more effortful the higher the anticipated distress. This result would need to be further validated in a larger sample.

4.4.5. Conclusion

Our findings demonstrate that attentional deployment modulates the neural activity related to affective forecasting in response to emotionally bivalent and medically relevant scenarios. We support prior work showing the selective engagement of the insula for the anticipation of negative events. The superior frontal gyrus, on the other hand, was involved in the anticipation of positive events. We find the frontal pole to be central to strategically regulating attention during emotionally complex prospection. Furthermore, multivariate results suggest a large and distributed network supports differential representations of gain and loss anticipation, spanning emotion, valuation, memory, and sensory integration systems. Our results underscore the neural complexity that underpins our ability to forecast future feelings, particularly when there are important emotional trade-offs and outcomes are consequential.

4.5. References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

Baumann, O., & Mattingley, J. B. (2022). Cerebellum and emotion processing. *Advances in Experimental Medicine and Biology*, *1378*, 25–39. https://doi.org/10.1007/978-3-030-99550-8_3

Bosch, G. J. V. D., Roos, R. A. N., Otten, R., Bockting, C., & Smulders, Y. M. (2021). Are patients accurate forecasters of their emotional response to medical conditions? A scoping review on affective forecasting. *BMJ Open*, *11*(12), e053370. https://doi.org/10.1136/bmjopen-2021-053370

Bray, S., Shimojo, S., & O'Doherty, J. P. (2010). Human medial orbitofrontal Ccrtex is recruited during experience of imagined and real rewards. *Journal of Neurophysiology*, *103*(5), 2506–2512. https://doi.org/10.1152/jn.01030.2009

Craig, D. A. (2009). How do you feel — now? The anterior insula and human awareness. *Nature Reviews Neuroscience*, *10*(1), 59–70. https://doi.org/10.1038/nrn2555

Ciapponi, C., Li, Y., Osorio Becerra, D. A., Rodarie, D., Casellato, C., Mapelli, L., & D'Angelo, E. (2023). Variations on the theme: Focus on cerebellum and emotional processing. *Frontiers in Systems Neuroscience*, *17*. https://doi.org/10.3389/fnsys.2023.1185752

Critchley, H. D., Wiens, S., Rotshtein, P., Öhman, A., & Dolan, R. J. (2004). Neural systems supporting interoceptive awareness. *Nature Neuroscience*, *7*(2), 189–195. https://doi.org/10.1038/nn1176

D'Argembeau, A., Xue, G., Lu, Z.-L., Van Der Linden, M., & Bechara, A. (2008). Neural correlates of envisioning emotional events in the near and far future. *NeuroImage*, *40*(1), 398–407. https://doi.org/10.1016/j.neuroimage.2007.11.025

Duerden, E. G., Arsalidou, M., Lee, M., & Taylor, M. J. (2013). Lateralization of affective processing in the insula. *NeuroImage*, *78*, 159–175. https://doi.org/10.1016/j.neuroimage.2013.04.014

Fermin, A. S. R., Friston, K., & Yamawaki, S. (2022). An insula hierarchical network architecture for active interoceptive inference. *Royal Society Open Science*, *9*(6), 220226. https://doi.org/10.1098/rsos.220226

Gilbert, D. T., & Wilson, T. D. (2009). Why the brain talks to itself: Sources of error in emotional prediction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1521), 1335–1341. https://doi.org/10.1098/rstb.2008.0305

Greenberg, T., Carlson, J. M., Rubin, D., Cha, J., & Mujica-Parodi, L. (2015). Anticipation of high arousal aversive and positive movie clips engages common and distinct neural substrates. *Social Cognitive and Affective Neuroscience*, *10*(4), 605–611. https://doi.org/10.1093/scan/nsu091

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271

Hassanpour, M. S., Simmons, W. K., Feinstein, J. S., Luo, Q., Lapidus, R. C., Bodurka, J., Paulus, M. P., & Khalsa, S. S. (2018). The insular cortex dynamically maps changes in cardiorespiratory interoception. *Neuropsychopharmacology*, *43*(2), 426–434. https://doi.org/10.1038/npp.2017.154

Hoerger, M., Scherer, L. D., & Fagerlin, A. (2016). Affective forecasting and medication decision making in breast-cancer prevention. *Health Psychology*, *35*(6), 594–603. https://doi.org/10.1037/hea0000324

Holmes, E. A., & Mathews, A. (2010). Mental imagery in emotion and emotional disorders. *Clinical Psychology Review*, *30*(3), 349–362. https://doi.org/10.1016/j.cpr.2010.01.001

Jackson, D. C., Mueller, C. J., Dolski, I., Dalton, K. M., Nitschke, J. B., Urry, H. L., Rosenkranz, M. A., Ryff, C. D., Singer, B. H., & Davidson, R. J. (2003). Now you feel it, now you don't: Frontal brain electrical asymmetry and individual differences in emotion regulation. *Psychological Science*, *14*(6), 612–617. https://doi.org/10.1046/j.0956-7976.2003.psci_1473.x

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Knutson, B., & Greer, S. M. (2008). Anticipatory affect: Neural correlates and consequences for choice. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1511), 3771–3786. https://doi.org/10.1098/rstb.2008.0155

Kroger, J., & Kim, C. (2022). Frontopolar cortex specializes for manipulation of structured information. *Frontiers in Systems Neuroscience*, *16*, 788395. https://doi.org/10.3389/fnsys.2022.788395

Kruschwitz, J. D., Waller, L., List, D., Wisniewski, D., Ludwig, V. U., Korb, F., Wolfensteller, U., Goschke, T., & Walter, H. (2018). Anticipating the good and the bad: A study on the neural correlates of bivalent emotion anticipation and their malleability via attentional deployment. *NeuroImage*, *183*, 553–564. https://doi.org/10.1016/j.neuroimage.2018.08.048

Li, S., Liu, Z., Che, L., Gong, Y., Liu, S., & Guo, X. (2022). The neural mechanisms underlying the modulation of attentional deployment on emotional stability. *Experimental Brain Research*, *240*(6), 1823–1832. https://doi.org/10.1007/s00221-022-06361-3

Liljeholm, M., Dunne, S., & O'Doherty, J. P. (2014). Anterior Insula Activity Reflects the Effects of Intentionality on the Anticipation of Aversive Stimulation. *Journal of Neuroscience*, *34*(34), 11339–11348. https://doi.org/10.1523/JNEUROSCI.1126-14.2014

Liu, Z., Cheng, X., Liu, S., Zhang, Z., Li, S., Li, L., & Guo, X. (2020). Attentional deployment training impacts neural responses to subsequent regret. *International Journal of Psychophysiology*, *157*, 23–31. https://doi.org/10.1016/j.ijpsycho.2020.08.002

Liu, Z., Li, L., Zheng, L., Xu, M., Zhou, F. A., & Guo, X. (2017). Attentional deployment impacts neural response to regret. *Scientific Reports*, *7*(1), 41374. https://doi.org/10.1038/srep41374

Mansouri, F. A., Koechlin, E., Rosa, M. G. P., & Buckley, M. J. (2017). Managing competing goals—A key role for the frontopolar cortex. *Nature Reviews Neuroscience*, *18*(11), 645–657. https://doi.org/10.1038/nrn.2017.111

Mauss, I. B., Bunge, S. A., & Gross, J. J. (2007). Automatic emotion regulation. *Social and Personality Psychology Compass*, *1*(1), 146–167. https://doi.org/10.1111/j.1751-9004.2007.00005.x

Okuda, J., Fujii, T., Ohtake, H., Tsukiura, T., Tanji, K., Suzuki, K., Kawashima, R., Fukuda, H., Itoh, M., & Yamadori, A. (2003). Thinking of the future and past: The roles of the frontal pole and the medial temporal lobes. *NeuroImage*, *19*(4), 1369–1380. https://doi.org/10.1016/S1053-8119(03)00179-4

Peters, E., Lipkus, I., & Diefenbach, M. A. (2006). The Functions of Affect in Health Communications and in the Construction of Health Preferences. *Journal of Communication*, *56*(suppl_1), S140–S162. https://doi.org/10.1111/j.1460-2466.2006.00287.x

R Core Team. (2021). *R: A language and envrionment for statistical computing.* [Computer software]. https://www.R-project.org/

Roelofs, K., Bramson, B., & Toni, I. (2023). A neurocognitive theory of flexible emotion control: The role of the lateral frontal pole in emotion regulation. *Annals of the New York Academy of Sciences*, *1525*(1), 28–40. https://doi.org/10.1111/nyas.15003

Sarinopoulos, I., Dixon, G. E., Short, S. J., Davidson, R. J., & Nitschke, J. B. (2006). Brain mechanisms of expectation associated with insula and amygdala response to aversive taste: Implications for placebo. *Brain, Behavior, and Immunity*, *20*(2), 120–132. https://doi.org/10.1016/j.bbi.2005.11.006

Sasse, L. K., Peters, J., Büchel, C., & Brassen, S. (2015). Effects of prospective thinking on intertemporal choice: The role of familiarity: Future Event Construction and Delay Discounting. *Human Brain Mapping*, *36*(10), 4210–4221. https://doi.org/10.1002/hbm.22912

Sharot, T., Riccardi, A. M., Raio, C. M., & Phelps, E. A. (2007). Neural mechanisms mediating optimism bias. *Nature*, *450*(7166), 102–105. https://doi.org/10.1038/nature06280

Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The Neural basis of loss aversion in decision-making under risk. *Science*, *315*(5811), 515–518. https://doi.org/10.1126/science.1134239

Van Overwalle, F. (2024). Social and emotional learning in the cerebellum. *Nature Reviews Neuroscience*, *25*(12), 776–791. https://doi.org/10.1038/s41583-024-00871-5

Vuilleumier, P., & Schwartz, S. (2001). Beware and be aware: Capture of spatial attention by fear-related stimuli in neglect. *NeuroReport*, *12*(6), 1119.

Wang, Q., Cagna, B., Chaminade, T., & Takerkart, S. (2020). Inter-subject pattern analysis: A straightforward and powerful scheme for group-level MVPA. *NeuroImage*, *204*, 116205. https://doi.org/10.1016/j.neuroimage.2019.116205

Wicker, B., Keysers, C., Plailly, J., Royet, J.-P., Gallese, V., & Rizzolatti, G. (2003). Both of us disgusted in my insula: The common neural basis of seeing and feeling disgust. *Neuron*, *40*(3), 655–664. https://doi.org/10.1016/S0896-6273(03)00679-2

Wright, P., He, G., Shapira, N. A., Goodman, W. K., & Liu, Y. (2004). Disgust and the insula: fMRI responses to pictures of mutilation and contamination. *NeuroReport*, *15*(15), 2347.

Zaki, J., Davis, J. I., & Ochsner, K. N. (2012). Overlapping activity in anterior insula during interoception and emotional experience. *NeuroImage*, *62*(1), 493–499. https://doi.org/10.1016/j.neuroimage.2012.05.012

5. Discussion

The current PhD thesis aimed to advance our understanding of the role of future-oriented affect (i.e., anticipatory and anticipated affect) in decision-making and its interaction with attentional processes. The thesis comprises three experimental studies. Across the first two studies, we investigated the effect of anticipatory affect in decision-making under risk. In the third study, we investigated the neural correlates of anticipated affect and how neural activity is modulated through the strategic focusing of attention on the positive or negative part of an outcome. To address the aims of the thesis, we employed a wide range of methodologies, including computational modeling, psychophysiology, and brain imaging. This allowed for a well-rounded investigation of the impact of future-oriented affect on decision-making. The following sections will review the main results from the three experimental studies, followed by a discussion of the implications of the thesis, as well as its limitations and directions for future research.

5.1. Study 1 & 2 - Anticipatory affect and decision-making under risk

The primary goal of study one was to investigate the psychophysiological markers of affect during decision-making in the affect gap. As a brief reminder, the affect gap describes systematic differences in decision behavior when anticipatory affect is high (affect-rich choice) vs. low (affect-poor choice). A secondary goal of the study was to investigate the sensitivity of the affect gap and psychophysiological measures to different levels of affective engagement and whether there were downstream effects of affect on participants' mood. We found significant differences in affective arousal across affect-rich and -poor choices, as indexed by skin conductance response amplitudes. Higher levels of anticipatory affect led to more risk-averse decisions and the use of simpler, non-compensatory decision-making strategies. This study was the first to provide direct evidence for differences in anticipatory arousal across

affect-rich and affect-poor choices. With regards to the secondary aims of the study, we show that the affect gap is robust to differences in affective engagement and persists even when making decisions for others. Furthermore, anticipatory affect did not translate into modulations of participants' state affect. The results were interpreted in line with the risk-as-feelings (Loewenstein et al., 2001) and affect-as-information (Clore & Storbeck, 2006; Schwarz & Clore, 2007) hypotheses, which center affect as a source of information in decision-making. A vast literature supports the idea that emotional valuations can outweigh cognitive or calculative ones, especially when decisions elicit high anticipatory affect. For instance, emotions are said to take precedence over cognitive evaluations when these clash (Loewenstein et al., 2001), emotional heuristics outperformed cognitive ones in predicting public choice on presidential elections (Wang, 2008), and under high uncertainty, people rely more on emotional processing in decision-making (Faraji-Rad & Pham, 2017).

Study two built on this work by investigating an alternative hypothesis for the effect of anticipatory affect on decision behavior under risk. Concretely, it has been suggested that the processing of affective information consumes cognitive resources (Channon & Baker, 1994; Eysenck, 1998; Kensinger & Corkin, 2003), leaving fewer resources for decision processes, thus resulting in simpler, less effortful decision strategies. To this end, we compared affect-rich and -poor choices of two groups of participants, one group that was asked to take their time to make a decision, and another that was put under time stress, thus taxing their cognitive resources. Our results did not support a cognitive constraint hypothesis. Rather, results support conclusions from the first study and show that the affect gap is robust to the influence of time pressure.

5.2. Study 3 - Anticipated affect: Affective forecasting and its modulation through attentional deployment

The third study aimed to investigate the neural correlates of affective forecasting for complex gains and losses and the modulation of the neural activity through attentional deployment. We show that when participants are instructed to focus on the positive or negative part of a bivalent outcome while engaging in affective forecasting, neural circuits for positive and negative affect are selectively recruited. We further show that the frontal pole is a key region for maintaining the top-down emotion regulation goal (i.e., focus positive/negative). This supports recent frameworks centering the frontal pole as playing an essential role in emotion awareness and regulation (Bramson et al., 2019; Roelofs et al., 2023). Results from the parametric modulation of neural activity through distress ratings of the stimuli indicate that maintaining focus on the positive part of the outcome was more effortful as the distress ratings increased. Meanwhile, focusing on the negative aspect of a stimulus while affective forecasting seems to result in more embodied emotion simulations, as suggested by the bilateral insula activation. Finally, compared with previous research on the neural correlates of affective forecasting with simple gains and losses, such as monetary ones, we see that activity is shifted relatively more anterior, reflecting the increased complexity of the forecasts.

5.3. Attention and future-oriented affect

The first two studies highlight the attention-capturing effect of emotionally salient information (Brown, 2022; Calvo & Nummenmaa, 2016; Compton, 2003; Öhman, 1997; Pessoa & Ungerleider, 2004; Robinson, 1998; Smith et al., 2003). We show that when choices elicit high anticipatory arousal, attention is directed towards the outcomes of a decision, at the expense of attention paid to probability information. This is reflected in the increased use of the affect heuristic in affect-rich choice. The affect heuristic assumes that participants will consider the “goodness” or “badness” of the outcomes and will choose the outcome that elicits

the highest positive emotion or lowest negative emotion (Finucane et al., 2000). Presumably, as a consequence of this attention-capturing effect and its downstream effects on information processing, we also observe increased risk aversion and fewer expected value maximizing choices in affect-rich decisions.

In the third study, we asked participants to apply a type of emotion regulation strategy that involves exogenous attention. In other words, participants had to strategically focus attention to achieve an emotion regulation goal, i.e., focus on positive/negative. We showed that top-down modulation of attention changes the neural circuits that are activated when engaging in affective forecasting. For example, when attention is directed towards the positive part of the outcome, then reward-based neural circuits are recruited. Regardless, we still found evidence for the negativity bias (i.e., negative affect is more salient and captures attention more easily than positive affect), as suggested by the parametric modulation of neural activity in the focus positive condition. With increasing distress ratings for the stimulus, activity in frontal regions, important for top-down processes of regulation and inhibition, increases when having to maintain focus on the positive.

These results highlight how intricately affect and attention are linked. Disentangling their effects can be difficult, and the downstream effects on information processes have important implications for decision behavior.

5.4. Implications

Given that both anticipatory and anticipated affect can modulate information processing, the implications for the findings of this thesis are quite broad. One important implication is that future-oriented affect will impact a person's risk perception. For instance, Slovic and colleagues (2000) have shown that forensic practitioners were more likely to discharge patients when the risk of violent offending was expressed as a frequency rather than a percentage. Authors argue that these alternate formats create different mental images that

change the emotional character of the message, thus resulting in changes in decision behavior. Furthermore, individuals often base their risk evaluations on "gut feelings", with positive gut feelings resulting in an evaluation of high benefit-low risk and negative gut feelings in low benefit-high risk evaluations (Rakow et al., 2015). Results converge on the idea that under affect-rich conditions, what is possible (i.e., the potential outcome) becomes more important than how likely it is (Rottenstreich & Hsee, 2001; Sunstein, 2002). Consequently, effective risk communication becomes essential, especially in contexts such as medical decision-making in which we need to ponder emotionally salient information that can be hard for us to understand. For instance, a person considering different treatment options may neglect an important piece of information, namely, probability. A wealth of research has investigated how to best communicate risk information, and specifically probability information. A recent review on how to present probability information effectively (Bonner et al., 2021) has highlighted four key recommendations:

1) **Standardize format used:** use frequencies or percentages over a set period of time with a clear denominator
2) **Enable unbiased comparison:** choose risk formats that allow for unbiased comparisons between outcomes and interventions
3) **Tailor to patient needs:** address the needs of patients who differ in numeracy by drawing attention to numbers, doing mathematical operations for the reader and using targeted evaluative explanations of the numbers (e.g., "high risk")
4) **Use consistent formats:** Use consistent formats across outcomes and interventions wherever possible.

Such decision aids are generally used to eliminate undue influence of emotions on the decision process and to ensure proper understanding and consideration of all relevant pieces of information. On the flip side, we have approaches that seek to leverage future-oriented affect for positive behavioral change. For instance, anticipatory worry and anticipated regret have received considerable attention in the medical decision-making literature as an effective tool to increase preventive health behaviors such as vaccinations (Chapman & Coups, 2006) and genomic testing (Gillman et al., 2023). Further examples of uses of emotion to "nudge" people in the right direction are the aversive images and warnings we find on cigarette packaging. While such interventions have received support, it is worthwhile to consider the ethical implications of nudging people. For example, it would be inappropriate to use nudging to bias a person's treatment decisions.

A further implication of this research is that decision behavior is highly context-dependent. Researchers should be cautious in generalizing results from studies using relatively simple and limited sets of stimuli. Models of decision behavior should be validated across contexts to ensure that they are robust to influences of emotion, format effects, and context-specific elements.

5.5. Limitations of the thesis and future directions

There are several limitations to consider for this body of work. First, we used healthy student samples from WEIRD (Western, Educated, Industrialized, Rich, and Democratic) countries. We should thus be cautious in generalizing results to other populations. Patient treatment decisions, for instance, are embedded in a particular social and affective context that is hard to simulate in the laboratory. Second, we used hypothetical outcomes for all experiments; as such, care should be taken to replicate results using real outcomes. Third, the experiments on the affect gap have explored two relevant hypotheses for what could be driving the affect gap. This does not exclude that alternative interpretations are possible. For instance,

it is conceivable that it is not just anticipatory affect alone that drives changes in decision behavior in the affect gap. Participants may also use anticipated affect, such as anticipated regret. Thus, regret minimization could be a driver of decision behavior in affect-rich choices. Info box three describes future directions that would address these limitations.

INFO BOX 3: Validation/quality control of findings

- **Improve ecological validity**: validate findings in patient populations, use proxies for social context of medical decisions (e.g., say one of medications is recommended by their doctor, patient treatment testimonials; etc.), include real outcomes
- **Rule out alternate hypotheses**: investigate the role of anticipated affect in the affect gap, e.g., by modeling choices using regret minimization frameworks
- **Replicate**: replicate findings, specifically findings which were not hypothesized a priori, such as the frontopolar activity in Study 3, is it active when using different stimulus sets reflecting complex gains and losses?

5.5.1. Future directions building on current research

Sometimes, the easiest way to find out why a person is behaving the way they are is to ask them. Using a mixed-methods approach, which integrates qualitative methods with quantitative ones, could be a useful avenue for understanding the affect gap. For instance, a think-aloud protocol could be implemented during the choice task for the affect gap paradigm. This would allow to get an insight into participants' decision process during decision making. A further important avenue for future research would be to investigate how to reduce the affect gap. For example, one could use the risk communication guidelines outlined earlier (see *implications*) to present choice alternatives to the participants and see whether the use of visual arrays such as pie charts or population frequency displays would modulate the affect gap.

Building on the results of study three, we could validate the non-hypothesized frontopolar activations by employing stimulus sets that are also embedded in a complex affective context, but differ in the content of prospections. Given the current political and actual climate of the world, seeing whether bivalent political or climate change-related forecasts would result in similar sets of activations. This would clarify the frontal pole's role in maintaining and/or implementing top-down emotion regulation goals when prospecting about complex gains and losses. Lastly, given the importance of affective forecasting for our decisions, researching interventions that can improve affective forecasts becomes crucial. Current directions in the literature involve improving emotional intelligence through emotion education interventions (Ellis et al., 2018; Ferrer et al., 2011), mindfulness interventions (Hong et al., 2016), as well as narrative patient testimonials (Hundal et al., 2024; Shaffer et al., 2016). These show initial promise for improving the accuracy of forecasts. Whether training to improve affective forecasts would modulate its neural signatures remains to be investigated and would allow a better understanding of the mechanisms driving affective forecasts.

5.6. Conclusion

The current PhD thesis examined the role of both anticipatory and anticipated affect in decision-making. The findings of the three experimental studies underscore the significant role of anticipatory emotions, revealing their capacity to shape choices and alter decision-making strategies. Specifically, heightened anticipatory arousal fosters risk-averse behavior and promotes the use of simplified, non-compensatory decision-making approaches. Notably, attention plays a crucial role in moderating the influence of affect, as observed in the modulation of neural circuits associated with affective forecasting through attentional deployment.

This body of work highlights how intricately interwoven affect and cognition are. This challenges dual system views promoting cognition as a purely "rational" and deliberative

process, and emotion as a “hot” process that hijacks cognition. Instead, the work provided in this dissertation supports a more integrated view of affect on cognition. From a behavioral perspective, we show that affect can influence decision-making by drawing attention and prioritizing information, which can in turn lead to a more simplistic approach to decision-making. From a neural perspective, we show that even frontal regions, which are more typically associated with cognitive functions, play a key role in emotion processing and regulation. These results suggest that affective dimensions exert a considerable influence on cognitive and information processes. Our comprehension of decision-making mechanisms is significantly enhanced by acknowledging the significance of emotions, paving the way for novel avenues of investigation and practical implementation in domains such as economics, healthcare, and policy formation.

5.7. References

Bonner, C., Trevena, L. J., Gaissmaier, W., Han, P. K. J., Okan, Y., Ozanne, E., Peters, E., Timmermans, D., & Zikmund-Fisher, B. J. (2021). Current best practice for presenting probabilities in patient decision aids: Fundamental principles. *Medical Decision Making*, *41*(7), 821–833. https://doi.org/10.1177/0272989X21996328

Bramson, B., Folloni, D., Verhagen, L., Hartogsveld, B., Mars, R. B., Toni, I., & Roelofs, K. (2019). *Human lateral Frontal Pole contributes to control over social-emotional action*. https://doi.org/10.1101/584896

Brown, C. R. H. (2022). The prioritisation of motivationally salient stimuli in hemi-spatial neglect may be underpinned by goal-relevance: A meta-analytic review. *Cortex*, *150*, 85–107. https://doi.org/10.1016/j.cortex.2022.03.001

Calvo, M. G., & Nummenmaa, L. (2016). Perceptual and affective mechanisms in facial expression recognition: An integrative review. *Cognition & Emotion*, *30*(6), 1081–1106. https://doi.org/10.1080/02699931.2015.1049124

Channon, S., & Baker, J. (1994). Reasoning strategies in depression: Effects of depressed mood on a syllogism task. *Personality and Individual Differences*, *17*(5), 707–711. https://doi.org/10.1016/0191-8869(94)90148-1

Chapman, G. B., & Coups, E. J. (2006). Emotions and preventive health behavior: Worry, regret, and influenza vaccination. *Health Psychology*, *25*(1), 82–90. https://doi.org/10.1037/0278-6133.25.1.82

Clore, G. L., & Storbeck, J. (2006). Affect as information about liking, efficacy, and importance. In J.Forgas (Ed.), *Affect in social thinking and behavior*. Psychology Press. New York, NY

Compton, R. J. (2003). The interface between emotion and attention: A review of evidence from psychology and neuroscience. *Behavioral and Cognitive Neuroscience Reviews*, *2*(2), 115–129. https://doi.org/10.1177/1534582303002002003

Ellis, E. M., Elwyn, G., Nelson, W. L., Scalia, P., Kobrin, S. C., & Ferrer, R. A. (2018). Interventions to engage affective forecasting in health-related decision making: A meta-analysis. *Annals of Behavioral Medicine*, *52*(2), 157–174. https://doi.org/10.1093/abm/kax024

Eysenck, N. D. M. W. (1998). Working memory capacity in high trait-anxious and repressor groups. *Cognition and Emotion*, *12*(5), 697–713. https://doi.org/10.1080/026999398379501

Faraji-Rad, A., & Pham, M. T. (2017). Uncertainty increases the reliance on affect in decisions. *Journal of Consumer Research*, *44*(1), 1–21. https://doi.org/10.1093/jcr/ucw073

Ferrer, R. A., Fisher, J. D., Buck, R., & Amico, K. R. (2011). Pilot test of an emotional education intervention component for sexual risk reduction. *Health Psychology*, *30*(5), 656–660. https://doi.org/10.1037/a0023438

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, *13*(1), 1–17. https://doi.org/10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S

Gillman, A. S., Iles, I. A., Klein, W. M. P., Biesecker, B. B., Lewis, K. L., Biesecker, L. G., & Ferrer, R. A. (2023). Future-oriented emotions and decisions to receive genomic testing results among U.S. adults of african ancestry. *Annals of Behavioral Medicine*, *57*(5), 418–423. https://doi.org/10.1093/abm/kaac069

Hong, P. Y., Lishner, D. A., Vogels, E. A., & Ebert, A. R. (2016). The effect of a mindfulness practice and dispositional mindfulness on affective forecasting. *Basic and Applied Social Psychology*, *38*(3), 153–165. https://doi.org/10.1080/01973533.2016.1182533

Hundal, K., Dobmeier, C. M., Walter, N., Nabi, R., & Scherr, C. L. (2024). Using emotional flow in patient testimonials to debias affective forecasting in health decision-making. *Communication Monographs*, *91*(1), 102–125. https://doi.org/10.1080/03637751.2023.2252486

Kensinger, E. A., & Corkin, S. (2003). Effect of negative emotional content on working memory and long-term memory. *Emotion*, *3*(4), 378–393. https://doi.org/10.1037/1528-3542.3.4.378

Knutson, B., & Greer, S. M. (2008). Anticipatory affect: Neural correlates and consequences for choice. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1511), 3771–3786. https://doi.org/10.1098/rstb.2008.0155

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Öhman, A. (1997). As fast as the blink of an eye: Evolutionary preparedness for preattentive processing of threat. In *Attention and orienting: Sensory and motivational processes* (pp. 165–184). Lawrence Erlbaum Associates Publishers.

Pessoa, L., & Ungerleider, L. G. (2004). Neuroimaging studies of attention and the processing of emotion-laden stimuli. In *Progress in Brain Research* (Vol. 144, pp. 171–182). Elsevier. https://doi.org/10.1016/S0079-6123(03)14412-3

Peters, E., Lipkus, I., & Diefenbach, M. A. (2006). The functions of affect in health communications and in the construction of health preferences. *Journal of*

Communication, *56*(suppl_1), S140–S162. https://doi.org/10.1111/j.1460-2466.2006.00287.x

Rakow, T., Heard, C. L., & Newell, B. R. (2015). Meeting three challenges in risk communication: Phenomena, numbers, and emotions. *Policy Insights from the Behavioral and Brain Sciences*, *2*(1), 147–156. https://doi.org/10.1177/2372732215601442

Robinson, M. D. (1998). Running from william James' bear: A review of preattentive mechanisms and their contributions to emotional experience. *Cognition and Emotion*, *12*(5), 667–696. https://doi.org/10.1080/026999398379493

Roelofs, K., Bramson, B., & Toni, I. (2023). A neurocognitive theory of flexible emotion control: The role of the lateral frontal pole in emotion regulation. *Annals of the New York Academy of Sciences*, *1525*(1), 28–40. https://doi.org/10.1111/nyas.15003

Rottenstreich, Y., & Hsee, C. K. (2001). Money, kisses, and electric shocks: On the affective psychology of risk. *PSYCHOLOGICAL SCIENCE*, *12*(3), 6.

Schwarz, N., & Clore, G. L. (2007). Feelings and phenomenal experiences. In *Social psychology: Handbook of basic principles, 2nd ed* (pp. 385–407). The Guilford Press.

Shaffer, V. A., Focella, E. S., Scherer, L. D., & Zikmund-Fisher, B. J. (2016). Debiasing affective forecasting errors with targeted, but not representative, experience narratives. *Patient Education and Counseling*, *99*(10), 1611–1619. https://doi.org/10.1016/j.pec.2016.04.004

Slovic, P., Monahan, J., & MacGregor, D. G. (2000). Violence risk assessment and risk communication: The effects of using actual cases, providing instruction, and employing probability versus frequency formats. *Law and Human Behavior*, *24*(3), 271–296. https://doi.org/10.1023/A:1005595519944

Smith, N. K., Cacioppo, J. T., Larsen, J. T., & Chartrand, T. L. (2003). May I have your attention, please: Electrocortical responses to positive and negative stimuli. *Neuropsychologia*, *41*(2), 171–183. https://doi.org/10.1016/S0028-3932(02)00147-1

Sunstein, C. R. (2002). Probability neglect: Emotions, worst cases, and law essay. *Yale Law Journal*, *112*(1), 61–108.

Wang, X. T. (2008). Decision heuristics as predictors of public choice. *Journal of Behavioral Decision Making*, *21*(1), 77–89. https://doi.org/10.1002/bdm.577

6. Appendix

6.1. Other research outputs

6.1.1. Study 4 – Brain mechanisms discriminating enactive mental simulations of running and plogging

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Brain mechanisms discriminating enactive mental simulations of running and plogging

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Abstract

Enactive cognition emphasizes co-constructive roles of humans and their environment in shaping cognitive processes. It is specifically engaged in the mental simulation of behaviors, enhancing the connection between perception and action. Here we investigated the core network of brain regions involved in enactive cognition as applied to mental simulations of physical exercise. We used a neuroimaging paradigm in which participants (N = 103) were required to project themselves running or plogging (running while picking-up litter) along an image-guided naturalistic trail. Using both univariate and multivariate brain imaging analyses, we find that a broad spectrum of brain activation discriminates between the mental simulation of plogging versus running. Critically, we show that self-reported ratings of daily life running engagement and the quality of mental simulation (how well participants were able to imagine themselves running) modulate the brain reactivity to plogging versus running. Finally, we undertook functional connectivity analyses centered on the insular cortex, which is a key region in the dynamic interplay between neurocognitive processes. This analysis revealed increased positive and negative patterns of insular-centered functional connectivity in the plogging condition (as compared to the running condition), thereby confirming the key role of the insular cortex in action simulation involving complex sets of mental mechanisms. Taken together, the present findings provide new insights into the brain networks involved in the enactive mental simulation of physical exercise.

Keywords: brain imaging, fMRI, action simulation, enactive cognition, physical exercise, running, plogging, insular cortex.

Introduction

The seamless merging of perception and action is essential for navigating daily life and engaging effectively with our environment. This dynamic can be understood as a form of "know-how" reflectivity leading to the formation of *enactive cognitions* that allow humans to form a sense of "what" and "when" to reflect on while interacting with their environment (Gallagher, 2005, 2011, 2017). These enactive processes of *action simulation* are crucial for potentializing the execution of actions that are adapted to the constant flow of information from the environment (Araùjo et al., 2006, 2010, 2019; Carvalho et al., 2013; Correia et al., 2012).

Research using functional magnetic resonance imaging (fMRI) has provided key insights into the understanding of action simulation processes. In particular, imagined movement has long been used as a relevant marker for studying the brain mechanisms underlying action simulation. A seminal finding from this literature is that the actual performance of a motor task and its mental simulation share overlapping neural substrates (Gerardin et al., 2000; Jeannerod & Decety, 1995). Meta-analyses of fMRI studies showed that, beyond this mere overlap between actual action and its mental simulation, the latter recruits an extended neural network including fronto-parietal-temporal regions, insular cortex, premotor areas, cingulate cortex, as well as subcortical (putamen, caudate, thalamus, and pallidum) and cerebellar regions (Filgueiras et al., 2018; Hétu et al., 2013). By triggering such an extended network of brain regions, action simulation has been conceptualized as a covert stage of action (i.e., a motor domain that does not involve overt movement) that supports various patterns of self-projection mechanisms, such as motor imagery, action planning, mental navigation, or prospective memory (Buckner & Carroll, 2007; Jeannerod, 2001). Besides, recent advance in neuroimaging research evidenced that this covert stage of action can unfold into different maps of brain networks, which underlie more advanced stages of mind body integration (e.g., the planning and implementation of action mapped by the cingulo-opercular "action-mode"

network; Dosenbach et al., 2024; postural control and action planning by the somato-cognitive action network; Gordon et al., 2023).

Currently, most action simulation fMRI tasks require participants to imagine an action without any external input from the environment (i.e., participants perform the task with their eyes closed and/or without guidance from visual or auditory stimuli; Filgueiras et al., 2018; Hétu et al., 2013). Several fMRI studies have also used conditions involving the observation of an action (video of a dynamic landscape or walking on a path from a first-person perspective; Pellicano et al., 2021; Zhao et al., 2020) or exposure to objects associated with specific overt actions (e.g., pictures of tools; Buchwal et al., 2018). However, while these studies contributed to the identification of the brain mechanisms underlying perceptual processes that are precursors of overt actions, they have not used perceptual conditions that require participants to project themselves into the actual performance of an action guided by external cues, as in everyday human-environment interactions.

Fewer fMRI studies have investigated action simulation by using experimental tasks that mimic life-like interactions. In a seminal paper from Cross and colleagues (2006), a sample of highly skilled dancers were instructed to imagine themselves performing the same dance movements as dancer models featured in a video projected in the scanner's laboratory environment. Participants were also asked to self-assess their ability to perform the dance sequences. Thus, an important distinction between the action simulation paradigm used in Cross et al.'s (2006) study and those typically used in the fMRI literature (including "mirror neuron" studies, which typically require monitoring and interpreting the actions of others; Kilner et al., 2013) is that participants had to imagine an action with external guidance (i.e., the dancers featured in the video), that is, visual stimuli that guided and constrained the motor simulation of the dancer participants. Cross et al. (2006) observed a modulation of brain reactivity (within the inferior parietal lobule and ventral premotor cortex) as a function of the

dancers' self-ratings of their own ability to perform the observed movements, as well as according to their training experience with the dance sequence. Other fMRI studies used comparable fMRI procedures, that is, by asking participants to project themselves into the realization of an action guided by external cues rather than simply imagining themselves performing a movement or to passively observing the movements of others (Conson et al., 2009; Di Nota et al., 2016; Nedelko et al., 2012; Vogt et al., 2013; Vrana et al., 2015; Villiger et al., 2013; Zapparoli et al., 2020). These studies show that action simulation under visual guidance elicits stronger brain activations than conventional "eyes-closed" imagined movement procedure. For example, a recent study by Zapparoli et al. (2020) showed that the addition of a visual cue to guide the mental simulation of walking (in-motion visual stimuli of a path in a park shown from a first-person perspective) increased temporo-occipito-parietal activation, as compared to the simulation of walking with eyes closed (to imagine walking along a path).

Taken together, the findings from these fMRI studies demonstrate that the brain correlates of action simulation are sensitive to visual cues embedded in environmental contexts, here referred to as *enactive action simulation*. However, further research is needed to better understand how the brain mechanisms of action simulation unfold when humans project themselves into bodily states triggered by naturalistic environmental stimuli. Here, we propose that investigating the projected enactment of physical exercise coupled with specific environmental settings has the potential to improve current knowledge of action simulation, as characterized by fMRI tasks aiming to better capture the phenomenological nature of the lived experience (i.e., its "what-it's-likeness"; Abraham, 2016; Makris, 2014; Pace Giannotta, 2021). Specifically, the present study aims to take a step forward in the understanding of the brain mechanisms underlying enactive mental simulation of different types of running behaviors. To

this end, we designed an experimental task that required participants to project themselves onto a naturalistic running trail. We have three main aims.

Our first main aim is to gain insight into how people project themselves onto two types of physical exercise, namely *running* and *plogging*. Plogging refers to the act of running while picking up litter. The term plogging comes up from the contraction of "jogging" and "plocka upp" (i.e., *to collect* in Swedish language). This form of environmentally friendly walking is becoming increasingly popular. For example, the ongoing global spread of plogging activities has led to the first edition of the World Plogging Championship in 2021 (Val Pellice, Piedmont, Italy). At a mechanistic level, the action of plogging requires individuals to identify litter, run towards it, pick it up, place it in a small hand-held litter bag, and then continue running along the trail. We can, therefore, expect plogging to trigger a more complex mental simulation, and thus a different pattern of brain activation than the mere mental simulation of running. This assumption is supported by fMRI studies showing that the activation of the action simulation network is modulated by action type (e.g., imagining performing upper limb versus lower limb movements), modality (e.g., motor representation, body representation, proprioceptive focus), simulation type (e.g., kinesthetic: mental rehearsal of movement control, when one feels one's body and how the movement execution feels, versus visual mental imagery: visualizing the execution of an action), and action complexity (e.g., imagining walking versus walking while talking; for reviews, see Filgueiras et al., 2018; Hétu et al., 2013). We use both univariate and multivariate methods to explore the brain mechanisms underlying running and plogging (see the Methods section for details).

Our second main aim is to examine whether participants' daily engagement in running moderates differences in brain reactivity between running and plogging mental simulations. The internal mechanism for simulating observed actions depends on the individual's motor expertise and familiarity with the actions. For example, athletes have a unique ability to

perceive body kinematics and simulate observed actions in sport sequences that are familiar to them (Aglioti et al., 2008; Cancer et al., 2024; Costa et al., 2023; Robertson et al., 2021; Aglioti et al., 2008; Urgesi et al., 2012). Specifically, levels of expertise in sports and music are associated with decreased brain activation in motor areas during mental simulation (Hund-Georgiadis & von Cramon, 1999, Krings et al., 2000, Lotze et al., 2003; Ross et al., 2003; Zhang et al., 2019; but see Kraeutner et al., 2020), as well as with increased activity in brain areas commonly involved in memory-based processes (parahippocampus; Wei & Luo, 2010). Accordingly, we investigate whether a varying commitment to running would result in either an economization (reduced brain activity) and/or a sensitization (increased brain activity) of the neural pathways activated during the mental simulation of running versus plogging.

Finally, the third aim of this study is to examine patterns of insula-centered functional connectivity in the mental simulation of running and plogging. Due to its involvement in homeostatic control and conscious interoception (Craig, 2002, 2009), the insular cortex constitutes a "gating system" in the dynamic interplay between neurocognitive processes (Droutman et al., 2015a, 2015b; Molnar-Szakacs & Uddin, 2022; Zhao et al., 2023). Particularly, the insula represents the integral hub of the "salience network" in the generation of an appropriate behavioral response to salient stimuli (Menon & Udin, 2010; Seeley, 2019), such as identifying and picking-up litter while plogging. Moreover, fMRI studies have already specified how the insula interacts with other brain regions to regulate physical efforts (for a review, see Brevers et al., 2024). For example, Hilty and colleagues (2011) observed that connectivity between the insula and the primary motor cortex increased from the beginning to the end of a cycling exercise. Here, we go one step further by examining whether insular cortex functional coupling is sensitive to the mental simulation of physical exercise. This research question is tested using psycho-physiological interaction (PPI) analyses, which allow for the identification of functional brain networks (rather than just functional brain activity; Friston et

al., 1997, 2011; O'Reilly et al., 2012) that are specifically associated with the mental simulation of running or plogging behaviors. PPI is examined separately for the right and left insular cortex. Previous research has shown that the right insula plays a more prominent role than the left insula in action simulation, such as the feeling of being involved in a movement (i.e., the sense of agency; e.g., Karnath & Baier, 2010; Scalabrini et al., 2021).

To sum up, the present study aims to advance current knowledge about the brain mechanisms underlying the enactive mental simulation of different types of running exercises, i.e., how people project themselves onto naturalistic visual cues that should provide a vivid sense of life-like individual-environment interactions while plogging or running.

Methods

Participants

One-hundred and four adults participated in this study (62 females, *mean* age = 19.30, *SD* = 1.44, range: 18-26). Participants were first year undergraduate students from UCLouvain Faculty of Psychology (n = 50) and Faculty of Motor Sciences (n = 54). All participants provided written informed consent to the experimental procedure, which was approved by the institutional review boards of Ghent University and the University of Luxembourg. All participants were right-handed, with normal or corrected-to-normal vision. Participants were advised to avoid drinking alcohol 24h prior to participation in the scanning session. Participants received a fixed amount of 45 euros as compensation for participation. All brain imaging sessions (N = 104) occurred in October 2021.

We recruited first-year Bachelor 1 students (excluding second year students who had to repeat their first year) and ran the study in the beginning of the academic year (October) to ensure that participants just arrived on the campus and were not familiar with the running trail depicted in the brain imaging task. Participants were recruited via online advertisements from September 15th to October 15th 2021. The ads asked for individuals (> 18 years old) to

participate in a neuroimaging study on running and plogging behaviors. Interested individuals completed an online survey. All participants were physically healthy according to their answers on an MRI screening form included in the online survey. The online survey was also used to exclude participants who were familiar with the running trail depicted (i.e., Louvain-la-Neuve 10 miles; see also "Experimental task and MRI procedure" section), or who reported having used mood stabilizers, antidepressants, antipsychotics, sleep medications, morphine, cocaine, heroin or cannabis in the past 12 months. The online screening tool also included questions on gender, academic year and type of study.

Experimental task and MRI procedure

We used a cue-exposure task (see **Figure 1**; adapted from Brevers al., 2021) where pictures of a running trail appeared separately on a screen (task length ≈ 11min 50sec). We informed participants to imagine themselves running on a specific trail and that the running route corresponds to the "Louvain-la-Neuve 10 Miles" (i.e., a running event of 16.09 kilometers that occur each year, in March, at Louvain-la-Neuve, Belgium). Due to a technical issue with the MRI head coil, one participant had to be excluded from the study, leaving 103 MRI sessions available for data analyses.

There were two types of blocks: the "running" blocks (see **Figure 1A**) and the "plogging" blocks (see **Figure 1B**). Each block was separated by a 5-sec white screen and consisted of the presentation of 6 pictures. Each block started with an intro cue (3sec) signaling the block type and the section of the trail corresponding to the pictures. For both the "running" and "plogging" blocks, each picture appeared for 5sec and was separated by a jittered delay (blank screen, range: 1.6-3sec). Participants were informed that each picture was taken 200 meters for each other and that each block corresponded to a section of 1.3 kilometers. Accordingly, the block succession strictly followed the chronological order of the Louvain-la-Neuve 10 Miles route. Participants were informed that the task consisted of 6 "running" and 6

"plogging" blocks (36 trials in each condition, 72 trials in total) and that the blocks were presented in an alternating order (i.e., there were no consecutive blocks of the same condition). Moreover, one half the participant (n = 52) started the task with a "plogging" block (i.e., task order 1: the first plogging block corresponded to the first section of 1.3 kilometers of the trail), and the other half (n = 52) with a "running" block (i.e., task order 2: the first running block corresponded to the first section of 1.3 kilometers of the trail). This procedure was implemented so that each section of trail (and corresponding pictures) matched equally the plogging or the running conditions across all participants. All pictures of the running and plogging conditions (for both task order 1 and task order 2) are available at https://osf.io/mvw68/files/osfstorage.

Each picture of the "plogging" blocks depicted a trail route with one piece of litter on it (it appeared in the center left, center, or center right with equal frequency). The pictures of the "running" blocks did not include any litter object. The absence of litter in the running condition was made to avoid participants mixing instructions across conditions and creating overlap between these conditions (e.g., the running condition might have triggered motor inhibitory mechanisms, that is, to avoid picking-up the litter). Participants were made aware of this aspect of the task. In the "running" blocks, when viewing each trail picture, participants were asked to imaging themselves running on the trail depicted in the picture. In the "plogging" blocks, for each cue exposure, participants were asked to imagine themselves running toward the litter, picking it up and putting it in a hand-held small garbage bag, and then continuing to run on the trail. For both the running and plogging conditions, participants were asked to take a first-person visual perspective (i.e., the world is imagined as it is encountered in everyday life, viewing only what would actually lie within participants' own visual field; e.g., Christian et al., 2013). Each block terminated with an slide (6sec) prompting participants to report orally the level of physical effort difficulty they would experience in real life when reaching the specific section of the trail (see **Figure 1**). The orally reported numbers (e.g., saying "three"

for “easy”) were recorded manually by the experimenter. The block-per-block procedure of physical effort ratings was based on resistance training protocols, where participants are typically asked to report their level of physical exertion at specific intervals of the session (e.g., during the last 10 seconds of each minute of a high-intensity interval exercise; Ekkekakis et al, 2011; Frazão et al., 2016). This procedure allowed us to consider individual variability in anticipated perceived exertion in the brain imaging analyses.

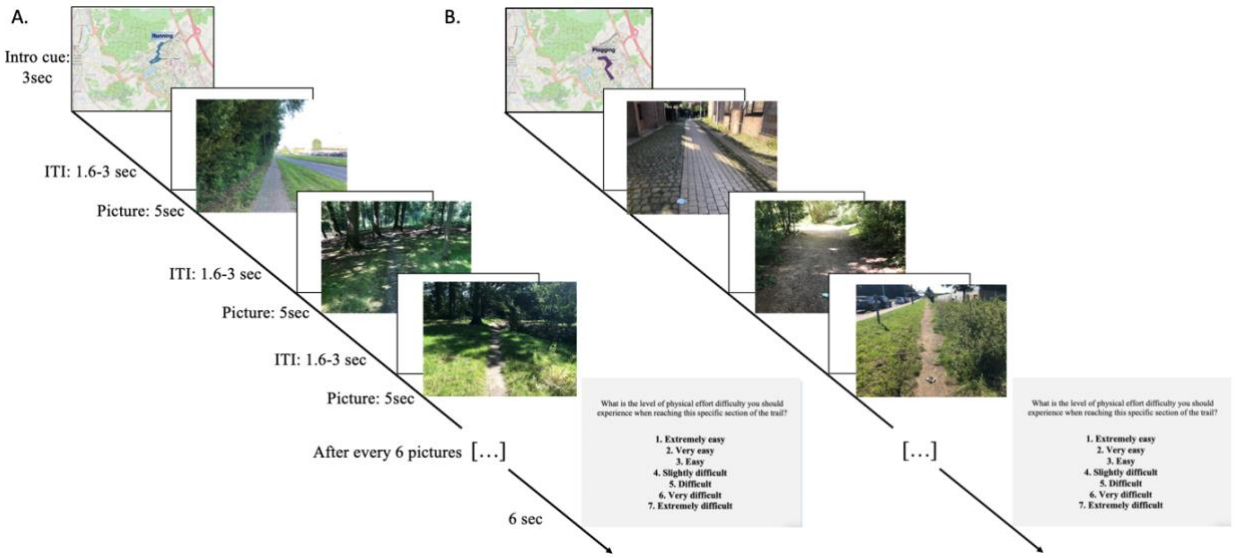

Figure 1. Examples of **(A)** “running” and **(B)** “plogging” pictures used during the brain imaging task. Each block started with an intro cue signaling the block type and the section of the trail corresponding to the pictures. In the “running” condition participants were asked to imagine themselves running on the trail depicted on the picture. In the “plogging” condition participants had to imagine themselves running toward the litter object, picking it up and putting it in a hand-held garbage bag, and then continuing to run on the trail. Each block terminated with an overview slide prompting participants to report orally the level of physical effort difficulty they should experience in real life when reaching the specific section of the trail. ITI, inter-trial interval.

Post-task questionnaires

Directly after the scanning session, participants had to fill-out several self-reported measures. These measures (except the index of plogging experience due to low scores and the lack of data variability, i.e., a floor effect) were used as covariates in the brain imaging analyses. The descriptive statistics of each variable are detailed in **Table 1**.

Quality of mental simulation. Directly after the scanning session, participants had to report (i) how well they were able to imagine themselves running during the running blocks

and (ii) how well they were able to imagine themselves "plogging" during the plogging blocks (5 points Likert scales from very poorly to very well).

Handedness - plogging condition. Participants were then shown three plogging pictures: one with the litter placed on the center left of the trail, one with the litter on the center, and one with the litter placed center right. For each picture, participants had to report which hand they would be more prone to use to pick-up the rubbish. Scores ranged from 0 to 3: a score of 0 indicates that the participant responded "left hand" to all three pictures, a score of 3 indicates that the participant responded "right hand" to all three pictures, and a score of 1 is majority left and 2 majority right.

Index of engagement toward running. Based on previous empirical and conceptual work on the psychological processes involved in the initiation and maintenance of health-related behaviors (Galla & Duckworth, 2015; Radel et al., 2017), we created a four-items index of behavioral engagement toward running behaviors. Specifically, participants had to estimate the degree of habit *("For me, going for a run is a habit"*), enjoyment (*"I enjoy going for a run"*), willpower (*"It takes me willpower to go running"*) and importance (*"To go running is important for me"*) associated with the action of going running in their daily life. Response options ranged from "not at all" (1) to "extremely" (5). Internal consistency between the four items (with the "willpower" item reverse scored) was high (Cronbach's $\alpha = .84$). Accordingly, we computed an aggregate score, with a higher score indicative of a higher engagement toward running.

Previous experience with plogging. We asked participants to indicate whether they already undertook a plogging session in their life (i.e., running while picking-up litter and by handling a garbage bag; response options: never = 0, once = 1, multiple times = 2).

Table 1. Descriptive statistics on post-task questionnaires.

	Mean	*Standard deviation*	*Range*	*Ratio*
Quality of mental simulation				
Plogging condition	3.82	0.68	2-5	/
Running condition	4.04	0.66	2-5	/
Handedness – number of right-hand versus left hand litter pick-up in the plogging condition				
Litter placed on the center left of the trail	/	/	/	50/53
Litter placed on the center of the trail	/	/	/	86/17
Litter placed on the center right of the trail	/	/	/	102/1
Total (0/1/2/3)	2.37	0.70	1-3	0/12/39/52
Running engagement				
Importance	2.89	1.05	1-5	/
Enjoyment	3.03	1.04	1-5	/
Habit	2.47	1.11	1-5	/
Willpower (reverse scored)	2.95	1.03	1-5	/
Aggregated score	2.84	0.87	1-5	/
Previous experience with plogging (0,1,2)	0.21	0.52	0-2	86/12/5

Brain imaging data acquisition

Cue presentation was implemented using Python 2.7.16 and Pygame 1.9.3 on an IBM compatible PC. fMRI imaging was conducted with a 3T Siemens MAGNETOM Prisma scanner at the GIfMI Center, UZ Ghent, Ghent University. Functional scanning used a z-shim gradient echo EPI sequence with PACE (prospective acquisition correction). This sequence was designed to reduce signal loss in the prefrontal and orbitofrontal areas. The PACE option helps to reduce the impact of head motion during data acquisition. The parameters were: TR = 1720ms; TE = 27ms; flip angle = 66°. Fifty-two 2.5mm axial slices were used to cover the whole cerebral cortex and most of the cerebellum without a gap. The slices were tilted approximately 30 degrees clockwise along the AC-PC plane to improve the signal-to-noise ratio. A 176-slice MPRAGE structural sequence was also acquired (1mm slice thickness; TI = 900ms; TR = 2250ms; TE = 4.18ms; flip angle 9°). Prior to the EPI sequence, standard Siemens magnetic field maps were collected with the same slice prescription as the functional scans using a multi-echo gradient echo acquisition (Effective EPI echo spacing = 0.52ms, EPI TE = 27ms, % signal loss threshold = 10). These field maps were used for correction of geometric

distortions in the EPI data caused by magnetic field inhomogeneity.

Image Preprocessing

Image pre-processing was carried out using the fMRI Expert Analysis Tool (version 6.00, part of the FSL package, FMRIB software library, version 5.0.9, www.fmrib.ox.ac.uk/fsl). The first three sets of each participant's functional data were discarded to allow the MR signal to reach a steady state. Functional data for each participant were motion-corrected using rigid-body registration, implemented in the FMRIB Software Library (FSL)'s linear registration tool, MCFLIRT (Jenkinson et al., 2002). All participants demonstrated less than 1.0mm of either absolute or relative motion, so no participant was excluded from the analyses. After motion correction and temporal high-pass filtering, each time series for geometric distortions caused by magnetic field inhomogeneity was corrected using field maps (Andersson et al., 2007a; Jenkinson et al., 2001). Data were spatially smoothed using a 5-mm full-width-half-maximum (FWHM) Gaussian kernel. The data were filtered in the temporal domain using a non-linear high pass filter with a 90sec cut-off (estimated using FSL's FMRI Export Analysis Tool, FEAT). A two-step registration procedure was used where EPI images were first co-registered to the MPRAGE structural image, and warped to standard (MNI) space, using FLIRT (Jenkinson et al., 2002; Jenkinson & Smith, 2002). Registration of MPRAGE structural image to MNI standard space was then further refined using FNIRT nonlinear registration (Andersson et al., 2007a, 2007b). Statistical analyses were performed in the native image space, with the statistical maps normalized to the standard space prior to higher-level analysis.

Behavioral analyses

Scores of physical efforts according to trail sections and physical exercise conditions.

We aimed to examine how the scores of physical effort (i.e., obtained during the overview slide that prompted participants to report the level of physical effort they should experience when reaching the specific section of the trail) varied according to block types (running vs. plogging),

and trail sections (1, 2, 3, 4, 5, and 6), while covarying for quality of mental imagery toward the plogging and running and of the index of engagement toward running. To do so, we ran linear mixed models (LMM) using the lme4 package (Bates et al., 2015) on Jamovi (Version 2.3.21.0). Significance was calculated using the lmerTest package (Kunzetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate *p*-values for mixed models. The model was run with the fixed effect of *bloc types*, *trail section*s, *quality of mental imagery toward plogging*, *quality of mental imagery toward running*, and *engagement toward running* with fixed slope:

*physical effort ~ 1 + bloc types + trail section*s *+ quality of mental imagery_plogging + quality of mental imagery_running + engagement_running +(1|participants)*

Associations between physical effort, quality of mental simulation, and engagement toward running. Bayes Factor Inference on Pairwise Correlations (using Pearson correlation coefficients *r,* JZS Bayes factor with default SPSS 27.0.0.0 priors and criteria) were run to examine the association between aggregated scores of physical effort toward the running (i.e., for each participant, we calculated a mean score across the 6 blocks of the running condition) and plogging (i.e., mean score across the 6 blocks of the plogging condition), quality of mental simulation toward plogging, quality of mental imagery toward running, and the index of engagement toward running.

Brain imaging analyses

In the present study, we used both univariate and multivariate methods to explore the brain mechanisms underlying running and plogging. The univariate approach evaluates the engagement of brain regions specific to an experimental condition (Friston et al., 1994, 1995). Thus, univariate analyses were used to examine the average brain activation compared across the experimental conditions (running versus plogging). We also performed univariate parametric contrasts to examine whether brain activation between running and plogging was

modulated by the level of physical effort that participants expected to experience on different sections of the running trail. Indeed, studies have shown that increases in subjective (e.g., ratings of perceived exertion, RPE) and objective (e.g., cardiovascular responses) markers of physical effort can occur during imagined physical exercise, that is, under conditions that do not elicit muscle afferent input (Abbiss et al., 2015; Williamson et al., 2001, 2002, 2006). Furthermore, because plogging requires carrying a garbage bag and squatting/bending one leg to pick up litter up from the ground, it can also be considered as a more strenuous form of running activity (e.g., Raghavan et al., 2022). In this context, the present study also aimed to investigate how predicted levels of physical effort modulate brain reactivity to the mental simulation between two types of running behaviors that differ in their default levels of physical effort (i.e., plogging > running).

In contrast to the univariate approach, multivariate pattern analyses allow for the investigation of distributed encoding of task-relevant information, even in the absence of mean activation (Mur et al., 2009). Specifically, whereas the univariate approach quantifies activation levels in local brain regions by the spatial extent of these signal changes (i.e., univariate voxel-wise changes; Friston et al., 1994, 1995), multivariate pattern analysis relies on activity patterns from multiple voxels and is sensitive to signal variability within spheres that roughly correspond to the local regions in the univariate analysis (Kriegeskorte et al., 2006; Jiruma & Poldrack, 2012). Therefore, multivariate analysis provides better specificity and sensitivity than univariate analysis, as it allows us to observe distributed response patterns, which can help inform how cognitive representations are encoded in the brain (Coutanche et al., 2013; Haynes, 2015; Weaverdyck et al., 2020). Univariate and multivariate methods are thus complementary and their combination can provide information about basic processing operations as well as on the dynamic representational content of a given cognitive function (Jimura & Poldrack, 2012; Yang et al., 2023).

Univariate brain imaging analyses. We compared blood-oxygen-level-dependent (BOLD) activity during the onset of "running" and "plogging" pictures (5ec). To this aim, the brain imaging data were modelled using event-related general linear model (GLM) within FSL's Improved Linear Model (FILM) module. First-level statistical analysis included the following explanatory variables (EV): EV1: onsets of the running trials, EV2: parametric modulation (PM) assessing physical effort for running trials, EV3: onsets of plogging trials, EV4: PM assessing physical effort for plogging trials; EV5 (of no-interest): overview slides (i.e., onset with duration of 6sec at the end of each block), leaving ITI as implicit baseline. Moreover, nuisance regressors in the form of first-order temporal derivatives of all event types and 24 motion regressors (six motion parameters, the derivatives of these motion parameters, the squares of the motion parameters, and the squares of the derivatives; comprising FSL's standard extended set of motion parameters) were added to the model. In order to examine individual variability in anticipated perceived exertion, we computed the PM regressors by mean centering the score of physical effort obtained in the end of each block (mean centering was undertaken separately for the running and the plogging blocks). The event onsets were convolved with canonical hemodynamic response function (HRF; double gamma) to generate regressors used in the GLM. For each participant, we computed the following contrasts: (i) running (EV1) minus plogging (EV3), (ii) plogging (EV3) minus running (EV1), (iii) PM running (EV2) minus PM plogging (EV4), (iv) PM plogging (EV4) minus PM running (EV2). These contrasts were then included into a random-effects model for group analysis across all of the participants. Importantly, 5 participants reported the same level of physical effort throughout the task, which made the PM contrasts unavailable for analyses (i.e., all values of the mean centered PM regressors were equal to 0). These 5 participants were thus excluded from this GLM analysis. Group analyses (n = 98) were performed using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple

comparisons across the whole brain.

Multivariate brain imaging analyses. Using a whole-brain searchlight approach (4mm radius), we ran an inter-subject pattern analysis (ISPA; Wang et al., 2020) to evaluate group-level multivariate effects (N = 103). Beta values for each condition, extracted from a GLM containing the following EV: EV1: onsets of running trials, EV2: onsets of plogging trials, EV3 (of no interest): 6-motion parameters, were used as input for the decoding algorithm. We implemented a leave-one-subject-out cross validation measure in the CoSMoMVPA toolbox v.1.1.0 (Osterhof et al., 2016), in which a linear support vector machine (SVM) algorithm was trained on the data of all subjects but one and then tested on the left-out participant. In this way each participant served as the test set once. We extracted the single-fold accuracy maps for n = 1000 non-parametric permutation testing with correction for multiple comparison using a FWE, $p < .05$ threshold in SnPM v.13.1.09 (Holmes et al., 2018), resulting in a group-level map of brain regions which decoded plogging from running conditions significantly better than chance.

Psychophysiological interaction (PPI). These analyses were performed on the contrast "plogging minus running", as it is the only contrast that triggered insular activation (see **Figure 2**). Since the PPI analyses did not involve the PM contrasts, these analyses were undertaken with a total of 103 participants (i.e., by including the 5 participants that were excluded from the GLM with PM regressors). We created left and right insular seed regressors by computing individual average time series using an insular seed mask obtained from Chang et al. (2013; see **Figure 2**). The insular seed masks were first transformed into individual space using FLIRT. Next, the time-course of each seed was extracted. For each subject, a first-level PPI model was set up using FSL including the following user-specified regressors: (1) the time course of the seed region; (2) the parametric regressor coding for the task contrasts and (3) the regressor coding interaction term, i.e. the positive and negative multiplications of time course

and the task contrast. Single-subject contrast images for each of these regressors were created. Each subject's PPI contrast image for the interaction regressor was then entered into a second-level random-effect analysis to test for group effects. The group analyses were performed using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain.

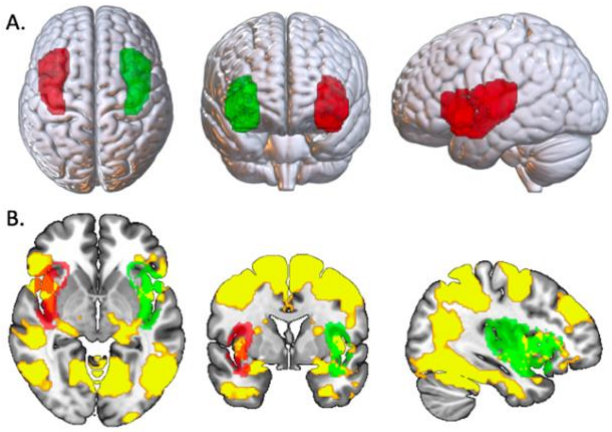

Figure 2. (A) The right (red) and left (green) insular seed masks used for the PPI analyses. **(B)** Overlap between the insular seeds and pattern of brain activation (yellow) obtained on the "plogging minus running" contrast (x = -36, y = 0, z = -4). Left on right.

Results

Behavioral findings

Scores of physical efforts according to trail section and physical exercise condition.

We built our multilevel model by adopting the following two-step sequence:

Step 1 (null model). We first ran the null model by including participants as a cluster variable with random effect, and *physical effort* as the dependent variable with the following model specification: *physical effort ~ + (1|participants) Step 1 (null model).* This first step in the model indicated an Intraclass Correlation Coefficient (ICC) of .31, which means that differences across participants account for about 31% of the variability in individuals' reported level of physical effort. As shown in **Table 2**, the intercept variance is .31 and the within-participant variance is 0.67. In short, results provide evidence for a nested data

structure that requires multilevel modeling rather than a single-level data analytic approach. Specifically, an ICC, even as small as .10 (Kahn, 2011), suggests that participants (Level 2 variable) explain the heterogeneity of physical effort scores. ICC value near zero suggests that a model including Level 1 variables only is appropriate, and, hence, there may be no need to use multilevel modeling (a simpler OLS regression approach may be more parsimonious).

Step 2: As a second step in the model-building process, we added the fixed effect of *bloc types*, *trail section*s, *quality of mental imagery toward plogging*, *quality of mental imagery toward running*, and *engagement toward running* with fixed slope: *physical effort ~ 1 + bloc types + trail section*s *+ quality of mental imagery_plogging + quality of mental imagery_running + engagement_running +(1|participants)*. Hence, this second step involved testing a model with random intercept and fixed slope of block type and trail sections, while also considering the effect of quality of mental and engagement toward running distance and average speed on physical effort. Indeed, the succession of bloc type and trail sections was constant across all participants. As shown in **Table 2**, results indicate that levels of physical effort significantly increase across the chronological section of the trail ($p < .001$). Bonferroni corrected post-hoc pairwise comparisons revealed that levels of physical effort significantly differed across all sections of the trail (all $p < 0.05$), except between section 5 and section 6 of the running trail (i.e., the last two sections of the trail, $p = 0.29$). The reported level of expected physical effort was also significantly higher in the plogging than in the running condition ($p < .001$; see **Figure 3Ai**). We also observed that the reported level of physical effort decreased as a function of the engagement toward running ($p < .001$; see **Figure 3Aii**). Importantly, -2 Log likelihood and AIC values indicate that there is an increased model fit between Step 1 and Step 2 (see **Table 2**). The conditional R^2 (which considers the variance of both the fixed and random effects) is .54, which is indicative of moderate effect sizes.

Table 2. Results of two-steps sequence Linear Mixed Model.

	Null (Step 1)	***Random Intercept and Fixed Raw Slope (Step 2)***
Variable		
Intercept	4.00*** (0.06)	3.99*** (0.16)
Bloc type		0.17*** (0.05)
Trail section		from 0.65*** (0.08) [section 1 vs. section 2]
		to 1.88***(0.08) [section 1 vs. section 6]
Running engagement		0.17 (0.05) ***
Quality of mental imagery_plogging		-0.10 (0.05)
Quality of mental imagery_running		-0.09 (0.05)
Variance components		
Within-participant variance	1.38	0.66
Intercept variance	0.37	0.31
Additional information		
ICC	0.32	
-2 Log likelihood (FILM)	3794.45	3188.38***
Number of estimated parameters	3	8
Conditional R^2	0.23	0.54
Pseudo R^2		0.33
AIC	3800.20	3223.59

*Note: FIML = full information maximum likelihood estimation; Total number of observations = 1235, number of participants = 103. Values in parentheses are standard errors; t-statistics were computed as the ratio of each regression coefficient divided by its standard error. *p < .05. **p < .01. *** p < .001.*

Associations between physical effort, quality of mental simulation, and engagement toward running. A scatter plot matrix with all pairwise correlations are reported in **Figure 3B**. Bayes Factor (BF) Inference on Pairwise Correlations (N = 103) revealed that the index of

engagement toward running was weakly positively associated with the quality of mental simulation toward the running condition, $r(103) = .26$, $BF10 = 2.75$, weakly negatively associated with the aggregated score of physical effort toward the plogging condition, $r(103) = -.28$, $BF10 = 5.85$, and moderately negatively associated with the aggregated score of physical effort toward the running condition, $r(103) = -.37$, $BF10 > 100$. There was no evidence for an association between the two indexes of quality of mental simulation and scores of physical effort toward the running condition.

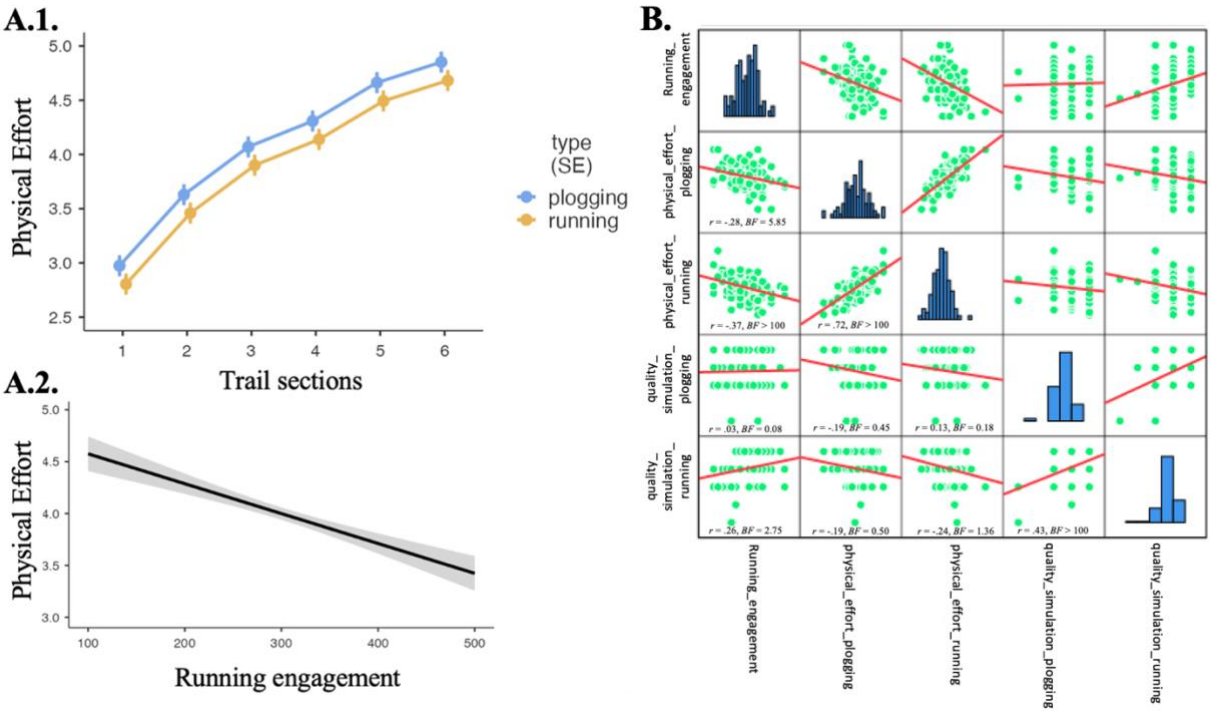

Figure 3. (A.1.) Fixed effect of trails section and block types on participants' reported levels of physical effort. Error bars indicate the standard error of the fixed effect. **(A.2.)** Fixed effect of running engagement on physical effort. Semi-transparent grey areas indicate the standard error of the fixed effect. **(B)** Scatter plot matrix to visualize bivariate relationships between running engagement, aggregated score of physical effort toward running, aggregated score of physical effort toward plogging, quality of mental simulation toward running, and quality of mental simulation toward plogging. Bar charts represent score distributions on each variable. *r* = Pearson coefficient, *BF 10* = Bayes factor 10.

Brain imaging findings from univariate analyses

Plogging versus running conditions. Across all participants (N = 98), for the "plogging minus running" contrast (see **Figure 4A**), we observed a very large cluster of activation (voxel

cluster size = 69184), with peak of activation in the bilateral lingual gyrus (peak = -6,-66,4; Z_{max} = 10.10), extending into bilateral brain regions encompassing the superior parietal lobule, the precentral gyrus, posterior and anterior cingulate gyri, insular cortex, central opercular cortex, amygdala, thalamus, cerebellum, inferior temporal gyrus, as well as the superior, middle, inferior, and orbito frontal gyri. Two other clusters of activation were observed: one with a peak of activation in the frontal pole and left middle frontal gyri (voxel cluster size = 1057, peak = -36,38,−30; Z_{max} = 5.76), the other with a peak of activation in the frontal pole, right middle and superior frontal gyri (voxel cluster size = 968, peak = 34,40,32; Z_{max} = 7.18).

For the "running minus plogging" contrast (see **Figure 4B**), significant clusters of activation were observed in the bilateral occipital pole (voxel cluster size = 1127, peak = -8,-98,12; Z_{max} = 8.22; voxel cluster size = 1051, peak = 10,-94,14; Z_{max} = 6.57), right parahippocampal gyrus (voxel cluster size = 444, peak = 25,-40,-12; Z_{max} = 7.09), left parahippocampal gyrus (voxel cluster size = 322, peak = -22,-40,-12; Z_{max} = 6.51), right precuneus cortex (voxel cluster size = 318, peak = 16 -52,14; Z_{max} = 6.21), posterior cingulate (voxel cluster size = 233, peak = -8,-56,14; Z_{max} = 4.92), and in the right angular gyrus (voxel cluster size = 127, peak = 12,-82,-4; Z_{max} = 4.44).

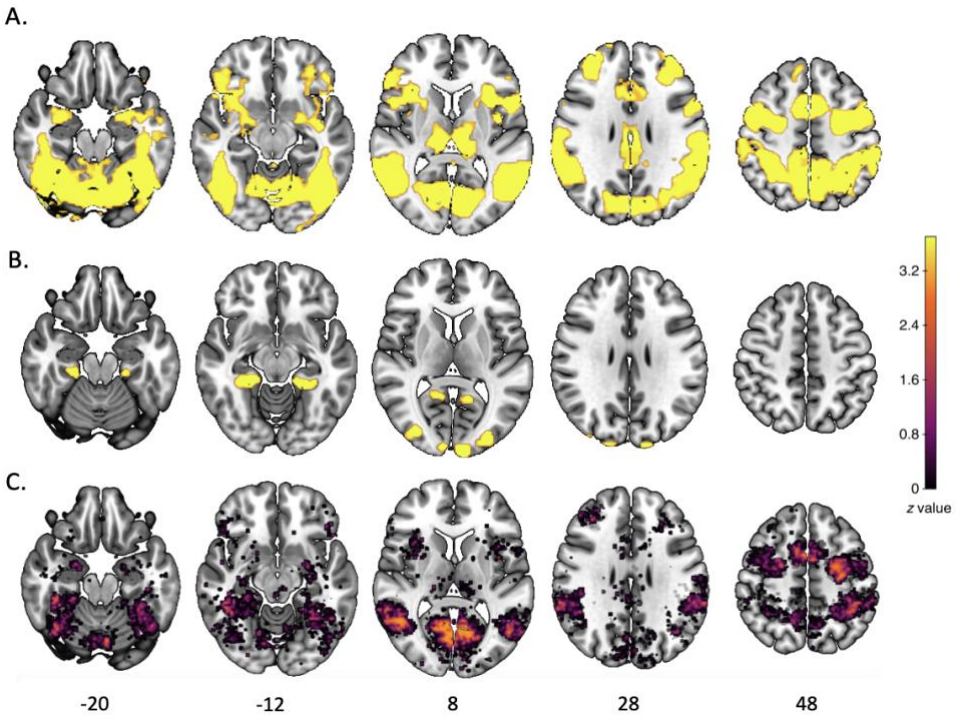

Figure 4. Univariate whole brain differences for **(A)** the "plogging minus running" and **(B)** the "running minus plogging" contrasts. These images were thresholded using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain. **(C)** Clusters of voxels which significantly decoded plogging from running conditions using multivariate analyses. These clusters of voxels were extracted using the single-fold accuracy maps for $n = 1000$ non-parametric permutation testing with correction for multiple comparison using a FWE, $p<0.05$ threshold.

Parametric modulations of physical effort. No significant activation was observed when comparing the parametric modulation of physical effort between the running and the plogging conditions (with either a height threshold of $z > 3.1$ or $z > 2.3$, and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain). No significant covariate effect of running engagement, quality of mental imagery and handedness was observed.

Covariates effects. We observed a covariate effect of scores engagement toward running and quality of mental simulation toward running on the "running versus plogging" contrasts. No other covariate effect was observed.

The covariate effect of engagement toward running was observed in the left posterior cingulate cortex (voxel cluster size = 259, peak = -10,-54,28; $Z_{max} = 3.91$; see **Figure 5A**). To

determine the directionality of this covariate effect, we undertook additional analyses with the two simple contrasts: “plogging (minus implicit baseline)” and “running (minus implicit baseline)”. We created a region of interest (ROI) mask from the cluster of voxels with significant covariate effect in posterior cingulate cortex for the “plogging versus running” contrasts. Using this posterior cingulate cortex mask, we performed separate ROI analyses (with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$) on the “plogging” and the “running” contrasts. We observed significant positive covariate effect in the posterior cingulate cortex for the “plogging” contrast, and no significant covariate effect for the “running” contrast. These supplementary analyses thus indicate that the “plogging” condition triggered a negative covariate effect of running engagement in the posterior cingulate cortex, when compared to the “running” condition.

The covariate effect of quality of mental simulation toward running was observed in the right hippocampus (voxel cluster size = 145, peak = 30,-33,-3; $Z_{max} = 4.08$), the left medial frontal gyrus (Brodmann Area 10; voxel cluster size = 118, peak = -14,54,-6; $Z_{max} = 4.38$), in the anterior cingulate gyrus (voxel cluster size = 114, peak = -14,40,16; $Z_{max} = 4.29$; see **Figure 5B**). To determine the directionality of this covariate effect, we undertook similar additional analyses that above but with the ROI mask from the cluster of voxels with significant covariate effect of quality of mental simulation toward running. Using this mask, we performed separate ROI analyses (with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$) on the “plogging” and the “running” contrasts. We observed significant positive covariate effect in the medial frontal gyrus and anterior cingulate for the “running” contrast, and significant negative covariate in the hippocampus for the “plogging” contrast. These analyses thus indicate that (i) the “running” condition triggered a positive covariate effect of the quality of mental simulation toward running in the medial frontal gyrus and anterior cingulate, when compared to the “plogging” condition, and (ii) the “plogging” condition triggered a negative covariate effect of

the quality of mental simulation toward running in the hippocampus, when compared to the "running" condition.

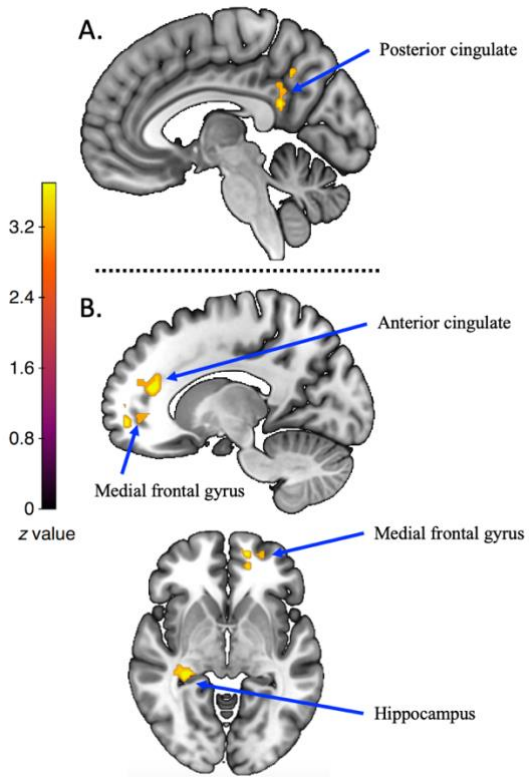

Figure 5. (A) Covariate effect of running engagement for the "plogging versus running" contrast. **(B)** Covariate effects of quality of mental simulation for the "plogging versus running" contrast. These images were thresholded using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < .05$, FWE corrected for multiple comparisons across the whole brain.

Brain imaging findings from multivariate analyses

The ISPA searchlight identified six clusters of voxels which significantly decoded plogging from running conditions (see **Figure 4C**). The first cluster (voxel cluster size = 1415, peak = -24,-10,60, t_{max} = 8.79) includes the left precentral gyrus and superior frontal gyrus. The second (voxel cluster size = 730, peak = -36,-46,64, t_{max} = 8.44) and third (voxel cluster size = 257, peak = 30,-50,60, t_{max} = 7.93) span the bilateral superior parietal lobule and postcentral sulcus and extend into bilateral parahippocampal gyrus. The fourth cluster (voxel cluster size = 1441, peak = -6,-68,8, t_{max} = 8.28) has its peak in the lingual gyrus and extends to intracalcerine cortex, posterior cingulate cortex, angular gyrus and post central gyrus. The fifth cluster (voxel cluster size = 132, peak = 8,-72,-26, t_{max} = 7.66) includes the cerebellar vermis and bilateral

cerebellar lobule VI. Finally, the last cluster (voxel cluster size = 673, peak = 56,-50,16, t_{max} = 7.46) peaks in the right angular gyrus, extending into temporoparietal junction, middle temporal gyrus and lateral occipital cortex.

Insular-centred functional connectivity

Across the whole sample (N = 103), for the "plogging minus running" contrast, the analyses identified both positive and negative PPI with the left and the right insular seeds.

For the left insular seed, a negative PPI (see **Figure 6Ai**) was observed between the right insular seed and the bilateral precentral gyri (voxel cluster size = 387, peak = -32,-2,54; Z_{max} = 5.18; voxel cluster size = 316, peak = -36,-4,48; Z_{max} = 4.34). Positive PPI (see **Figure 6Bi**) was observed with the left posterior cingulate cortex (voxel cluster size = 187, peak = -12,-50,6; Z_{max} = 4.19), superior temporal gyrus (voxel cluster size = 159, peak = -42,-24,2; Z_{max} = 5.13), and occipital pole (voxel cluster size = 133, peak = -8,-98,16; Z_{max} = 4.39).

For the right insular seed, we observed a negative PPI (see **Figure 6Aii**) between the right insular seed and the left inferior temporal gyrus (voxel cluster size = 389, peak = -38,-6,-46; Z_{max} = 4.61) and the bilateral precentral gyri (voxel cluster size = 237, peak = 32,-2,54; Z_{max} = 4.21). Positive PPI (see **Figure 6Bii**) was observed between the right insular seed and the left occipital pole (voxel cluster size = 473, peak = -8,-98,16; Z_{max} = 4.80) and the left posterior cingulate cortex, extending into the superior temporal gyrus (voxel cluster size = 182, peak = -12,-58,12; Z_{max} = 4.16).

To further determine the directionality of these PPI findings, we undertook additional PPI analyses with the two simple contrasts: "plogging (minus implicit baseline)"; "running (minus implicit baseline)". We created two ROI masks from the cluster of voxels with significant positive (ROI_PPI_positive) and negative (ROI_PPI_negative) PPI for the "plogging minus running" contrast with either the left insula or the right insular seeds, respectively. Using these masks, we performed separate ROI analyses (with a height

threshold of z > 3.1 and a cluster probability of $p < .05$) on the "plogging" and the "running" contrasts. When using the ROI_PPI_positive or ROI_PPI_negative masks for the "plogging" contrast, we observed significant positive and negative PPI in all clusters of voxels obtained with the "plogging minus running" contrast, for either the right or left insular seeds. When undertaken for the "running" contrast, the ROI_PPI_positive or ROI_PPI_negative masks resulted in an absence of significant PPI, for both the right or left insular seeds. No significant negative PPI was observed with ROI_PPI_positive mask (for either "plogging" or "running" contrasts). These supplementary analyses confirm that the "plogging" condition triggered increased (positive and negative) PPI, as compared to the "running" condition.

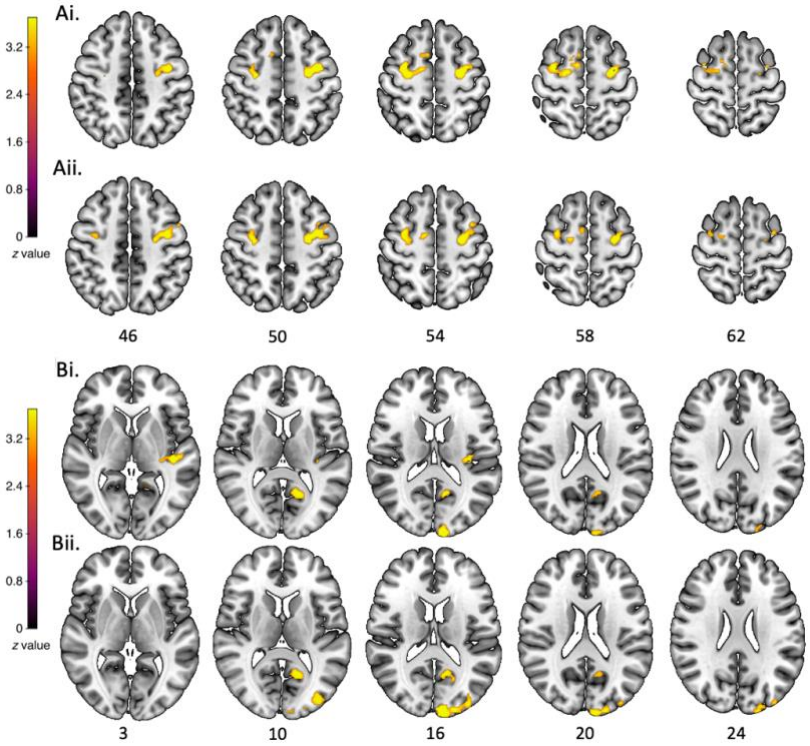

Figure 6. (A) Significant negative PPI with the **(i)** left insula and **(ii)** right insular seeds for the "plogging versus running" contrast. **(B)** Significant positive PPI with the **(i)** left insula and **(ii)** right insular seeds for the "plogging versus running" contrast. These images were thresholded using FSL FLAME 1, with a height threshold of $z > 3.1$ and a cluster probability of $p < 0.05$, FWE-corrected for multiple comparisons across the whole brain.

Discussion

The enactive view of cognition stresses the central role of action simulation processes to potentialize the connection between perception of the external environment and action. This study aimed to advance current knowledge on brain correlates of enactive action simulation by examining how individuals project themselves into the enactment of two types of physical exercises coupled with visual stimuli representing a naturalistic running trail environment. We examined: (i) the brain correlates of mental simulation triggered by the action of running or plogging and their associated levels of physical effort, (ii) the impact of daily-life engagement toward running on the brain reactivity to running and plogging mental simulations, and (iii) patterns of insular-centered functional connectivity associated with the mental simulation of running versus plogging.

On a behavioral level, we observed that participants' ratings of physical efforts increased across the chronological sections of the running trail. Moreover, in line with previous research on the physical strain of plogging (Raghavan et al., 2022), we observed that expected level of physical effort was significantly higher in the plogging than in the running condition. This finding represents a relevant manipulation check for the effectiveness of our experimental task to trigger ratings of physical effort that vary according to the chronological sections of a running trail. We also observed that the expected level of physical effort decreased as a function of participants' daily-life engagement toward running. The index of engagement toward running was also positively associated with the quality of mental simulation toward the running condition. These findings provide some evidence for the external validity of our four-items index of running engagement. Moreover, these observations are in line with behavioral and brain imaging studies on mental simulation in athletes and expert individuals (for reviews, see Mizuguchi et al., 2012; Morone et al., 2022), in showing that daily-life involvement toward running behavior is linked with an increase in the quality of mental simulation.

On a brain imaging level, univariate analyses revealed that the mental simulation of plogging activated a large pattern of brain activation, as compared to the simulation of running (and despite that the visual stimuli were very similar in both condition, expect for the presence of the litter in the plogging condition). This observation is also consistent with studies showing that the extended brain networks of action simulation are sensitive to actions that are more complex (Filgueiras et al., 2018; Hétu et al., 2013). In the present study, these patterns of activation were observed in frontal, parietal, motor, insular, temporal, amygdalar, thalamic, cingulate, and cerebellar areas. These results probably illustrate the intricate processes activated during the mental simulation of plogging actions (i.e., detect and run toward the waste, pick it up and put it in a hand-held small garbage bag, and then continue running on the trail), as compared to the mental simulation of running). For instance, higher activation in (pre)motor and cerebellar areas might be related to higher need of spatial localization and motor planification in the plogging condition (Seiler et al., 2015). Importantly, the mental simulation of running also triggered a specific cluster of activations, as compared to the plogging condition. These patterns were observed in the occipital pole, parahippocampal gyrus, precuneus cortex, posterior cingulate cortex, and the angular gyrus.These regions are all parts of the "contextual association network", which is critical for tasks that require to mentally construct a rich spatial context (Gilmore et al., 2021; Ritchey & Cooper, 2020). Therefore, one explanation for this finding is that the lower complexity of the action of running (as compared to plogging) might have sensitized the activation of some core processes of action simulation, such as visuo-spatial judgment for the angular gyrus (Sack et al., 2007, 2009; Singh-Curry & Husain, 2009; Seghier, 2013), topographical memory and mental navigation for the parahippocaampal gyrus (Berthox, 1997; Maguire et al., 1998; Mellet et al., 2000), coordination of spatial attention and vigilance for the posterior cingulate cortex (Leech & Sharp, 2014; Naito & Ehrsson, 2001; Rolls et al., 2019), the processing of complex visual

scenes for the precuneus (Tanaka & Kirino, 2021), and vividness of mental imagery for the occipital pole (Andersson et al., 2019).

Another important observation from the univariate analyses is that the "plogging" condition was associated with a negative covariate effect of running engagement in the posterior cingulate cortex, when compared to the "running" condition. As mentioned above, the posterior cingulate cortex plays a key role in supporting internally directed cognition and attentional focus. Hence, this covariate effect indicates that increased daily-life engagement toward running leads to an "economization" of attentional resources needed for mentally simulating the action of plogging. Importantly, the plogging versus running contrasts was also associated with significant covariate effects of the quality of mental simulation toward running. Specifically, the running condition was associated with a positive covariate effect of the quality of mental simulation toward running in regions involved in self-awareness and willed generation of virtual motor commands (the medial frontal gyrus and anterior cingulate cortex; Hanakawa et al., 2008). By contrast, the plogging condition was associated with a negative covariate effect of the quality of mental simulation toward running in a region commonly involved in memory-based spatial processing (the hippocampus; Bird & Burgess, 2008). Together, these covariate effects suggest that the quality of mental simulation toward running is associated with (i) a downregulation of memory-based processes when simulating another form of running exercise (i.e., plogging), and (ii) a sensitization of higher-order cognitive processes when simulating a typical form of running exercise.

We also examined the mental simulation of plogging and running with multivariate analyses. Searchlight approaches, also referred to as information-based functional mapping (Kriegeskorte et al., 2006), are well suited when distributed response patterns are expected. Given the complexity and variety of recruited mental processes observed in the univariate analyses, this approach lends an ideal extension of results, as to uncover the network of

distributed response patterns encoding the representational content of these processes. Importantly, we employed an inter-subject pattern approach (ISPA), which ensures consistency in the nature of information across sampled individuals, has greater detection power compared to other group-based MVPA approaches and offers a straightforward interpretation (Wang et al., 2020). Concretely, finding a positive result indicates that the information that has been identified is consistent through the population that was sampled. In line with and largely overlapping with univariate results, we found a wide network of regions which encode task relevant information. Identified brain areas are largely consistent with regions relevant to motor imagery (Cengiz & Boran, 2016; Gonzáles et al., 2005; Hétu et al., 2013; Grèzes & Decety, 2001; Munzert et al., 2008; Ryding et al., 1993), and spatial cognition (Burianová et al., 2013; du Boisgueheneuc et al., 2006; Spreng et al., 2009). For instance, the bilateral cerebellum (lobule VI), precentral gyrus, superior parietal lobule, cerebellar vermis, right post-central gyrus, and left superior frontal gyrus (lSFG) have all been identified as regions consistently activated by motor imagery in an ALE meta-analysis of 75 articles (median sample size 12 participants, range 5-60 participants, see Hétu et al., 2013). In addition, the lSFG, posterior cingulate cortex, temporoparietal junction, middle temporal gyrus, and angular gyrus have consistently shown associations with memory retrieval (Kim, 2010; Spaniol et al., 2009), spatial cognition (Ciaramelli et al., 2008; Gottlieb, 2007; Sack, 2009; Singh-Curry & Husain, 2009), as well as prospection (Spreng et al., 2009; Seghier, 2013). There were two regions that were identified with the multivariate but not univariate approach: the post central gyrus and middle temporal gyrus. The post central gyrus contains the primary somatosensory cortex, which may suggest the engagement of differentiable motor representations for running and plogging conditions. The middle temporal gyrus is suggested to support semantic retrieval to be adapted to a task or context (Davey et al., 2016), its engagement may thus reflect the retrieval of task-relevant information across conditions. Taken together, multivariate results support

univariate findings in highlighting the complexity and variety of representational content recruited in the mental simulation of physical activity. Regions that reliably decoded plogging and running conditions across participants, encode task-relevant information, drawing on visual, spatial, and memory-related representational content.

The last main brain-imaging finding of this study is the observation of increased patterns of positive and negative insular-centered functional connectivity toward the plogging condition, as compared to the running condition. These patterns were highly convergent between the right and left insular seeds. Positive insula-centered PPI were observed with the occipital pole, the posterior cingulate cortex, and the superior temporal gyrus, that is, areas commonly involved in vision, attention-regulation, and action representation processes (Vander Wyk et al., 2012), respectively. Extended negative insula-centered PPI was observed with primary motor areas (precentral gyrus). The right insula was also negatively coupled with inferior temporal gyrus, which is a key brain area for the internal representation of objects, places, faces, and colors (e.g., Federico et al., 2023). The observation of both positive and negative patterns of functional connectivity suggests that the insular cortex plays a key role in the dynamic interplay of action simulation that involve complex self-projection mechanisms, such as the mental simulation of plogging behaviors.

There are several limitations to the present study that should be considered. First, our sample was limited to young university students. This aspect may restrict the generalizability of the present findings. In future studies, it will therefore be important to examine whether the brain mechanisms of physical exercise simulation differ according to age. For instance, a recent study showed that the motor-cognitive mechanisms of action simulation reorganize during healthy aging (e.g., Sacheli et al., 2023). Accordingly, focusing on age differences could be a valuable target to further validate and extend the current findings, especially since physical activity is a key determinant for healthy aging (for recent review, see Szychowska, A., &

Drygas, 2022). Second, despite the fact that the plogging condition was associated with higher self-reported scores of physical efforts than the running condition, we did not observe significant activation when comparing the parametric modulation of physical effort between the running and the plogging conditions. Future studies should thus use experimental procedures that allow for better estimates of the effect of physical effort on the brain correlate of action simulation. One option is to use a plogging condition that explicitly requires participants to focus on bodily sensations (i.e., internal focus; e.g., to center on the physical sensation of plogging), as compared to a plogging condition that requires participants to focus on the environmental task-relevant information outside of the performer's body (i.e., external focus; e.g., to focus on picking-up litter while running; Bazgir et al., 2013). Moreover, action simulation was guided by pictures, rather than videos, of the running trail. We chose to use pictures as it allowed participants to personalize the simulation of running and plogging (e.g., agency in the speed of movement, and which hand to use while picking-up the waste). Nevertheless, the use of pictures only offered a partial guidance of action simulation. Hence, it can be less immersive and engaging than videos (Macdonald et al., 2015, 2017), which might have decreased the level of accuracy of ratings of physical effort triggered by our experimental task.

Third, one main finding of this study is that running engagement decreased posterior cingulate response to the mental simulation of plogging behaviors, thereby suggesting that expert runners need less cognitive resources for simulating the enactment of another type of running behavior. However, this effect alone does not allow to infer how actual previous experience with plogging modulates brain reactivity to the mental simulation of plogging. In fact, very few participants in our sample had any plogging experience. Besides, the mental simulation of plogging might have also resulted from the ability of our participants to merge two simulations of behaviors they already experienced (i.e., even if an individual had never

plogged, they have already picked up litter before). Hence, the mental simulation of plogging might refer to a combination of simulating a run and simulating picking-up litter, rather than the ability to simulate a new activity. These aspects are important as previous fMRI studies observed that the brain reactivity to mental simulation of action with an external guidance (i.e., a comparable procedure of enactive mental simulation that in the present study) is modulated by participants' training experience with the simulated action (i.e., the motor learning of a novel dance choreography; Cross et al., 2006; Di Nota et al., 2016). Future studies should therefore extend the present findings by adding pre-scanning sessions of running and/or plogging, using the exact same trail route that the one featured on the fMRI experimental task. Such an approach would offer a more fine-grained understanding on how actual experience of plogging and running (and not only a proxy of running expertise) impact brain mechanisms underlying enactive mental simulation of physical exercise.

Fourth, while this study aimed to adopt an enactive approach of the mental simulation of plogging, it still only provides a limited understanding of this form of physical exercise. Indeed, recent studies showed that the practice of plogging increases pro-environmental awareness and attitudes, and serves also as a prosocial behavior that bolsters relationships (Kim et al., 2023; Lee & Choi, 2023; Martínez-Mirambell et al., 2023a,b). This dynamic should offer promising perspectives for studies investigating how the human mind processes pro-environmental physical exercise. For instance, simulation should compare experimental conditions where participants are asked to simulate the action of plogging (as in the present study) versus a condition where they are asked to (re-)experience the positive sensation of behaving in a pro-environmental way while plogging. This functional approach of plogging should complement the neuroscience-based literature on the restorative effects of natural environments on attention and cognitive performances (for a review, see Doell et al., 2023).

Finally, it is also important to study brain mechanisms of plogging while using

alternatively brain imaging techniques, such as functional near-infrared spectroscopy (fNIRS). Although, fNIRS has limited sensitivity to hemodynamic changes occurring in brain regions below the cortical surface (e.g., insular cortex; Kovacsova et al., 2018), it has a portable modality that allows the study of neurocognitive processes in real environments without any restrictions on the participant's posture and motion (for a review, see Herold et al., 2018). Accordingly, fNIRS can be used for studying both the simulation and the execution of whole-body movements (e.g., Batula et al., 2017; Shen et al., 2024), while fMRI only allows for the examination of physical exercise simulation. Future studies should thus capitalize on these advantages of fNIRS to examine how brain activity is modulated by the simulation and the enactment of plogging (versus running) activity within real-life immersive environments. This appraoch would enhance our knowledge on how the human mind processes pro-ecological modalities of exercise.

To conclude, this study identified brain activity patterns in response to different types of enactive simulation of physical exercise, that is, either by projecting in a visual guided simulation of running or plogging across a naturalistic trail. These findings open new paths for a better understanding of how humans project themselves into specific types of physical exercise while interacting with their environment.

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AUTHOR CONTRIBUTIONS

RP: Data curation, Formal analysis, Investigation, Methodology, Writing, review & editing; CB: Funding acquisition, Methodology, Project administration, Resources, Writing, review & editing; JB: Funding acquisition, Methodology, Project administration, Resources, Writing, review & editing. JH: Investigation, Writing, review & editing; PM: Writing, review & editing; IM: Investigation, Writing, review & editing; ITO: Writing, review & editing; AB: Investigation, Writing, review & editing; GS: Funding acquisition, Methodology, Resources, Writing, review & editing; Claus Vögele: Funding acquisition, Methodology, Project administration, Resources, Writing, review & editing; DB: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing, review & editing.

DATA & CODE AVAILABILITY

The raw brain imaging data are available on openneuro: doi:10.18112/openneuro.ds004946.v1.0.0. The unthresholded statistical maps are available on Neurovault.org: https://neurovault.org/collections/16413/. The behavioral data are available on the Open Science framework (OSF) website: https://osf.io/3rpk6. The experimental task code and stimuli are available on the OSF website: https://osf.io/mvw68/files/osfstorage.

References

Abbiss, C. R., Peiffer, J. J., Meeusen, R., Skorski, S. (2015). Role of Ratings of Perceived Exertion during Self-Paced Exercise: What are We Actually Measuring? *Sports Medicine 45*(9), 1235–1243. https://doi.org/10.1007/s40279-015-0344-5

Abraham A. (2016). The imaginative mind. *Human brain mapping*, *37*(11), 4197–4211. https://doi.org/10.1002/hbm.23300

Aglioti, S. M., Cesari, P., Romani, M., & Urgesi, C. (2008). Action anticipation and motor resonance in elite basketball players. *Nature neuroscience*, *11*(9), 1109–1116. https://doi.org/10.1038/nn.2182

Andersson JLR, Jenkinson M, Smith S. Non-linear optimisation (FMRIB T*echnical Report 557 TR07JA1). 2007a. Oxford, UK: FMRIB Analysis Group.* Retrieved from www.fmrib.ox.ac.uk/datasets/techrep

Andersson, J. L. R., Jenkinson, M., & Smith, S. (2007b). *Non-linear registration, aka spatial normalisation (FMRIB Technical Report TR07JA2).* Oxford, UK: FMRIB Analysis Group. Retrieved from www.fmrib.ox.ac.uk/datasets/techrep

Andersson, P., Ragni, F., & Lingnau, A. (2019). Visual imagery during real-time fMRI neurofeedback from occipital and superior parietal cortex. *NeuroImage*, *200*, 332–343. https://doi.org/10.1016/j.neuroimage.2019.06.057

Araùjo, D., Keith D., Robert H. (2006). The Ecological Dynamics of Decision Making in Sport. *Psychology of Sport and Exercise*, *7*, 653–676.

Araùjo, D. Travassos, B., Vilar, L. (2010). Tactical Skills Are Not Verbal Skills: A Comment on Kannekens and Colleagues. *Perceptual and Motor Skills*, *110*, 1086–1088.

Araújo, D., Davids, M., McGivern, P. (2019). “The irreducible embeddedness of action choice in sport” in *Handbook of embodied cognition and sport psychology*. ed. M. L. Cappuccio (Cambridge, MA: The MIT Press), 537–556.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Batula, A. M., Mark, J. A., Kim, Y. E., & Ayaz, H. (2017). Comparison of Brain Activation during Motor Imagery and Motor Movement Using fNIRS. Computational intelligence and neuroscience, 2017, 5491296. https://doi.org/10.1155/2017/5491296

Bazgir, B., Shamseddini, A., Hogg, J. A., Ghadiri, F., Bahmani, M., & Diekfuss, J. A. (2023). Is cognitive control of perception and action via attentional focus moderated by motor imagery?. *BMC psychology*, *11*(1), 12. https://doi.org/10.1186/s40359-023-01047-z

Berthoz A. (1997). Parietal and hippocampal contribution to topokinetic and topographic memory. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *352*(1360), 1437–1448. https://doi.org/10.1098/rstb.1997.0130

Bird, C. M., & Burgess, N. (2008). The hippocampus and memory: insights from spatial processing. *Nature reviews. Neuroscience*, *9*(3), 182–194. https://doi.org/10.1038/nrn2335

Brevers, D., Baeken, C., Maurage, P. *et al.* (2021). Brain mechanisms underlying prospective thinking of sustainable behaviours. *Nature Sustainability, 4,* 433–439. https://doi.org/10.1038/s41893-020-00658-3

Brevers, D., Billieux, J., de Timary, P., Desmedt, O., Maurage, P., Perales, J. C., Suárez-Suárez, S., & Bechara, A. (2024). Physical Exercise to Redynamize Interoception in Substance use Disorders. *Current neuropharmacology*, Advance online publication. https://doi.org/10.2174/1570159X21666230314143803

Buchwald, M., Przybylski, Ł., & Króliczak, G. (2018). Decoding Brain States for Planning Functional Grasps of Tools: A Functional Magnetic Resonance Imaging Multivoxel Pattern Analysis Study. *Journal of the International Neuropsychological Society*, *24*(10), 1013–1025. doi:10.1017/S1355617718000590

Buckner, R. L., & Carroll, D. C. (2007). Self-projection and the brain. *Trends in cognitive sciences*, *11*(2), 49–57. https://doi.org/10.1016/j.tics.2006.11.004

Burianová, H., Marstaller, L., Sowman, P., Tesan, G., Rich, A. N., Williams, M., Savage, G., & Johnson, B. W. (2013). Multimodal functional imaging of motor imagery using a novel paradigm. *NeuroImage*, *71*, 50–58. https://doi.org/10.1016/j.neuroimage.2013.01.001

Cancer, A., Pirola, C., Fogassi, L., & Antonietti, A. (2024). Influence of sport expertise in facilitating and inhibiting the recognition of the opponent's intentions in sailing. *Frontiers in human neuroscience*, *17*, 1285963. https://doi.org/10.3389/fnhum.2023.1285963

Carvalho, H., Correia C., Araùjo, D. (2013). A Constraints Led Approach to Skill Enhancement in Tennis. *ITF Coaching and Sport Science Review*, *60*, 10–11.

Ciaramelli, E., Lin, O., & Moscovitch, M. (2009). Episodic memory for spatial context biases spatial attention. *Experimental brain research*, *192*(3), 511–520. https://doi.org/10.1007/s00221-008-1548-9

Cengiz, B., & Boran, H. E. (2016). The role of the cerebellum in motor imagery. *Neuroscience letters*, *617*, 156–159. https://doi.org/10.1016/j.neulet.2016.01.045

Chang, L. J., Yarkoni, T., Khaw, M. W., & Sanfey, A. G. (2013). Decoding the role of the insula in human cognition: functional parcellation and large-scale reverse inference. *Cerebral Cortex*, *23*(3), 739–749. https://doi.org/10.1093/cercor/bhs065

Conson, M., Sarà, M., Pistoia, F., & Trojano, L. (2009). Action observation improves motor imagery: specific interactions between simulative processes. *Experimental brain research*, *199*(1), 71–81. https://doi.org/10.1007/s00221-009-1974-3

Correia, V., Araùjo, D., Cummins A., Craig, C.M. (2012). Perceiving and Acting upon Spaces in a VR Rugby Task: Expertise Effects in Affordance Detection and Task Achievement. *Journal of Sport and Exercise Psychology*, *34*, 305–321.

Costa, S., Berchicci, M., Bianco, V., Croce, P., Di Russo, F., Quinzi, F., Bertollo, M., & Zappasodi, F. (2023). Brain dynamics of visual anticipation during spatial occlusion tasks in expert tennis players. *Psychology of sport and exercise*, *65*, 102335. https://doi.org/10.1016/j.psychsport.2022.102335

Coutanche, M. N., & Thompson-Schill, S. L. (2013). Informational connectivity: identifying synchronized discriminability of multi-voxel patterns across the brain. *Frontiers in human neuroscience*, *7*, 15. https://doi.org/10.3389/fnhum.2013.00015

Craig, A. D. (2002). How do you feel? Interoception: the sense of the physiological condition of the body. *Nature Review Neurosciences, 3*, 655–666.

Craig A. D. (2009). How do you feel--now? The anterior insula and human awareness. *Nature reviews. Neuroscience*, *10*(1), 59–70. https://doi.org/10.1038/nrn2555

Christian, B. M., Miles, L. K., Parkinson, C., & Macrae, C. N. (2013). Visual perspective and the characteristics of mind wandering. *Frontiers in psychology*, *4*, 699. https://doi.org/10.3389/fpsyg.2013.00699

Cross, E. S., Hamilton, A. F., & Grafton, S. T. (2006). Building a motor simulation de novo: observation of dance by dancers. *NeuroImage*, *31*(3), 1257–1267. https://doi.org/10.1016/j.neuroimage.2006.01.033

Davey, C. G., Pujol, J., & Harrison, B. J. (2016). Mapping the self in the brain's default mode network. *NeuroImage*, *132*, 390–397. https://doi.org/10.1016/j.neuroimage.2016.02.022

Di Nota, P. M., Levkov, G., Bar, R., & DeSouza, J. F. X. (2016). Lateral occipitotemporal cortex (LOTC) activity is greatest while viewing dance compared to visualization and

movement: learning and expertise effects. *Experimental brain research*, *234*(7), 2007–2023. https://doi.org/10.1007/s00221-016-4607-7

Doell, K. C., Berman, M. G., Bratman, G. N. *et al.* (2023). Leveraging neuroscience for climate change research. *Nature Climate Change*, *13*, 1288–129. https://doi.org/10.1038/s41558-023-01857-4

Droutman, V., Bechara, A., & Read, S. J. (2015a). Roles of the Different Sub-Regions of the Insular Cortex in Various Phases of the Decision-Making Process. *Frontiers in Behavioral Neuroscience*, *9*, 309. https://doi.org/10.3389/fnbeh.2015.00309

Droutman, V., Read, S. J., & Bechara, A. (2015b). Revisiting the role of the insula in addiction. *Trends in Cognitive Sciences*, *19*(7), 414–420. https://doi.org/10.1016/j.tics.2015.05.005

du Boisgueheneuc, F., Levy, R., Volle, E., Seassau, M., Duffau, H., Kinkingnehun, S., Samson, Y., Zhang, S., & Dubois, B. (2006). Functions of the left superior frontal gyrus in humans: a lesion study. *Brain*, *129*(Pt 12), 3315–3328. https://doi.org/10.1093/brain/awl244

Federico, G., Osiurak, F., Ciccarelli, G., Ilardi, C. R., Cavaliere, C., Tramontano, L., Alfano, V., Migliaccio, M., Di Cecca, A., Salvatore, M., & Brandimonte, M. A. (2023). On the functional brain networks involved in tool-related action understanding. *Communications Biology*, *6*(1), 1163. https://doi.org/10.1038/s42003-023-05518-2

Filgueiras, A., Quintas Conde, E. F., & Hall, C. R. (2018). The neural basis of kinesthetic and visual imagery in sports: an ALE meta - analysis. *Brain Imaging and Behavior*, *12*(5), 1513–1523. https://doi.org/10.1007/s11682-017-9813-9

Friston, K. J. (2011). Functional and effective connectivity: a review. *Brain Connectivity.* 1(1):13–36.

Friston, K. J., Buechel, C., Fink, G. R., et al. (1997). Psychophysiological and modulatory interactions in neuroimaging. *Neuroimage,* 6(3), 218–29.

Friston, K. J., Holmes, A. P., Poline, J. B., Grasby, P. J., Williams, S. C., Frackowiak, R. S., & Turner, R. (1995). Analysis of fMRI time-series revisited. *NeuroImage*, *2*(1), 45–53. https://doi.org/10.1006/nimg.1995.1007

Friston, K. J., Holmes, A. P., Worsley, K. J., Poline, J. P., Frith C. (1994). Frackowiak RS. Statistical parametric maps in functional imaging: a general linear approach. *Human brain mapping, 2(4),* 189–210.

Galla, B. M., & Duckworth, A. L. (2015). More than resisting temptation: Beneficial habits mediate the relationship between self-control and positive life outcomes. *Journal of personality and social psychology*, *109*(3), 508–525. https://doi.org/10.1037/pspp0000026

Gallagher, S. (2005). *How the Body Shapes the Mind*. New York: Oxford University Press.

Gallagher, S. (2011). Interpretations of Embodied Cognition. In W. Tschacher and C. Bergomi (Eds), *The Implications of Embodiment: Cognition and Communication* (pp. 59–70). Exeter, UK: Imprint Academic..

Gallagher, S. (2017) *Enactivist Interventions: Rethinking the Mind*. Oxford: Oxford University Press.

Gerardin, E., Sirigu, A., Lehéricy, S., Poline, J. B., Gaymard, B., Marsault, C., Agid, Y., & Le Bihan, D. (2000). Partially overlapping neural networks for real and imagined hand movements. *Cerebral cortex (New York, N.Y. : 1991)*, *10*(11), 1093–1104. https://doi.org/10.1093/cercor/10.11.1093

González, B., Rodríguez, M., Ramirez, C., & Sabaté, M. (2005). Disturbance of Motor Imagery After Cerebellar Stroke. *Behavioral Neuroscience, 119*(2), 622–626. https://doi.org/10.1037/0735-7044.119.2.622

Gottlieb J. (2007). From a different point of view: extrastriate cortex integrates information across saccades. Focus on "Remapping in human visual cortex". *Journal of neurophysiology*, *97*(2), 961–962. https://doi.org/10.1152/jn.01225.2006

Grèzes, J., & Decety, J. (2001). Functional anatomy of execution, mental simulation, observation, and verb generation of actions: a meta-analysis. *Human brain mapping*, *12*(1), 1–19. https://doi.org/10.1002/1097-0193(200101)12:1<1::aid-hbm10>3.0.co;2-v

Haynes J. D. (2015). A Primer on Pattern-Based Approaches to fMRI: Principles, Pitfalls, and Perspectives. *Neuron*, *87*(2), 257–270. https://doi.org/10.1016/j.neuron.2015.05.025

Herold F, Wiegel P, Scholkmann F, Müller NG. Applications of Functional Near-Infrared Spectroscopy (fNIRS) Neuroimaging in Exercise–Cognition Science: A Systematic, Methodology-Focused Review (2018). *Journal of Clinical Medicine*, 7(12):466. https://doi.org/10.3390/jcm7120466

Hétu, S., Grégoire, M., Saimpont, A., Coll, M. P., Eugène, F., Michon, P. E., & Jackson, P. L. (2013). The neural network of motor imagery: an ALE meta-analysis. *Neuroscience and biobehavioral reviews*, *37*(5), 930–949. https://doi.org/10.1016/j.neubiorev.2013.03.017

Hilty, L., Langer, N., Pascual-Marqui, R.. Boutellier, U., Lutz, K. (2011). Fatigue-induced increase in intracortical communication between mid/anterior insular and motor cortex during cycling exercise. *European Journal of Neurosciences*, *34(12)*, 2035–2042. https://doi.org/10.1111/j.1460-9568.2011.07909.x

Holmes A., Nichols T., Xi Y., Thomas E., Maumet C. (2018). *SnPM (version 13.1.09).* Available online at: http://www.nisox.org/Software/SnPM13

Hund-Georgiadis, M., & von Cramon, D. Y. (1999). Motor-learning-related changes in piano players and non-musicians revealed by functional magnetic-resonance signals. *Experimental brain research*, *125*(4), 417–425. https://doi.org/10.1007/s002210050698

Jeannerod M. (2001). Neural simulation of action: a unifying mechanism for motor cognition. *NeuroImage*, *14*(1 Pt 2), S103–S109. https://doi.org/10.1006/nimg.2001.0832

Jeannerod, M., & Decety, J. (1995). Mental motor imagery: a window into the representational stages of action. *Current opinion in neurobiology*, *5*(6), 727–732. https://doi.org/10.1016/0959-4388(95)80099-9

Jenkinson, M. (2004). *Improving the registration of B0-disorted EPI images using calculated cost function weights.* Paper presented at Tenth International Conference on Functional Mapping of the Human Brain, Budapest, Hungary.

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *NeuroImage, 17*, 825–841. https:// doi.org/10.1006/nimg.2002.1132

Jenkinson, M., & Smith, S. (2001). A global optimisation method for robust affine registration of brain images. Medical Image Analysis, 5, 143–156.

Jimura, K., & Poldrack, R. A. (2012). Analyses of regional-average activation and multivoxel pattern information tell complementary stories. *Neuropsychologia*, *50*(4), 544–552. https://doi.org/10.1016/j.neuropsychologia.2011.11.007

Kahn, J. H. 2011. Multilevel modeling: Overview and applications to research in counseling psychology. *Journal of Counseling Psychology, 58*, 257-271.

Karnath, H. O., & Baier, B. (2010). Right insula for our sense of limb ownership and self-awareness of actions. *Brain structure & function*, *214*(5-6), 411–417. https://doi.org/10.1007/s00429-010-0250-4

Kovacsova, Z. *et al.* (2018). Investigation of Confounding Factors in Measuring Tissue Saturation with NIRS Spatially Resolved Spectroscopy. In: Thews, O., LaManna, J., Harrison, D. (eds) Oxygen Transport to Tissue XL. Advances in Experimental Medicine and Biology, vol 1072. Springer, Cham. https://doi.org/10.1007/978-3-319-91287-5_49

Kilner, J. M., Kraskov, A., & Lemon, R. N. (2014). Do monkey F5 mirror neurons show changes in firing rate during repeated observation of natural actions? *Journal of neurophysiology*, *111*(6), 1214–1226. https://doi.org/10.1152/jn.01102.2012

Kim H. (2010). Dissociating the roles of the default-mode, dorsal, and ventral networks in episodic memory retrieval. *NeuroImage*, *50*(4), 1648–1657. https://doi.org/10.1016/j.neuroimage.2010.01.051

Kim, J., Sujin K., & Jinwook C. (2023). Examining the Relationship between Pro-Environmental Attitudes, Self-Determination, and Sustained Intention in Eco-Friendly Sports Participation: A Study on Plogging Participants. *Sustainability 15(15)*, 11806. https://doi.org/10.3390/su151511806

Kraeutner, S. N., Stratas, A., McArthur, J. L., Helmick, C. A., Westwood, D. A., & Boe, S. G. (2020). Neural and Behavioral Outcomes Differ Following Equivalent Bouts of Motor Imagery or Physical Practice. *Journal of cognitive neuroscience*, *32*(8), 1590–1606. https://doi.org/10.1162/jocn_a_01575

Kriegeskorte, N., Goebel, R., & Bandettini, P. (2006). Information-based functional brain mapping. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(10), 3863–3868. https://doi.org/10.1073/pnas.0600244103

Krings, T., Töpper, R., Foltys, H., Erberich, S., Sparing, R., Willmes, K., & Thron, A. (2000). Cortical activation patterns during complex motor tasks in piano players and control subjects. A functional magnetic resonance imaging study. *Neuroscience letters*, *278*(3), 189–193. https://doi.org/10.1016/s0304-3940(99)00930-1

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lee, W., & Choi, Y. (2023).Examining Plogging in South Korea as a New Social Movement: From the Perspective of Claus Offe's New Social Movement Theory. *International Journal of Environmental Research and Public Health*, *20(5)*, 4469. https://doi.org/10.3390/ijerph20054469

Leech, R., & Sharp, D. J. (2014). The role of the posterior cingulate cortex in cognition and disease. *Brain : a journal of neurology*, *137*(Pt 1), 12–32. https://doi.org/10.1093/brain/awt162

Lotze, M., Scheler, G., Tan, H.-R. M., Braun, C., & Birbaumer, N. (2003). The musician's brain: functional imaging of amateurs and professionals during performance and imagery. *NeuroImage*, *20*(3), 1817–1829. https://doi.org/10.1016/j.neuroimage.2003.07.018

Maguire, E. A., Burgess, N., Donnett, J. G., Frackowiak, R. S., Frith, C. D., & O'Keefe, J. (1998). Knowing where and getting there: a human navigation network. *Science (New York, N.Y.)*, *280*(5365), 921–924. https://doi.org/10.1126/science.280.5365.921

Makris S. (2014). Sport neuroscience revisited (?): a commentary. *Frontiers in human neuroscience*, *8*, 929. https://doi.org/10.3389/fnhum.2014.00929

Macdonald, S., van den Heiligenberg, F., Culham, J., Makin, T. (2015). Localizing tool and hand-selective areas with fMRI: Comparing video and picture stimuli. *Journal of Vision*, *15(12),* 982. https://doi.org/10.1167/15.12.982.

Macdonald, S., van den Heiligenberg, F., Makin, T., Culham, J. (2017). Videos are more effective than pictures at localizing tool- and hand-selective activation in fMRI. *Journal of Vision*, *17(10)*, 991. https://doi.org/10.1167/17.10.991.

Martínez-Mirambell, C., Boned-Gómez, S., Urrea-Solano, M., & Baena-Morales, S. (2023). Step by Step towards a Greener Future: The Role of Plogging in Educating Tomorrow's Citizens. *Sustainability*, *15(18)*, 13558. https://doi.org/10.3390/su151813558

Martinez-Mirambell, C., García-Taibo, O., Ferriz-Valero, A. & Baena-Morales, S. (2023) Plogging improves environmental awareness in high school physical education students. *Journal of Adventure Education and Outdoor Learning,* DOI: 10.1080/14729679.2023.2235705

Mellet, E., Briscogne, S., Tzourio-Mazoyer, N., Ghaëm, O., Petit, L., Zago, L., Etard, O., Berthoz, A., Mazoyer, B., & Denis, M. (2000). Neural correlates of topographic mental exploration: the impact of route versus survey perspective learning. *NeuroImage*, *12*(5), 588–600. https://doi.org/10.1006/nimg.2000.0648

Menon, V., & Uddin, L. Q. (2010). Saliency, switching, attention and control: a network model of insula function. *Brain structure & function*, *214*(5-6), 655–667. https://doi.org/10.1007/s00429-010-0262-0

Mizuguchi, N., Nakata, H., Uchida, Y., & Kanosue, K. (2012). Motor imagery andsport performance. *Journal of Physical Fitness and Sports Medicine, 1*, 103–111.

Molnar-Szakacs, I., & Uddin, L. Q. (2022). Anterior insula as a gatekeeper of executive control. *Neuroscience and Biobehavioral Reviews*, *139*, 104736. https://doi.org/10.1016/j.neubiorev.2022.104736

Morone, G., Ghanbari Ghooshchy, S., Pulcini, C., Spangu, E., Zoccolotti, P., Martelli, M., Spitoni, G. F., Russo, V., Ciancarelli, I., Paolucci, S., et al. (2022). Motor Imagery and Sport Performance: A Systematic Review on the PETTLEP Model. Applied ScienceS, 12, 9753.

Munzert, J., Zentgraf, K., Stark, R., & Vaitl, D. (2008). Neural activation in cognitive motor processes: comparing motor imagery and observation of gymnastic movements. *Experimental brain research*, *188*(3), 437–444. https://doi.org/10.1007/s00221-008-1376-y

Mur, M., Bandettini, P. A., & Kriegeskorte, N. (2009). Revealing representational content with pattern-information fMRI--an introductory guide. *Social cognitive and affective neuroscience*, *4*(1), 101–109. https://doi.org/10.1093/scan/nsn044

Nedelko, V., Hassa, T., Hamzei, F., Schoenfeld, M. A., & Dettmers, C. (2012). Action imagery combined with action observation activates more corticomotor regions than action observation alone. *Journal of neurologic physical therapy : JNPT*, *36*(4), 182–188. https://doi.org/10.1097/NPT.0b013e318272cad1

Naito, E., & Ehrsson, H. H. (2001). Kinesthetic illusion of wrist movement activates motor-related areas. *Neuroreport*, *12*(17), 3805–3809. https://doi.org/10.1097/00001756-200112040-00041

O'Reilly, J. X., Woolrich, M. W., Behrens, T. E., Smith, S. M., & Johansen-Berg, H. (2012). Tools of the trade: psychophysiological interactions and functional connectivity. *Social Cognitive and Affective Neuroscience*, *7*(5), 604–609. https://doi.org/10.1093/scan/nss055

Oosterhof, N. N., Connolly, A. C., & Haxby, J. V. (2016). CoSMoMVPA: Multi-Modal Multivariate Pattern Analysis of Neuroimaging Data in Matlab/GNU Octave. *Frontiers in neuroinformatics*, *10*, 27. https://doi.org/10.3389/fninf.2016.00027

Pace Giannotta, A. (2021). Autopoietic Enactivism, Phenomenology, and the Problem of Naturalism: A Neutral Monist Proposal. *Husserl Studies, 37(3)*, 209-228.

Pellicano, A., Mingoia, G., Ritter, C., Buccino, G., & Binkofski, F. (2021). Respiratory function modulated during execution, observation, and imagination of walking via SII. *Scientific reports*, *11*(1), 23752. https://doi.org/10.1038/s41598-021-03147-5

Radel, R., Pelletier, L., Pjevac, D., & Cheval, B. (2017). The links between self-determined motivations and behavioral automaticity in a variety of real-life behaviors. *Motivation & Emotion, 41*(4), 443–454. https://doi.org/10.1007/s11031-017-9618-6

Raghavan, R., Panicker, W., & Emmatty, F. (2022). Ergonomic risk and physiological assessment of plogging activity. *Work, 72(4)*, 1337-1348. https://doi.org/10.3233/WOR-205210

Robertson, K., De Waelle, S., Deconinck, F. J., & Lenoir, M. (2022). Differences in expertise level for anticipatory skill between badminton 'in game' strokes and serves. *International Journal of Sports Science & Coaching*, *17*(4), 782-791. https://doi.org/10.1177/17479541211046910

Rolls E. T. (2019). The cingulate cortex and limbic systems for action, emotion, and memory. *Handbook of clinical neurology*, *166*, 23–37. https://doi.org/10.1016/B978-0-444-64196-0.00002-9

Ross, J. S., Tkach, J., Ruggieri, P. M., Lieber, M., & Lapresto, E. (2003). The mind's eye: functional MR imaging evaluation of golf motor imagery. *AJNR. American journal of neuroradiology*, *24*(6), 1036–1044.

Ryding, E., Decety, J., Sjöholm, H., Stenberg, G., & Ingvar, D. H. (1993). Motor imagery activates the cerebellum regionally. A SPECT rCBF study with 99mTc-HMPAO. *Brain research. Cognitive brain research*, *1*(2), 94–99. https://doi.org/10.1016/0926-6410(93)90015-w

Sacheli, L. M., Verga, C., Zapparoli, L., Seghezzi, S., Tomasetig, G., Banfi, G., & Paulesu, E. (2023). When action prediction grows old: An fMRI study. *Human brain mapping*, *44*(2), 373–387. https://doi.org/10.1002/hbm.26049

Sack A. T. (2009). Parietal cortex and spatial cognition. *Behavioural brain research*, *202*(2), 153–161. https://doi.org/10.1016/j.bbr.2009.03.012

Sack, A. T., Kohler, A., Bestmann, S., Linden, D. E., Dechent, P., Goebel, R., & Baudewig, J. (2007). Imaging the brain activity changes underlying impaired visuospatial judgments: simultaneous FMRI, TMS, and behavioral studies. *Cerebral cortex, 17*(12), 2841–2852. https://doi.org/10.1093/cercor/bhm013

Scalabrini, A., Wolman, A., & Northoff, G. (2021). The Self and Its Right Insula-Differential Topography and Dynamic of Right vs. Left Insula. *Brain sciences*, *11*(10), 1312. https://doi.org/10.3390/brainsci11101312

Seeley W. W. (2019). The Salience Network: A Neural System for Perceiving and Responding to Homeostatic Demands. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, *39*(50), 9878–9882. https://doi.org/10.1523/JNEUROSCI.1138-17.2019

Seiler, B. D., Monsma, E. V., & Newman-Norlund, R. D. (2015). Biological evidence of imagery abilities: intraindividual differences. *Journal of sport & exercise psychology*, *37*(4), 421–435. https://doi.org/10.1123/jsep.2014-0303

Seghier M. L. (2013). The angular gyrus: multiple functions and multiple subdivisions. *The Neuroscientist : a review journal bringing neurobiology, neurology and psychiatry*, *19*(1), 43–61. https://doi.org/10.1177/1073858412440596

Shen, Q. Q., Hou, J. M., Xia, T., Zhang, J. Y., Wang, D. L., Yang, Y., Luo, R., Xin, Z. L., Yin, H. C., & Cui, L. (2024). Exercise promotes brain health: a systematic review of fNIRS studies. *Frontiers in psychology*, *15*, 1327822. https://doi.org/10.3389/fpsyg.2024.1327822

Singh-Curry, V., & Husain, M. (2009). The functional role of the inferior parietal lobe in the dorsal and ventral stream dichotomy. *Neuropsychologia*, *47*(6), 1434–1448. https://doi.org/10.1016/j.neuropsychologia.2008.11.033

Spaniol, J., Davidson, P. S., Kim, A. S., Han, H., Moscovitch, M., & Grady, C. L. (2009). Event-related fMRI studies of episodic encoding and retrieval: meta-analyses using activation likelihood estimation. *Neuropsychologia*, *47*(8-9), 1765–1779. https://doi.org/10.1016/j.neuropsychologia.2009.02.028

Spreng, R. N., Mar, R. A., & Kim, A. S. (2009). The common neural basis of autobiographical memory, prospection, navigation, theory of mind, and the default mode: a

quantitative meta-analysis. *Journal of cognitive neuroscience*, *21*(3), 489–510. https://doi.org/10.1162/jocn.2008.21029

Szychowska, A., & Drygas, W. (2022). Physical activity as a determinant of successful aging: a narrative review article. *Aging clinical and experimental research*, *34*(6), 1209–1214. https://doi.org/10.1007/s40520-021-02037-0

Tanaka, S., & Kirino, E. (2021). The Precuneus Contributes to Embodied Scene Construction for Singing in an Opera. *Frontiers in human neuroscience*, *15*, 737742. https://doi.org/10.3389/fnhum.2021.737742

Urgesi, C., Savonitto, M. M., Fabbro, F., & Aglioti, S. M. (2012). Long- and short-term plastic modeling of action prediction abilities in volleyball. *Psychological research*, *76*(4), 542–560. https://doi.org/10.1007/s00426-011-0383-y

Vander Wyk, B. C., Voos, A., & Pelphrey, K. A. (2012). Action representation in the superior temporal sulcus in children and adults: an fMRI study. *Developmental cognitive neuroscience*, *2*(4), 409–416. https://doi.org/10.1016/j.dcn.2012.04.004

Villiger, M., Estévez, N., Hepp-Reymond, M. C., Kiper, D., Kollias, S. S., Eng, K., & Hotz-Boendermaker, S. (2013). Enhanced activation of motor execution networks using action observation combined with imagination of lower limb movements. *PloS one*, *8*(8), e72403. https://doi.org/10.1371/journal.pone.0072403

Vogt, S., Di Rienzo, F., Collet, C., Collins, A., & Guillot, A. (2013). Multiple roles of motor imagery during action observation. *Frontiers in human neuroscience*, *7*, 807. https://doi.org/10.3389/fnhum.2013.00807

Vrana, A., Hotz-Boendermaker, S., Stämpfli, P., Hänggi, J., Seifritz, E., Humphreys, B. K., & Meier, M. L. (2015). Differential Neural Processing during Motor Imagery of Daily Activities in Chronic Low Back Pain Patients. *PloS one*, *10*(11), e0142391. https://doi.org/10.1371/journal.pone.0142391

Wang, Q., Cagna, B., Chaminade, T., & Takerkart, S. (2020). Inter-subject pattern analysis: A straightforward and powerful scheme for group-level MVPA. *NeuroImage*, *204*, 116205. https://doi.org/10.1016/j.neuroimage.2019.116205

Weaverdyck, M. E., Lieberman, M. D., & Parkinson, C. (2020). Tools of the Trade Multivoxel pattern analysis in fMRI: a practical introduction for social and affective neuroscientists. *Social cognitive and affective neuroscience*, *15*(4), 487–509. https://doi.org/10.1093/scan/nsaa057

Wei, G., & Luo, J. (2010). Sport expert's motor imagery: Functional imaging of professional motor skills and simple motor skills. *Brain research*, *13(41)*, 52-62. https://doi.org/10.1016/j.brainres.2009.08.014

Williamson, J. W., Fadel, P. J., Mitchell, J. H. (2006). New insights into central cardiovascular control during exercise in humans: A central command update. *Experimental Physiology*, *91(1)*, 51–58. https://doi.org/10.1113/expphysiol.2005.032037

Williamson, J. W., McColl, R., Mathews, D., Mitchell, J. H., Raven, P. B., Morgan, W. P. (2001). Hypnotic manipulation of effort sense during dynamic exercise: Cardiovascular responses and brain activation. *Journal of Applied Physiology*, *90*(4), 1392–1399. https://doi.org/10.1152/jappl.2001.90.4.1392

Williamson, J. W., McColl, R., Mathews, D., Mitchell, J. H., Raven, P. B., Morgan, W. P. (2002) Brain activation by central command during actual and imagined handgrip under hypnosis. *Journal of Applied Physiology*, *92(3)*, 1317-1324. https://doi.org/10.1152/japplphysiol.00939.2001

Yang, Y., Yang, H., Imai, F., & Ogawa, K. (2023). Distinct neural representations of hand movement direction between motor imagery and execution in the presupplementary motor area. *Neuroscience research*, *191*, 57–65. https://doi.org/10.1016/j.neures.2023.01.001

Zapparoli, L., Seghezzi, S., Sacheli, L. M., Verga, C., Banfi, G., & Paulesu, E. (2020). Eyes wide shut: How visual cues affect brain patterns of simulated gait. *Human brain mapping*, *41*(15), 4248–4263. https://doi.org/10.1002/hbm.25123

Zhang, L., Qiu, F., Zhu, H., Xiang, M., & Zhou, L. (2019). Neural Efficiency and Acquired Motor Skills: An fMRI Study of Expert Athletes. *Frontiers in psychology*, *10*, 2752. https://doi.org/10.3389/fpsyg.2019.02752

Zhao, H., Turel, O., Bechara, A., & He, Q. (2023). How distinct functional insular subdivisions mediate interacting neurocognitive systems. *Cerebral Cortex*, *33*(5), 1739–1751. https://doi.org/10.1093/cercor/bhac169

Zhao, X., Wang, J., Li, J., Luo, G., Li, T., Chatterjee, A., Zhang, W., & He, X. (2020). The neural mechanism of aesthetic judgments of dynamic landscapes: an fMRI study. *Scientific reports*, *10*(1), 20774. https://doi.org/10.1038/s41598-020-77658-y

6.2. Co-authored publications

Pillet, I., Cerrahoğlu, B., **Philips, R. V.,** Dumoulin, S., & Op de Beeck, H. (2024). A 7T fMRI investigation of hand and tool areas in the lateral and ventral occipitotemporal cortex. *Plos one*, *19*(11), https://doi.org/10.1371/journal.pone.0308565.

Pillet, I., Cerrahoğlu, B., **Philips, R. V**., Dumoulin, S., & de Beeck, H. O. (2024). The position of visual word forms in the anatomical and representational space of visual categories in occipitotemporal cortex. *Imaging neuroscience*, *2*, 1-28. https://doi.org/10.1162/imag_a_00196

Traxler J., Gaggini, E., **Philips, R.V**., Warny, A., Peters, M.L., Crombez, G., Vlaeyen, J.W.S. (in press). Measurement instruments of pain-related avoidance in chronic pain: A systematic review of psychometric properties. *Pain*

6.3. Supplementary materials

6.3.1. Supplementary materials – Study 2

Table S1.

Descriptive statistics for stress ratings

	No time pressure			Time pressure		
	Baseline	Affect-rich	Affect-poor	Baseline	Affect-rich	Affect-poor
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Stress rating	2.16 (1.12)	1.88 (1.01)	1.85 (0.98)	1.98 (1.01)	2.05 (1.03)	2 (0.99)

Table S2.

Descriptive statistics for response times

	No time pressure		Time pressure	
	Affect-rich	Affect-poor	Affect-rich	Affect-poor
	Mdn (IQR)	Mdn (IQR)	Mdn (IQR)	Mdn (IQR)
Response times	4.59 (4.51)	4.95 (4.71)	3 (2.23)	2.93 (2.57)

Table S3.

Mean affect ratings of side effects and their monetary equivalents

	Side effect	Monetary equivalent
	M (SD)	M (SD)
Depression	8.04 (2)	6.12 (2.4)
Diarrhea	5.64 (2.18)	4.29 (2.37)
Dizziness	5.99 (1.81)	4.76 (2.29)
Fatigue	4.48 (2.05)	3.29 (2.1)
Fever	5.44 (2.14)	4.46 (2.26)
Flatulence	4.75 (2.33)	3.65 (2.25)
Hallucinations	7.67 (2.08)	5.53 (2.38)
Insomnia	6.87 (2.14)	5.14 (2.48)
Itching	5.84 (2.12)	4.28 (2.32)
Memory loss	8.13 (1.88)	6.51 (2.19)
Speech Disorder	6.92 (2.16)	5.38 (2.44)
Trembling	5.44 (2.15)	4.04 (2.38)

Sensitivity analyses: Dominant choice options

To evaluate whether there were dominant choice options in the stimulus set, we checked whether there were trials on which there was a lesser loss (as evaluated by the WTP amount) that was also more likely than the larger loss. Those trials were excluded (N = 1404, 15% of trials), and analyses were repeated. We also repeated these sensitivity analyses using the affective rating instead of the WTP to identify dominant options, so if there is a choice option in which the outcome is rated as less aversive that is more probable than the more aversive outcome, we excluded that trial (N = 1550, 16% of trials). The table below shows the results of the fixed effects analysis across the different analyses. All results but one were robust to the sensitivity analyses. The interaction between affect condition and time pressure on EV maximization is no longer statistically significant when dominant choice options are removed.

Table S4.

Result of sensitivity analyses for EV maximization and risk attitudes

Fixed effect	Full dataset		No dominant option based on WTP		No dominant options based on affect rating	
EV maximization	$\chi^2(1)$	*p*	$\chi^2(1)$	*p*	$\chi^2(1)$	*p*
Interaction	4.13	<0.05	1.11	0.29	0.89	0.34
TP	0.01	0.93	0.17	0.68	0.32	0.56
Affect	297.38	<0.001	2.78	<0.001	336.27	<0.001
Risk	$\chi^2(1)$	p	$\chi^2(1)$	p	$\chi^2(1)$	p
Interaction	10.58	<0.001	5.24	<0.05	5.35	<0.05

Table S5.

Result of sensitivity analysis on log-linear analysis for decision-making strategies

	Full dataset		No dominant option based on WTP		No dominant options based on affect rating	
Retained model	Deviance	p	Deviance	p	Deviance	p
Affect*Strategy	29.13	<0.001	110.94	<0.001	91.31	<0.001
Coefficient	Estimate (SE)	p	Estimate (SE)	p	Estimate (SE)	p
Affect-rich*Affect heuristic	2.04 (0.54)	<0.001	3.18 (0.48)	<0.001	2.84 (0.47)	<0.001

Figure S1.

Average stress ratings across timepoints.

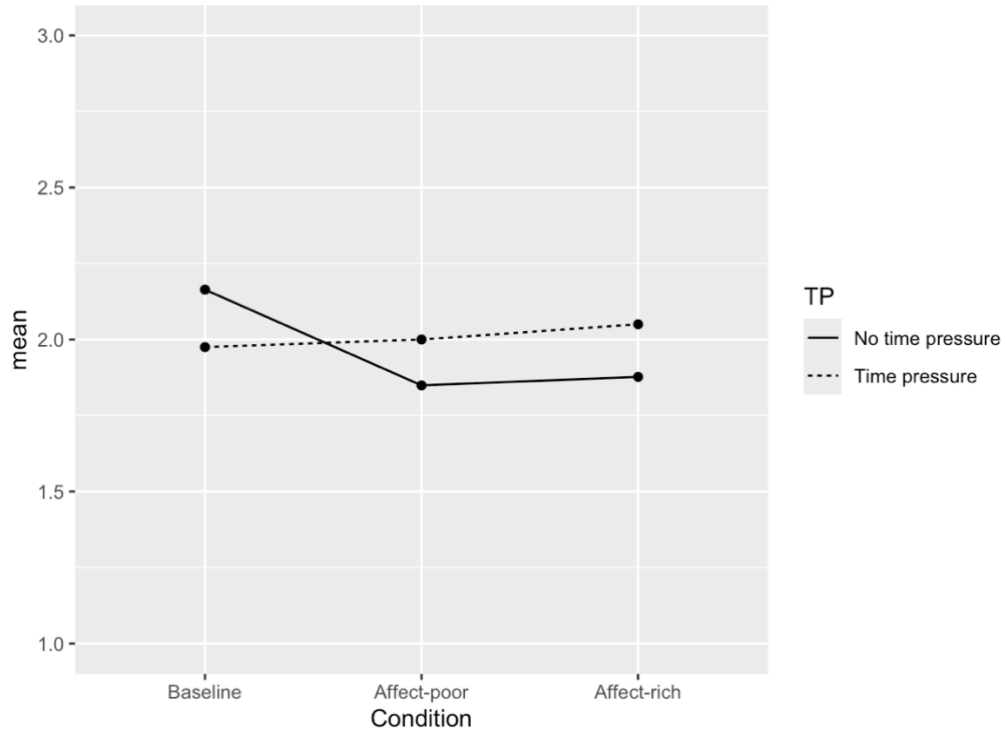
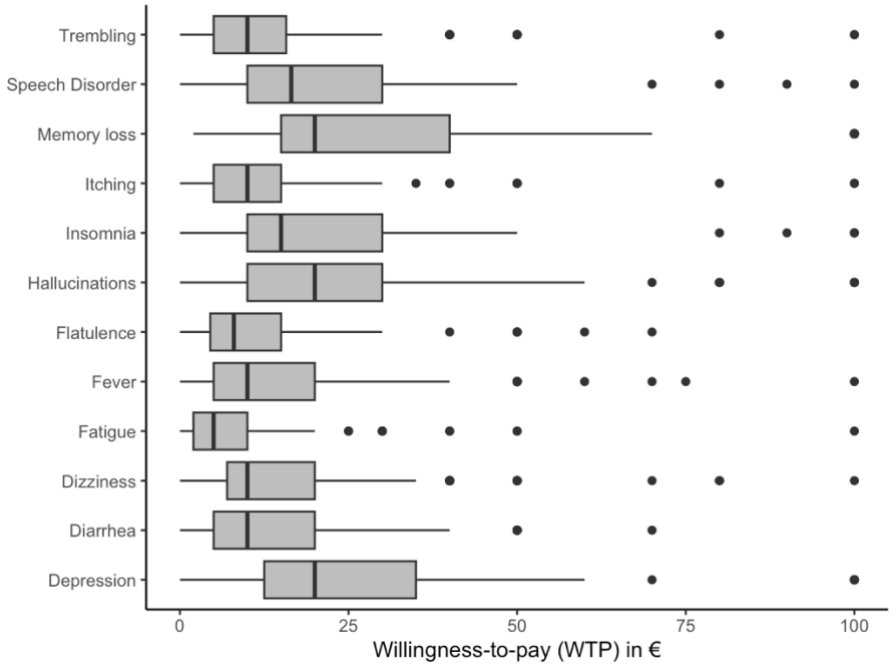


Figure S2.

Monetary evaluation task: Distribution of willingness-to-pay amounts in €



Note. The x-axis is truncated at 100€ for better visibility of the boxplots.

6.3.2. Supplementary materials – Study 3

Table S6.

Descriptive statistics for distress and familiarity ratings

Side effect	Distress		Familiarity	
	Mean	SD	Mean	SD
Anxiety	3.74	0.86	3.32	1.25
Blurry sight	3.42	1.06	2.35	1.28
Breathlessness	2.5	0.79	2.53	1.11
Chest pain	3.06	1.04	2.09	1.11
Chills	1.79	0.77	3.06	1.01
Confusion	3.47	1.02	1.91	1.03
Constipation	2.91	1.11	2	1.07
Dry mouth	1.88	0.72	2.76	0.92
Fatigue	3.38	1.04	3.94	0.78
Fever	3.38	0.89	2.62	1.10
Flatulence	2.53	0.83	2.56	1.05
Hair loss	3.62	1.13	1.68	1.12
Headache	3.85	0.82	3.41	1.10
Insomnia	3.76	1.18	2.29	1.36
Irritability	3.38	1,04	2.82	1.11
Itching	3.06	1.07	2.82	1.09
Loss of appetite	2.65	1.07	2.18	0.99
Vomiting	3.94	0.98	2.44	0.99

Table 1. Descriptives of distress and familiarity ratings across side effects presented

Table S7.

Average vividness score of forecasts per condition

Condition	Vividness	
	Mean	SD
Side effect	3.62	0.78
Remission	3.12	0.84

Table S8.

Regions activated exclusively for side effect and remission conditions respectively

Contrast	Cluster	K	MNI coordinates			z-max	p	Anatomical region
			x	y	z			
'Side effect minus remission'	1	209	-36	62	-6	4.32	0.002	Frontal pole
	2	169	50	6	-8	4.09	0.007	Planum polare, temporal pole
	2		46	-8	4	3.92		Heschl's gyrus, Insular cortex
	2		42	-14	2	3.8		Insular cortex, Heschl's gyrus
	2		44	0	0	3.57		Insular cortex, Central opercular cortex
	2		58	2	0	3.55		Planum polare, central opercular cortex, superior temporal gyrus (anterior division)
	3	119	-40	-2	-10	4	0.03	Insular cortex
	3		-44	-4	2	3.92		Insular cortex, central opercular cortex, planum polare
'Remission minus side effect'	1	492	36	24	52	4.91	<0.0001	Middle frontal gyrus, superior frontal gyrus
	1		18	34	54	4.35		Superior frontal gyrus, frontal pole
	2	283	26	50	8	4.91	0.0002	Frontal pole

Note. Results are based on the Harvard-Oxford cortical and subcortical structural atlases. Local maxima that fall into an already mentioned anatomical region are omitted. *K*: cluster size. *p* is family-wise error corrected at p<0.05

Table S9.

Regions activated for positive/negative affective forecasting

Contrast	Cluster	K	MNI coordinates			z-max	p	Anatomical region
			x	y	z			
'Side effect minus baseline'	1	2068	-40	8	-2	5.26	<0.0001	Insular cortex, central opercular cortex
	1		-46	34	-14	5.19		Frontal orbital cortex, frontal pole
	1		-52	14	-2	5.15		Inferior frontal gyrus (pars opercularis)
	2	1742	-24	-98	-8	6.76	<0.0001	Occipital pole
	2		-32	-96	-10	6.43		Occipital pole, lateral occipital cortex (inferior division)
	3	1307	-4	6	58	5.37	<0.0001	Juxtapositional lobule cortex, superior frontal gyrus
	4	1263	32	-96	-4	6.19	<0.0001	Occipital pole, lateral occipital cortex (inferior division)
	5	399	38	-80	-36	4.74	<0.001	Right crus I, right crus II
	6	252	40	10	0	4.92	0.0007	Central opercular cortex, frontal operculum cortex, insular cortex
	6		56	18	-4	3.74		Infrerior frontal gyrus (pars opercularis, pars triangularis), temporal pole

	6		56	24	-6	3.72		Inferior frontal gyrus (pars triangularis), frontal orbital cortex
	6		58	34	-2	3.28		Inferior frontal gyrus (pars triangularis), frontal pole
'Remission minus baseline'	1	1642	-6	8	64	5.68	<0.0001	Juxtapositional lobule, superior frontal gyrus
	1		-10	42	44	4.32		Frontal pole, superior frontal gyrus
	1		-4	18	50	4.19		Paracingulate gyrus, superior frontal gyrus
	2	1544	-24	-96	-6	6.75	<0.0001	Occipital pole, lateral occipital cortex (inferior division)
	3	1478	-50	16	0	5.35	<0.0001	Inferior frontal gyrus (pars opercularis, pars triangularis), frontal operculum cortex
	3		-46	42	2	5.22		Frontal pole
	4	1184	32	-94	-2	6.17	<0.0001	Occipital pole, lateral occipital cortex (inferior division)
	5	583	-34	58	10	4.55	<0.0001	Frontal pole
	5		-12	54	16	4.25		Superior frontal gyrus, frontal pole
	6	178	44	-62	-28	4.61	0.004	Right crus I
	7	150	28	-80	-40	4.56	0.009	Right crus I, right crus II

Note. Results are based on the Harvard-Oxford cortical and subcortical structural atlases. Cerebellar regions were identified using the 'Cerebellar Atlas in MNI152 space after normalization with FNIRT' atlas. Local cluster maxima that fall into an already mentioned anatomical region are omitted. *K*: cluster size. *p* is family-wise error corrected at p<0.05

Table S10.

Parametric modulation of neural activity by anticipated distress score

Contrast	Cluster	K	MNI coordinates			z-max	p	Anatomical region
			x	y	z			
'Side effect minus baseline'	1	1608	30	-60	-26	3.92	<0.0001	Right VI
	1		32	-66	-24	3.74		Right VI, right crus I
	1		6	-62	-24	3.15		Vermis VI, right V, right VI
	1		-4	-66	-36	3.11		Vermis VIIIa
	2	1570	-16	-74	58	3.39	<0.0001	Lateral occipital cortex (superior division)
	2		-22	-90	30	3.24		Occipital pole
	2		-6	-76	54	3.24		Precuneous cortex, lateral occipital cortex (superior division)
	2		-10	-88	30	3.18		Cuneal cortex, occipital pole, lateral occipital cortex (superior division)
	3	602	-42	-58	-28	3.5	0.008	Left Crus I
	3		-18	-70	-24	3.25		Left VI
	4	552	-40	-2	62	3.49	0.013	Middle frontal gyrus, precentral gyrus
	4		-44	-12	64	2.78		Precentral gyrus, postcentral gyrus
	4		-46	18	32	2.64		Middle frontal gyrus, inferior frontal gyrus (pars opercularis)

	5	513	0	-8	8	3.95	0.019	Thalamus
	5		-6	-2	8	3		Thalamus, Caudate
	6	443	50	4	50	3.53	0.043	Precentral gyrus, middle frontal gyrus
	6		22	-8	72	2.9		Superior frontal gyrus, precentral gyrus
'Remission minus baseline'	1	654	-50	-66	40	3.39	0.003	Lateral occipital cortex (superior division), angular gyrus
	2	606	-46	52	0	3.61	0.005	Frontal pole
	2		-6	54	-18	3		Frontal medial cortex, frontal pole
	3	509	-66	-32	-18	4.1	0.01	Middle temporal gyrus (posterior division), inferior temporal gyrus (posterior division)
	3		-60	-14	-8	3.04		Middle temporal gyrus (posterior, anterior divisions), superior temporal gyrus (posterior, anterior divisions)

Note. Results are based on the Harvard-Oxford cortical and subcortical structural atlases. Cerebellar regions were identified using the 'Cerebellar Atlas in MNI152 space after normalization with FNIRT' atlas. Local cluster maxima that fall into an already mentioned anatomical region are omitted. *K*: cluster size. *p* is family-wise error corrected at $p<0.05$, importantly we used a threshold of $z>2.3$ for the current analysis