The Role of Self-Reported Predecisional Affect in Recurrent Decision-Making

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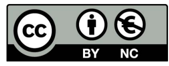

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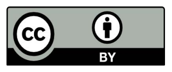

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Abstract

This thesis explores the role of self-reported affect in recurrent decision-making, with a particular focus on how both current and expected emotions influence choices over time. Three studies were conducted to investigate the impact of current and expected valence on decision-making in various contexts. The first study examined the predictive power of expected affect in a recurrent gambling task, where expected valence was found to be the strongest predictor of choice. The second study expanded on this by exploring the interaction between current and expected affect, revealing that both types of emotions contribute to decision-making depending on task context. The third study emphasized the importance of time horizons, showing that short-term and long-term expectations interact differently based on the nature of the decision, such as point-loss versus point-omission scenarios. These findings suggest that emotional expectations, as well as current emotional states, are essential components in predicting choices and that the subjective affective system adapts to varying contextual demands. The results also highlight the need for a more nuanced approach to measuring affect, integrating both expected and current emotions to better understand decision-making across a range of contexts. This work provides valuable insights into how emotions guide choices in both financial and non-financial domains, offering implications for future research on emotion-driven decision-making.

1. Theoretical Background

Efendic (2017) provides a comprehensive overview of research in Judgment and Decision Making (JDM), which can be divided into four periods. The first period (1954-1972) marks the beginning of a systematic approach, introducing key concepts such as the dichotomy between normative (what people should do) and descriptive perspectives (what people actually do; see Edwards, 1961). The second period (1972-1986), known as the "cognitive revolution in JDM", saw developments in the heuristics and biases approach and the introduction of prospect theory (Kahneman & Tversky, 2013). Prospect theory introduced the concept of bounded rationality, which posits that humans are inherently influenced by heuristics and biases; For example, the Availability Heuristic, the Representativeness Heuristic, and the Anchoring Heuristic. The Availability Heuristic involves assessing the probability of an event based on how easily examples come to mind; for instance, after seeing news reports of plane crashes, an individual might overestimate the danger of flying despite its statistical safety. The Representativeness Heuristic entails judging the probability of an event by comparing it to an existing mental prototype, such as when someone described as Linda, a 31-year-old philosophy major concerned with social justice, is incorrectly judged to be more likely a feminist bank teller than just a bank teller, leading to the conjunction fallacy. The Anchoring Heuristic involves relying heavily on the first piece of information encountered, such as in salary negotiations where an initial offer of $80,000 skews perceptions and subsequent offers, even if the fair market salary is closer to $70,000. These heuristics illustrate how cognitive shortcuts can lead to biased and sometimes irrational judgments, affecting everyday decision-making. The third period (1986-2002) incorporated emotions, motivations, and culture into JDM, spreading its ideas to other fields like social psychology, marketing, and economics. The fourth period (2002-2014) encompasses multidisciplinary research applications in areas such as

business, medicine, law, and public policy (for a more detailed historical overview see Keren & Wu, 2015).

Early JDM theories were primarily normative, characterized by the concept of "homo economicus", an idealized rational decision-maker. However, descriptive accounts have since shown that these normative approaches often misrepresent how people actually make decisions. Research to explain this discrepancy proposes that affective processes might play a crucial role (Kahneman & Tversky, 2013; Lerner et al., 2015; Mellers et al., 1999; Mellers et al., 2021; Nabi et al., 2020). In the next sections, I will elaborate on relevant theories and important empirical findings to elucidate the affective involvement in decision-making.

1.1. Decision Making

Von Nitzsch (2024) provides a comprehensive overview of Decision Science in his recently published book. Decision Science is a multidisciplinary field dedicated to understanding and improving how individuals and groups make choices. It is broadly divided into two complementary branches: descriptive decision science and prescriptive decision science. Descriptive decision science focuses on how decisions are made in practice, emphasizing the cognitive, emotional, and contextual factors that shape behavior. By uncovering systematic patterns and biases, it provides a realistic portrayal of human decision-making and highlights deviations from idealized rational models. In contrast, prescriptive decision science explores how decisions should be made to optimize outcomes. This branch develops tools and frameworks, such as decision trees and utility models, to guide individuals toward more rational and structured choices.

One of the fundamental insights in descriptive decision science is the role of cognitive constraints in shaping decision-making behavior (Lebiere & Anderson, 2011). Limitations in attention, memory, and information processing capacity often force individuals to simplify complex decisions (McKenna & Martin-Smith, 2005; Onken et al., 1985). For instance, selective perception leads decision-makers to focus on certain aspects of available information while ignoring others, potentially resulting in biased interpretations (Beyer et al., 1997). Similarly, constraints on working memory restrict the amount of information that can be processed simultaneously, prompting the use of heuristic shortcuts to reduce cognitive load (Lemaire, 1996). Heuristics, as discussed extensively by Tversky and Kahneman (1974), are mental shortcuts that allow individuals to make decisions more efficiently but can lead to systematic biases (see above for examples).

Beyond cognitive shortcuts, emotions and motivations significantly influence decision-making. Emotions such as fear, regret, and anticipation shape risk assessments and choice preferences (Loomes & Sugden, 1987; Mellers et al., 1999; Wake et al., 2020). Fear, for instance, amplifies perceived risks and leads to overly cautious behavior (Wake et al., 2020), while regret aversion often motivates individuals to avoid decisions that might result in negative outcomes, even when such avoidance is not rationally justified (Loomes & Sugden, 1987). Motivational factors, such as the control motive described by Langer (1975), reflect a desire to maintain agency over outcomes, influencing how individuals perceive and engage with risky decisions. Von Nitzsch (2024) further highlights the need for cognitive consistency, where individuals align their decisions with existing beliefs and values, often post-rationalizing choices to reduce dissonance.

Furthermore, decision-making can be categorized into various types based on the context and the information available to decision-makers. *Decisions under certainty* involve choices with clear and predictable outcomes, where all relevant information is known, and consequences can

be anticipated (Weber, 1997). *Decisions under risk*, on the other hand, require evaluating probabilistic outcomes, often framed within expected utility theory, where individuals weigh the likelihood of risks against potential rewards (Mishra, 2014). In contrast, *decisions under uncertainty* occur in scenarios where probabilities are unknown or ambiguous, prompting reliance on heuristics or subjective judgments (Johnson & Busemeyer, 2010). *Recurrent decisions* are those made repeatedly over time, often incorporating feedback and requiring strategy adjustments, such as in iterative learning or habit formation (Betsch & Haberstroh, 2014; Sutton & Barto, 1999). *One-time decisions* typically involve high stakes and require deliberative, careful planning, such as career or medical choices (Guo, 2011). Additionally, *social decisions* involve interactions with others and are influenced by factors such as trust, cooperation, and competition (Bruch & Feinberg, 2017), while *moral and ethical decisions* address conflicts between values, fairness, and consequences (Van Lange et al., 2013; Weber et al., 2004). These categories illustrate the diverse nature of decision-making across different contexts and the varying challenges they present.

This thesis is situated at the intersection of decisions under uncertainty and recurrent decision making, addressing the challenges individuals face when making repeated choices in dynamic environments with incomplete information. Decisions under uncertainty involve scenarios where outcomes are not fully predictable, and probabilities may be unknown or ambiguous, requiring decision-makers to rely on heuristics, feedback, and adaptive strategies (Tversky et al., 1982; Tversky & Kahneman, 1974). In recurrent decision making, choices are made iteratively over time, with each decision informed by the outcomes and experiences of previous ones, as seen in financial investments, habit formation, or iterative learning tasks (Betsch & Haberstroh, 2014; Rakow & Newell, 2010; Sutton & Barto, 1999). This thesis examines how individuals navigate the interplay between uncertainty and feedback in such contexts, exploring the cognitive and affective mechanisms underlying decision-making processes. By focusing on

these areas, the research contributes to a deeper understanding of how people adapt and refine their strategies in uncertain, evolving environments and the biases and limitations that influence these processes.

1.2. Affective Involvment in Decision-Making

As both decisions and emotions are complex phenomena, it is not surprising that there have been many different categorization approaches. They all aim at structuring research on affective involvement in decision-making. Furthermore, the judgment and decision-making literature has previously utilized various affect measures, including physiological ones, to explore their influence on choice behavior. In contrast, my work focuses mainly on how self-reported affect predicts decision outcomes. Efendic (2017) summarized the major reviews on the topic, which outlines different possibilities how self-reported affect might influence the decision-making process. Reading this article, it becomes evident that almost every research group on the topic developed their own categorization approach. In my opinion, it does not make sense to add another categorization approach to the literature but to use pragmatic categories that can be used to accumulate empirical evidence. In turn, this enables future theorizing to generate empirically based categories. Hence, for the purpose of this thesis, I use broad, pragmatic categories that are in line with previous research findings. My goal is to generate a solid empirical research base that can inform future theorizing. More detailed categorization approaches might be useful in the future but are not yet grounded in empirical evidence.

Understanding how subjective feeling states influence decision making requires clarifying the meaning of affect and emotion, and how these feelings unfold across the decision process. In the present work, I use the terms affect and emotion interchangeably to describe

general subjective feeling states characterized by their valence and arousal. While prominent theoretical models (Loewenstein & Lerner, 2003; Russell, 1980, 2003; Russell & Barrett, 1999) draw a distinction between core affect—a fundamental, object-free sense of pleasantness or unpleasantness and activation or deactivation—and more complex, object-directed emotional episodes involving appraisal and action tendencies, however, this differentiation is not critical for the questions addressed here. Specifically, the self-reported feeling states that accompany valuation and choice in decision contexts do not neatly fit into either category: they are neither purely undirected core affect nor fully elaborated, discrete emotions. Instead, they reflect consciously accessible, context-related feelings that shape and respond to decision processes. Based on this broad understanding, the following sections will further differentiate these feeling states along different dimensions.

Thus, I distinguish between two key dimensions of emotions in decision-making processes. First, as highlighted by Mellers et al. (1999), it is useful to differentiate between pre-decisional and post-decisional emotions. Pre-decisional emotions are the emotions that an individual experiences before a decision is made. These emotions may influence the decision-making process itself by shaping preferences or biases toward choices. On the other hand, post-decisional emotions arise after the decision has been made and the outcome has been realized (Västfjäll & Slovic, 2013). These post-decisional emotions are often a response to how the individual perceives the consequences of their choice, potentially including feelings of satisfaction, regret, or relief (Rottenstreich & Shu, 2004).

Second, Loewenstein and Lerner (2003) offer a broader framework for understanding the emotional experience during decision-making by distinguishing between expected and immediate emotions. Expected emotions involve the anticipation of future emotional re-

actions that might result from different outcomes depending on the decision (Rottenstreich & Shu, 2004). These are prospective emotions, where individuals try to predict how they will feel based on the outcome of their choice. For example, a person might choose a safer option because they expect to feel relieved in the future if things go well. In contrast, immediate emotions, or current feelings, are the emotional states that individuals experience in real-time while they are actively making a decision. Both types of emotions—expected and immediate/current—play a crucial role in decision-making (Västfjäll & Slovic, 2013).

Last, in decision-making research, valuation models and discrete emotions serve distinct but complementary functions. Valuation models typically focus on how individuals assess and prioritize options based on expected outcomes, often incorporating a dimensional perspective on affect characterized by valence (the intrinsic attractiveness or aversiveness of an option) and arousal (the level of physiological activation). In contrast, discrete emotions—such as happiness, sadness, or fear—are viewed as specific emotional responses that can influence decision-making in nuanced ways. While valuation models may quantify preferences by mapping choices onto a valence-arousal framework, discrete emotions can provide immediate, context-dependent signals that shape perceptions and drive behaviors. Together, they highlight how both cognitive evaluations and emotional experiences intertwine in the complex landscape of human decision-making (Lerner et al., 2023). For this thesis, I focus on valuation models examining the self-reported valence and arousal dimension in the context of various theory classes, which are presented in the next chapter.

1.3. Theory Classes in Affective Decision-Making

A comprehensive understanding of self-reported affect in decision-making requires examining three distinct theory classes: direct causation approaches (Jäger & Rüsseler, 2016; Kahneman & Tversky, 2013; Reimann & Bechara, 2010), indirect causation approaches (Charpentier et al., 2016; DeWall et al., 2016; Jäger et al., 2020; B. Mellers et al., 1999), and interaction approaches (e.g. Jäger et al., 2022; Lerner et al., 2015b). Direct causation theories assert that emotions directly influence decision-making, creating a clear connection between emotional states and choices. In contrast, indirect causation approaches emphasize the role of cognitive processes, suggesting that emotions affect decisions by shaping perceptions and evaluations of anticipated risks and rewards. Meanwhile, interaction approaches highlight the intricate interplay between emotional and cognitive factors, exploring how they jointly influence decisions in varying contexts. This chapter will delve into each of these theoretical frameworks, elucidating their unique contributions to our understanding of the role of affect in decision-making by giving some examples.

1.3.1. Direct Causation Approaches

One approach explaining how emotions influence decisions is the Direct Causation Approach. The fundamental idea here is that decision-making is primarily influenced by emotions felt at the moment the decision is made (Baumeister et al., 2007).

An example of this approach is Prospect Theory, one of the most well-known theories on decision-making in risky situations (Kahneman & Tversky, 2013). Such situations include, for instance, those involving monetary gains or losses. The theory gained attention because it diverged from previous models by suggesting that people are irrational decision-

makers who use heuristics instead of adhering to the rules of mathematical rationality (Tversky & Kahneman, 1974).

According to prospect theory, humans are primarily influenced by the immediate emotional consequences of gains and losses rather than by the long-term prospects of wealth and overall utility. A key concept is loss aversion, which posits that losses weigh more heavily than gains. This explains why participants in experiments tend to choose smaller gains when it means facing a lower risk of loss (Tversky et al., 1982). A common example is a coin toss: if heads comes up, one wins €150; if tails do, one loses €100. Most people decline to participate in such a game. Loss aversion is explained by the idea that emotions tied to losses and gains are weighted asymmetrically in the decision-making process (see also Tversky et al., 1982).

Building on the idea that emotions directly shape decision-making, the somatic marker theory offers a neurobiological perspective on how affective signals guide choices. Bechara and Damasio (2005) propose that decision-making is deeply intertwined with emotional processes, particularly through the mechanism of somatic markers—visceral, bodily responses that become associated with specific outcomes during emotional experiences. These markers, which involve changes in autonomic functions such as heart rate, skin conductance, and gut feelings, are encoded in the brain, particularly in the ventromedial prefrontal cortex (vmPFC). When facing a decision, these somatic markers are reactivated—often unconsciously—and serve to bias attention and behavior by signaling which options may lead to positive or negative consequences, thereby enabling faster and more adaptive choices. This mechanism becomes especially crucial in complex, uncertain, or emotionally laden situations where logical reasoning alone may be insufficient. Robust empirical evidence supports the theory. In the seminal Iowa Gambling Task, Bechara et al. (1997) demonstrated that neurologically healthy participants gradually learn to avoid

high-risk decks and develop anticipatory skin conductance responses (SCRs) before choosing disadvantageous options, reflecting engagement of somatic markers. In the task, participants select cards from four decks (A, B, C, and D), each associated with variable rewards and penalties. Two decks (A and B) yield high immediate gains but lead to larger long-term losses, making them disadvantageous. The other two decks (C and D) offer smaller immediate gains but result in net positive outcomes over time. The goal is to maximize profit, encouraging them to learn from feedback and shift toward the advantageous decks. In contrast, individuals with vmPFC damage persistently make risky choices and fail to exhibit anticipatory SCRs, despite understanding the task contingencies at a cognitive level—suggesting that their impaired decision-making arises from a disruption in the emotional signaling system rather than from defective reasoning. Subsequent neuroimaging studies further confirmed the involvement of the vmPFC, as well as the amygdala, in integrating affective information during value-based decisions (Bechara & Damasio, 2005; Fellows, 2006). Additionally, patients with amygdala lesions also fail to generate somatic responses and show deficits in emotional learning and risk evaluation, indicating that somatic markers rely on a network of emotional and interoceptive structures (Adolphs et al., 1995; Bechara et al., 1999). Together, this body of research supports the claim that emotions—encoded through bodily states—are not just consequences of decisions but integral components of the decision-making architecture. Somatic marker theory thus provides a compelling neurobiological account of how affectively mediated physiological signals can directly predict and guide decisions, often leading to more adaptive outcomes than purely deliberative reasoning—particularly in contexts characterized by uncertainty, complexity, or high emotional salience (Adolphs et al., 1995; Bechara et al., 1997, 1999; Bechara & Damasio, 2005; Fellows, 2006; Reimann & Bechara, 2010).

Expanding on the somatic marker theory's insight that emotional signals help guide behavior by encoding bodily states linked to past outcomes, the affective signaling hypothesis proposes that affect—especially brief, negatively valenced emotional responses—is central to how the brain monitors and adjusts cognitive control. According to Inzlicht et al. (2015), when individuals encounter conflict or commit errors, they experience immediate negative affect, which is detected by the anterior cingulate cortex (ACC) and related neural systems. This affective signal then triggers regulatory adjustments aimed at preventing future conflict or mistakes. The hypothesis outlines a three-stage loop: (1) conflict or error elicits negative affect, (2) the performance-monitoring system registers this affect, and (3) control is adapted to mitigate future conflict. Empirical support for this comes from neuroimaging and electrophysiological studies showing that conflict activates regions such as the amygdala and insula, and modulates control-related signals like the error-related negativity (ERN; Moser et al., 2013). Additionally, recent work by Dignath et al. (2020) strengthens this model by integrating findings across neuroscience, emotion, and control research. They review converging evidence that the ACC serves not just as a conflict detector but also as an integrator of affective signals, modulating control in response to emotional salience. For example, people with high trait anxiety exhibit larger ERN amplitudes and more pronounced conflict adaptation, suggesting a heightened sensitivity to affective signals (see also Moser et al., 2013).

However, the Direct Causation Approach has been criticized. A central criticism of both the somatic marker theory (SMT) and the affective signaling hypothesis (ASH) is the assumption that emotional responses automatically and directly guide decisions or control adjustments. Empirical findings increasingly show that while affect plays a role, its influence is indirect, contingent, and often mediated by cognitive insight. In a landmark critique of SMT, Maia and McClelland (2004) showed that participants in the Iowa Gambling

Task could verbally articulate which card decks were advantageous before exhibiting anticipatory somatic markers (e.g. skin conductance), undermining the claim that bodily affect drives behavior in the absence of conscious awareness. Further evidence from Fernie and Tunney (2006) demonstrated that participants' gambling behavior aligned more closely with explicit knowledge of outcome probabilities than with physiological reactivity, reinforcing the argument that cognitive processes—not somatic cues—often steer decisions. Similarly, in the realm of cognitive control, the affective signaling hypothesis suggests that negative affect following conflict leads to adaptive regulation, but studies show this is not always the case. For instance, Egner et al. (2008) found that conflict adaptation was modulated by task goals, not just affective responses, suggesting that top-down intentions and strategies play a significant role in control adjustments. Additionally, Fröber and Dreisbach (2014) observed that positive affect can both impair and enhance cognitive flexibility depending on context, challenging the assumption that specific affective states reliably drive control adaptations. In individuals with high trait anxiety or depression, Moser et al. (2013) enhanced error monitoring (ERN) without corresponding behavioral improvement, highlighting a dissociation between emotional reactivity and effective regulation. These findings collectively suggest that while emotions are part of the decision and control architecture, they do not operate in isolation. Instead, they are interpreted, regulated, and sometimes overridden by conscious context-sensitive cognitive mechanisms—casting doubt on the idea that felt emotions or somatic markers are sufficient to directly guide choices or adaptations.

1.3.2. Expectancy Approaches

The Expectancy Approach can be seen as an alternative Approach to the Direct Causation Approach. While the latter focuses on emotions felt in the moment, the Expectancy Ap-

proach suggests that decisions are primarily influenced by anticipated/expected emotions (e.g. Mellers et al., 1999). According to this view, when individuals face a decision, they consider how they will feel in the future depending on the choice they make. Expected emotions thus help prepare for the future and influence decision-making .

Decision Affect Theory (DAT), developed by Mellers et al. (1997), is a prominent expectancy-based model that explains how anticipated emotions guide decision-making. Instead of emotions exerting direct influence at the moment of choice, DAT suggests that people mentally simulate how they expect to feel about possible outcomes, and these forecasts shape their preferences. DAT identifies three key psychological mechanisms that influence emotional expectations: (1) outcome expectations, (2) comparisons to alternatives, and (3) counterfactual thinking. First, people respond more strongly to outcomes that deviate from their expectations—a phenomenon known as emotional amplification by surprise. For example, unexpectedly winning $50 when expecting nothing feels better than receiving $50 when expecting $100. Second, people compare outcomes to foregone alternatives, leading to emotions like regret or relief. A person who chooses Stock A and earns a 5% return may feel worse if Stock B, which they considered, gained 15%. Third, people engage in counterfactual thinking—imagining how things could have turned out better or worse. For instance, a lottery player who misses the jackpot by one number feels more disappointed than someone who was far from winning, even though the outcomes are objectively the same. Empirical studies support each of these mechanisms. Mellers et al. (1997) showed that emotional reactions were stronger when outcomes differed from expectations and when better alternatives were available. Mellers and McGraw (2001) demonstrated that people anticipate such emotional responses in advance and choose options accordingly. Similarly, Mellers et al. (1999) found that even subtle changes in framing could shift people’s affective forecasts and thereby alter their decisions. Thus, DAT

provides a structured account of how anticipated emotional reactions—shaped by expectations, comparisons, and counterfactuals—serve as internal guides that influence human choice.

The Emotion-as-Feedback Hypothesis (EFT; Baumeister et al., 2007) builds on and refines Decision Affect Theory (DAT) by emphasizing that it is not emotions felt before a decision that guide behavior, but rather the emotions experienced at the outcome of prior decisions that serve as feedback for future choices. According to DAT, individuals seek to make choices that maximize positive and minimize negative emotional outcomes, guided by their anticipated feelings. The Emotion-as-Feedback Hypothesis aligns with this but adds that these anticipated emotions are shaped by the emotional consequences of past decisions — The regret, pride, guilt, or satisfaction people feel after making a choice become internalized and used to predict how they will feel in similar situations moving forward. Over time, people learn to anticipate these emotional outcomes and make decisions that steer them toward preferred emotional states. Baumeister et al.'s (2007) meta-analytic review of over 100 studies found limited evidence that emotions directly cause behavior in the moment, but strong evidence that emotions influence behavior via post-decision feedback and learned anticipation. For example, Zeelenberg et al. (1998) showed that regret is related to behavior-related counterfactual thoughts; Tangney et al. (2007) argued in a review that anticipated guilt, informed by prior emotional outcomes, motivated prosocial and moral behavior; and DeWall et al. (2008) found that social exclusion only enhanced self-regulation when the emotional experience was reflected upon after the fact. Finally, Brown and McConnell (2011) showed that anticipated emotions are adjusted based on past mismatches between desired and actual feelings, refining future decisions to reduce such discrepancies. Together, this body of evidence supports the view that emotions function as a feedback-based learning system, allowing people to forecast future

emotional outcomes based on past experiences and to optimize decision-making over time.

Expectancy-based decision theories have been critiqued for their oversimplified assumptions about human affective forecasting. One prominent issue is focalism in DAT, where individuals disproportionately focus on one aspect of an outcome—typically the emotional peak—while neglecting broader contextual variables or adaptation effects (T. D. Wilson et al., 2000). This can lead to systematically biased affective predictions, as demonstrated in studies showing that people overestimate emotional reactions to both positive and negative events (Gilbert et al., 1998). Moreover, EFT fails to incorporate the dynamic and interactive nature of decision contexts, where emotional anticipations compete with habitual, social, or normative influences—factors well-documented in decision science but largely absent from the theory's framework (Lerner et al., 2015). This highlights a key limitation of EFT: while affective predictions may correlate with decisions, they do not always serve as reliable or optimal guides across diverse and complex scenarios.

1.3.3. Interaction Approaches

The Emotion-Imbued Choice Model (EICM; Lerner et al., 2015b) provides a theoretically integrative account of how emotions shape decision-making, emphasizing that emotions are not incidental but constitutive elements of evaluative processes. The model posits that decisions are guided by the interaction of current emotional states—whether integral to the decision context or incidental—and anticipated emotions, i.e. affective responses individuals expect to experience as a consequence of potential outcomes (Lerner et al., 2015, 2023). These two affective sources dynamically inform judgments, modulate attention, and influence how options are construed and compared. For instance, an individual may feel anxious while choosing between job offers, which heightens sensitivity to potential losses (current emotion), while also imagining the regret or pride they may feel in the

future, thereby shaping preferences toward options that maximize anticipated positive affect or minimize negative outcomes (Mellers et al., 1997; Zeelenberg et al., 1998). While the model allows for general affective influences (e.g., valence and arousal), it also emphasizes the distinct functional roles of discrete emotions—such as fear, anger, sadness, or happiness—which each carry appraisal tendencies that influence decision processes in emotion-specific ways (Lerner & Keltner, 2000). For example, fear typically involves appraisals of uncertainty and lack of control, promoting risk-averse choices, whereas anger, associated with certainty and control, may foster risk-seeking behavior (Lerner & Tiedens, 2006). These discrete emotion effects are not reducible to general mood valence and are often predictive of divergent behavioral outcomes, even among emotions of the same valence (Han et al., 2007). The EICM thus synthesizes emotion theory with decision science by highlighting that emotions—both felt in the moment and projected into the future—are central to how people evaluate options, assess risks, and make choices. This dual focus on present and anticipated affect offers a nuanced framework for understanding emotions' role in choice behavior across domains such as consumer decisions, policy judgments, and moral evaluations (Lerner et al., 2023). Crucially, it positions emotional processes as goal-directed and meaning-laden, rather than irrational or disruptive.

The Emotion-Imbued Choice (EIC) model has been influential in highlighting the role of both immediate and anticipated emotions in decision-making, but it faces two key criticisms. First, the model lacks specificity regarding the conditions under which different emotional influences dominate, offering little guidance on how immediate versus anticipated emotions interact or compete in complex decisions. For example, in high-stakes contexts such as medical choices or ethical dilemmas, it remains unclear whether current fear, anticipated guilt, or social emotions like pride should take precedence in shaping choice behavior (see also Pham, 2007). Second, the model's broad scope and flexibility

make it difficult to falsify: it can account for a wide range of behaviors by invoking different emotional mechanisms post hoc, without offering precise, testable predictions. This limits its utility for generating hypotheses that can be empirically discriminated from those of competing models.

Some of the key limitations of the Emotion-Imbued Choice (EIC) model particularly its lack of specificity in predicting whether immediate or anticipated emotions dominate decision-making, and its limited falsifiability may be addressed by integrating dual-process theories of cognition. These theories differentiate between intuitive (Type 1) and deliberative (Type 2) processing (Evans & Stanovich, 2013a), allowing for more precise predictions about how and when emotional influences are likely to affect choice. For instance, studies show that under cognitive load or time pressure, immediate emotional responses (e.g. anxiety) disproportionately shape risk preferences (Finucane et al., 2000; Shiv & Fedorikhin, 1999), whereas deliberative contexts foster the integration of anticipated emotions like regret or pride (Mellers et al., 1997, 2021). Embedding the EIC model within this dual-process framework enhances its predictive power and testability by clarifying the cognitive conditions under which different emotional signals influence decision behavior.

1.4. Methodological Approaches

Methodological approaches to studying self-reported affect in decision-making often employ experimental designs that simulate real-world decision contexts, such as one-shot gambles and recurrent decision scenarios (Charpentier et al., 2016; Hayes & Wedell, 2020; Mellers et al., 1997; Schlösser et al., 2016; Schlösser et al., 2013). In one-shot gambles, participants make decisions involving uncertain outcomes, where probabilities may be either explicitly presented or left open for interpretation. These designs allow researchers to investigate how self-reported affect influences risk preferences and decision-

making under uncertainty. Self-reported affect is typically assessed through ratings of emotional states before, during, or after the decision, providing a direct measure of how emotions may shape choices (Charpentier et al., 2016; Mellers et al., 1997; Schlösser et al., 2016; Schlösser et al., 2013; Tversky et al., 1982; Tversky & Kahneman, 1974). In recurrent decision paradigms, participants repeatedly make decisions over time, receiving feedback on previous choices, which allows researchers to explore the role of affect in learning from experience and adjusting subsequent decisions (Bechara et al., 1997; Hayes & Wedell, 2020; Reimann & Bechara, 2010). These recurrent decision tasks provide valuable insights into how emotional states influence choice behavior in dynamic contexts, where prior experiences and feedback may shape future decisions. Both approaches rely on self-reported measures of affect to examine the role of emotions, both current and expected, in guiding decisions within various temporal and informational contexts.

1.4.1. One-Shot Gambles

One-shot gambles, where participants decide once between a certain outcome and a probabilistic alternative, are widely used to examine decision-making under risk without the confounds of feedback or learning (Hertwig & Erev, 2009; Tversky & Kahneman, 1974). These tasks typically involve monetary stakes, either hypothetical or incentivized, and are combined with self-reports of anticipated and experienced affect or physiological and neural measures (Coricelli et al., 2005; Rolls et al., 2022). Their strength lies in isolating anticipatory processes that drive choices.

Classic studies using one-shot gambles revealed systematic violations of expected utility. Kahneman and Tversky (2013) showed that participants overweigh small probabilities and undervalues large ones, producing the probability-weighing functions central to Prospect Theory. Mellers et al. (1997) extended this work by demonstrating that anticipated

emotions predict choice over and above expected value. In their experiments, participants decided between certain and risky options, then rated their expected feelings before the decision and their experienced affect afterward. A key finding was that outcomes were judged relatively to counterfactuals: narrowly missing a larger payoff evoked stronger disappointment than objectively equivalent but expectation-consistent outcomes.

Other traditions build on the same paradigm. Research on near-miss effects shows that losses resembling wins trigger heightened striatal and insula responses and paradoxically increase gambling motivation, despite being equivalent to losses (Clark et al., 2009). Neuroimaging evidence further indicates that anticipating emotions, such as regret, recruits orbitofrontal and amygdala regions, with participants adapting behavior to minimize negative affect (Coricelli et al., 2005; Rolls et al., 2022). Physiological indices, such as skin conductance, similarly predict avoidance of regret-inducing choices (Sokol-Hessner et al., 2009). Beyond the laboratory, one-shot paradigms have been applied to health, consumer, and moral decisions, showing that anticipated regret, pride, or relief predicts vaccination uptake (Brewer et al., 2016), consumer choices (Cooke et al., 2001), and prosocial giving (Moche et al., 2020).

Taken together, findings across these traditions converge on three lessons. First, one-shot gambles consistently demonstrate that anticipated affect—ranging from regret and disappointment to pride and relief—shapes choices alongside cognitive evaluations of risk and value (Hopfensitz & Reuben, 2009; Loomes & Sugden, 1987; Mellers et al., 1999; Mellers et al., 1997; Mellers & McGraw, 2001). Second, decisions are not based on absolute outcomes but are strongly influenced by counterfactual comparisons and near-miss experiences (Clark et al., 2009; Van Dijk & Zeelenberg, 2005; Wu et al., 2017; Zeelenberg et al., 1998). Third, converging physiological and neural evidence confirms that affective forecasting is not epiphenomenal but a core component of valuation processes (Clark et al.,

2009; for an overview see Rolls et al., 2022). One-shot gambles therefore provide a rigorous and widely generalizable methodological window into the integration of affect and cognition in decision-making under uncertainty.

Despite their usefulness in isolating anticipatory processes, one-shot gamble tasks face several criticisms. First, they suffer from limited ecological validity, as real-world risky choices often involve repeated feedback and learning. In contrast, one-shot tasks exaggerate the description–experience gap, where choices from description diverge systematically from those based on experience (Barron & Erev, 2003; Hertwig & Erev, 2009). Second, their reliance on highly stylized payoff formats makes results sensitive to framing and design, potentially overstating biases such as loss aversion (Crosetto & Filippin, 2016; Ert & Erev, 2013). Third, since each participant provides only one choice, the method has low diagnostic power and may conflate stable preferences with noise (Erev et al., 2010). These limitations caution against overgeneralizing findings from one-shot gambles, even as they remain valuable for identifying baseline cognitive–affective mechanisms.

1.4.2. Recurrent Decision Tasks

Research in recurrent decisions in psychology typically employs experimental methodologies that involve repeated decision-making tasks with feedback to investigate how individuals learn from experience and adjust their behavior over time. These methodologies often combine behavioral data with self-reported measures to assess both the decisions participants make and the emotional or cognitive states influencing those decisions (Bechara et al., 1997; Betsch & Haberstroh, 2014; Turnbull et al., 2014).

In experience-based learning tasks, participants are generally asked to repeatedly choose from a set of options, with outcomes that are uncertain but reveal information about the consequences of different actions through feedback. Common tasks used in this approach include the Iowa

Gambling Task (Aram et al., 2019; De Vries et al., 2008; Hayes & Wedell, 2020; Steingroever et al., 2013; Turnbull et al., 2014), where participants choose from decks of cards with varying risk-reward profiles, and other probabilistic learning tasks that involve learning about the payoff structure based on past decisions. In these tasks, learning is typically measured by observing changes in choice patterns over time as individuals adapt to the feedback they receive.

Reinforcement learning (RL) studies in psychology often employ computational models to formalize the learning process. These models simulate how individuals update their expectations or value assessments of different options based on rewards and punishments, reflecting a process of optimizing behavior over time (Sutton & Barto, 1999). Experimental designs often involve tasks where participants must make decisions under uncertain conditions and receive feedback on the outcomes. The feedback is used to update their decision-making strategies, and researchers track how well participants' choices align with RL models, such as temporal difference learning or Q-learning, which predict how individuals might adjust their behavior based on the reward structure (e.g. Daw & Doya, 2006).

Taken together, both experience-based learning and RL research typically employ a combination of behavioral tracking, computational modeling, and self-report measures to provide insights into the underlying cognitive and emotional processes driving adaptive decision-making. The use of these methodologies allows researchers to assess how experience, feedback, and reinforcement shape behavior over time and how individuals optimize their decisions in uncertain environments. Recent evidence confirms that the Iowa Gambling Task (IGT) effectively models how individuals adapt decisions over time by integrating feedback and learning to prioritize long-term over short-term outcomes (Buelow & Suhr, 2009; Steingroever et al., 2013). However, numerous studies have shown that many participants adopt suboptimal or inconsistent strategies in the IGT, such as favoring decks with frequent rewards despite long-term losses, failing to shift away from disadvantageous choices, or relying on simple heuristics rather

than integrating outcome probabilities over time (Fernie & Tunney, 2006; Must et al., 2013; Weller et al., 2010). Neuroimaging research links this learning process to the ventromedial pre-frontal cortex and striatum, which support valuation and reward-based learning, as well as to the anterior cingulate cortex and insula, which are involved in risk monitoring, error detection, and behavioral adaptation under uncertainty (Clark et al., 2008; Lawrence et al., 2009; Li et al., 2010). Computational modeling adds further insight by identifying prediction errors—the difference between expected and actual outcomes—as a key mechanism that drives learning across trials (Sutton & Barto, 1999). These prediction errors are tracked by dopaminergic brain circuits, particularly within the striatum and midbrain, and play a central role in updating value estimates and guiding future behavior (Garrison et al., 2013; Jocham et al., 2011). Factors such as learning rate and feedback sensitivity vary as a function of environmental volatility, task demands, and perceived control, with individuals adjusting learning adaptively under uncertainty (Behrens et al., 2007; Nassar et al., 2012). A meta-analysis supports the robustness of these mechanisms across different learning contexts (Fontanesi et al., 2019). Together, this research shows that people learn from experience by gradually shifting from exploring uncertain options to exploiting known ones (e.g. Wilson et al., 2014), using heuristics and outcome feedback to identify stable reward patterns (Worthy et al., 2013).

1.4.3. The Methodological Approach of this Thesis

Combining one-shot gambles and recurrent decision approaches offers a more comprehensive perspective on how self-reported affect influences decision-making. One-shot gamble experiments, while useful for examining decision-making under uncertainty, have notable limitations besides the short-comings that I have already mentioned. These tasks typically involve isolated decisions that lack the dynamic feedback and learning inherent in many real-world decision-making processes (Aram et al., 2019). Additionally, these designs often focus on immediate emotional responses, which may not capture the longer-term effects of emotions that unfold

across repeated decisions (Betsch & Haberstroh, 2014). On the other hand, experience-based learning tasks offer valuable insight into how individuals adapt their decisions over time based on feedback (Daw & Doya, 2006; Hayes & Wedell, 2020; Turnbull et al., 2014). However, these tasks introduce complexity by requiring participants to integrate multiple rounds of decision-making, which can make it difficult to isolate the influence of self-reported affect at any given moment. Moreover, the emotional effects may become diluted as participants accumulate experience and refine their strategies, making it harder to measure the immediate impact of emotions on decisions.

In this thesis, I combine both approaches to address these limitations. First, the experience-based learning task allows participants to gather experience and adapt their decisions over time, simulating more complex, real-world decision-making contexts where feedback plays a key role in shaping choices. In the test phase, participants made choices based on this accumulated experience, which provides an opportunity to study how self-reported affect influences decisions after learning had taken place. Second, incorporating a one-shot gambles set-up in the test phase enables me to isolate the impact of self-reported emotions on immediate, risk-related decisions, addressing the limitation of experience-based tasks, where feedback and learning can obscure the influence of current emotions. Finally, combining both approaches allows for an exploration of the interaction between immediate and learned emotional states, providing a more nuanced understanding of how both types of affect—current and expected—guide decision-making. By incorporating both types of decision-making contexts, I offer a comprehensive view of emotions' influence on decision-making over time and across different types of decisions.

2. The current studies

The extant body of literature on affective decision-making is characterized by mixed empirical evidence, which has precluded the formulation of definitive conclusions regarding the underlying mechanisms at play. The inconsistencies in findings across various studies can be attributed to a multitude of factors, including methodological limitations, variations in experimental designs, and differences in the operationalization of key constructs such as emotion and decision-making processes (Baumeister et al., 2007; Charpentier et al., 2016; DeWall et al., 2016; Mellers et al., 1997, 1999; Mellers & McGraw, 2001; Schlösser et al., 2016; Schlösser et al., 2013). These discrepancies underscore the need for a more rigorous and systematic approach to investigating these phenomena.

To address these issues and to advance our understanding of affective decision-making, I developed a novel experimental task specifically designed to overcome the shortcomings identified in prior research. This new task incorporates several methodological improvements aimed at enhancing the reliability and validity of the findings. First, the task employs a within-subjects design to directly compare the effects of current versus expected emotions on decision-making, thereby providing a more robust test of competing theoretical models. Second, it includes comprehensive measures of both valence and arousal, ensuring a more holistic assessment of emotional influences. Additionally, the task is structured to mimic real-world decision-making scenarios more closely by introducing elements of uncertainty, experience-based processes and incomplete information, thereby increasing its ecological validity.

In summary, the design of this new experimental task represents an advancement in the study of affective decision-making. By addressing the limitations of previous research designs and incorporating methodological innovations, this task aims at providing clearer

insights into the complex interplay between emotion and decision-making processes. The outcomes of this research hold the potential to contribute to a more nuanced and comprehensive understanding of how emotions influence human behavior, thereby informing both theoretical models and practical applications in fields such as psychology, behavioral economics, and decision sciences.

3. Empirical Part

3.1. Study 1: Expected valence predicts choice in a recurrent decision task

3.1.1. Background

I started with the research question, which affective construct would best predict choices, as I wanted to understand how affect guides choices. Mixed empirical evidence did not allow a definite conclusion. Therefore, I designed a new experimental task to address the shortcomings of previous research designs.

The body of research on affective decision-making has illuminated many critical aspects of how emotions influence choices, but it also exhibits several important limitations. De-Wall et al. (2016) addressed a central question in this field by conducting a meta-analysis of 82 articles published between 1986 and 2013 in the Journal of Personality and Social Psychology (JPSP), encompassing 245 published mediation tests. Their aim was to compare two theoretical accounts of emotion's role in social judgment and behavior: the emotion-as-direct-causation model, which predicts that currently experienced emotions serve as mediators linking situational events to outcomes, and the emotion-as-feedback model, which emphasizes the influence of anticipated future emotions. The results were strikingly asymmetrical: only 22% of tests supported the direct causation model, whereas 87% of tests supported the feedback model, despite the latter being tested far less frequently. This pattern suggests that anticipated emotions are a more consistent predictor of social behavior and judgment than immediate emotional states, challenging the long-standing assumption that in-the-moment affect primarily drives action. However, important limitations remain. The analysis was constrained to published mediation studies, raising concerns about publication bias, and it relied heavily on self-reported, consciously

accessible emotions, which may underestimate the role of automatic or nonconscious affective processes. Furthermore, because the meta-analysis aggregated across diverse designs, it did not permit a direct experimental comparison of current versus anticipated emotions within the same framework, leaving questions about the causal mechanisms linking affect and decision-making unanswered.

In another notable study, Charpentier et al. (2016) investigated how subjective emotional experiences influence decision-making processes, comparing their predictive accuracy to that of traditional value-based models. In the study, participants were asked to make a series of monetary gamble decisions while simultaneously reporting their expected emotional responses—specifically, their anticipated valence (i.e. how positive or negative they expected to feel about each outcome). These self-reported emotional forecasts were then used as predictors of choice behavior and compared to predictions generated by conventional economic models based on expected utility theory. Charpentier et al. (2016) found that subjective feelings—particularly expected valence—could more accurately predict decision outcomes than computations based purely on expected value. This suggests that integrating emotional expectations into decision models can enhance their predictive power. However, the study focused exclusively on expected valence, neglecting the arousal component of emotion, which captures the intensity or physiological activation associated with an experience. Furthermore, the study neglected immediate emotional experiences. This omission limits the completeness of the emotional profile considered, as arousal and immediate emotions have been shown to shape how individuals perceive risk, urgency, and the motivational significance of outcomes. Therefore, while the study offers valuable insight into the role of emotion in decision-making, its reliance on expected valence alone may overlook important dimensions that further illuminate the mechanisms at play.

Decision Affect Theory (DAT), as developed by Mellers et al. (1999), provides a theoretical framework suggesting that decisions are influenced by the anticipation of pleasure or pain. According to DAT, people weigh potential outcomes based on the expected emotional reactions they will elicit. While this theory has been supported by various experimental findings, the methodologies employed often involve scenarios where probabilities and outcomes are fully displayed to participants (see chapter 1.3.2 and chapter 1.3.2 for examples). This approach simplifies the decision-making context, making it more artificial. In real-world situations, individuals frequently make decisions under conditions of uncertainty, with incomplete or ambiguous information. The ecological validity of DAT findings is therefore limited, as they may not fully capture the complexity and unpredictability of real-world decision-making environments.

The Iowa Gambling Task (IGT; Bechara et al., 1997) is a widely used experimental paradigm for studying decision-making. The IGT was designed to simulate real-life decision-making by requiring participants to choose cards from different decks with varying risk and reward profiles. Participants are presented with four decks of cards (A, B, C, D), each offering varying patterns of rewards and penalties. The goal is to maximize profits by selecting cards over a series of trials. Two of the decks (A and B) are high-risk, offering large immediate rewards but substantial penalties over time, leading to an overall net loss. The other two decks (C and D) are low-risk, providing smaller immediate rewards but smaller penalties, resulting in a net gain in the long run. Initially, participants are unaware of these patterns and must learn through trial and error which decks are advantageous. The task assesses the ability to make adaptive decisions by weighing short-term benefits against long-term consequences, reflecting the role of emotional and cognitive processes in decision-making. It is commonly used to study impairments in decision-making observed in conditions such as addiction or brain injury, particularly damage to the prefrontal cortex.

Hence, in theory using this task to study emotional involvement in decision-making could be a useful methodological approach. However, the simultaneous presentation of all decks may affect participants' focus and strategy, as they can compare and contrast options in a way that might not reflect more sequential, real-world decision-making processes. This means, that participants might have subjective emotional reactions or expectations towards each deck, but the task design makes it impossible to measure these. These methodological issues can obscure the clarity and reliability of the insights gained from the IGT, raising concerns about its ability to accurately model the dynamics of decision-making in naturalistic settings.

3.1.2. Summary of findings

Hence, I developed a gambling task that varies contextual factors (feedback consistency, learning experience, feedback balance) while maintaining ecological validity (Jäger et al., 2020). In Experiment 1, I designed a gambling task to systematically investigate how contextual factors—feedback consistency, feedback balance, and learning experience—influence decision-making and affective responses. The task presented participants with four symbols (circle, triangle, square, cross), each associated with a unique payoff schedule. The payoff schedules were defined by two primary dimensions: feedback consistency (consistent vs. inconsistent) and feedback balance (positive vs. negative). Consistent symbols produced deterministic outcomes; for instance, a consistently positive symbol always resulted in a gain of 15 points when gambled, while a consistently negative symbol always resulted in a loss of 15 points. Inconsistent symbols, by contrast, offered probabilistic outcomes; for example, a positive inconsistent symbol had a 66.6% probability of gaining 15 points and a 33.3% probability of losing 15 points. Similarly, a negative inconsistent symbol had a 33.3% chance of gaining 15 points and a 66.6% chance of losing 15 points. Participants began with a balance of 500 points and were instructed to maximize

their points by making decisions to gamble or pass on each trial. Each trial began with the presentation of a symbol, followed by the participant's decision. If they chose to gamble, feedback (gain or loss) was immediately displayed based on the symbol's payoff schedule. If they chose to pass, no points were gained or lost. The task comprised three learning blocks, each consisting of 82 trials, during which participants learned about the payoff schedules through trial and error. These blocks were interspersed with questionnaire blocks, where participants rated their current and expected affective states on a Self-Assessment Manikin (SAM) scale for each symbol without making decisions. This design allowed for systematic manipulation and measurement of learning and affective responses as participants experienced the contingencies associated with each symbol over time. I hypothesized based on metaanalytic findings (DeWall et al., 2016) that expected affect, especially expected valence, would be a better predictor of decision-making than current affect.

The analysis strategy for Experiment 1 focused on understanding how contextual factors influenced affective responses and identifying which affective constructs best predicted gambling choices. Affective ratings (current valence and arousal, expected valence and arousal for gambling and passing) were analyzed using repeated-measures ANOVAs to examine the effects of feedback consistency (consistent vs. inconsistent), feedback balance (positive vs. negative), and time (three measurement points). Interactions among these factors were also tested. Correlation analyses were performed to assess relationships between affective constructs. Highly correlated measures, such as expected valence for gambling and passing, were combined into a difference score to reduce redundancy and collinearity. To predict gambling choices, a generalized linear mixed-effects model (GLMM) was used. The model included gambling choice (gamble or pass) as the depend-

ent variable and expected valence difference, current valence, expected arousal (for gambling and passing), and current arousal as predictors. Participant ID was modeled as a random intercept to account for individual differences. Model comparison using likelihood ratio tests identified significant predictors of gambling behavior. The findings from Experiment 1 demonstrate that expected valence is the key predictor of gambling choices, while current affect and arousal play no significant role in guiding decision-making. Participants were more likely to gamble when their expected valence for gambling exceeded that for passing, emphasizing the importance of anticipatory affect in decisions under uncertainty. Contextual factors such as feedback consistency and feedback balance influenced affective ratings, with consistent and positively balanced symbols eliciting stronger expected valence and arousal ratings. However, the lack of predictive power for current affect and arousal raises questions about their broader role in decision-making processes. While these findings highlight the primacy of future-oriented affective evaluations, they leave unanswered how these constructs are represented at a neural level and whether the observed relationships hold in a broader, more diverse sample. To address these gaps, Experiment 2 employed an exploratory fMRI design to investigate the neural correlates of predecisional affect during the anticipation phase. Additionally, it aimed at replicating the behavioral findings of Experiment 1 in a more diverse sample to test the robustness and generalizability of the results across different populations and experimental conditions.

In Experiment 2, the gambling task from Experiment 1 was adapted for an fMRI environment to explore the neural correlates of predecisional affect and replicate the behavioral findings in a more diverse sample. The task retained the core structure of varying feedback consistency (consistent versus inconsistent outcomes) and feedback balance (posi-

tive versus negative outcomes) while introducing modifications to accommodate the constraints of the fMRI setting and enhance the neural interpretability of results. Five symbols were used in this version, compared to four in Experiment 1. Four of the symbols followed the original structure of consistent and inconsistent feedback patterns combined with positive or negative balances. The fifth symbol served as a control condition and had no monetary impact, regardless of the participant's decision. This control symbol provided a baseline for isolating affect-related brain activity during the anticipation phase.

In the fMRI phase, Participants engaged in a series of trials, each consisting of an anticipation phase, a decision phase, and a feedback phase. In the anticipation phase, participants viewed a fixation cross followed by the presentation of a symbol. They were then asked to decide whether to gamble or pass, in response to the question "Do you want to gamble?" displayed on the screen. Participants had up to 2,500 milliseconds to respond using a button press. If they failed to respond within the time limit, they were shown feedback indicating a missed trial, which did not affect their monetary balance. When a decision was made, feedback was displayed, reflecting either a monetary gain or loss based on the symbol's probabilistic payoff schedule. Outcomes were expressed in real monetary terms, with gains or losses of 20 cents per trial to enhance engagement and the neural relevance of decisions. To improve the temporal resolution of neural activity analyses and reduce predictability, the inter-trial interval was jittered between 2,000 and 3,000 milliseconds. The task included several phases. Initially, participants completed a short practice phase to familiarize themselves with the task and timing parameters. This practice did not impact their monetary balance. They then progressed through three learning blocks, each consisting of 52 trials. During these blocks, they made decisions and learned about the symbols' payoff schedules through trial and error. The learning blocks were followed by

the fMRI phase, which included two blocks of 50 trials each. During this phase, participants performed the gambling task inside the scanner. To measure predecisional affect, participants completed a Predecisional Affect Questionnaire (PAQ) Block after the fMRI phase. In this block, they rated their current valence and arousal, as well as their expected valence and arousal for gambling and passing decisions, for each of the five symbols. These ratings were collected using a paper-and-pencil format with a 9-point Self-Assessment Manikin (SAM) scale, consistent with Experiment 1. This task design maintained the systematic manipulation of feedback consistency and balance from Experiment 1 while enabling behavioral replication and exploratory analysis of neural mechanisms underlying predecisional affect in decision-making.

The analysis strategy for Experiment 2 focused on replicating the behavioral findings from Experiment 1 and exploring the neural correlates of predecisional affect during decision anticipation using fMRI. Behavioral data were analyzed using the same methods as Experiment 1, including repeated-measures ANOVAs to examine the effects of contextual factors on affective ratings and a generalized linear mixed-effects model to predict gambling choices based on affective constructs. For details, refer to the behavioral analysis description in Experiment 1. The fMRI data were preprocessed and analyzed using standard pipelines, including motion correction, normalization, and modeling of neural activity during the anticipation phase. Contrasts were calculated to compare activation patterns across different symbol conditions (e.g., feedback balance, feedback consistency, and control symbols). For more specific details on fMRI analysis, refer to the original study. This combined approach allowed for the replication of behavioral findings and an exploratory investigation of the neural basis of predecisional affect. Experiment 2 replicated the behavioral findings from Experiment 1, showing that expected valence was the primary predictor of gambling choices, while current affect and arousal did not significantly influence

decision-making. Contextual factors such as feedback balance and feedback consistency influenced affective ratings, with positive and consistent symbols eliciting higher expected valence ratings than negative or inconsistent symbols. Current valence ratings evolved over time, becoming more distinct between positive and negative feedback balance as learning progressed, but they did not predict choices. Arousal ratings, though sensitive to feedback balance, similarly failed to predict gambling behavior. The fMRI results revealed significant neural activity during the anticipation phase associated with decision-making. Brain regions such as the nucleus accumbens, thalamus, anterior cingulate cortex, and superior frontal cortex showed activation. Negative feedback balance was associated with greater activity in the temporal gyrus, while contextual factors such as feedback consistency showed limited influence on neural activation patterns. These findings provide preliminary evidence on the neural correlates of predecisional affect and its relationship with decision-making processes.

Overall, these findings suggest that self-reported expected valence is a key predictor of decision-making in gambling tasks, while self-reported arousal does not significantly influence decisions. The results were consistent across both a student sample and a more heterogeneous sample in terms of age and educational background.

3.1.3. Discussion

The findings of the study might appear clear and in favor of the indirect causation theory as DeWall et al. (2016) and Mellers et al. (1999) would suggest. Expected valence ratings were the only predictor of subsequent choices. However, we measured brain activation that resembled brain activity of emotional experiences (compare to Lindquist et al., 2016). Hence, I thought of two possible explanations: First, valence expectations could activate

the same brain regions as current feelings do. Second, there might have been current subjective feelings, which we did not measure with our measurement procedure. If I could not rule out the second explanation, theorizing about the first explanation would not make sense. When looking more closely at how we measured current valence ("How do you feel at the moment?"), it became obvious to me that this question might have been phrased too broadly. This question does not only capture integral current affect but also the general mood participants came to the experiment with. Thus, the conclusion that only expected feelings guide choices, but not current feelings might be wrong. Furthermore, in the questionnaire blocks participants still received immediate feedback depending on their gambling choices. Although I counterbalanced and randomized presentation order, this might have affected valence ratings as the emotional reactions to the presented outcomes might have construed the following predecisional affect ratings.

Taken together, in the first article I introduced a new experimental paradigm that made it possible to investigate predecisional affective influences in an experience-based learning task systematically. Nevertheless, limitations like a suboptimal measurement of current affect hamper the generalizability of results and await further investigation.

3.2. Study 2: Current and expected affective valence interact to predict choice in recurrent decisions

3.2.1. Background

In a next step, I conducted many pilot tests to improve the newly developed task. The results of the previous article and impressions from the pilot tests resulted in the following adjustments of the task. First, I presented the questionnaire blocks at the end of the learning phase without presenting immediate outcomes anymore. This was supposed to ensure a more precise measurement of predecisional affect based on past experiences. Second, I changed the question that should capture current affect to "How do you feel

when looking at the symbol." This lead the focus away from current mood, asking more specifically about integral current affect. Last, as self-reported arousal did not show any predictive value (Asutay et al., 2021; Jäger et al., 2020), I decided to no longer ask for this affective component to reduce the number of ratings participants had to fill out which might have also hampered the validity of self-reported affective ratings.

As mentioned before, after adjusting the experimental procedure to the needs of predecisional affective valence measurement, I had doubts that solely current feelings or solely expected feelings guided choice. Additionally, previous research had demonstrated that both immediate affect and anticipated emotional outcomes influence choice behavior, yet it remains unclear whether these constructs operate independently or synergistically. My goal was to understand how the interaction of these affective and cognitive components guides decision-making, as suggested by interaction models (Lerner et al., 2015) and by default-interventionist dual process models (Evans & Stanovich, 2013).

To address this gap, I utilized an adjusted gambling task like the one I used in the previous study (Jäger et al., 2020). Hence, it involved learning symbol-outcome contingencies over repeated trials. By manipulating symbol contingencies after an initial learning phase—changing previously positive symbols to negative outcomes and vice versa—I created a scenario in which participants' acquired expectations were contrary to the current feelings they had towards the symbols. Thus, the study aimed at demonstrating that current feelings and cognitive expectations are distinct constructs by measuring each separately and observing their unique contributions to decision-making. Finally, I aimed at providing empirical evidence supporting the hypothesis that, when properly disentangled, cognitive expectations and current feelings interact to predict decision-making outcomes, aligning with interaction models and dual process theories (Evans & Stanovich, 2013; Lerner et al., 2015).

3.2.2. Summary of findings

Based on the previously mentioned adjustments, in this study (Jäger et al., 2022) I created an experimental context in which emotional experiences were disentangled from emotional expectations. Participants were asked to maximize their score by deciding whether to gamble or pass when presented with one of four symbols. Each symbol was associated with a specific probabilistic outcome: two symbols had a positive reinforcement balance (winning in 90% of cases) while the other two had a negative reinforcement balance (losing in 90% of cases). Participants were not informed of the contingencies and had to learn them through trial and error across eight learning blocks, each consisting of 20 trials. During each trial, a symbol was displayed, and participants chose to gamble or pass. Gambling could result in a gain or loss of 15 points, while passing left their score unchanged. Symbols were presented in random order, and feedback was provided after each trial to reinforce learning. After the learning phase, the contingencies of two symbols were reversed: a previously positive symbol became negative and vice versa. Participants were explicitly informed of this change and completed additional decision-making blocks. In these blocks, participants also rated their current valence (how they felt when seeing a specific symbol) and expected valence for both gambling and passing options. These ratings were collected using a Self-Assessment Manikin (SAM) scale on a digital interface.

Findings indicate that current and expected valence are distinct constructs, both predicting choice, with expected valence showing a greater effect size. Additionally, current and expected valence interacted to predict choice; specifically, current valence was more predictive when future valence expectations were unclear or positive. This supports the interaction approach to affective involvement in recurrent decision-making (Lerner et al., 2015) and integrates previous findings from other theoretical frameworks (Bechara et al.,

1997; Charpentier et al., 2016; Schlösser et al., 2013). In this study, current valence predicted decisions when expectations were positive, but not when they were negative. This suggests that negative expectations may enhance the influence of expected valence on choice, aligning with dual process theories (Evans & Stanovich, 2013), where negative valence triggers increased self-monitoring and reduces the influence of current valence processed by system one. This interpretation also aligns with the affective signaling theory, which posits that negative affect drives adaptive changes in attention and performance (Dignath et al., 2020).

3.2.3. Discussion

As previously noted, my research aims at exploring how emotional factors influence decision-making. This study demonstrated that not only do expectations about future feelings (valence expectations) influence choices, but current emotional states (current valence) also play a role. I believe this finding opens up important directions for future research.

The first paper found no effect of current valence on choice prediction, whereas this study demonstrates that current valence does influence choices under certain conditions. This suggests that achieving a common understanding of affective constructs requires careful attention to how questions are posed and whether the resulting conceptualization effectively predicts choices. By showing that the measured constructs can predict choices, this study provides a foundation for refining the way affective variables are assessed in decision-making research.

Second, results showed that the predictive power of the affective constructs is context dependent. After the contingency of the symbols changed, there was an interaction effect between current valence and expected valence. Hence, a change of the context of the symbols resulted in changes in the predictive power of affective constructs. This offers a first

clue that theory in affective decision-making needs to incorporate the context of the decision. Past research tested predictions under specific context conditions which yielded different results (Bechara et al., 1997; Schlösser et al., 2013). Thus, experimental designs on the topic have to be able to be adapted to different contexts.

Taken together, the adaptions to the experimental task have been helpful. Measurement of affective constructs is more precise now. Furthermore, I could show that contextual variation of the task is possible and needed for advancements in the science of affective decision-making.

3.3. Study 3: Time matters: on the predictive power of current, short- and long-term expected valence in an experience based learning task

3.3.1. Background

The motivation for study 3 lies in exploring how current and expected valence influence decision-making, particularly in relation to different time horizons. In Studies 1 and 2, I could demonstrate that the impact of current versus expected emotions on decision outcomes depends on both the context and the specific task at hand. This highlights the need to consider both immediate emotional responses and expected emotions when studying decision-making processes. However, a critical gap in the existing literature on self-reported predecisional affect is its failure to account for varying time horizons. In the real world, people often face a conflict between short-term and long-term expectations, where immediate emotions—whether positive or negative—are in tension with longer-term outcomes, which may be either more favorable or less favorable (Hughes et al., 2010; Kopainsky et al., 2019; Mueller et al., 2017). For example, individuals preparing for an exam may feel stress and anxiety in the short-term, but anticipate the long-term rewards of academic achievement and career opportunities once the exam is over. Similarly, someone may endure the discomfort of a difficult workout, knowing that it will lead

to improved health and fitness in the future. Another example can be seen in financial decision-making: individuals may choose to save money, which requires giving up immediate pleasures (e.g. buying a new gadget), but they do so in expectation of future financial security or purchasing power. Furthermore, little attention has been paid to how people weigh immediate comforts against long-term losses. For example, people often prioritize immediate gratification, such as indulging in unhealthy food, even when they know it might negatively impact their long-term health. This tendency to favor short-term pleasure over long-term consequences is a common challenge in decision-making and has been well documented in studies of self-control and temporal discounting (e.g. Guarana et al., 2021; Hunte et al., 2024; Seaman et al., 2022)

To address these gaps in the literature, I designed the final experiment of this thesis to investigate how participants navigate the balance between immediate rewards or losses and the potential long-term losses or gains associated with their decisions. By manipulating both short-term and long-term emotional expectations, this study aims at providing deeper insights into how different time horizons interact in shaping decision-making processes. Understanding how individuals weigh the immediate satisfaction of a choice against its future consequences is critical for advancing our understanding of affective decision-making in real-world contexts, such as health decisions, financial planning, and career choices.

3.3.2. Summary of findings

In Experiment 1 of the final paper in this thesis, I aimed at demonstrating that short-term and long-term affective expectations independently predict choices in a recurrent gambling task and that situational demands influence the predictive power of these affective variables. By manipulating the presentation probabilities of a symbol based on participants' choices, I forced participants to accept short-term point losses to maximize long-

term outcomes. This setup created negative short-term and positive long-term expectations for one symbol. In Experiment 1, participants started with 500 points and were asked to maximize their score over six gambling rounds, each consisting of 27 trials. On each trial, participants were presented with one of three symbols associated with specific probabilistic outcomes: two symbols had fixed probabilities of negative outcomes (90% loss), while the third had a 90% probability of a positive outcome (gain). Participants chose whether to gamble or to pass. Gambling resulted in a potential gain or loss of 15 points based on the symbol's probability, while passing left their score unchanged. At the same time, gambling reduced the presentation frequency of one negative symbol (positive long-term consequence). Passing increased its frequency of presentation (negative long-term consequence). The task was divided into two phases. In the first phase, participants completed the task without knowing its internal structure, relying solely on trial-and-error learning. Afterwards, they rated their current valence and short-term and long-term expected valence for each symbol using a Self-Assessment Manikin (SAM) scale. Following this, participants were informed of the task structure, including the strategy of accepting short-term losses associated with a specific symbol (negative outcome) to achieve long-term gains (positive outcome). This strategy capitalized on decreasing the probability of encountering the negative symbol over time. In the second phase, participants repeated the task with this insight, allowing me to examine how awareness of the task structure influenced the predictive power of affective variables. Predecisional valence ratings were collected again after this phase. The structured manipulation of task knowledge enabled a comparison of decision-making strategies and affective predictors before and after gaining insight into the underlying contingencies of the task.

The results showed that participants adapted their choices in the second round, altering presentation probabilities and self-rated valence expectations as intended. Notably, long-

term valence expectations became more positive after gaining insight into the task structure. Participants adjusted their choices to accept short-term losses more often to maximize overall outcomes. Findings indicated that long-term, short-term, and current valence are independent predictors of choice, consistent with hypotheses. However, insight into the task structure decreased the predictive power of short-term valence expectations but unexpectedly increased the predictive power of current valence. This suggests that, although participants were informed of the optimal strategy, the counterintuitive nature of the information might have induced uncertainty, leading to greater reliance on current feelings.

Experiment 2 sought to confirm that the situational demands determine which affect variables predict choice. In Experiment 1, participants had to accept point losses to win more points overall, highlighting potential loss aversion, which could have impacted the predictive power of long-term expectations. Given that framing effects and reference points influence affective reactions (Mellers et al., 2021; Nabi et al., 2020; Nygren, 1998) the omission framing in Experiment 2 provided a critical contrast to the loss framing in Experiment 1. Hence, I sought to replicate the findings of Experiment 1 in a point-omission context. To achieve this, I manipulated the presentation probabilities of symbols based on participants' choices, necessitating point omissions to maximize overall outcomes. Unlike Experiment 1, this setup associated positive short-term expectations and negative long-term expectations with one symbol. Participants performed the task twice; initially without insight into the task structure, and subsequently with such insight in the second round. The manipulation was successful, with participants adapting their choices in the second round, altering presentation probabilities and self-rated valence expectations accordingly. Notably, long-term valence expectations for the manipulated symbol became more positive post-insight. Participants increasingly omitted points for the manipulated

symbol in the second round to maximize overall outcomes. The results demonstrated main effects for current and long-term expected valence, and interaction effects for current valence and short-term expected valence with insight into the task structure. Contrary to my hypotheses, expected valence did not significantly predict gambling choices, and long-term expected valence showed an interaction effect with task structure insight in the point-omission context.

Overall, findings from the two experiments indicate that the human subjective affective system flexibly adapts to varying choice contexts. Current valence, short-term valence expectations, and long-term valence expectations were significant predictors in various contexts. The predictive value of each affective variable depended on the specific choice situation, with individual differences among participants further influencing these outcomes. Providing task structure insight altered the predictive power of valence constructs depending on the context (losing points versus omitting points). Insight into the task structure increased the reliance on current valence in both contexts. This might be due to the counterintuitive nature of the optimal strategy, which created uncertainty and cognitive dissonance, thereby enhancing reliance on current feelings. This pattern aligns with previous research (Jäger et al., 2022).

3.3.3. Discussion

The study offers valuable insights into how the human subjective feeling system adapts to different choice situations, particularly by examining the predictive role of current, short-term expected valence, and longer-term expected valence in decision-making. One of the key contributions of the study is its exploration of how the influence of emotional expectations changes based on the time frame of those expectations. The findings demonstrate that the predictive power of each emotional variable is context-dependent and varies between short-term and long-

term emotional expectations. In Experiment 1, where participants lost points, short-term emotional expectations were more influential in predicting decision-making, whereas in Experiment 2, where points were omitted, participants relied more heavily on longer-term emotional expectations. This highlights the dynamic nature of decision-making processes and the importance of the time horizon in shaping how expected emotions guide choices. This focus on the discrepancy between short-term and long-term expected emotions is a central finding, as it shows that the relationship between emotional expectations and decision-making is not static but evolves depending on the time frame involved.

This pattern is particularly important because it underscores the complexity of decision-making in situations where individuals must balance immediate discomforts or rewards with the anticipation of future outcomes. For example, short-term expectations, which are often linked to more immediate rewards or losses, can prompt decisions that prioritize quick gratification or avoidance of short-term losses. In contrast, long-term expectations—related to future goals or outcomes—may lead individuals to make more cautious, delayed choices, aligning with future rewards or benefits. These findings are consistent with research on emotional valence in decision-making, such as Charpentier et al. (2016) and Mellers et al. (1999), which suggest that expected emotions, particularly those related to future outcomes, significantly drive decision-making. The current study expands on this by demonstrating that the balance between short-term and long-term expectations plays a crucial role in human decision-making, especially in situations of risk and uncertainty. While the findings align with prior research, my findings add an important layer by showing that long-term emotional expectations become more influential when the decision context involves an understanding of future consequences. This reflects a more nuanced view than previous theories (e.g. Baumeister et al., 2007; Loewenstein et al., 2001; Mellers et al., 1997; Schlösser et al., 2013), as it highlights that both current and future emotional states shape decision-making, often in conflicting ways.

Despite these important contributions, the study has several limitations. The reliance on self-reported measures of affect may have introduced biases such as demand characteristics, which can distort the true emotional experience. While self-reports provide valuable insight into conscious reflections, they may not fully capture unconscious or automatic emotional responses (Gendolla, 2017). Future research could incorporate physiological measures or behavioral proxies to complement self-report and offer a more comprehensive understanding of emotional processing. Future research could benefit from a more refined statistical approach, especially considering the complex interaction between emotional expectations and task structure. Despite these limitations, I believe that self-report still provides meaningful data.

4. General Discussion

In this thesis, I explore the role of self-reported predecisional affect in recurrent decision-making, with a particular focus on how expected as well as current affective states influence decisions over time. Across three studies, I developed a new experimental paradigm that allows for a more nuanced understanding of how emotional states, both current and expected, shape choice behavior in dynamic, real-world-inspired contexts. The first study revealed that expected affect, particularly expected valence, was a primary predictor of decisions, whereas the second study highlighted the interaction between current and expected emotions. The third study could show that the time horizon regarding expectations predicts choice in certain contexts. These findings suggest that emotional states do not operate in isolation but rather interact in complex ways depending on the task context and time frame. In the general discussion, I will address the theoretical implications of these results, providing insights into possible elaborations of current decision-making models. I will also offer practical research recommendations based on the challenges encountered during the study and propose avenues for future research that could further illuminate the intricate relationship between emotion and decision-making.

4.1. Theoretical Implications

The findings from the three studies suggest that the best predictor of choice in recurrent decision-making depends on both the context and the temporal structure of the emotional expectations. In Study 1, expected emotion, particularly expected valence, was the primary predictor of decisions (Jäger et al., 2020), which aligns with previous research emphasizing the role of expected emotions in guiding behavior (see Mellers et al., 1997). However, the findings from Studies 2 and 3 reveal a more complex picture, highlighting that both current emotions and expected emotions interact to predict choices, with the

context influencing their relative importance. In situations where participants faced uncertainty or cognitive dissonance—particularly when expectations about future outcomes were unclear—current emotions became more predictive (Jäger et al., 2022). This finding suggests that the subjective emotional system is adaptable, with current and expected emotions playing distinct yet interconnected roles depending on the decision context. Study 3 demonstrated that time horizons add complexity to choice prediction, with short-term and long-term expectations influencing decisions depending on the context, such as the loss versus omission scenario (Jäger & Rüsseler, 2025)

This complexity in the relationship between current and expected emotions challenges previous models that primarily emphasize one type of emotion. Theories like Decision Affect Theory (Mellers et al., 1997) and models focusing on expected emotions (Baumeister et al., 2007; Charpentier et al., 2016) have suggested that expected emotions are the key drivers of decision-making. However, my findings show that the influence of current emotions cannot be dismissed and that these two emotional states—current and expected—operate in a dynamic interplay rather than independently. In Study 2, for instance, when participants were presented with a scenario where expectations were unclear or positive, current emotions became more influential. However, when expectations were negative, expected emotions took precedence. This pattern indicates that while expected emotions guide decisions, especially in situations where future outcomes are certain or highly anticipated, current emotions are more likely to shape decisions when uncertainty or immediate emotional reactions are salient. This adds a new layer to our understanding of how emotional states interact in decision-making processes, revealing that the influence of affect is far more nuanced than initially hypothesized.

Furthermore, the theory of affect as subjective value, as articulated by Vollberg and Sander (2024) offers a significant strength by extending the understanding of decision-

making beyond financial lottery games to encompass a broader range of human behavior. The theory explores the relationship between affect and subjective value, focusing on how affective responses, including both expected and experienced feelings, play a key role in shaping subjective valuations of outcomes. The authors propose that affect can serve as a proxy for subjective value, suggesting that feelings associated with decision outcomes—both positive and negative—are integral to choice evaluation. A central idea in the paper is the application of reinforcement learning concepts to affect, particularly the notion of prediction errors. Just as individuals learn from the discrepancy between expected and actual rewards, they also adjust their behavior based on the difference between expected and experienced affect. This concept of affective prediction errors becomes critical in understanding subjective value and the influence of emotional experiences on decisions. The paper also discusses the complexities of subjective value, noting that it is influenced by a wide range of factors, including motivational and incidental states, and that these factors are often difficult to measure directly. The authors emphasize the challenge of capturing subjective value and propose that affective responses, particularly affective prediction errors, offer a more accessible approximation. They highlight that while the objective value of outcomes can be quantified (e.g., monetary rewards), the subjective value is shaped by a combination of internal emotional states and external conditions. This allows for a more dynamic and personalized understanding of decision-making, where individuals' emotional reactions influence the decisions they make, potentially beyond the objective rewards available to them.

The findings of this thesis align with this framework, particularly in demonstrating that emotional expectations, both short-term and long-term, are crucial predictors of decision-making. Specifically, all my studies showed that expected valence was the primary predictor of choices, supporting the idea that emotional expectations shape subjective value.

Furthermore, Study 3 highlighted the interaction between short-term and long-term emotional expectations, suggesting that the context of the decision influences the relative weight of these affective variables in guiding choices. One area where Vollberg and Sander's (2024) theory could be further developed is in clarifying the specific types of affect reflected in the subjective valuation of decision options. My research suggests that multiple affective variables, including both current emotional states and expectations about future emotional outcomes, influence choice depending on the context. This poses the question of how these various affective constructs translate into the subjective value individuals assign to options. Future work should explore this relationship in more detail, examining how different types of affects, in interaction with contextual factors, contribute to the subjective valuation process in decision-making.

Finally, the findings of this thesis underscore the adaptive nature of the subjective affective system, which flexibly adjusts to various contextual demands and time horizons, in guiding decision-making. As demonstrated in the studies, the subjective affective system can integrate both current and expected emotional experiences to navigate complex decision-making scenarios. This adaptability posits that the affective system helps individuals maximize emotional rewards and avoid emotional pain by continuously updating subjective valuations based on emotional feedback, much like reinforcement learning mechanisms (Sutton & Barto, 1999; Vollberg & Sander, 2024). In the studies presented, expected valence was the strongest predictor of choices, but this role was modulated by the time frame of expectations, suggesting that the system is not rigid but adapts depending on whether the emotional outcomes are perceived as imminent or distant (Jäger & Rüsseler, 2025). In addition to expected valence, the influence of current valence further illustrates the flexibility of the affective system. By reacting to real-time emotional feedback, individuals can adjust their decisions on the fly, depending on how they feel in the moment. This

dynamic interplay between current and expected emotions reveals that the subjective affective system does not rely solely on fixed emotional cues but is instead highly responsive to the temporal and situational context. Whether in a short-term situation requiring quick, emotionally-driven decisions or a long-term choice where future rewards are weighed more heavily, the affective system adapts by prioritizing the most relevant emotional information. This adaptive capacity is not limited to financial or risk-related decisions but might extend to a broad range of decision contexts, including moral (Garrigan et al., 2018), social (Bruch & Feinberg, 2017), and interpersonal decisions (Van Kleef et al., 2010). By considering how emotional experiences interact with contextual factors and time horizons, the findings from this thesis contribute to a more comprehensive understanding of how the subjective affective system operates as a flexible, adaptive mechanism that aids in decision-making across various scenarios.

4.2. Practical Research Recommendations

When continuing research in this area, several practical recommendations emerge. First, the literature is highly fragmented, with each research group developing and using its own definitions of affective constructs. To navigate this complexity, it's crucial to carefully read the methods sections of papers to understand exactly how questions about subjective feelings are phrased. Even minor differences in question wording can lead to different interpretations of the emotional constructs under study. This understanding can resolve apparent contradictions in the literature, as seemingly opposing findings may actually stem from subtle variations in the definitions of hypothetical constructs (e.g. compare definitions Lerner et al., 2015; Schlösser et al., 2013; Västfjäll & Slovic, 2013).

Second, the context of an experiment plays a crucial role in shaping how participants understand and react to the task. As evidenced by my own research, contextual variations

can significantly alter the predictive power of emotional constructs. I conducted several practice sessions and followed up with participant interviews to ensure that the task structure was clear and to capture participants' task perception. These pilot studies were invaluable in fine-tuning the experimental design and gaining insight into how task context might influence decision-making.

Lastly, it is essential to recognize that self-reported affective measures, while informative, do not capture the full spectrum of emotions. These measures focus on one aspect—how individuals perceive and anticipate their emotional experiences—but do not encompass the physiological or behavioral dimensions of emotion. In interpreting results, researchers should be cautious when extrapolating findings from self-reports to other emotion domains, such as physiological measures or neural activity, which may provide a more comprehensive picture of emotional experience. Future studies should incorporate multimodal approaches that integrate self-report with physiological and neuroimaging data to gain a deeper understanding of the emotional processes underlying decision-making. Teoh et al. (2023) offer an insightful framework that conceptualizes affective self-reports as dynamic affective decisions. Engaging with their perspective may help refine the conceptual and methodological foundations of one's own self-report measures. Traditionally, self-reports are used to measure emotions, but these reports are often criticized for being inconsistent or unreliable. The authors suggest that self-reports should be framed as decisions, where individuals accumulate evidence over time (from sensory, interoceptive, and situational sources) to reach a conclusion about their emotional state. This is modeled using sequential sampling models (SSMs), which help capture the noisy nature of self-reports by considering both the content of the report and the time taken to make it. By treating self-reports as evidence-based decisions, the authors argue that researchers can

gain a better understanding of the psychological processes underlying affective experiences and the various moderators that influence them, such as individual differences, emotion regulation, and cultural factors. This framework is proposed to improve affective science by incorporating decision-making models, potentially bridging the gap between emotion and decision research.

4.3. Future Research

Future research should aim at extending this paradigm to more every day, non-financial decisions, similar to those individuals face when deciding how to spend their free time. This represents the next logical step in testing the applicability of the affective decision-making framework to real-world contexts. For instance, an experiment could propose different short tasks—such as exercising, reading, or socializing—and ask participants to rate their subjective feelings before completing each task. Participants would then decide whether they want to complete each task based on their emotional experiences. This would allow researchers to see if the same affective constructs—such as expected and current valence—predict choices in these daily, non-financial decisions. If the findings can be successfully replicated in this context, the next step would be to analyze the nature of the tasks themselves. Researchers could explore how different types of tasks—ranging from physically demanding to socially rewarding—produce distinct contexts that rely on different affective variables. For example, tasks requiring physical exertion might be influenced more by short-term emotional expectations, while tasks tied to long-term goals, like learning a new skill, might be driven more by long-term expected affect. By examining how various contexts shape emotional decision-making, we can better understand how people navigate everyday choices and manage the competing demands of immediate rewards and future benefits.

Moreover, the area of affect and decision-making could be enriched by applying the research paradigm developed in this thesis to social decision-making contexts (Garrigan et al., 2018; Schlösser et al., 2016; Van Kleef et al., 2010; Van Lange et al., 2013). For example, integrating scenarios that involve social decisions, or moral dilemmas could deepen our understanding of how emotional expectations shape choices in real-world situations. One interesting experiment could involve a cooperative versus competitive decision-making task in which participants must decide whether to work together or compete for a reward. In this context, researchers could manipulate expected short-term and long-term emotional outcomes, such as anticipated feelings of satisfaction from cooperation or pride from winning in a competitive scenario, to examine how these emotional expectations drive choices in social settings. Similarly, researchers could design experiments around moral decisions, such as deciding whether to lie or tell the truth to benefit oneself or others. This could help explore how expected affect guides moral decision-making, particularly when the emotional consequences are of a long-term or uncertain nature.

Another important avenue for future research involves considering individual differences as an internal contextual factor. People vary in their emotional sensitivity (Jagiellowicz et al., 2016), coping strategies (Afshar et al., 2015), and decision-making styles (Busic-Sontic et al., 2017; Davis et al., 2007; Lauriola & Levin, 2001), which may influence how they weigh their current and expected emotions when making choices. One experiment could involve assessing emotion regulation strategies in participants by measuring their ability to downregulate or upregulate emotional responses to stress or uncertainty in decision-making tasks. For instance, participants could be asked to make decisions under conditions of high risk (e.g. uncertain financial investment) and low risk, while their self-reported emotional regulation strategies are measured to see if those who are more adept at regulating their emotions make more rational or risk-averse decisions, compared to

those who are less emotionally regulated. Researchers could also explore how emotionally reactive individuals differ in their reliance on short-term versus long-term emotional expectations. For example, an experiment could investigate how people with high emotional sensitivity are more likely to act on current emotional responses, while individuals with lower emotional sensitivity may focus more on long-term emotional consequences.

5. Conclusion

In conclusion, this thesis contributes to the growing body of research on the role of emotions in decision-making by offering a comprehensive investigation into the interplay between current and expected affect. Through a series of experiments, this work highlights the contextual and temporal complexities involved in how emotions influence choices. The findings emphasize that the predictive power of emotional states depends not only on the immediate emotional experience but also on the emotional expectations related to both short-term and long-term outcomes. By distinguishing between these types of emotional expectations and examining their interaction, this research sheds light on the nuanced ways in which individuals navigate decisions that involve risk, uncertainty, and delayed gratification.

Furthermore, this thesis demonstrates the importance of considering contextual factors, such as task structure, in emotional processing when studying emotional decision-making. The results suggest that a more detailed understanding of how people perceive and react to emotional outcomes—particularly in relation to both current and expected feelings—can lead to more refined models of decision-making that account for the complexity of choices.

This work also raises important methodological considerations for future research. It stresses the need for more precise measurements of emotional constructs and emphasizes the importance of contextual understanding in experimental design. The research provides valuable directions for incorporating diverse decision contexts, individual differences, and multidimensional emotional experiences, including physiological measures, to deepen our understanding of how emotions shape behavior.

Ultimately, the findings presented in this thesis might have practical implications for various fields, including behavioral economics, health decision-making, and even moral and social psychology. By incorporating more dynamic, time-sensitive emotional constructs into decision-making models, future research can further uncover how emotional expectations guide decision-making processes in complex, real-life scenarios, offering deeper insights into human judgment and behavior.

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Appendix A: Full Text of „Expected Valence Predicts Choice in a Recurrent Decision Task."

This appendix contains the complete version of the article:

Jäger, D. T., Boltzmann, M., Rollnik, J. D., & Rüsseler, J. (2020). Expected Valence Predicts Choice in a Recurrent Decision Task. *Frontiers in Neuroscience*, *14*, 1177. https://doi.org/10.3389/fnins.2020.580970

The article is included here in its original publisher format to document the research forming the basis of this dissertation. Please note that the pagination within the article follows the publisher's layout and does not continue the page numbering of the dissertation.

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Expected Valence Predicts Choice in a Recurrent Decision Task

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There is empirical evidence that expected yet not current affect predicts decisions. However, common research designs in affective decision-making show consistent methodological problems (e.g., conceptualization of different emotion concepts; measuring only emotional valence, but not arousal). We developed a gambling task that systematically varied learning experience, average feedback balance and feedback consistency. In Experiment 1 we studied whether predecisional current affect or expected affect predict recurrent gambling responses. Furthermore, we exploratively examined how affective information is represented on a neuronal level in Experiment 2. Expected and current valence and arousal ratings as well as Blood Oxygen Level Dependent (BOLD) responses were analyzed using a within-subject design. We used a generalized mixed effect model to predict gambling responses with the different affect variables. Results suggest a guiding function of expected valence for decisions. In the anticipation period, we found activity in brain areas previously associated with valence-general processing (e.g., anterior cingulate cortex, nucleus accumbens, thalamus) mostly independent of contextual factors. These findings are discussed in the context of the idea of a valence-general affective work-space, a goal-directed account of emotions, and the hypothesis that current affect might be used to form expectations of future outcomes. In conclusion, expected valence seems to be the best predictor of recurrent decisions in gambling tasks.

Keywords: affect, decision, predecisional, expected valence, anticipation, goal-directed emotion, fMRI, Iowa Gambling Task

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INTRODUCTION

According to Prospect Theory (Kahneman and Tversky, 2013), human decision-making is not solely rational but rather subject to inherent biases that influence judgement, decision-making, and human behavior. Other authors have also suggested an affective involvement in decision-making and behavior regulation (Mellers et al., 1997; Loewenstein and Lerner, 2003; Lerner et al., 2015; DeWall et al., 2016). However, the exact role of emotions in decision-making and behavior regulation is the subject of ongoing debate. One important issue in this context is how to conceptualize different components of emotions. In our opinion, there are two dimensions that need to be separated. First, it appears useful to differentiate between pre- and post-decisional emotions (Mellers et al., 1997). *Predecisional emotions* are present before the decision is made while *postdecisional emotions* arise after the decision when experiencing the feedback. Second, Loewenstein and Lerner (2003) broadly distinguished expected from immediate emotions.

Expected emotions refer to the prediction of future emotional consequences depending on the respective decision or action while *current/immediate emotions* refer to emotions that are present while the decision is made.

In our view, distinguishing between expected and current emotions also benefits research concerning the role of predecisional emotions in recurrent decision-making. This distinction mirrors dual process accounts that have been proposed in the decision-making literature (Lerner et al., 2015; Beer, 2017). These accounts propose that decision-making consists of two kinds of processes. First, cognitive processes that require time, deliberation, and cognitive resources; and, second, automatic processes that work in a quick and dirty fashion and thereby incorporate current emotions as a mediating variable between stimulus and response. In a meta-analysis, DeWall et al. (2016) examined whether during the anticipation period current emotions or expected emotions (they called it anticipated emotions) guide decisions and behavior. They concluded that there is weak evidence to support the claim that current emotions cause decisions but stronger preliminary evidence that expected emotions do so. This contradicts the default assumption of the described dual process accounts which assume that current emotions directly cause behavior (e.g., Loewenstein et al., 2001). However, DeWall et al. (2016) did not pit each theory against each other but rather tested them separately. Furthermore, they included studies in their analysis that asked about distinct emotion categories and, therefore, for conscious emotions. We think that this level of analysis might neglect causal mechanisms among emotion components. Thus, we propose to look at emotion components and causal mechanisms among them. For example, it could be fruitful to examine subjective feelings and how they relate to decisions as, for example, Charpentier et al. (2016) did. They showed that feelings could predict choices in a gambling task better than a value-based prediction model. However, they did not use a two dimensional feelings model but just measured expected valence. Barrett and Bliss-Moreau (2009) argued that the core of generating subjective feelings relies on two affect dimensions: *valence or pleasantness* and *arousal or activation* (Feldman and Russell, 1998). Thus, they suppose that humans continuously monitor how pleasant and arousing something is and use this to construct an emotional episode. In sum, Charpentier et al. (2016) have not taken a two-dimensional perspective on feelings as they neglected arousal in their experiments. Moreover, they did not investigate? how predecisional current affect and expected affect relate to one another and the respective decision.

Decision Affect Theory offers a theoretical foundation for the role of anticipated pleasure in choice prediction (Mellers et al., 1999; Mellers and McGraw, 2001). Simply put, this theory posits that ". . . when making decisions, people anticipate the pleasure or pain of future outcomes, weigh those feelings by the chances they will occur, and select the option with greater average pleasure" (Mellers and McGraw, 2001, p. 210). In several experiments they have identified several contextual factors which influence anticipated pleasure ratings. They used pie charts and, therefore, fully displayed associated probabilities and outcomes. Moreover, participants received information about their unchosen options. Each decision participants made referred to a new gambling situation with different probabilities and outcomes. Hence, participants knew probabilities in advance, could not learn from feedback, and could not avoid gambling. Based on this experimental paradigm, the authors identified four effects which influenced anticipated pleasure ratings. First, outcome effects (the higher the outcome, the higher anticipated pleasure ratings and vice versa). Second, suprise effects (the less probable an outcome the more pronounced are outcome effects). Last, regret and disappointment effects can be subsumed under comparison effects which show that the unobtained outcomes or unchosen outcomes also influence anticipated pleasure ratings. Finally, the authors could show that expected pleasure ratings were correlated with decisions participants made (Mellers and McGraw, 2001).

Another common method to investigate the role of emotions in decision-making is the Iowa Gambling Task (IGT; Aram et al., 2019). Participants have to draw a card from one of four decks. They do not know that there are good and bad decks. Bad decks produce high wins in the short term but on average losses in the long term as possible losses are also higher. However, good decks result in small wins in the short term but on average wins in the long term as possible losses are even smaller. Participants have to figure this out via trial and error. Patients with damaged prefrontal brain regions performed worse in the IGT and did not show increased anticipatory autonomous activity before making their decision. In contrast, neurologically healthy adults displayed an increase in electrodermal activity prior to a decision that was present even before participants gained conscious insight into the task structure (Bechara et al., 1997). Consequently, results suggest that electrophysiological correlates, which could be termed as current affect or somatic markers, as Bechara and Damasio (2005) call it, are essential to advantageous decision-making. At the same time, the interpretation of results and the task design have been criticized and alternative explanations have been proposed (Dunn et al., 2006). We want to highlight two major points regarding IGT's task design: decks are not presented in a counterbalanced order and all four decks are presented simultaneously which makes it impossible to see which deck is attended. If feelings guide choices, knowing which deck participants focus attention on, is crucial as several expected and current feelings might be present at the same time.

Taken together, previous research in choice prediction has neglected the two-dimensional nature of affect (Mellers and McGraw, 2001; Charpentier et al., 2016) or used only clustered data for choice prediction (Schlösser et al., 2013). As described, research has produced inconsistent findings. Additionally, some experiments conducted in this area of research used gambling tasks with fully displayed probabilities for each choice option and did not incorporate learning experience. In more ecologically valid tasks like the IGT, choice prediction based on predecisional subjective feelings has to our knowledge not been employed. As we wanted to understand causal mechanisms among emotional components on a subjective and neuronal level of analysis, we measured both dimensions of affect (arousal and valence) and examined both expected and current affect. To get an understanding of how contextual factors translate into emotion components and neural activations in a recurrent decision task,

we designed two experiments. In Experiment 1 we examined how the proposed constructs are influenced by contextual factors and which feeling constructs predict choice best. In Experiment 2 we tried to replicate Experiment 1's main findings regarding contextual influences on predecisional affective constructs. At the same time, we exploratively looked at brain activity of our gambling task to get a preliminary understanding of how contextual factors might influence brain activity and predecisional affect ratings.

EXPERIMENT 1

We designed a gambling task that was similar to the IGT in the way that participants had to make recurrent decisions and did not know gambling probabilities in advance. We did so to address the previously mentioned shortcomings of the IGT. At the same time our task had a similar ecologically valid structure as the IGT as outcome probabilities were unknown in advance (like most times in real life), participants could avoid certain outcomes, and they had to adapt their behavior based on previous experiences.

Thus, our task presented only one choice option at a time and allowed to vary contextual factors like feedback consistency, learning experience (time), and feedback balance in a systematic way. Feedback consistency refers to the probability of certain outcomes (see **Table 1**), feedback balance refers to the average outcome that could be obtained (see **Table 1**), and learning experience refers to three different time points we took measurements of predecisional affect. Four different symbols were used in the task. Each symbol had a unique pay-off schedule that was unknown to the participants. For each symbol, participants could decide whether they wanted to gamble or not. If participants decided not to gamble, their current balance remained unaffected. Thus, participants had the option of avoiding certain actions. If participants decided to gamble, however, they could win or lose points. Two symbols returned consistent positive or negative feedback while the other two symbols returned inconsistent feedback. Furthermore, the overall balance was positive for two symbols and negative for the other two symbols.

TABLE 1 | Example of Symbol-Feedback contingencies depending on the average feedback balance and the feedback consistency in Experiment 1.

Average feedback balance	Feedback consistency	Symbol	$P_{(+15points)}$ (%)	$P_{(-15points)}$ (%)
Positive	Consistent		100	0
	Inconsistent		66.6	33.3
Negative	Consistent		0	100
	Inconsistent		33.3	66.6

$P_{(+15points)}$ refers to the probability of winning 15 points and $P_{(-15points)}$ to the complementary probability of losing 15 points if the participant decided to gamble. Please note that symbol-feedback condition mapping was randomly assigned for each participant.

To better understand the affective involvement in our task and how affective components develop with task experience, we measured different kinds of affect at three different time-points. We took a two-dimensional perspective and, therefore, measured current valence and current arousal. Additionally, we looked at the expected valence and expected arousal for each option (gambling, passing). In a first step we analyzed whether the proposed affect constructs were sufficiently different from one another. Second, we wanted to show that contextual factors like feedback balance, feedback consistency, and learning experience had an effect on self-reported affect constructs. Finally, we hypothesized in line with the previously presented research (Mellers and McGraw, 2001; Dunn et al., 2006; Charpentier et al., 2016; DeWall et al., 2016) that expected affect and especially expected valence are better predictors for decision-making than current affect.

Materials and Methods

Participants

Data were collected from 25 healthy adults (M_{age} = 24.1 years, SD = 3.6 years, 10 men). Participants had normal or corrected to normal vision; 21 participants were right-handed, four were left-handed; all participants were students at the University of Bamberg and received course credit for participation. The study was conducted in accordance with the Declaration of Helsinki. Participants gave their written informed consent and were told that they could refrain from the study at any point without consequences. The study protocol was approved by the local ethics commission.

Materials

The experiment consisted of two types of blocks: Learning Blocks and Predecisional Affective Questionnaire (PAQ) Blocks. For stimulus presentation, we used the software NBS Presentation[1]. For answer collection, we used a two keyed Cedrus Response Box (RB-380) and paper-pencil questionnaires.

Gambling task in the learning blocks

The main goal of the gambling task for participants was to maximize points. Each participant started with a balance of 500 points. By making advantageous decisions participants could accumulate wins and avoid losses. In each trial of the gambling task, one of four symbols (circle, triangle, square, cross) was displayed (see **Table 1**). The presented symbol served as a clue for the possible feedback based on previous experience the participants made with this symbol (see **Figure 1** for timing parameters, ITI = 500 ms, and **Figure 2A** for trial structure). Thus, in each trial the participant had to decide whether she wanted to gamble or have a pass on the symbol. If the participant decided not to gamble (pass), the feedback was always ± 0 points irrespectively of the previously presented symbol. If the participant decided to gamble, feedback was determined based on constant symbol dependent winning and losing probabilities

[1] http://www.neurobs.com

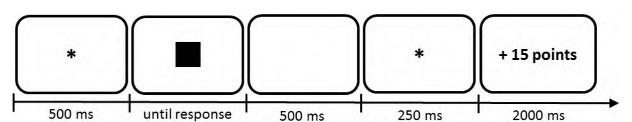

FIGURE 1 | Example trial to illustrate the timing of the Gambling Task. Numbers characterize presentation durations in ms. In this case the participant would have chosen to gamble and subsequently won 15 points. ITI = 500 ms. * Indicates a fixation dot.

TABLE 2 | Overview of experimental factors, number of symbols, procedure, and dependent measures in examining affective constructs and BOLD (Blood Oxygen Level Dependent) response for both experiments.

	Experiment 1	Experiment 2
Factors	Average feedback balance (positive/negative) Feedback consistency (consistent/inconsistent) Time (Questionnaire Block 1/2/3)	Average feedback balance (positive/negative) Feedback consistency (consistent/ inconsistent)
Number of symbols	Four (see **Table 1** for more details)	Five (see **Table 1** + control symbol)
Procedure	Practice Block (8 trials) Learning Block 1 (82 trials) PAQ Block 1 (4 trials) Learning Block 2 (82 trials) PAQ Block 2 (4 trials) Learning Block 3 (82 trials) PAQ Block 3 (4 trials)	Behavioral Practice Block (10 trials) Learning Block 1 (52 trials) Learning Block 2 (52 trials) Learning Block 3 (52 trials) fMRI Practice Block (5 trials) fMRI Block 1 (50 trials) fMRI Block 2 (50 trials) PAQ Block (4 trials)
Dependent measures	Current valence, current arousal, expected valence difference, expected arousal if gambling, expected arousal if passing	Current valence, current arousal, expected valence difference, expected arousal if gambling, expected arousal if passing; BOLD response

PAQ, Predecisional Affect Questionnaire; fMRI, functional Magnet Resonance Imaging.

(see **Table 1** for an example). Moreover, participants were not told a symbol's objective winning probability. They were rather instructed to figure out via trial and error for which symbol they expected a positive point balance. Symbol–probability pairings depended on two factors (average feedback balance, average feedback consistency) and were randomly assigned for each participant (see **Table 1** for an example and **Table 2** for an overview). The factor feedback balance coded whether symbols yield positive or negative feedback on average. The factor feedback consistency coded whether symbols returned consistent or inconsistent/mixed feedback. Hence, there were three possible outcomes depending on the previously presented symbol and the decision. In our example from **Table 1**: the square had a 100% probability of winning 15 points (and 0% losing probability); the circle had a 66.6% probability of winning 15 points (33.3% losing probability); the cross had a 33.3% probability of winning 15 points (66.6% losing probability); the circle had a 0% probability of winning 15 points (100% losing probability). Thus, to maximize gains, participants should gamble when experiencing an overall positive balance (square and triangle) and should avoid gambling when experiencing an overall negative balance (circle and cross). In each block the two symbols producing consistent feedback (100 and 0% winning probability) were each presented 14 times; inconsistent symbols (66 and 33% winning probability) were each presented 27 times. Symbols were presented in a randomized order.

Predecisional affect questionnaire block

Questionnaire blocks measured self-reported predecisional affect. In the questionnaires blocks, after looking at the symbol and

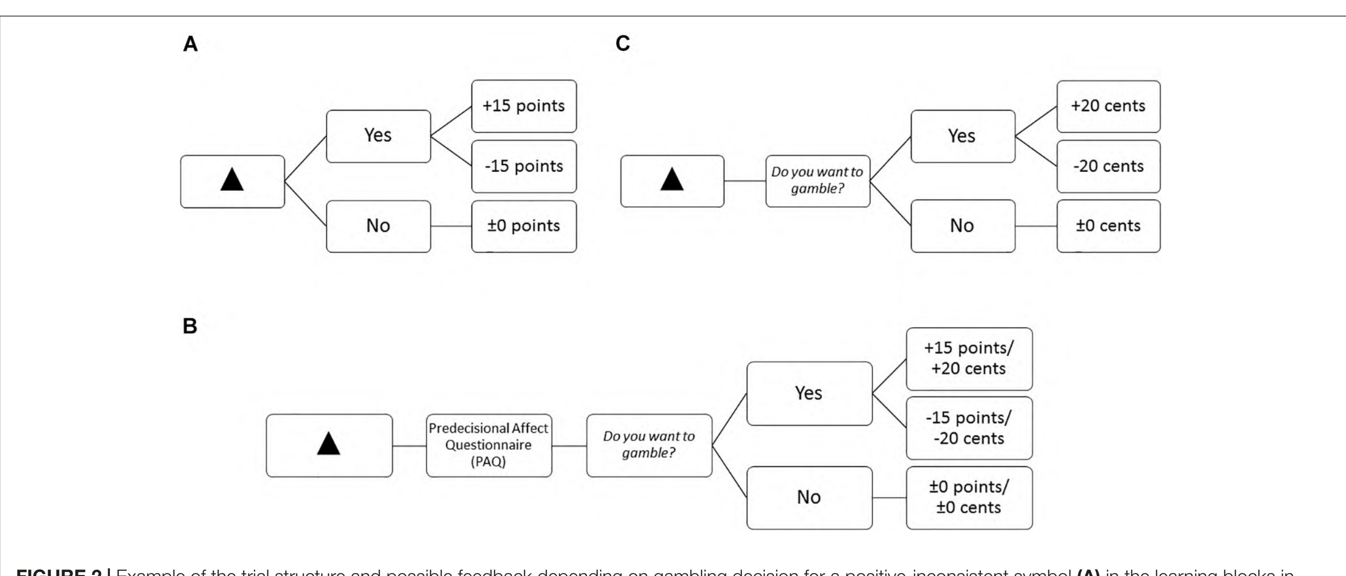

FIGURE 2 | Example of the trial structure and possible feedback depending on gambling decision for a positive-inconsistent symbol **(A)** in the learning blocks in Experiment 1, and **(B)** the questionnaire blocks for both experiments (Participants could win or lose points in Experiment 1 and cents in Experiment 2), and **(C)** the learning and fMRI blocks in Experiment 2.

before deciding for or against gambling, participants filled in a paper-pencil questionnaire (see **Figure 2B** for an example trial structure). In this questionnaire they rated their affective state from three different perspectives each on the dimensions of *valence* and *arousal* using a 9-point Self-Assessment Manikin Scale (SAM; Bradley and Lang, 1994). The first perspective asked participants to rate their current affective state: *"Please rate how you are feeling now."* The second perspective asked them to rate their expected affective state if they would decide to gamble: *"Please rate how you would feel if you decided to gamble."* The third perspective asked them to rate their expected affective state if they decide not to gamble: *"Please rate how you would feel if you decided not to gamble."* Below each question we presented a SAM Valence Scale and a SAM Arousal Scale. Hence, we asked one question for each perspective but collected two ratings (valence, arousal) per perspective resulting in six variables: Current Valence/Arousal, Expected Valence/Arousal if gambling, and Expected Valence/Arousal if passing (see **Table 2**). In the questionnaire blocks each symbol was randomly presented once, resulting in four trials. For every symbol participants filled in the above mentioned questionnaire in a paper-pencil format. Taken together, we collected 24 ratings per questionnaire block. Question presentation was not randomized: they were first asked to rate their current affective state, then their expected affective state if gambling, and last their expected affective state if passing.

Procedure

At the beginning, participants were welcomed, filled in a demographic questionnaire, and gave their written informed consent to the experimental procedure. For an overview of experimental factors, dependent variables, and the chronological procedure (see **Table 2**). Participants could gain or lose points in the gambling task. They were informed that the 10 highest scoring participants would win 10 euros each. Each participant started the experiment with a balance of 500 points. The current score was presented after each block. Thus, participants got an immediate feedback after each block on how much points they won or lost in the preceding block. First, participants completed a practice block of eight trials which did not affect their balance. Then they started the first of the three learning blocks (for more details see section "Materials"). Participants indicated their gambling decision by pressing the assigned yes- or no-button. Key assignment was counterbalanced across participants. After each learning block there was a PAQ block (for more details see section "Materials"). Hence, we measured predecisional affect at three different time points which constituted the factor time (see **Table 2**). Participants could take a short self-timed break between blocks if they wanted to. At the very end, participants were debriefed.

Results

First, we show that the experimental factors impact the self-report ratings. In a second step, we want to examine which self-reported affect variables predict gambling choices best. To begin with, we analyzed how the proposed valence constructs were correlated with one another. We used the rmcorr package in R (Bakdash and Marusich, 2017). Both expected valence variables (expected gambling and expected passing) were highly correlated ($r = -0.53$, $p < 0.001$), however, all other constructs were only moderately correlated ($< r = 0.35$). Therefore, we decided to compute a difference score for the expected valence perspectives (Expected Valence Difference = "Expected Valence if gambling"– "Expected Valence if passing") as Charpentier et al. (2016) did to avoid collinearity in the analysis.

Expected Valence

We submitted the difference scores of self-reported expected valence ratings for the three TIMES and each symbol to a 3 × 2 × 2 repeated measures ANOVA. The factor BALANCE had two levels: positive, for symbols that won on average, and negative, for symbols that lost on average. The factor CONSISTENCY also had two levels, consistent, for symbols that returned consistent positive or negative feedback, and inconsistent, for symbols that returned mixed feedback. The three-way interaction TIME × BALANCE × CONSISTENCY was non-significant, $F(2, 48) = 22.19$, $p = 0.07$. However, the interaction BALANCE × CONSISTENCY turned out to be significant, $F(1, 24) = 8.96$, $p = 0.006$, $\eta_p = 0.272$ (see **Table 3**). As it was a semi-disordinal interaction only the main effect BALANCE was interpretable, $F(1, 24) = 22.19$, $p < 0.001$, $\eta_p = 0.480$. Symbols which had a positive balance, $M = 1.273$, $SE = 0.307$, had significantly higher difference scores than symbols which had a negative balance, $M = -0.973$, $SE = 0.307$, $p < 0.001$. Thus, the effect of a positive balance on expected valence ratings was even more pronounced for symbols returning consistent positive feedback in comparison to symbols returning inconsistent positive feedback.

Current Valence

We submitted the self-reported current valence ratings to a 3 × 2 × 2 ANOVA for repeated measures. As in the expected valence analysis, we used the factors TIME, BALANCE, CONSISTENCY. The three-way interaction TIME × BALANCE × CONSISTENCY was significant, $F(2, 48) = 6.49$, $p = 0.003$, $\eta_p = 0.213$ (for means and other statistics see **Table 4**). For resolving this interaction we conducted three additional 2 × 2 ANOVAs for repeated measures with the factors BALANCE and CONSISTENCY, one for each time point. For time 1, there were no significant differences between current valence ratings. However, for time 2, there was a significant CONSISTENCY × BALANCE interaction effect, $F(1, 24) = 8.29$, $p = 0.008$, $\eta_p = 0.257$. *Post-hoc* Bonferroni corrected *t*-tests indicated that current valence ratings were smaller for consistent negative

TABLE 3 | Estimated Marginal Means, Standard Errors (SE), and 95% Confidence Interval for the two-way interaction BALANCE × CONSISTENCY in the Analysis of Expected Valence Difference ratings.

				95% Confidence Interval	
Balance	**Consistency**	**Mean**	**SE**	**Lower**	**Upper**
Positive	Consistent	1.91	0.350	1.2082	2.605
	Inconsistent	0.64	0.350	−0.0585	1.338
Negative	Consistent	−1.08	0.350	−1.7785	−0.382
	Inconsistent	−0.87	0.350	−1.5651	−0.168

TABLE 4 | Estimated Marginal Means, Standard Errors (SE), and 95% Confidence Interval for the threeway-way interaction TIME × BALANCE × CONSISTENCY in the Analysis of Current Valence ratings.

					95% Confidence Interval	
Time	**Balance**	**Consistency**	**Mean**	**SE**	**Lower**	**Upper**
Time 1	Positive	Consistent	6.24	0.285	5.67	6.81
		Inconsistent	6.60	0.285	6.03	7.17
	Negative	Consistent	6.52	0.285	5.95	7.09
		Inconsistent	6.40	0.285	5.83	6.97
Time 2	Positive	Consistent	6.92	0.285	6.35	7.49
		Inconsistent	6.24	0.285	5.67	6.81
	Negative	Consistent	6.08	0.285	5.51	6.65
		Inconsistent	6.56	0.285	5.99	7.13
Time 3	Positive	Consistent	7.12	0.285	6.55	7.69
		Inconsistent	6.68	0.285	6.11	7.25
	Negative	Consistent	6.28	0.285	5.71	6.85
		Inconsistent	6.28	0.285	5.71	6.85

symbols compared to consistent positive symbols, $p < 0.016$. For time 3, there was a significant main effect for BALANCE, $F(1, 24) = 11.45$, $p = 0.002$, $\eta_p = 0.323$. Symbols with an overall positive balance, $M = 6.90$, $SE = 0.265$, had higher current valence ratings than symbols with an overall negative balance, $M = 6.28$, $SE = 0.265$, irrespective of feedback consistency.

Expected Arousal

Analogous to the expected valence analysis, we submitted the difference scores of self-reported expected arousal ratings for the three TIMES and each symbol varying in CONSISTENCY and BALANCE to a 3 × 2 × 2 repeated measures ANOVA. All interaction and main effects were non-significant.

Current Arousal

For self-reported current arousal we performed a 3 × 2 × 2 ANOVA for repeated measures with the factors TIME, BALANCE, and CONSISTENCY. All three- and two-way interactions were non-significant, however, the main effect of BALANCE was significant, $F(1, 24) = 7.97$, $p = 0.009$, $\eta_p = 0.249$. Symbols with a positive balance, $M = 4.39$, $SE = 0.29$, had higher self-reported current arousal ratings than symbols with a negative balance, $M = 3.97$, $SE = 0.29$.

Choice Prediction

To test which affect variables predicted choice best, we ran a generalized mixed effects model using the glmer function from the lme4 package in R (Bates et al., 2015). As correlation analysis showed that both expected valence variables were highly correlated, we decided to compute a difference score to reduce collinearity. All other variables were only mildly correlated which is why we entered them separately into the model. We modeled the Participant ID as a random intercept and entered each affect variable as a fixed effect into the model resulting in the formula: Choice ∼ Difference Expected Valence + Current Valence + Expected Gambling Arousal + Expected Not Gambling Arousal + Current Arousal + (1| Participant ID). Significance was assessed

TABLE 5 | Generalized linear mixed effect estimates for the choice prediction model including the proposed affective predictors.

Predictors	Odds ratios	CI	p
(Intercept)	0.37	0.03–4.15	0.419
Difference expected valence (gambling–passing)	3.28	2.37–4.54	**<0.001**
Expected gambling arousal	1.05	0.76–1.45	0.760
Expected not gambling arousal	1.21	0.87–1.67	0.256
Current valence	1.24	0.92–1.68	0.156
Current arousal	0.80	0.55–1.16	0.233
Random effects			
σ^2	3.29		
$\tau_{00\ \text{Participant}}$	0.40		
ICC	0.11		
$N_{\text{Participant}}$	25		
Observations	300		
Marginal R^2/Conditional R^2	0.733 / 0.762		

Fixed Effects: Odds Ratios, Confidence Intervals (CI), and p-values. Random Effects: σ^2 = within-person residual variance, $\tau_{00\ \text{Participant}}$ = between-person variance, ICC = Proportion of variance explained by between-person differences; Marginal R^2 = variance explained by fixed effects, Conditional R^2 = variance explained by fixed and random effects. Significant results are printed in bold.

via model comparison with an Alpha of 0.05. Expected Valence was the only significant predictor for gambling choice, $\beta = 1.19$, $SE = 0.17$, $X^2(1) = 150.2$, $p < 0.001$. This means, the higher the difference score of expected valence ratings (gambling—not gambling) were, the more likely participants chose to gamble. For more details regarding fixed and random effect structure (see **Table 5**).

Discussion

In Experiment 1, we wanted to examine how subjective feelings are part of the decision process in a recurrent gambling task with unknown outcome probabilities. Hence, we developed a gambling task that was similar to the Iowa Gambling Task. However, our task varied feedback consistency, average feedback balance, and the learning experience in a systematic, controllable way. For measuring subjective feelings we took different classifications into account. Thus, we measured valence and arousal under the perspective of current and expected feelings. Our most important research question studied which of the proposed subjective feeling construct would predict choice. We found that expected valence was the only predictor for choices participants made. All other constructs were non-significant. Hence, the difference of expected valence ratings but not current valence or arousal constructs predicted choices which is in line with our hypotheses and previous research (Mellers et al., 1997; Charpentier et al., 2016; DeWall et al., 2016). At the same time, our findings challenge a decision guiding function of arousal. We found that self-reported current arousal indeed varied between good and bad symbols, however, it did not predict subsequent choices. As self-reported arousal ratings might be unreliable, it might be useful to simultaneously assess physiological arousal measures to enhance predictive power (Asutay et al., 2019). Future studies should further examine these findings and include

physiological measures of autonomous activity instead of self-reported arousal in their choice prediction models.

Furthermore, we examined whether the measured variables were sufficiently different from one another. We found that most constructs correlated only mildly or moderately and, therefore, differed sufficiently. However, expected valence ratings of the two choice options were highly correlated which is why we computed a difference score for expected valence ratings (for a similar procedure, see Charpentier et al., 2016). Moreover, we examined how contextual factors like feedback consistency, learning experience, and average feedback balance influence the proposed subjective feelings variables. In general, we found that most self-reported ratings were influenced by contextual factors, yet, in different ways. Most constructs, except for current valence, were insensitive to time of measurement which implies a relatively early manifestation of constructs. As predicted, expected valence ratings distinguished between symbols with a positive and negative balance and for positive balanced symbols also between consistent and inconsistent symbols. This was the case over all measurement points, indicating an early manifestation of expectancy constructs. The impact of contextual factors on current valence ratings changed over time. After the first block there was no significant difference between ratings, at time 2 consistent positive symbols were rated higher than all other symbols, at time 3 positive balanced symbols (consistent and inconsistent) had higher current valence ratings than negative balanced symbols. In other words, current valence changed as participants learned symbol-feedback contingencies. This posits that current valence manifests over time as learning takes place. The difference of expected arousal ratings was not affected by contextual factors. Taken together, contextual factors influenced most of the proposed constructs but not expected arousal ratings.

EXPERIMENT 2

In Experiment 1 we found that self-reported affect ratings were influenced in different ways by feedback consistency, feedback balance, and learning experience. As a next step, we wanted to examine how these contextual factors determine predecisional affective brain activity. Lindquist et al. (2016) tested three competing hypotheses regarding neural representation of affect in a meta-analysis of the human neuroimaging literature. The bipolarity hypothesis assumes that pleasant and unpleasant feelings are endorsed by a brain system that monotonically increases and decreases along the valence dimension. Second, the bivalent hypothesis posits two independent brain systems for positive and negative affect. Last, the affective workspace hypothesis suggests that valence is best represented on a neuronal level as a valence general neural workspace which recruits a flexible set of valence-general areas. Results clearly favored the affective workspace hypothesis while evidence for both other theories was rather weak. Valence-general activations were found in the bilateral anterior insula, thalamus, dorsal ACC, bilateral lateral orbitofrontal cortex, supplementary motor area, bilateral amygdala, the ventral striatum, dorsomedial prefrontal cortex, bilateral ventro-lateral prefrontal cortex, and lateral portions of the right temporal/occipital cortex. At the same time, the authors acknowledge that it might be a possibility that the arousal component of affect might contribute to valence-general activation patterns as separating arousal from valence is both a statistically and theoretically complex endeavor.

As in Experiment 1, our task design varied the symbol's balance and its feedback consistency. In accordance with the hypothesis of a valence-general affective workspace, we expected that all symbols, which varied in contextual factors and therefore also in affect ratings, recruit the same brain regions. In line with the presented evidence we supposed to find brain activity in the anterior cingulate cortex, the accumbens area, the thalamus, the amygdala, the insula, and the prefrontal cortex. In addition to that, we hypothesized that the symbol's balance or its feedback consistency would have a rather small or no effect on observed brain activity as valence-general brain regions work together to produce different valence intensities.

Materials and Methods

Participants

Data were collected from 22 adults of which five (M_{age} = 50.4 years, SD = 2.7 years, two men) were excluded because they had not learned the symbol-feedback contingencies after the third block. Exclusion criteria were set at a gambling rate below 70% for the 100% chance condition as well as a gambling rate above 30% for the 0% chance condition. The final sample consisted of 17 adults (six men) aged between 20 and 57 (M_{age} = 35.5 years, SD = 12.0 years). Hence, the dropout seems to be age-related, meaning that older participants had difficulties learning the symbol-feedback contingencies. Furthermore, after the MRI block one participant decided to end the study. Therefore, the sample for the questionnaire block comprised 16 adults (six men) aged between 20 and 57 (M_{age} = 36.4 years, SD = 11.8 years). Participants had normal or corrected to normal vision; 16 participants were right-handed, one was left-handed; six participants had at least an educational degree of a German high school diploma, whereas the others had a German Middle School Degree.

The study was conducted in accordance with the Declaration of Helsinki. Participants gave their written informed consent and were told that they could refrain from the study at any point without consequences. The study protocol was approved by the ethics committee of the Hannover Medical School with the study ID 7416.

Materials

The general materials did not change much in comparision to Experiment 1, however, we adapted the procedure and timing parameters to the needs of the fMRI setting. In all blocks (learning, fMRI, and PAQ Block) participants did not respond to the symbol directly but rather to the question *"Do you want to gamble?"* as presented in **Figure 2C**. We thought that it would be easier for participants to have a consistent task structure. Moreover, we introduced a control symbol to the gambling task, which regardless of choice did not affect participants' score. As we wanted to isolate affect-related brain activity, we needed

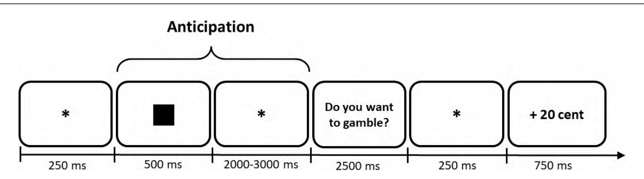

FIGURE 3 | Example trial to illustrate the timing of the fMRI Monetary Gambling Task. Numbers characterize presentation durations in ms. In this case the participant would have chosen to gamble and subsequently won 20 cents. Only the anticipation period was used for analysis of brain activity. *Indicates a fixation dot.

the control symbol to compute difference contrasts (see "Data Analysis" section for more details). Finally, we decided to use real money instead of points because we hoped this would result in stronger neural activations. Participants could win or lose 20 cents in each trial. "Gamble" and "Pass" key assignment was counterbalanced over participants. For stimulus presentation, we used the software NBS Presentation[2].

The learning blocks consisted of 52 randomized trials: eight consistent-positive feedback symbols, eight consistent-negative feedback symbols, eight control symbols, 14 inconsistent-positive feedback symbols and 14 inconsistent-negative feedback symbols. We decided to present more inconsistent symbols to make it easier for participants to learn these contingencies. Each trial had the following timing parameters: fixation asterisk (250 ms), symbol (500 ms), fixation asterisk (500–800 ms), choice ("*Do you want to gamble?*," until response), feedback depending on the decision and the symbol's winning probability (750 ms), inter trial interval (ITI; 500–800 ms).

The fMRI blocks consisted of 50 randomized trials (10 repetitions of each symbol). We also adjusted the timing parameters to fit the fMRI method (see **Figure 3**). The inter trial interval (ITI) and the anticipation period were both jittered with an average duration of 2,500 ms, ranging from 2,000 to 3,000 ms. Participants could answer within 2,500 ms when they were requested to indicate their decision (see **Figure 3**). If they did not respond within this time frame, *"XXX"* appeared as feedback which did not affect their momentary balance. However, participants were still asked to give an answer although a no-decision would have yielded a similar result for the participant's overall balance. We did so to reduce missed trials, which cannot be used in analysis, to a minimum.

Last, in the PAQ Block we did not change trial structure (see **Figure 2B**). However, we presented five symbols instead of four, as we had one additional control symbol in Experiment 2. Again, participants indicated their predecisional affective states on a paper-pencil questionnaire. Hence, the PAQ Block consisted of five trials (see **Table 2**).

Procedure

For an overview of experimental factors and the procedure in comparison to Experiment 1 (see **Table 2**). First, participants were welcomed, filled in a demographic questionnaire, and gave their written informed consent to the experimental procedure. We placed five euros in front of each participant to underline that they could win and lose real money during the experiment. Each participant started the experiment with a balance of five euros. The participant's current money balance was presented after each block. Thus, participants got an immediate feedback after each block how much they won or lost in the respective block. Practice blocks did not affect the participants' balance in any part of the experiment. After completing the practice block consisting of 10 trials (each symbol was presented twice), they started the three learning blocks. Participants could indicate their gambling decision by pressing the assigned gamble or pass button on a two keyed Cedrus Response Box (RB-380). In the learning phase, participants could take a short self-timed break between blocks if they wanted to. Before each task change, participants completed a practice block to get used to the procedure or the changed trial timing. After the fMRI practice block (five trials), they completed two fMRI blocks starting with a 6 s fixation trial. Between both blocks a 50 s break was inserted and the balance of monetary gains or losses in the preceding block was presented. In this phase we used NordicNeuroLab's VisualSystem for stimulus presentation in the MRI scanner and ResponseGrip to collect their answers. The VisualSystem goggles were placed on the head coil where participants could adjust the visual acuity depending on their visual condition. Participants were instructed to use their right and left thumb to indicate their decision. After the fMRI phase, participants completed the PAQ Block. At the very end, participants were debriefed and got paid their overall balance.

fMRI Data Acquisition

Data were collected using a 1.5 T Magnetom Avanto scanner (Siemens Medical Systems, Erlangen, Germany) with an 18-channel head coil. Functional images were obtained using a T2*-weighted echo planar imaging (EPI) sequence with TR = 2,000 ms, TE = 35 ms and flip angle = 80°, 498 volumes, resulting in a duration of 16.6 min. Each functional image consisted of 23 axial slices, with 64 × 64 matrix, 200 mm × 200 mm field of view (FOV), 5 mm thickness, 1 mm gap, and 3.125 mm × 3.125 mm inplane resolution. Structural images were obtained using a 3D structural sagittal T1-weighted MPRAGE image. Each structural image consisted of 192 contiguous slices, with 256 mm × 250 mm matrix size and 1 mm slice thickness.

Data Analysis

Behavioral

Behavioral data were analyzed by computing a repeated measures ANOVA for each dependent variable of interest as we did in the behavioral analysis of Experiment 1. As we had a small sample size and just one measurement for each affect construct, we decided to skip the choice prediction analysis.

fMRI

Data were preprocessed and analyzed using SPM12[3]. The first three volumes were discarded due to longitudinal magnetization equilibration effects. First, structural and functional images were roughly reoriented using the EPI-derived MNI template (ICBM

[2]http://www.neurobs.com

[3]http://www.fil.ion.ucl.ac.uk/spm/

305, Montreal Neurological Institute). After realignment, the structural images were coregistered to the EPI images, and the six movement parameters (x, y, z, pitch, yaw, roll) saved to include them as covariates in the first level analysis. Then EPI images were time shifted to the middle slice to correct differences in slice acquisition timing. In a further step, both structural and functional images were directly normalized to the MNI template. The normalized EPI images were smoothed with a Gaussian kernel of 8 mm full-width half-maximum (FWHM) and filtered with a high-pass filter of 128 s.

In the first level analysis, we specified conditions, estimated parameters, and computed contrasts for each participant using the canonical hemodynamic response function (HRF) and a general linear model. Therefore, we defined the time-locked anticipation periods (see **Figure 3**) of the five symbols as regressors and included the six motion parameters as covariates to reduce signal-corrected motion effects. Regardless of the later gambling decision, anticipation periods of the symbols were each modeled as a separate regressor. Response, feedback, and between-block pause periods were still modeled but not included in the analysis. Additionally, anticipation periods of missed trials were treated the same way, the ITI serving as implicit baseline. Then, we applied classical parameter estimation with a one-lag autoregressive model and a masking threshold of 0.8 to minimize false positive voxels. Finally, we computed the t-contrasts of the symbols compared to the control symbol to isolate brain activity of potential wins and losses in the anticipation period. Thus, we computed the contrasts "positive-consistent > control," "positive-inconsistent > control," "negative-inconsistent > control," and "negative-consistent > control" to take them to the second level group analysis.

In the second level group analysis, we defined a 2 × 2 full factorial design for repeated measures with the factors BALANCE and CONSISTENCY while AGE was included as a covariate due to the previously discovered age related dropouts caused by learning difficulties. We assigned the factor levels in the same way as in the behavioral analysis. For computation, we entered each participant's t-contrasts of each symbol in comparison to the control condition which were calculated in the first level analysis. For each factor, variances were assumed to be unequal and independence was not given. Furthermore, we applied implicit masking and carried out a classical parameter estimation.

Results

Behavioral

Expected valence

We submitted the difference scores of self-reported expected valence ratings for each symbol to a 2 × 2 repeated measures ANOVA as in Experiment 1. The interaction BALANCE × CONSISTENCY turned out to be significant, $F(1, 15) = 4.98$, $p = 0.041$, $\eta_p = 0.241$. As it was a semi-disordinal interaction, only the main effect BALANCE was interpretable, $F(1, 15) = 13.63$, $p = 0.002$, $\eta_p = 0.476$. Symbols which had a positive balance, $M = 2.06$, $SE = 0.558$, had significantly higher difference scores than symbols which had a negative balance, $M = -1.16$, $SE = 0.558$. Thus, the effect of a positive balance on expected valence ratings was even more pronounced for symbols returning consistent positive feedback in comparison to symbols returning inconsistent positive feedback.

Current valence

We submitted the self-reported current valence ratings to a 2 × 2 ANOVA for repeated measures. The main effect CONSISTENCY proved to be significant, $F(1, 15) = 6.05$, $p = 0.027$, $\eta_p = 0.287$, with consistent symbols, $M = 7.44$, $SE = 0.334$, having significantly higher current valence ratings than inconsistent symbols, $M = 6.72$, $SE = 0.334$. The main effect BALANCE was only marginally significant, $F(1, 15) = 4.45$, $p = 0.052$, $\eta_p = 0.229$.

Expected arousal

As before, we submitted the difference scores of self-reported expected arousal ratings for each symbol varying in CONSISTENCY and BALANCE to a 2 × 2 repeated measures ANOVA. All interaction and main effects were non-significant.

Current arousal

For self-reported current arousal we performed a 2 × 2 ANOVA for repeated measures with the factors BALANCE and CONSISTENCY. The two-way interaction was non-significant, $F(1, 15) < 1$, however, the main effect BALANCE reached significance, $F(1, 15) = 11.50$, $p = 0.004$, $\eta_p = 0.434$. Symbols with a positive balance, $M = 4.16$, $SE = 0.447$, had significantly higher self-reported current arousal ratings than symbols with a negative balance, $M = 3.31$, $SE = 0.447$.

fMRI

Results of the full factorial analysis are presented in **Table 6** and **Figures 4**, **5** at $p < 0.001$ (uncorrected) and a minimum voxel cluster of 40. Despite the possibility of false positive results, we decided to conduct the analysis to give an idea of potentially activated brain regions. Main and interaction effects which are not reported did not approach significance. For all symbols,

TABLE 6 | Group maximum *T*-values and MNI Coordinates of activation foci for the t-contrast Condition (general activation averaged over anticipation periods of the four symbols; $p < 0.001$, uncorrected; $n = 17$) and the t-contrast Balance (negative > positive; $p < 0.001$, uncorrected; $n = 17$).

Region	H	*x*	*y*	*Z*	*t*	Size
Condition						
Cerebellum exterior	R	12	–46	–20	4.45	49
Accumbens area	L	0	4	–4	4.40	49
Thalamus proper	R	2	–2	6	4.05	44
Anterior cingulate	L	–10	40	–4	4.25	43
Medial superior frontal	R	4	40	24	4.07	60
Superior frontal	R	18	20	56	3.73	56
Balance						
Superior temporal	L	–54	–20	0	4.80	91
		–64	–48	16	4.79	52
Middle temporal	L	–48	–60	4	4.47	65
		–52	–60	12	3.53	45

Size, number of activated voxels; L, left; R, right; H, hemisphere.

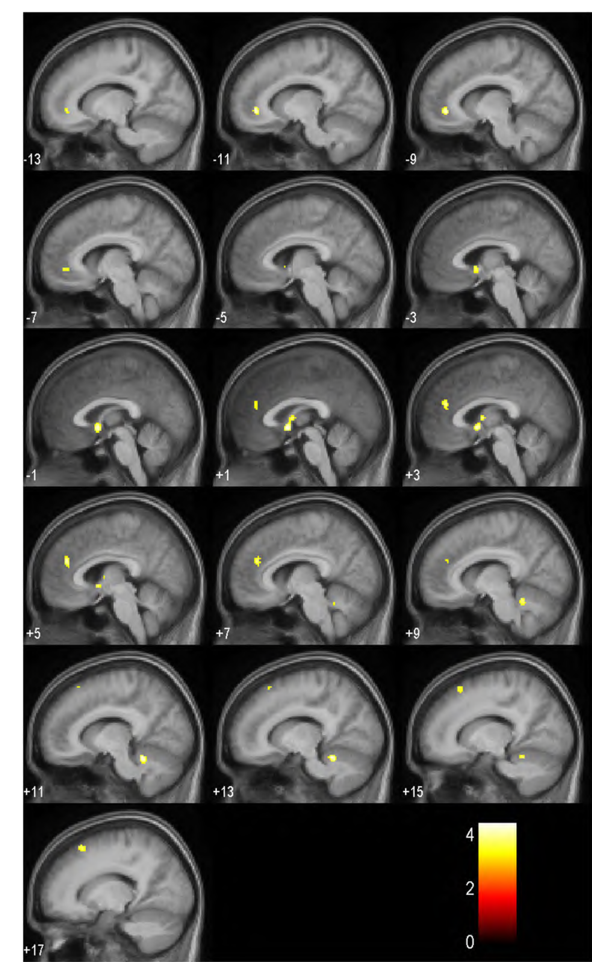

FIGURE 4 | Activation patterns in the anticipation period as listed in **Table 6** for all symbols in comparison to the control symbol ($p < 0.001$, uncorrected; $n = 17$). Positive values represent the number of sagittal slices from the center to the right hemisphere. Negative values indicate the number of sagittal slices from the center to the left hemisphere. The colored bar specifies the respective t-value's magnitude.

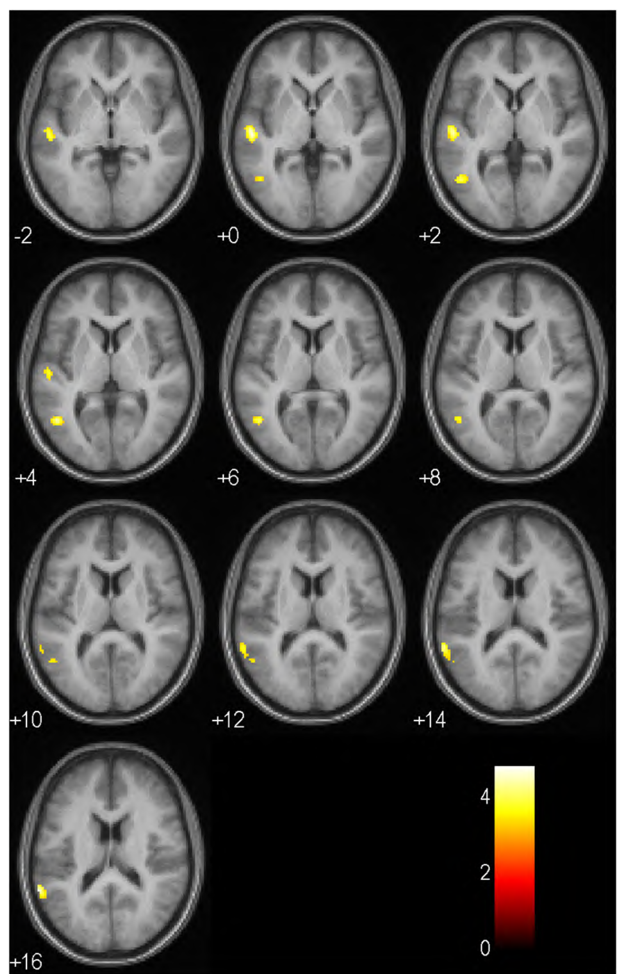

FIGURE 5 | Activation patterns in the anticipation period as listed in **Table 6** for negative balanced in comparison to positive balanced symbols (main effect balance, no > yes; $p < 0.001$, uncorrected; $n = 17$). Positive values represent the number of axial slices from the center downwards. Negative values indicate the number of sagittal slices from the center upwards. The colored bar specifies the respective t-value's magnitude.

which returned positive or negative feedback in comparison to a control symbol, which regardless of choice returned a null feedback, we found general activations in the anticipation period. As presented in **Figure 4**, symbols associated with positive or negative feedback showed more activity in the anticipation period in the Cerebellum Exterior, the Accumbens Area, the Thalamus Proper, the Anterior Cingulate Cortex, the Medial Superior Frontal Cortex, and the Superior Frontal Cortex. Furthermore, we found that negative balanced symbols produced stronger activations in the Superior Temporal and Middle Temporal Cortex in the anticipation period in comparison to positive balanced symbols (see **Figure 5**).

Discussion

In Experiment 2 we adapted the gambling task from Experiment 1 to the fMRI environment. We were interested in predecisional affect in the anticipation period of a complex decision-making task. Therefore, we wanted to exploratively examine affective brain-activity and varied feedback consistency and average feedback balance. We could only show brain activity for uncorrected p-values which is due to our small sample size. Nevertheless, we think that our exploratory results are still worth reporting since future hypothesis testing research can use our findings as a starting point. In line with previous research (Lindquist et al., 2016), we could observe most activity in the valence-general condition which indicated activity independent of experimental factors in the accumbens area, thalamus proper, anterior cingulate cortex, medial superior frontal cortex, superior frontal cortex, and the cerebellum exterior. A negative average feedback balance produced activity in the superior temporal and middle temporal gyrus. Analysis of expected valence ratings replicated findings from Experiment 1 meaning that expected valence ratings differed between positive and negative

balanced symbols and for positive balanced symbols between consistent and inconsistent symbols. Findings of current arousal could also be replicated with positively balanced symbols having higher arousal ratings than negatively balanced symbols. Findings of expected arousal and current valence could only partially replicate findings from Experiment 1. Overall, the presented evidence suggests that valence-general regions are also recruited in the anticipation period of our decision-making task. During the anticipation period self-reported expected valence and current arousal ratings are robustly influenced by contextual factors.

Our results indicate some overlapping activity with results of the meta-analysis by Lindquist et al. (2016). However, there is still a considerable difference between valence-general active regions as we did not find activity in the amygdala, the insula, and prefrontal regions, for example. The absence of activity in prefrontal regions could be explained by findings from Oldham et al. (2018). They conducted a meta-analysis on fMRI studies that used the monetary incentive delay task. This task makes it possible to disentangle the anticipation period from the feedback period as well as gains from losses. Their findings suggest that there is great overlapping neural activity between the anticipation of gains and losses including the amygdala, thalamus, striatum, and insula which is in line with Lindquist et al.'s (2016) findings and the affective work-space hypothesis. Furthermore, activity in orbitofrontal/ventromedial prefrontal regions was only observed during the reward feedback period which could explain the absence of activity in our findings. In general, Wilson et al. (2018) replicated the findings in another meta-analysis and analyzed active brain regions in more detail. This resulted in similar activations like we found adding activity in the cerebellum, the superior frontal gyrus, and the medial superior frontal gyrus to the meta-analytic evidence. However, we could not observe activity in the insula and the amygdala which has been a robust finding in the presented meta-analyses (Lindquist et al., 2016; Oldham et al., 2018; Wilson et al., 2018). Both brain areas have been identified as key nodes of the so called salience network which appears to serve the function of detecting novel stimuli across different modalities (Uddin, 2015). As we examined neural activity in relation to a control symbol, this could be the reason why we did not observe neutral activity in these areas of the salience network. Participants continuously viewed different symbols intermitted by fixation asterisks and the feedback presentation. We argue that the recognition of the control symbol, like all other symbols, also elicited a salience response. Hence, the control symbol was as novel as the other symbols in our experimental design which resulted in no greater or lesser neural activity in the salience regions.

GENERAL DISCUSSION

In two experiments, we examined the involvement of subjective feelings in the decision-making process. We studied how contextual factors influence current and expected subjective feelings and which constructs predict choice behavior best. We addressed the problems of common research designs like the IGT (Dunn et al., 2006) by developing a recurrent decision task that can vary contextual factors (feedback consistency, average feedback balance, learning experience) in a systematic way. Furthermore, we presented only one symbol at a time and could, therefore, solve the previously mentioned problem of the IGT without losing ecological validity. To our knowledge this is the first study that took a two-dimensional affect approach (valence, arousal) for measuring self-reported expected and current affect in a recurrent decision task. This provides a fuller picture of involved affective processes in recurrent decision-making. Furthermore, we exploratively looked at neural activations depending on contextual factors. Our results suggest that expected valence is the main and only self-reported subjective feeling component that predicts decisions. Hence, self-reported expected valence yet not self-reported current affect predicted decisions. Additionally, we observed valence-general neural activity in Experiment 2 while participants' self-reported expected valence depended on contextual factors. Although self-reported current affect ratings also depended on contextual factors, the observed effect size and effect consistency for expected valence was substantially bigger. In sum, we observed valence-general activity in line with the presented meta analyses (Lindquist et al., 2016; Oldham et al., 2018; Wilson et al., 2018) and observed inconsistent and smaller contextual effects for self-reported current valence than for self-reported expected valence.

We carefully interpret our findings in the way that based on past experiences symbols induced current affect (fMRI findings, self-report current affect ratings) which in turn prompted further cognitive processes like expectancies of future outcomes (expected valence). If this is the case, participants would feel something and use this feeling to build their expectancies upon this feeling which is reflected in differential expected affect ratings. However, we did not find clear self-reported current affect patterns and no high correlation between current valence and expected valence which limits our interpretation. The reason for this contradiction could be the way we asked for current affect. Västfjäll and Slovic (2013) suggest, additionally to the proposed dimensions, to distinguish *incidential affect*, which is unrelated to the decision problem, from *integral affect* which is inherently linked to the decision problem. Hence, to get a more sensitive measure of incidential current affect we might have asked participants how they felt while seeing the symbol. This might have led to more consistent findings and a bigger predictive power of current affect. Keeping this in mind, we should be careful with this interpretation as our findings have limitations that make it impossible to draw final conclusions. Future research should focus on how current and expected affect interact or do not interact with each other. Experimental designs would have to make sure that the measurement of current affect is more precise and should examine whether it is even possible to separately manipulate expected affect and current affect. If it is not possible, this will provide more evidence for the described interpretation.

Complementing our interpretation, Moors and Fischer (2019) suggest that from a theoretical perspective there is no need to assume an intervening emotion variable to cause behavior. Even cases incorporating maladaptive emotions can be reinterpreted in a goal-directed way. For example, a student is paralyzed

during her presentation in class as she is afraid. Her goal could be not to make a mistake which she tries to control through increased self-monitoring (Clark and Wells, 1995). This limits her cognitive resources which makes committing mistakes more likely. Thus, she tries to control the first mistake with increased self-monitoring. This results in a vicious cycle which eventually paralyzes her. In her logic, if she stops speaking, she cannot make mistakes which is her overarching goal. Consequently, in this model of explaining the student's behavior, there is no need of a mediating emotion variable. The authors conclude that "emotions may point in imprecise ways to other factors (values and expectancies) that do the actual causal work. If so, it may be time to replace explanations in terms of emotions with explanations in terms of these other factors" (Moors and Fischer, 2019, p. 98). In our findings we can also see that expectancies are a much better predictor than current affect. Incorporating subjective feelings and expectancies of subjective feelings into one model shows that there is no predictive power of current affect as a goal-directed account of emotions would predict.

As mentioned before, there are some limitations to our study we would like to address now. First, in the fMRI analysis we report uncorrected *p*-values. Hence, cumulated alpha errors could have led to false positive results. However, we conducted an explorative fMRI analysis which is useful for generating hypotheses and should not be taken as conclusive knowledge. Adding to that, we would like to point out that we had a relatively small sample size in both experiments which underlines the robustness of effects regarding expected valence. However, it is still possible that we missed smaller effects due to the low power of our study. Future research should replicate the main findings with a larger sample size. Moreover, we did not present questions in a randomized order which could have led to systematic biases in affect ratings. Future research should counterbalance or randomize question presentation to make sure that there is no hidden bias. We expect though that findings regarding affect ratings will not change in a meaningful way. Taken together, our findings can only be preliminary due to the described limitations. Nevertheless, we still think that our results make a valuable contribution to inspire future research and neurocognitive decision theories.

Future research should also measure current affect in a more sensitive way as we proposed before. This would be the first step to further study how current and expected affect might work together. Furthermore, experimental designs should try to separately manipulate current affect and expected affect. We have two ideas how this could be accomplished. First, we could present symbol-feedback contingencies in the beginning and start with a questionnaire block. This would mean that participants have not experienced any outcome but draw on their knowledge and should therefore report differential valence expectancy ratings. Following reinforcement learning models (Holroyd and Coles, 2002), having not experienced an outcome before, might eliminate current affective experiences when viewing the symbol. A second option would be to switch symbol-feedback contingencies after a learning phase and before a questionnaire phase. Participants should be told which symbols have changed, so that they could adjust their expectations accordingly. This way participants would have current affect ratings based on their learning history and expected valence ratings based on the new information they received. Studying how these changes in experimental design affect subsequent gambling decisions could elucidate how current and expected affect work together and which is causal for decisions. Moreover, we would like to point out that self-reported arousal might not be the best way to measure an emotional arousal component as it produces inconsistent results (Asutay et al., 2019). It might be better to additionally use physiological arousal measures.

CONCLUSION

Examining the relations among current and expected affective constructs in causing decision is a sensible way for future theorizing and empirical research on the affective involvement in decision-making.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation, to any qualified researcher.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the ethics committee of the Hannover Medical School. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

DJ, JR, and MB designed the study. DJ and MB collected and analyzed the data, DJ, MB, JR, and JDR wrote the manuscript. All authors approved the final version of the manuscript.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix B: Full Text of „Current and expected affective valence interact to predict choice in recurrent decisions.“

This appendix contains the complete version of the article:

Jäger, D. T., Behrens, C., & Rüsseler, J. (2022). Current and expected affective valence interact to predict choice in recurrent decisions. *Cognition & Emotion*, *36*(3), 560–567. https://doi.org/10.1080/02699931.2021.2020730

The article is included here in its accepted manuscript format to document the research forming the basis of this dissertation. Please note that the pagination within the article follows the accepted manuscript layout and does not continue the page numbering of the dissertation.

Current and Expected Affective Valence Interact to Predict Choice in Recurrent Decisions

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The data that support the findings of this study are available in [open science framework] at https://osf.io/fzq53/, reference number [10.17605/OSF.IO/FZQ53].

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Abstract

Research on the role of affect in decision-making indicates that both predecisional current and expected affective valence predict choice. However, the exact role of current and expected affect for recurrent decision-making is still a matter of debate. We used a generalized mixed effect model to predict gambling responses in an experience-based learning task from ratings of current and expected affective valence. Results indicate that current and expected affective valence interact to predict choice. While expected valence had the biggest effect size, current valence and the interaction still contributed significantly to the prediction of choice. Resolving the interaction showed that participants relied more on the current valence if expectations were unclear or positive. These findings are discussed in the context of dual-process accounts and the affective signalling hypothesis. In conclusion, current and expected valence depend on one another and interact to predict choice in recurrent decision tasks.

Keywords: predecisional affect, decision-making, current affective valence, expected affective valence

Introduction

In the past decades an expanding body of literature provides evidence for the emotional involvement in judgement and decision-making (Bechara et al., 1997; Dunning et al., 2017; Lerner et al., 2015; Loewenstein & Lerner, 2003; Mellers et al., 1999; Schlösser et al., 2013). Most researchers agree to separate predecisional and postdecisional affect (Lerner et al., 2015). There are three different theories on how affect guides choice. First, direct causation approaches assume that it is the actually felt affect which guides choices and behaviour (Bechara et al., 1997). Second, expectancy approaches posit that cognitive expectations of future emotional consequences of outcomes predict choices (Charpentier et al., 2016; Jäger et al., 2020; Mellers et al., 1999). Third, interaction approaches argue that current feelings and emotional expectancies work together to guide choices (Lerner

et al., 2015; Loewenstein et al., 2001; Reimann & Bechara, 2010). Moreover, dual process models do not focus on an affective involvement but rather distinguish between rapid autonomous processes (Type 1) and higher order reasoning processes (Type 2). These processes work in the way that Type 1 processes yield default responses unless intervened on by Type 2 processes (for a comprehensive review see Evans & Stanovich, 2013).

Evidence either favors the direct causation approach (Schlösser et al., 2013) or the expectancy approach (Charpentier et al., 2016; Jäger et al., 2020). When looking more closely at the employed measures it appears that results converge. Asking participants "how they feel when considering a decision option" – termed immediate affect for some groups (e.g. Schlösser et al., 2013) – predicts subsequent choice across a variety of tasks. The same holds for asking participants "how they expect to feel after receiving the outcome of the decision" - termed expected affect (Charpentier et al., 2016; Jäger et al., 2020). However, anticipating the emotional consequences of a particular outcome (e.g. "Consider winning 5 € in this gamble, how would that make you feel?") does not have the same predictive power (Schlösser et al., 2013). Taken together, decision options elicit a current feeling and at the same time an expectation of future feelings that both predict subsequent choice based on winning probabilities and winning amounts (Jäger et al., 2020; Mellers et al., 1999; Schlösser et al., 2013). An alternative interpretation of these findings posit that these two different types of questions actually measure the same construct, which would make the theoretical distinction superfluous.

We still think that the distinction could be useful. However, in most experimental paradigms immediate affect and cognitive expectations align. In everyday life, this is often not the case. To most decisions there are past experiences that are no longer relevant to the current choice. Some groups proposed to separate background from immediate emotions that are integral to the decision problem (Dunning et al., 2017). There are good

theoretical and empirical reasons to make this distinction; however, feelings are based on an average of all available information (Asutay et al., 2021; Efendić et al., 2020). Cognitive expectations, past emotional experiences, and other information types serve as inputs to current feelings and predict valuation judgements (Efendić et al., 2020). Hence, for the affective system there seems to be no distinction between relevant and irrelevant information in decision problems, which means a measurement of immediate background emotions would be an artificial category. For choice prediction, it is more plausible to measure a variable that summarizes all current feelings. This is the reason we speak of current affect, which we define as the current self-reported feeling that incorporates immediate background as well as integral affect (Lerner et al., 2015).

In the present experiment, we tried to disentangle current feelings and cognitive expectations. Thus, we used a gambling task similar to the one employed by Jäger et al. (2020). In this task, there are four symbols. Two symbols have an overall positive reinforcement balance while the other two have an overall negative reinforcement balance. Over several trials, participants have to decide for each symbol if they want to gamble or have a pass. Hence, participants can learn symbol-outcome contingencies and adjust their current affect and expectations accordingly. Second, we manipulated participants' expectations. After a learning phase, we informed them that symbol contingencies for two symbols were exchanged but not for the other two. We changed contingencies in the way that a previously positive symbol resulted in a loss of points afterwards and vice versa. Participants continued the gambling task and rated their current and expected valence before making the decision. Previous research has shown that arousal measures are not reliable (Asutay et al., 2021) and that the predictive value of arousal measures is negligible (Jäger et al., 2020), which is why we just measured the valence dimension of affect. Thus, participants should now have a learning experience

differing from their expectations. We wanted to show three things: First, current feelings and cognitive expectations measure different constructs. Second, each construct has its own predictive power. Third, if the confound is resolved, cognitive expectations and current feelings interact to predict choice as interaction models (Lerner et al., 2015) and default-interventionist dual process models (Evans & Stanovich, 2013) propose.

Method

Participants

Sample size was determined by simulating data of a pilot study using the SIMR package in R (Green & MacLeod, 2016). Alpha was set at 0.05, interaction and main effect slopes for choice prediction were set at 0.75, which corresponds to a medium effect size (predicted from earlier results of Jäger et al., 2020). For 50 simulations, the power remained above 0.8 for all effects and indicated an optimal sample-size of thirty-five participants ($M_{\text{age}} = 23.7$ years, $SD = 3.72$; 31 right-handed; normal or corrected to normal vision). All participants were students at the University of Bamberg and received course credit for participation. As an additional incentive, the best five participants each gained 20 euros. All of them gave their written informed consent and were debriefed afterwards. The local ethics commission approved the study protocol.

Materials

The experiment consisted of two parts: A Learning Phase and Predecisional Valence Questionnaire blocks. For stimulus presentation, we used the NBS Presentation software. For answer collection, we used a two-keyed Cedrus Response Box (RB-380).

Gambling Task. Starting with a balance of 500 points, the participants of the gambling task were instructed to earn as many points as possible. In each trial, one of four different

symbols was presented, and participants had to decide whether to gamble or not. If a participant decided to pass, the score always remained unaffected (+/- 0). If a participant decided to gamble, they could either win or lose points (+/- 15 points), depending on constant probability pairing for each symbol. The fundamental objective of the learning phase was to acquire and consolidate the symbols´ probability pairings. While two of the four symbols gained points in 90% of the cases, the remaining two resulted in a loss of points with 90 % certainty. Symbol-probability pairings were randomly assigned for each participant. However, we did not inform participants about the incentive values of the symbols. They had to obtain insight into the task structure via trial and error (for trial structure and timing parameters see Figure 1, for symbol-contingency pairings see Table 1). A reasonable strategy would be to gamble on positive symbols and pass on the negative ones. Eight learning blocks encompassing five presentations of each symbol were administered (i.e. 20 trials per block). Symbols were displayed in a randomized order.

Predecisional Valence Questionnaire Task. In the questionnaire blocks, participants continued the gambling task, aware that contingencies for two symbols had been exchanged. We measured self-reported predecisional valence using a digital questionnaire format. Each time a symbol was presented, participants rated their current and expected valence before making the decision (see Figure 1). Using a Self-Assessment Manikin Scale (Bradley & Lang, 1994), they marked their individual position on the visual analog scale by moving the mouse. The computer recorded the chosen point in a value ranging from -255 for a very unpleasant feeling to +255 for a very pleasant feeling. Starting point was always in the middle of the scale. Taken together, we recorded three different question perspectives of valence for each symbol. The first perspective asked participants to rate their current valence *("How did you feel seeing this symbol?")*. The

other two question perspectives referred to the expected valence: One in relation to the decision to gamble ("*Please imagine, you decide to gamble. How will you feel after you received the outcome of your decision?*") and the other one to the decision to pass (“*Please imagine, you decide to pass. How will you feel after you received the outcome of your decision?*”). The presentation of these questions and the respective symbols was randomized. Participants did not receive immediate feedback after responding, they merely obtained aggregated feedback by receiving their current score after each block. In total, questionnaire blocks consisted of three blocks, including 16 trials each, which means that we collected 48 ratings per questionnaire block.

Procedure

Participants gave their written informed consent and completed a demographic questionnaire. Afterwards, they received instructions for the experimental task. In total, the experiment consisted of two rounds. In each round, participants completed the Learning Phase and the Predecisional Valence Questionnaire Task. The initial balance for each participant was 500 points. Moreover, they received their current score after each block and had the opportunity for a brief self-timed pause. Participants performed a practice block that did not affect their balance. Afterwards, they started the first of the eight learning blocks. After completing the Learning Phase, a notification appeared on the screen, which informed participants that outcome contingencies for two symbols were from now on exchanged, i.e. one of the previous positive symbols mainly resulted in a loss of points and vice versa. We ensured that participants had properly understood this information and handed them a note sheet to write down the corresponding symbols. Thus, participants knew and wrote down which symbols changed contingencies. Subsequently, participants processed the predecisional valence questionnaire task. The

whole procedure was repeated with different symbol – outcome pairings. Taken together, the study lasted 60 minutes.

Results

Manipulation Check

To analyze how the experimental manipulation influenced gambling frequencies, current and expected affective valence ratings, and the correlation between both affective constructs, we conducted several analyses. For the expected valence perspectives, we computed a difference score (Expected Valence Difference = "Expected Valence if gambling" – "Expected Valence if passing", possible values ranging from -510 to +510). For post-hoc t-test, Bonferroni-corrected p-values are reported.

Gambling Frequencies. To ensure that our experimental manipulation was successful, we conducted a 2 x 2 x 2 ANOVA for repeated measures analyzing the gambling frequencies before and after the exchange. Thus, the factor TIME had two levels: Pre-Exchange, and Post-Exchange. The factor BALANCE had two levels: positive, for symbols that won on average, and negative, for symbols that lost on average. The factor EXCHANGE had the levels yes, for symbols that changed contingencies, and no, for symbols that did not change contingencies. The three-way interaction TIME x EXCHANGE x BALANCE was significant, $F(1, 34) = 47.2$, $p < 0.001$, $\eta_p^2 = 0.581$. For resolving this interaction, we used the pre-exchange data to conduct a 2 x 2 ANOVA with the factors BALANCE and EXCHANGE. The results showed a significant main effect of BALANCE, $F(1, 34) = 1005.2$, $p < 0.001$, $\eta_p^2 = 0.967$. Gambling frequency was significantly higher for positive symbols, $M = 0.94$, $CI = [0.90, 0.97]$, than for negative ones, $M = 0.11$, $CI = [0.07, 0.15]$. Next, we conducted a repeated measure ANOVA with the factors Balance and Exchange for the post-exchange data. There was a significant BALANCE x

EXCHANGE interaction effect, $F(1, 34) = 44.8$, $p < 0.001$, $\eta_p^2 = 0.569$, describing a disordinal interaction. Positive-changed-to-negative symbols, $M = 0.34$, $CI = [0.23, 0.45]$, showed a significantly lower gambling frequency than non-exchanged positive ones, $M = 0.80$, $CI = [0.68, 0.91]$, $p < 0.001$. In contrast, negative-changed-to-positive symbols, $M = 0.85$, $CI = [0.73, 0.96]$, indicated a significantly higher gambling frequency than non-exchanged negative ones, $M = 0.35$, $CI = [0.23, 0.46]$, $p < 0.001$. Besides, gambling frequency did not significantly differ between positive-changed-to-negative and non-exchanged negative symbols, $p > 0.05$; such as between negative-changed-to-positive and non-exchanged positive ones, $p > 0.05$.

Expected Valence. For expected valence difference scores we computed a 2 x 2 ANOVA for repeated measures. There was a significant interaction effect BALANCE x EXCHANGE, $F(1, 34) = 100.1$, $p < 0.001$, $\eta_p^2 = 0.746$, describing a disordinal interaction. Post-hoc t-tests demonstrated that difference scores of positive-changed-to-negative symbols, $M = -141$, $CI = [-182, -99.6]$, were significantly lower than negative-changed-to-positive symbols, $M = 144$, $CI = [140, 221.9]$, $p < 0.001$. In contrast, expected difference scores for positive non-exchanged symbols, $M = 181$, $CI = [140, 221.9]$, were significantly higher than negative non-exchanged ones, $M = -174$, $CI = [-215, -133.4]$, $p < 0.001$. Besides, expected valence difference scores did not differ significantly between positive-changed-to-negative and non-exchanged negative symbols, $p > 0.05$; such as between negative-changed-to-positive and non-exchanged positive ones, $p > 0.05$.

Current Valence. For current valence ratings, we computed a 2 x 2 ANOVA for repeated measures. The interaction BALANCE x EXCHANGE was significant, $F(1, 34) = 43.7$, $p < 0.001$, $\eta_p^2 = 0.562$, describing a disordinal interaction. Current valence ratings for

positive-changed-to-negative symbols, M = -1.0, CI = [-23.3, 21.3], did not differ from negative-changed-to-positive symbols, M = 23.0, CI = [0.7, 45.3], $p > 0.05$. For all symbols with unchanged contingencies, current valence ratings for positive symbols, M = 96.9, CI = [74.6, 199.2], were significantly higher than for negative ones, M = -60.7, CI = [-83.0, -38.4], $p < 0.001$, than for all exchanged symbols, for both $p < 0.001$. Furthermore, negative symbols differed significantly from positive-changed-to-negative symbols, $p = 0.002$, and from negative-changed-to-positive symbols, $p < 0.001$.

Correlation between Current and Expected Valence. To analyse how the experimental manipulation changed correlations between Current Valence and Expected Valence we used the R package correlation (Makowski et al., 2020) to account for the multilevel structure of our data. Expected and Current Valence ratings for symbols that did not change contingencies were highly correlated, $r = .75$. For symbols that did change contingencies the correlation dropped to, $r = .37$.

The manipulation check showed that participants adapted their choices according to the new expectations and adjusted their expected and current valence ratings in the predicted way. Furthermore, the analysis of the note sheets showed that all participants noted the contingency change correctly. Moreover, the manipulation considerably lowered the correlation among current and expected valence. Thus, the experimental manipulation was successful.

Choice Prediction

To test how Expected and Current Valence predict choice, we ran a generalized mixed effects model (Bates et al., 2015). Thus, as data fitting procedure the maximum likelihood method and a logit link function were used. We modelled expected valence and current valence as fixed effects. In addition, we entered an interaction term that

included the interaction of expected valence, current valence and the contingency change factor. We included Participant ID and the Symbol ID as random factors and started modelling with the maximal random effect structure, which did not converge. Hence, we reduced the random effect structure until we arrived at an intercept only structure that eventually converged. This resulted in the formula: Choice ~ Expected Valence + Current Valence + Expected Valence:Current Valence:Contingency Change + (1| Participant ID) + (1| Symbol ID). In addition to model inherent significance indicators, we assessed significance via model comparison with an Alpha of 0.05. For details regarding odds ratios, fixed and random effect structure see Table 1. The predictor Expected Valence had the highest *Odds Ratio* above 1, $X^2(1) = 598.1$, $p < .001$, meaning that the higher the Expected Valence the higher the probability of gambling and vice versa. The predictor Current Valence had an *Odds Ratio* above 1, $X^2(1) = 35.65$, $p = .001$, meaning that the higher the Current Valence Ratings the higher the probability of gambling and vice versa. The interaction of Expected Valence and Current Valence for changed contingencies had an *Odds Ratio* above 1, $X^2(1) = 9.03$, $p = .011$. Figure 1 shows choice prediction functions for Current Valence in the changed contingency condition including *CI*s for different values of Expected Valence. The predictive power of Current Valence depended on Expected Valence Ratings for changed contingencies. Specifically, if Expected Valence was around or above 0, Current Valence Ratings predicted choice. For Expected Valence Scores below 0, Current Valence did not predict choice. Finally, choice prediction functions of Expected Valence were not different from one another for different Current Valence values.

Discussion

We studied the role of current and expected affective valence in recurrent decision-making. Participants learned outcome contingencies of four different symbols in an

experience-based learning task. Hence, they learned which symbols to approach as they won on average and which symbols to avoid as they lost on average. After a learning phase, we told participants that we switched outcome contingencies of one advantageous with one disadvantageous symbol. Participants knew which symbols switched; however, they did not receive immediate feedback anymore. Results indicate that current and expected valence are sufficiently distinct from one another and both predicted choice. However, expected valence demonstrated a much bigger effect size compared to current valence. In addition, we found that expected valence and current valence interact to predict choice. Hence, current valence has the strongest predictive power if future valence expectations are unclear or positive. This is in line with an interaction approach of the affective involvement in recurrent decision-making (Lerner et al., 2015) and integrates previous findings of the other two theory classes (Bechara et al., 1997; Charpentier et al., 2016; Jäger et al., 2020; Schlösser et al., 2013). Taken together, we showed that previous findings for single decisions also hold true for recurrent decision making.

Other groups have repeatedly found that immediate affect is the strongest predictor of subsequent choice (Schlösser et al., 2013; Schlösser et al., 2016). We want to point out that our findings do not contradict these results, as these groups measured immediate affect in a similar way as we measured expected affect (for more details see introduction). The fact that changed expectations also changed current feelings adds more evidence to the interpretation that expectations produce immediate affect (Jäger et al., 2020). In other words, expected and immediate affect both measure a similar construct that has both a cognitive and an immediate affective nature. The results propose that this construct is the strongest predictor of choice. At the same time, an average of current feelings that are attached to a decision cue independently predicts choice, too.

In the present study, current valence predicted decisions when expectations were positive, but not when expectations were negative. Hence, one possible interpretation could be that for negative expectations the predictive influence of expected valence on choice predominates the predictive power of current valence. Furthermore, our findings are compatible with a dual process account (e.g. Evans & Stanovich, 2013), which means that negative valence expectations trigger increased self-monitoring. Thus, system two becomes more active which pushes the influence of current valence processed by system one to the background. This interpretation reminds of the affective signalling theory which posits that a control system notices negative affect driving adaptive changes in attention and performance (Dignath et al., 2020).

There are some limitations to the generalizability of our findings. First, in human decision making and reward learning a large part of the variability is attributable to computational noise, which increases in volatile environments (Findling & Wyart, 2021). In the present task, we had almost sure losses and gains and clear instructions, which means that our findings are only valid for this kind of environment. Second, other studies (e.g. Schlösser et al., 2013) have incorporated a subjective probability measure to show the predictive power of affect variables beyond subjective probability. This was not our main research question, which is why we decided not to incorporate that measure. However, it could be possible that our measures do not predict choice beyond subjective probability. Given previous research findings, we do not think this is a major issue.

In conclusion, current and expected valence depend on one another and at the same time interact to predict choice. Further examining their dependency and interaction are promising avenues for future research.

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Table 1. Example of Symbol-Feedback contingencies depending on the average feedback balance in the learning phase and when Symbol-Feedback contingencies were exchanged in the Predecisional Affective Questionnaire Phase. P refers to the probability of obtaining the respective outcome if the participant decides to gamble. Please note that symbol-feedback condition mapping was randomly assigned for each participant.

			Pre-Exchange		Post-Exchange	
Average Learned Balance	Exchange	Symbol	P = 0.9	P = 0.1	P = 0.9	P = 0.1
positive	yes		+15	-15	-15	+15
positive	no		+15	-15	+15	-15
negative	yes		-15	+15	+15	-15
negative	no		-15	+15	-15	+15

Table 2. Generalized linear mixed effect estimates of the choice prediction model for symbols with changed contingencies. Fixed Effects: Odds Ratios, Confidence Intervals (CI), and p-values. Random Effects: σ^2 = within-person residual variance, $\tau_{00\ \text{Participant}}$ = between-person variance, ICC = Proportion of variance explained by between-person differences; Marginal R^2 = variance explained by fixed effects, Conditional R^2 = variance explained by fixed and random effects; Significant results are printed in bold;

	Response		
Predictors	*Odds Ratios*	*CI*	*p*
(Intercept)	2.57	1.05 – 6.33	**0.040**
Expected Valence	5.59	4.75 – 6.58	**<0.001**
Current Valence	2.68	1.94 – 3.71	**<0.001**
Expected Valence x Current Valence x No Contingency Change	0.78	0.51 – 1.21	0.267
Expected Valence x Current Valence x Contigency Change	1.95	1.17 – 3.24	**0.010**
Random Effects			
σ^2	3.29		
$\tau_{00\ \text{Subject_ID}}$	6.34		
$\tau_{00\ \text{Symbol_Code}}$	0.18		
ICC	0.66		
N Subject_ID	35		
N Symbol_Code	8		
Observations	3360		
Marginal R^2 / Conditional R^2	0.255 / 0.750		

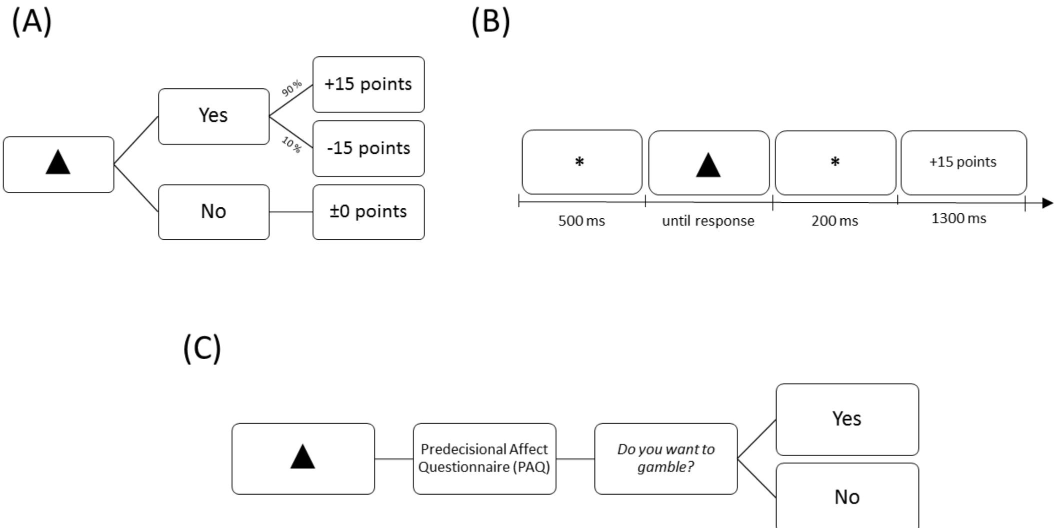

Figure 1. Example of the trial structure and possible feedback depending on gambling decision for a positive symbol (A) in the learning blocks and (C) the Predecisional Affective Questionnaire (PAQ) blocks. (B) Example trial to illustrate the timing of the Gambling Task. Numbers characterize presentation durations in ms. In this case the participant would have chosen to gamble and subsequently won 15 points. * Indicates a fixation dot.

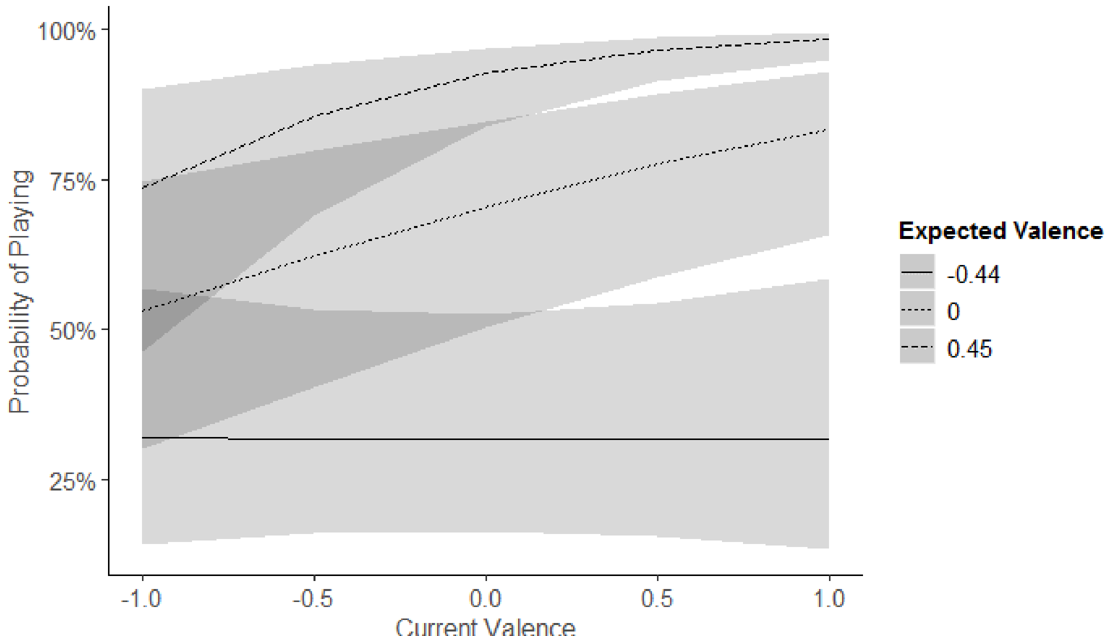

Figure 2. Choice Prediction function of Current Valence based on different Expected Valence Ratings; grey shades indicate Confidence Intervals.

Appendix C: Full Text of „Time matters: On the predictive power of current, short- and long-term expected valence in an experience based learning task.“

This appendix contains the Author‘s Proof version of the accepted manuscript:

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The article is included here in its original publisher format to document the research forming the basis of this dissertation. Please note that the pagination within the article follows the publisher’s layout and does not continue the page numbering of the dissertation.

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Time matters: on the predictive power of current, short- and long-term expected valence in an experience based learning task

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This study investigates the predictive power of current, short-, and long-term expected valence in decision-making within an experience-based learning task. Across two experiments participants engaged in a gambling task where they had to balance short- and long-term outcomes to maximize gains. In Experiment 1 participants had to accept short-term losses to achieve long-term gains, while in Experiment 2 they had to omit short-term gains. Results from generalized mixed-effects models revealed that all three valence constructs (current, short-term, and long-term expected valence) were significant predictors of risky choices, with their influence modulated by the specific choice context. In a loss context participants relied more on short-term expectations, while in an omission context long-term expectations played a stronger role. These findings align with existing literature on the influence of emotional valence on decision-making and demonstrate the adaptability of the subjective valuation system across different choice scenarios. The study highlights the importance of considering multiple emotional self-report dimensions in decision-making processes.

KEYWORDS

current valence, expected valence, subjective value, loss aversion, framing effects, recurrent decisions

Introduction

Emotions are an integral part of decision making (e.g., Bechara et al., 1997; Charpentier et al., 2016; Dunning et al., 2017; Jäger et al., 2020; Lerner et al., 2015; Mellers et al., 1999; Schlösser et al., 2016). Theories in the field of emotions and decision-making often provide broad conceptualizations of emotions. Hence, these models lack the necessary precision to fully account for the complexity of emotional involvement in decision-making. For example, the Somatic Marker Hypothesis (SMH; Bechara et al., 1997; Reimann and Bechara, 2010) posits that physiological arousal serves as a "marker" for emotional activation that guides decision making. Importantly, the SMH postulates that conscious cognitive processes, at least in some situations, do not guide decisions, and that decisions are guided by emotions tied to the decision object. This central claim has been challenged by studies showing a parallel development of verbalizable knowledge about task structure and skin conductance responses (index of emotional arousal) in the pre-decision phase (Maia and McClelland, 2004). While the SMH offers valuable insights into the role of emotion in decision-making, it does underestimate the role of (conscious or unconscious) cognitive processes in decision making. In contrast, Lerner et al.'s (2015, 2023) framework provides a more detailed conceptualization by distinguishing between current and expected emotions. Nevertheless, this distinction does

not sufficiently capture the variability of emotional expectations across different timeframes. Lerner's model treats expected emotion as a singular construct, but it does not differentiate between short-term and long-term expectations, which have been shown to have distinct effects on decision-making (e.g., Ariely and Loewenstein, 2000; Seaman et al., 2022).

Hence, disagreement still exists on how to best conceptualize the different self reported emotion types that are involved in the decision process (Lerner et al., 2015; Loewenstein and Lerner, 2003; Västfjäll and Slovic, 2013). It has been proposed to separate *predecisional* from *postdecisional* emotions (Västfjäll and Slovic, 2013). *Predecisional* emotion is present before the decision is made. *Postdecisional* emotion is present after the decision is made, which is also referred to as *outcome emotion*. However, there is disagreement on how to conceptualize predecisional emotional constructs (Lerner et al., 2015; Västfjäll and Slovic, 2013). One possibility is to distinguish between two main predecisional emotional concepts: *current emotion* and *expected emotion*. We define *current emotion* as the current self-reported feeling that incorporates both immediate background emotions and integral emotions (directly related to the decision task at hand), drawing on an average of all available emotional information while including past experiences and cognitive expectations (Efendić et al., 2020; Lerner et al., 2015). Although some propose distinguishing between background and integral emotions (Dunning et al., 2017), research suggests that the emotional system does not separate relevant from irrelevant information. Instead, current emotions summarize all present feelings, whether tied to the current decision or past experiences (Asutay et al., 2021). *Expected emotion* refers to the anticipation of future emotional consequences based on the available choice options. Expected short-term emotion refers to the emotions individuals expect experiencing as a result of an immediate outcome of a decision, such as the immediate pleasure of a win or the discomfort of a loss. This type of emotion is closely tied to the anticipation of an immediate gain or loss following a decision (for more details see Jäger et al., 2022). In contrast, expected long-term emotion refers to emotions anticipated in the future, often after a longer period of time, such as the end of an experiment or a long-term goal, where outcomes might include greater rewards or costs (Duckworth et al., 2007). Understanding how these different timeframes of expected emotions influence the decision making process allows for a better grasp of how people navigate the tension between immediate outcomes and future consequences in decision-making (e.g., Ariely and Loewenstein, 2000).

Self-reported emotions might be a window into the subjective valuation of choice options (Vollberg and Sander, 2024). There are two main group of theories of value-based choice: prospect theory (Kahneman, 1979) and reinforcement learning theories (Sutton and Barto, 1999). Both theories offer key insights into how individuals assess and compare the subjective value of different choice options. These models go beyond traditional rational approaches like expected utility theory, emphasizing that decision making is influenced not only by logical calculation but also by psychological and emotional factors. Prospect theory highlights how people evaluate potential outcomes as gains or losses in relation to a reference point, often showing an aversion to losses that outweighs their preference for equivalent gains (e.g., Mellers et al., 2021; Nabi et al., 2020; Prietzel, 2020). For instance, individuals tend to prefer a sure gain of €500 over a 50% chance to win €1,000, demonstrating risk aversion when it comes to gains. However, the same individuals might take risks to avoid a loss, such as preferring a 50% chance to lose €1,000 over a guaranteed loss of €500, reflecting risk-seeking behavior in the domain of losses. The theory's value function is concave for gains, convex for losses, and steeper for losses. Reinforcement learning theories focus on how individuals learn to make decisions over time by using feedback from their environment. These theories describe how people adjust their behavior based on rewards and punishments gradually learning to maximize long-term gains by choosing options that have led to positive outcomes in the past. Reinforcement learning models often involve trial and error through which individuals estimate the value of each option and update their choices based on new experiences (Sutton and Barto, 1999). Both models highlight the role of subjective value in decision making, yet they emphasize different mechanisms: prospect theory focuses on the emotional biases that affect risk perception, while reinforcement learning explains how choices evolve through experience and feedback. Together, these models provide a good understanding of how people weigh their options and make decisions, especially in uncertain situations. However, how subjective value is determined and how emotions contribute to the development of subjective value remains to be specified.

To further explore how self-reported emotions influence decision-making, Charpentier et al. (2016) conducted an experiment to examine the relationship between people's feelings and their choices. They used self-reported feelings to develop a "feeling function," quantifying how emotions associated with different outcomes relate to objective value. The study tested whether this "feeling function" could predict participants' choices in subsequent decision-making tasks, while exploring the symmetry of feelings toward gains and losses and their influence on risk-related decisions. The results revealed that the "feeling function" was concave for gains and convex for losses, similar to the value function in prospect theory. This curvature reflects diminishing sensitivity, meaning that the emotional impact of smaller gains or losses—such as winning or losing $10—was felt more intensely than that of larger amounts like $100. Surprisingly, the study found no inherent asymmetry between feelings related to gains and losses, challenging the assumption that losses evoke stronger emotions than equivalent gains. However, when it came to decision-making, participants gave more weight to their feelings about losses than to those about gains, aligning with loss aversion. This suggests that while gains and losses may evoke similar intensity of emotional responses, people focus more on potential losses when making decisions, leading to risk-averse behavior in mixed gamble scenarios.

In the present paper we are interested in the subjective valuation of choice options, which we hypothesize is reflected in self-reported emotion measures (Vollberg and Sander, 2024). Our goal is to model the role of feelings in a reinforcement model based on subjective emotions, as previous research has shown to be feasible (Hayes and Wedell, 2020). Specifically, we aim to investigate how emotional constructs at a given time point can predict subsequent choices. In other words, we intend to examine predecisional emotional constructs with respect to different time frames and assess their predictive power in influencing choice behavior. As an example, Schlösser et al. (2013) found that immediate feelings experienced at the moment of decision-making predict risky choices, even more so than anticipated emotions or subjective probabilities. This underlines the role of real-time emotion in shaping behavior, particularly in high-stakes scenarios where decisions may be influenced by emotional responses to the

options themselves rather than consideration of potential outcomes. Expectancy approaches, in contrast, argue that expected emotions, such as expected regret or pleasure, are the key drivers of choice. Research by Mellers et al. (1999) demonstrated that individuals often base their decisions on forecasts of how they will feel after various outcomes. For example, people might avoid a risky gamble because they anticipate the regret they would experience after a potential loss, highlighting the importance of cognitive expectations of future emotional consequences. Interaction approaches suggest that both current and expected emotions work together to influence decision-making. Jäger et al. (2022) found that in recurrent decision tasks, both current and expected emotional valence interact to predict choice. Valence refers to the intrinsic pleasantness or unpleasantness of an emotional experience and is a fundamental dimension of emotional states (Colombetti and Kuppens, 2024; Russell, 1980). Furthermore, Jäger et al. (2022) showed that while expected valence had the strongest influence on decision-making, current valence and its interaction with expected valence still significantly contributed to the prediction of choice. Interestingly, participants relied more on current emotional states if their expectations were unclear or positive, indicating a dynamic relationship between the two types of predecisional emotions. These findings suggest that the interaction between current feelings and future expectations is essential for understanding how individuals make decisions, particularly in repeated or experience-based tasks.

Despite the valuable insights from these theories, there is still limited research into how the time horizons of expected emotion influence decision-making. Most studies do not thoroughly examine whether people's decisions are better predicted by their expectations of immediate emotional reactions or long-term outcomes (Charpentier et al., 2016; Jäger et al., 2020, 2022; Mellers et al., 1999; Schlösser et al., 2013). This distinction is important because emotional reactions can shift over time—what seems immediately appealing might not result in long-term satisfaction, and decisions that seem painful initially could offer benefits later on (e.g., Jennison, 2004; Kopainsky et al., 2019; Mueller et al., 2017). Investigating different time horizons could help to clarify how short-term versus long-term emotional expectations shape decision-making strategies, providing a more nuanced understanding of how expected emotions influence decision behavior. We were curious if adding a time horizon to predecisional valence expectations would result in another predictor of choice.

Manipulating expectations is essential for understanding how individuals make decisions, especially when emotions and time horizons are involved. Research has shown that narratives can shift people's focus (Morag and Loewenstein, 2024). Similarly, altering the presentation of future outcomes, such as revealing the structure of a task, can change decision-making behavior (Jäger et al., 2022). Studies also show that people underweight factors like duration in decision-making (Ariely and Loewenstein, 2000). A recent meta-analysis found no significant relationship between age and preferences for immediate versus delayed rewards (Seaman et al., 2022). Hence, by reframing task structures and highlighting long-term benefits, researchers can manipulate time horizons, helping to reveal how individuals balance short-term and long-term considerations in their choices. Therefore, we designed two experiments to fully capture the time frames of emotional expectations. In the first experiment, participants had to accept losses to achieve long-term wins, while in the second experiment, they had to omit points to maximize overall wins. These experiments were designed to examine how different self-reported emotional constructs—current valence, expected short-term valence, and expected long-term valence—predict choice under different contextual demands, such as point-loss versus point-omission. By manipulating these decision contexts, we aimed to investigate how current and expected emotions across different time frames influence decision-making under varying conditions.

Experiment 1

In a gambling task similar to previous experiments (Jäger et al., 2020, 2022) participants could earn points over the course of the experiment. The five participants with the highest score each received a movie theater voucher of 20 euros. In the experiment we confronted participants with decisions where they had to accept a short-term loss to achieve the long-term goal of winning as many points as possible. Thus, short-term and long-term goals did not align any more. First, participants did the task without knowing the internal structure of the task. After that, we assessed current feelings, short-term expectations and long-term expectations prior to the respective choice. In the second round, participants received information about the task structure and the most beneficial strategy of accepting short-term losses to win more points over the course of the experiment. Knowing this, they performed the task a second time. Thereafter, we assessed the same emotional variables again.

Based on the idea that the predictive power of emotional variables depends on the particular situation and the lack of research concerning the predictive power of long-term emotional valence, we wanted to show four things:

1. Long-term expected valence is an additional predictor of human choice besides current valence and short-term expected valence. Hence, we expected main effects of long-term expected valence, short-term expected valence and current valence.
2. Insight into the task structure increases the predictive power of long-term expected valence, because the instruction focuses on long-term benefits. Thus, we expected an interaction between insight (first vs. second round) and long-term expected valence.
3. Insight into the task structure decreases the predictive power of short-term expected valence, because the instruction defines the short-term losses as no obstacle towards the overall goal. Thus, we expected an interaction between insight (first vs. second round) and short-term expected valence.
4. Insight into the task structure should not influence the predictive power of current valence. Hence, we expected no significant interaction between insight (first vs. second round) and current valence.

Method

Participants

Sample size was determined by simulating data of a pilot study using the SIMR package in R (Green and MacLeod, 2016). Alpha was set at 0.05, interaction and main effect slopes for choice prediction were set at 0.75, which corresponds to a medium effect size (Jäger

et al., 2020, 2022 found effects within this range). For 50 simulations, the power remained above 0.8 for all effects and indicated an optimal sample-size of 35 participants (M_{age} = 24.2 years, SD = 3.87; 34 identified as female; 30 right-handed; normal or corrected to normal vision). All participants were students at the University of Bamberg and received course credit for participation. As an additional incentive, the best five participants each gained 20 euros as a voucher for a local movie theater. All of them gave their written informed consent and were debriefed afterwards. The local ethics committee approved the study protocol.

Materials

The experiment consisted of two parts, which each had a Learning Phase and Predecisional Valence Questionnaire blocks. For stimulus presentation, we used the NBS Presentation software. For answer collection, we used a two-keyed Cedrus Response Box (RB-380). For a more detailed description of the gambling task's trial structure see Jäger et al. (2020, 2022).

Gambling task

Starting with a balance of 500 points, the participants of the gambling task were instructed to earn as many points as possible. In each trial, one of three different symbols was presented, and participants had to decide whether to gamble or not. If a participant decided to pass, the score always remained unaffected (+/− 0). If a participant decided to gamble, they could either win or lose points (+/− 15 points) depending on constant winning probability pairings for each symbol. The fundamental objective of the learning phase was to acquire and consolidate the symbols´ probability pairings. Moreover, at the beginning of the experiment, the symbols are randomly distributed to a Cue Contingency (CC) that determines the winning probabilities of the symbols. Symbols with CCs 1 and 2 result negatively 90% of the time (i.e., −15 points). Symbols with CC 3, on the other hand, are positive 90% of the time (i.e., +15 points). Based on the CC, the symbols differ in probabilities of occurrence, which can be represented using the example of an urn model: Assuming an urn is filled with balls, 10 of these balls are labeled with CCs 2 and 3 each. At the same time, 15 balls are assigned to CC 1. While the number of balls labeled with CCs 2 and 3 in this "imaginary urn" remains constant, the number of balls with CC 1 changes as follows: if a participant decides to play the symbol, a ball is drawn from the urn (at least one ball always remains in the urn). This reduces the probability of occurrence. Conversely, if they decide not to play the symbol, an additional ball is added to the urn. Consequently, the probability of occurrence of this symbol increases whenever the negative consequence of −15 points is avoided. After several trials participants find themselves in a situation where they have to constantly avoid CC1 symbols. Whenever the negative consequence is accepted one ball is removed from the urn, and therefore, the probability of occurrence of this symbol diminishes while the occurrence probabilities of the other two symbols increase. This means, over the whole course of the experiment it is beneficial to accept the losses of the CC1 symbols to get more opportunities to win points with the other symbols.

Predecisional valence questionnaire task

In the questionnaire blocks, participants continued the gambling task. We measured self-reported predecisional valence using a digital questionnaire format. Each time a symbol was presented, participants rated their current, expected short-term, and expected long-term valence before making the decision. Using a Self-Assessment Manikin Scale (Bradley and Lang, 1994), they marked their individual position on the visual analog scale by moving the mouse. The computer recorded the chosen point in a value ranging from −255 for a very unpleasant feeling to +255 for a very pleasant feeling. Starting point was always in the middle of the scale. Overall, we recorded three different question perspectives of valence for each symbol. The first perspective asked participants to rate their current valence ("How do you feel seeing this symbol?"). The other two question perspectives referred to the expected valence: One in relation to short-term expectations ("Please imagine you decide to gamble. How will you feel after you received the outcome of your decision?") and the other one to long-term expectations ("Please imagine you decide to gamble. How will you feel when you see your score at the end of the experiment?"). The presentation of these questions and the corresponding symbols were randomized. Participants did not receive immediate feedback after responding, they merely obtained aggregated feedback by receiving their current score after each block.

Procedure

In the course of the study, participants first received a brief introduction to the procedure from the experimenter. As part of this, participants gave their informed consent to participate in the study and completed a short questionnaire that collected demographic data. Following this, participants were encouraged to ask questions at any time if something was unclear, and they were informed that they could withdraw from the study at any time. Participants were naive to the aims of the study.

Instructions were presented in written form and explained by the experimenter if necessary. A brief practice session for the Gamble Task followed. In this session, each symbol was presented once. After each decision, feedback was provided that 0 points were won, regardless of which key participants pressed. Participants should not form opinions about the symbols at this stage.

Further practice trials followed to familiarize participants with the questionnaire. In this session, participants were asked to assess their current valence, their expected valence after the decision, and at the end of the study in relation to the symbol. In the practice session, three questions about two symbols each were asked. After these three questions about a symbol, participants had to decide again whether they wanted to gamble or not ("Do you want to gamble?"). In the questionnaire section they did not receive immediate feedback on whether they had won or lost points.

After the two practice sessions, six gambling rounds followed, each with 27 trials (a total of 162 trials). Only now did the game decisions contribute to the starting score of 500. After each round, participants were offered a short break, and their total point score was displayed. To conclude the first half of the study, the questionnaire followed. In three rounds, participants had to answer 12 trials each with 3 questions (36 trials, 108 questions). In one round, each of the three symbols appeared four times. After participants answered all three questions about a symbol, they were asked if they would gamble ("Do you want to gamble?"). Unlike during the Gambling Task, they did not receive immediate feedback on whether they had won or lost points. After each round, participants had the opportunity to take a short break, and their point score was displayed.

In the second part of the study, participants received new instructions related to one of the three symbols, revealing a suitable gambling strategy. The instruction on the screen revealed the inner logic of the gambling task. That means, participants were told that it is more beneficial to accept losses with symbol CC1 as this decreases its probability. At the same time, the probability of occurrence of the other positive symbol increases which gives the opportunity to gather more points. Participants could ask questions until they told the experimenter that they understood the inner logic of the gambling task. The procedure of the second part of the study was identical to the first part. At the end of both halves of the study, participants were asked to report their point score to the experimenter. Subsequently, an explanation of the purpose and content of the study took place.

Analysis plan

First, we checked if our experimental manipulation worked as intended (manipulation check). After that, we built a model that predicted individual choices based on the proposed valence ratings. We used jamovi for data analysis (The jamovi project, 2023) conducting mixed effects models to test our hypotheses. For each model, we first reduced the random effect structure until the null model converged. Thereafter, we included the fixed effects according to our hypotheses. Valence variables were standardized before we included them in the respective models. Significant t-values are Bonferroni corrected.

Results

Manipulation check

Presentation probabilities in the learning blocks for CC1 symbol

We computed a linear mixed effects model for the presentation probabilities of the CC1 symbol. The described urn model determined presentation probabilities. Hence, for each trial we computed the presentation probability for CC1 symbols by the following formula: $(CC1) = \frac{N_{CC1}}{N_{CC1} + N_{CC2} + N_{CC3}}$, presentation probabilities for CC2 and CC3 symbols can be determined by the following formula: $P(CC2) = \frac{1 - P(CC1)}{2} = P(CC3)$. We included the interaction of BLOCKxROUND and the main effects of BLOCK and ROUND as fixed effects in our model. The model converged including SUBJECT_ID as random effect, which resulted in the formula of CC1 PRESENTATION PROBABILITY ~ BLOCK*ROUND + (1|SUBJECT_ID). Estimates were fit by REML. There was a significant BLOCK*ROUND interaction, $F(5, 11{,}294) = 391.0$, $p < 0.001$, and two significant main effects: ROUND, $F(1, 11{,}294) = 9592.0$, $p < 0.001$, and BLOCK, $F(5, 11{,}294) = 257.0$, $p < 0.001$. The interaction revealed that in round 1, before participants had insight into the task structure, the mean presentation probabilities of CC1 symbols increased over the blocks, $M_{Block1} = 0.429$, $CI = [0.388, 0.471]$, $M_{Block2} = 0.489$, $CI = [0.448, 0.530]$, $M_{Block3} = 0.561$, $CI = [0.520, 0.603]$, $M_{Block4} = 0.631$, $CI = [0.589, 0.672]$, $M_{Block5} = 0.685$, $CI = [0.643, 0.726]$, $M_{Block6} = 0.729$, $CI = [0.688, 0.770]$. However, in round 2, after participants had insight into the task structure, the mean presentation probabilities of CC1 symbols remained stable after an initial decrease, $M_{Block1} = 0.380$, $CI = [0.388, 0.471]$, $M_{Block2} = 0.308$, $CI = [0.267, 0.350]$, $M_{Block3} = 0.292$, $CI = [0.250, 0.333]$, $M_{Block4} = 0.300$, $CI = [0.259, 0.342]$, $M_{Block5} = 0.318$, $CI = [0.277, 0.360]$, $M_{Block6} = 0.328$, $CI = [0.287, 0.370]$. See also Figure 1.

Valence ratings

Figure 2 presents descriptives of current, expected short-term and expected long-term valence ratings dependent on the cue contingency of the symbol and whether participants had insight into the task structure. More details and statistical tests can be found in the Supplementary materials.

Behavioral adaption in the questionnaire blocks

More details and statistical tests can be found in the Supplementary materials.

Choice prediction

We computed a generalized mixed effect model with participants' choice as binary dependent variable. The link function was logit and the distribution binomial. We included the main effects of CURRENT VALENCE, SHORT-TERM-EXPECTED VALENCE, LONG-TERM-EXPECTED-VALENCE, INSIGHT and the interactions of INSIGHT with all three variables. This resulted in the formula: CHOICE ~ CURRENT VALENCE + SHORT-TERM-EXPECTED-VALENCE + LONG-TERM-EXPECTED-VALENCE +INSIGHT + INSIGHT: CURRENT_VALENCE + SHORT-TERM-EXPECTED-VALENCE: INSIGHT + LONG-TERM-EXPECTED-VALENCE: INSIGHT + (1 + LONG-TERM-EXPECTED-VALENCE + CURRENT VALENCE | SUBJECT_ID). The model was based on 2,520 observations,

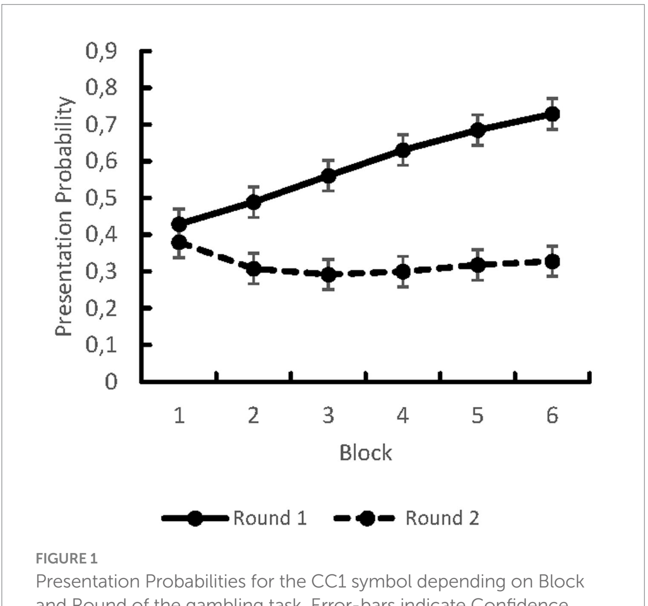


FIGURE 1
Presentation Probabilities for the CC1 symbol depending on Block and Round of the gambling task. Error-bars indicate Confidence Intervals.

$R^2_{marginal} = 0.531$, $R^2_{conditional} = 0.915$, For fixed and random effect estimates see Table 1. For visualization of interactions see Figure 3.

We conducted a *post hoc* power analysis to evaluate the reliability of our findings and ensure adequate sensitivity to detect significant effects in our dataset. Using a bootstrap resampling procedure, we refitted a generalized linear mixed-effects model to 1,000 resampled datasets. For each iteration, we recorded whether each predictor's *p*-value was below 0.05. *Post hoc* power was estimated as the proportion of iterations in which each predictor was statistically significant. The analysis demonstrated high power (≥ 0.75) for most predictors, including

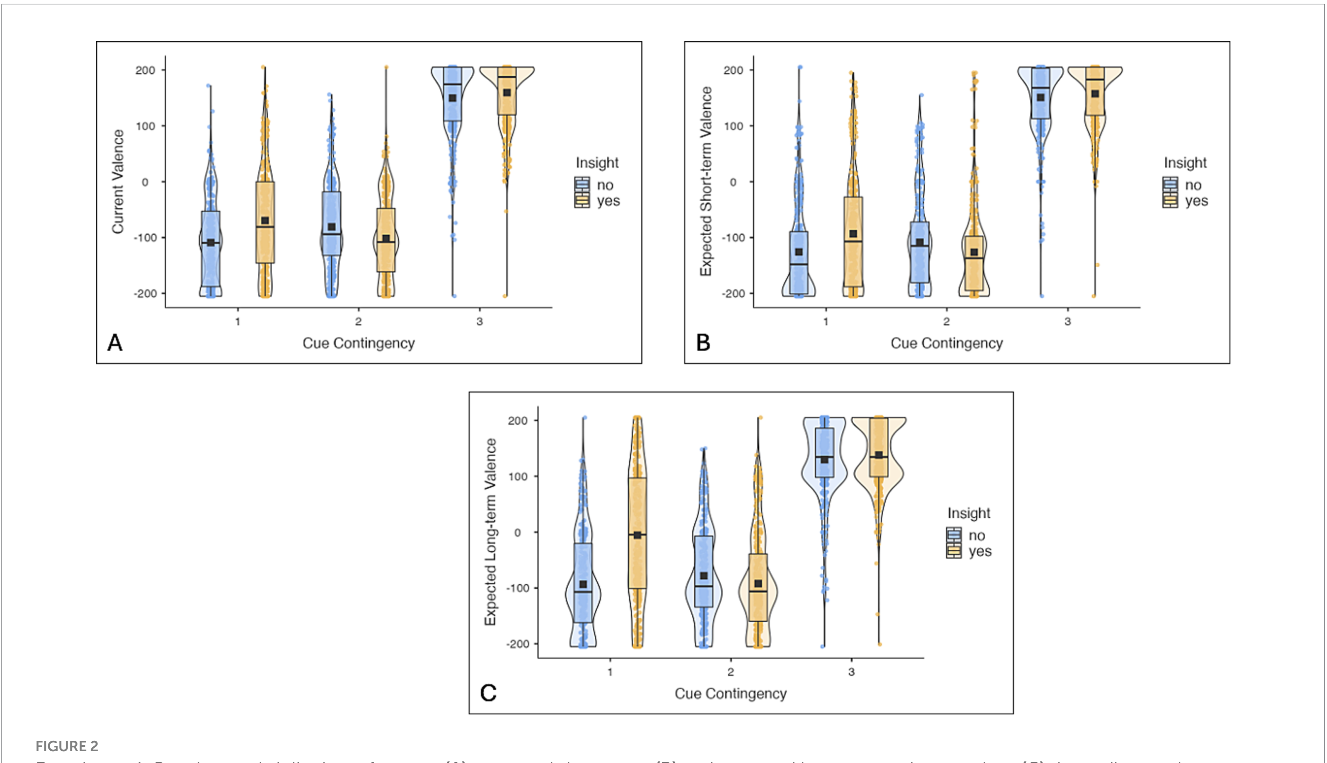
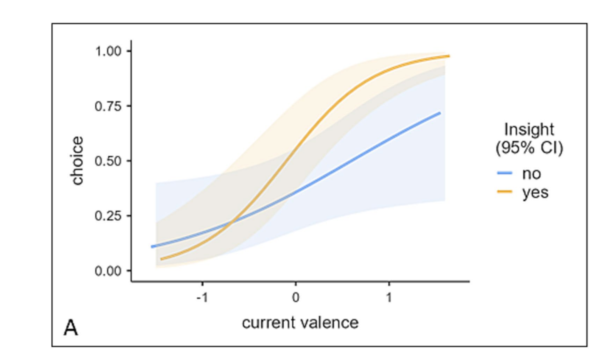


FIGURE 2
Experiment 1: Boxplots and violinplots of current **(A)**, expected short-term **(B)** and expected long-term valence ratings **(C)** depending on the cue contingency of the symbol (CC1, CC2, CC3) and whether participants had insight into the task structure. Black squares represent the mean, the black line in the box the median. More details and statistical tests can be found in the Supplementary materials.

TABLE 1 Generalized linear mixed effect estimates of the choice prediction model of Experiment 1.

Predictors	Response		
	Exp(B)	CI	*p*
(Intercept)	0.529	0.221–1.269	0.154
Long-term expected valence	7.680	2.738–21.542	**< 0.001**
Short-term expected valence	5.030	2.598–9.739	**< 0.001**
Current Valence	2.678	1.040–6.894	**0.041**
Insight	2.610	1.816–3.751	**<0.001**
Insight × Current valence	3.231	1.477–7.071	**0.003**
Insight × Short-term expected valence	0.329	0.150–0.723	**0.006**
Insight × Long-term expected valence	1.160	0.576–2.333	0.678
Random components			
Groups		Variance	ICC
Subject ID	(Intercept)	5.26	0.615
Long-term expected valence		4.80	
Current valence		3.42	
Residuals		1.00	

Fixed Effects: Estimates, Confidence Intervals (CI), and *p*-values. Random Effects: Variance Estimates for the random intercepts of Subjects and random slopes for Long-term Expected Valence and Current Valance; ICC = proportion of variance explained by between-person differences; significant results are printed in bold.



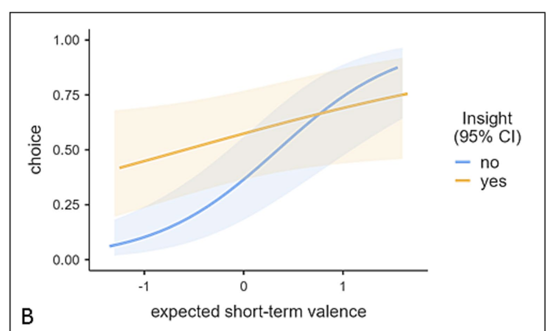


FIGURE 3
Choice prediction based on the current valence x insight interaction **(A)** and the short-term valence x insight interaction **(B)**. Transparent areas indicate 95% Confidence Intervals. Current valence and expected short-term valence are standardized to avoid large Eigenvalues.

EXPECTED LONG-TERM VALENCE (1.000), EXPECTED SHORT-TERM VALENCE (1.000), INSIGHT (1.000), CURRENT VALENCE: INSIGHT (0.826), and EXPECTED SHORT-TERM VALENCE: INSIGHT (0.758). Moderate power was observed for CURRENT VALENCE (0.539). However, power was low for the INTERCEPT (0.014) and the interaction between EXPECTED LONG-TERM VALENCE and INSIGHT (0.064). These results suggest that while the main effects and most interactions were reliably detected, certain effects, particularly the interaction involving EXPECTED LONG-TERM VALENCE and INSIGHT, may require larger sample sizes or stronger underlying effects to achieve sufficient sensitivity. This underscores the importance of interpreting these effects with caution.

Furthermore, to better understand how low statistical power affected the null effects, we analyzed binary choice data using Bayesian generalized linear mixed-effects models (GLMMs) with a Bernoulli likelihood, as implemented in the R package brms (Bürkner, 2017). All models included subject-specific random intercepts and random slopes for selected predictors. Weakly informative priors [normal(0, 1)] were placed on all fixed effects. Model estimation was performed via Markov Chain Monte Carlo sampling using Stan (Carpenter et al., 2017), with four chains, 4,000 iterations per chain, and default diagnostics checked for convergence. To evaluate the contribution of specific predictors and interactions, we conducted Bayes factor model comparisons based on marginal likelihood estimation (Kass and Raftery, 1995).

Hence, we compared a full model including the interaction between INSIGHT and EXPECTED LONG-TERM VALENCE against a reduced model without this interaction. The Bayes factor favored the null model ($BF_{10} = 0.48$), providing anecdotal evidence that the interaction term does not improve model fit, and supporting the interpretation of a negligible effect.

Discussion

In Experiment 1 we wanted to show that short-term and long-term emotional expectations independently predict choice in a recurrent gambling task. Furthermore, we wanted to show that situational demands have an impact on the predictive power of different emotional choice predictors. Therefore, we designed Experiment 1 to examine short-term and long-term expectations by manipulating presentation probabilities of one symbol depending on choices participants made. Thus, participants had to accept a small loss of points in order to maximize their outcome over the whole course of the experiment. This means, negative short-term expectations and positive long-term expectations were attached to one symbol. Participants did the same gabling task twice; however, at first they had no insight into the previously mentioned task structure. Only in the second round, they got insight into the task structure.

Results show that our experimental manipulation was successful as participants adapted their choices in the second round and, therefore, presentation probabilities changed as intended. Moreover, self-rated valence expectations changed as intended. Most importantly, long-term valence expectations were rated more positively after they had insight into the task structure. Last, participants adapted their choices in the questionnaire blocks. After they had insight into the task structure, they accepted short-term losses for the manipulated symbol more often to maximize their overall outcomes. Regarding our main research questions, results indicate that long-term, short-term and current valence are predictors of choice, which is in line with our hypotheses. Additionally, insight into the task structure decreased the predictive power of short-term valence expectations. Contrary to our hypotheses, insight into the task structure did not increase the predictive power of long-term valence but increased the predictive power of current valence.

Taken together, in Experiment 1 we could show that expected long-term valence is an additional predictor that should be considered in recurrent decision contexts. Furthermore, insight into the task structure additionally changed the predictive power of the investigated predictors. Participants still expected a negative emotional short-term outcome, but they did no longer base their choice on short-term expectations. However, after receiving insight into the task structure participants relied more on their current feelings than before. One reason could be that the information they received about the task was counterintuitive which triggered uncertainty. In other words, although participants were told the optimal gambling strategy, they still questioned the usefulness of this information as it was opposed to their intuition. This resulted in a cognitive dissonance, which makes automatic processes like current feelings more accessible. In previous experiments a similar pattern emerged after instructions were changed (see Jäger et al., 2022).

Experiment 2

In the previous experiment, we examined short- and long-term expectations. However, participants had to accept a loss of points to win more points over the whole course of the experiment. People are loss averse over different domains and different contexts (Nabi et al., 2020) and framing effects seem to impact emotional reactions (Nygren, 1998). Having to accept a short-term loss, could potentially hamper the predictive power of long-term expectations, as losses loom larger than gains. Furthermore, participants might have stronger emotional reactions to short-term losses, which leads to a bigger predictive value of current feelings and short-term expectations. In addition to that, the reference point seems to determine whether gain seeking or loss aversion is more dominant (Mellers et al., 2021). A positive reference point encourages loss aversion whereas a negative reference point promotes gain seeking. Hence, results might not be applicable to situations in which participants have to omit positive short-term consequences to achieve long-term gains, as it could be easier for participants to omit points than to lose points for a long-term gain. Additionally, framing effects and reference points could influence the interplay of the different emotion variables.

As mentioned before, we theorize that the predictive power of the different emotion variables depends on the situational demands. We designed Experiment 1 mainly to show that long-term valence expectations are an independent predictor of choices participants make. Therefore, it is necessary to show that this effect remains stable in a point-omission-context and cannot merely be attributed to loss aversion, reference points or framing effects. To rule this out, we designed Experiment 2. We examined short-term and long-term expectations in our design. However, instead of accepting a loss of points to maximize points as in Experiment 1, participants had to omit points to do so. Participants still had to win as many points as possible and performed two rounds of the task. In the first round, they had no insight into the task structure. Only in the second round, participants were informed about short-term and long-term outcomes of their decision strategies. At the end of each round, we assessed current feelings, short-term expectations and long-term expectations prior to the respective choice in a short questionnaire block. We wanted to show four things in Experiment 2:

1. Long-term expected valence is an additional predictor of human choice besides current valence and short-term expected valence in a point-omission-context. Hence, we expected main effects of long-term expected valence, short-term expected valence and current valence.
2. Insight into the task structure does not influence the predictive power of long-term expected valence (see Experiment 1). Thus, we did not expect an interaction between insight (first vs. second round) and long-term expected valence.
3. Insight into the task structure decreases the predictive power of short-term expected valence, because the instruction defines the short-term losses as no obstacle towards the overall goal. Thus, we expected an interaction between insight (first vs. second round) and short-term expected valence.
4. Insight into the task structure should influence the predictive power of current valence as it did in Experiment 1. Hence, we expected a significant interaction between insight (first vs. second round) and current valence.

Method

Participants

Sample size was determined in accordance to the sample size in Experiment 1. We wanted the effect sizes to be comparable between the two experiments, so powering Experiment 2 based on the effect size from Experiment 1 would distort this comparison. If we based Experiment 2's sample size on Experiment 1's effect size, we risked making one experiment over- or under-powered. This would result in significant effects that are not truly comparable across the two contexts. Hence, we decided to use the same sample size. The sample consisted of a convenience sample of 36 individuals. Participants could receive course credit for taking part in the study. Additionally, as an incentive, a raffle of two cinema vouchers for five people each was offered. The age range of the participants was from 18 to 30 years (M_{age} = 21.0; SD = 3.12), including 27 women, 8 men, and 1 non-binary person; 32 were right-handed. All participants were psychology students. All of them gave their written informed consent and were debriefed afterwards. The local ethics commission approved the study protocol.

Materials

The experiment consisted of two parts, which each had a Learning Phase and Predecisional Valence Questionnaire blocks, as in Experiment 1.

Gambling task

We employed the same gambling task but changed Cue Contingencies (CC). At the beginning of the experiment, the symbols are randomly associated with a CC that determines the winning probabilities of the symbols. Symbols with CC 2 lead to negative results 90% of the time (i.e., −15 points). Symbols with CC1 and CC 3, on the other hand, are positive 90% of the time (i.e., +15 points). Moreover, we changed the urn model: 10 of balls are labeled with CCs 2 and 3 each. At the same time, 15 balls are assigned to CC 1. While the number of balls labeled with CCs 2 and 3 change, the number of balls with CC1 remain the same: If a participant decides to play the CC1 symbol (90% positive outcome), one CC3 symbol (90% positive outcome) is removed from the urn and one CC2 symbol (90% negative outcome) is added to the urn. This reduces the probability of occurrence of CC3 symbols. Conversely, if they decide not to play the CC1 symbol, it is the other way round. One CC3 symbol is added to the urn while a CC2 symbol is removed. This increases the probability of occurrence of CC3 symbols. Consequently, the probability of occurrence of the CC2 symbol increases whenever the positive consequence of +15 points is accepted. After several trials, the participants find themselves in a situation where they constantly must avoid CC2 symbols. This means, over the whole course of the experiment it is beneficial to omit the wins of the CC1 symbols to get more opportunities to win points with the other symbols.

Predecisional valence questionnaire task

We did not change the task except for the cue contingency structure in comparison to Experiment 1.

Procedure

The procedure remained the same as in Experiment 1. We only adjusted instructions according to the new cue contingency structure.

Analysis plan

We did not change our analysis strategy. See Experiment 1 for more details.

Results

Manipulation check

Presentation probabilities in the learning blocks for CC2 and CC3 symbols

We computed a linear mixed effects model for the presentation probabilities of the CC2 and CC3 symbols. Presentation probabilities for each trial were determined using the same formulas as in Experiment 1. We included the interaction of BLOCKxROUNDxSYMBOL, BLOCKxSYMBOL, ROUNDxSYMBOL, BLOCKxROUND and the main effects of SYMBOL, BLOCK and ROUND as fixed effects in our model. The model converged including SUBJECT_ID as a random effect, which resulted in the formula of PRESENTATION PROBABILITY ~ BLOCK*ROUND*SYMBOL + (1|SUBJECT_ID). Estimates were fit by REML. There was a significant disordinal BLOCK*ROUND*SYMBOL interaction, $F(5, 23{,}269) = 850{,}5$, $p < 0.001$ (see Figure 4). The interaction revealed that in Round 1, before participants had insight into the task structure, the mean presentation probabilities of CC2 symbols increased over the blocks, $M_{Block1} = 0.0.397$, $CI = [0.387, 0.408]$, $M_{Block2} = 0.517$, $CI = [0.506, 0.527]$, $M_{Block3} = 0.6011$, $CI = [0.591, 0.612]$, $M_{Block4} = 0.658$, $CI = [0.647, 0.668]$, $M_{Block5} = 0.707$, $CI = [0.697, 0.718]$, $M_{Block6} = 0.740$, $CI = [0.730, 0.751]$. The mean presentation probabilities of CC3 symbols decreased and then remained stable over the blocks, $M_{Block1} = 0.270$, $CI = [0.259, 0.280]$, $M_{Block2} = 0.1533$, $CI = [0.143, 0.164]$, $M_{Block3} = 0.090$, $CI = [0.079, 0.100]$, $M_{Block4} = 0.055$, $CI = [0.044, 0.066]$, $M_{Block5} = 0.028$, $CI = [0.018, 0.039]$, $M_{Block6} = 0.019$, $CI = [0.008, 0.029]$. In contrast in Round 2, after participants had had insight into the task structure, the mean presentation probabilities of CC2 symbols remained stable after an initial decrease, $M_{Block1} = 0.272$, $CI = [0.262, 0.283]$, $M_{Block2} = 0.184$, $CI = [0.173, 0.194]$, $M_{Block3} = 0.164$, $CI = [0.154, 0.175]$, $M_{Block4} = 0.171$, $CI = [0.160, 0.182]$, $M_{Block5} = 0.1833$, $CI = [0.173, 0.194]$, $M_{Block6} = 0.193$, $CI = [0.182, 0.203]$. The mean presentation probabilities of CC3 symbols remained stable after an initial increase, $M_{Block1} = 0.394$, $CI = [0.384, 0.405]$, $M_{Block2} = 0.487$, $CI = [0.476, 0.498]$, $M_{Block3} = 0.524$, $CI = [0.514, 0.535]$, $M_{Block4} = 0.538$, $CI = [0.527, 0.548]$, $M_{Block5} = 0.543$, $CI = [0.533, 0.5536]$, $M_{Block6} = 0.548$, $CI = [0.537, 0.558]$. See also Figure 4.

Valence ratings

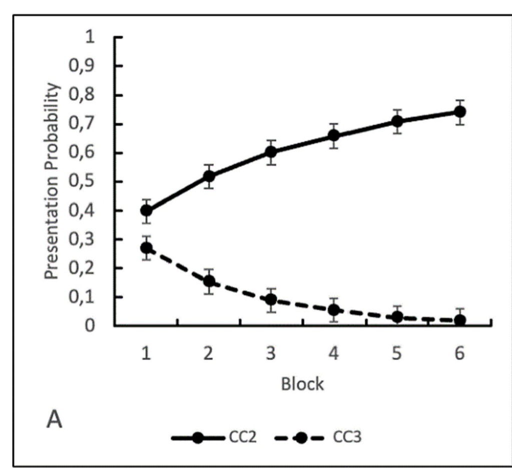
Figure 5 presents descriptives of current, expected short-term and expected long-term valence ratings depending on the cue contingency of the symbol and whether participants had insight into the task structure. More details and statistical tests can be found in the Supplementary materials.

Behavioral adaption in the questionnaire blocks

More details and statistical tests can be found in the Supplementary materials.

Choice prediction

We computed a generalized mixed effect model with participants' choice as binary dependent variable. The link function was logit and the distribution binomial. We included the main effects of CURRENT VALENCE, SHORT-TERM-EXPECTED VALENCE, LONG-TERM-EXPECTED-VALENCE, INSIGHT and the interactions with INSIGHT with all three variables. This resulted in the formula: CHOICE ~ CURRENT VALENCE + SHORT-TERM-EXPECTED-VALENCE + LONG-TERM-EXPECTED-VALENCE +INSIGHT + INSIGHT: CURRENT VALENCE + SHORT-TERM-EXPECTED-VALENCE: INSIGHT + LONG-TERM-EXPECTED-VALENCE: INSIGHT + (1 + LONG-TERM-EXPECTED-VALENCE + CURRENT VALENCE +SHORT-TERM-EXPECTED_VALENCE |



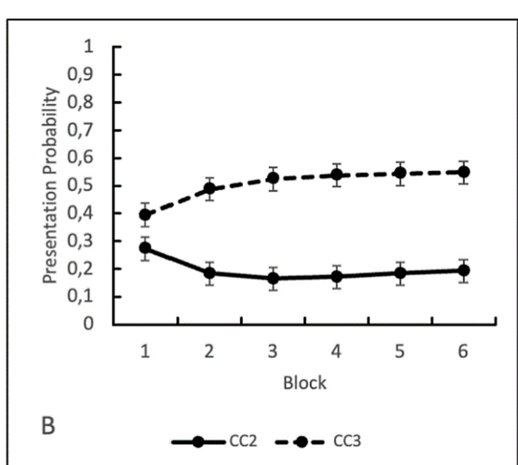


FIGURE 4
Presentation Probabilities in Experiment 2 for the CC2 and CC3 symbols depending on Block and Round of the gambling task. **(A)** Round 1 before insight; **(B)** Round 2 after insight. Error-bars indicate Confidence Intervals.

SUBJECT_ID). The model was based on 23,592 observations, $R^2_{marginal} = 0.405$, $R^2_{conditional} = 0.897$. For fixed and random effect estimates see Table 2. Significant interactions are displayed in Figure 6.

To assess the sensitivity and robustness of our analysis in the second experiment, we conducted a *post hoc* power analysis using a bootstrap resampling procedure. The generalized linear mixed-effects model was refitted to 1,000 resampled datasets, and the significance of each predictor was evaluated in each iteration. Power was estimated as the proportion of iterations in which each predictor reached statistical significance ($p < 0.05$). The results showed high power for

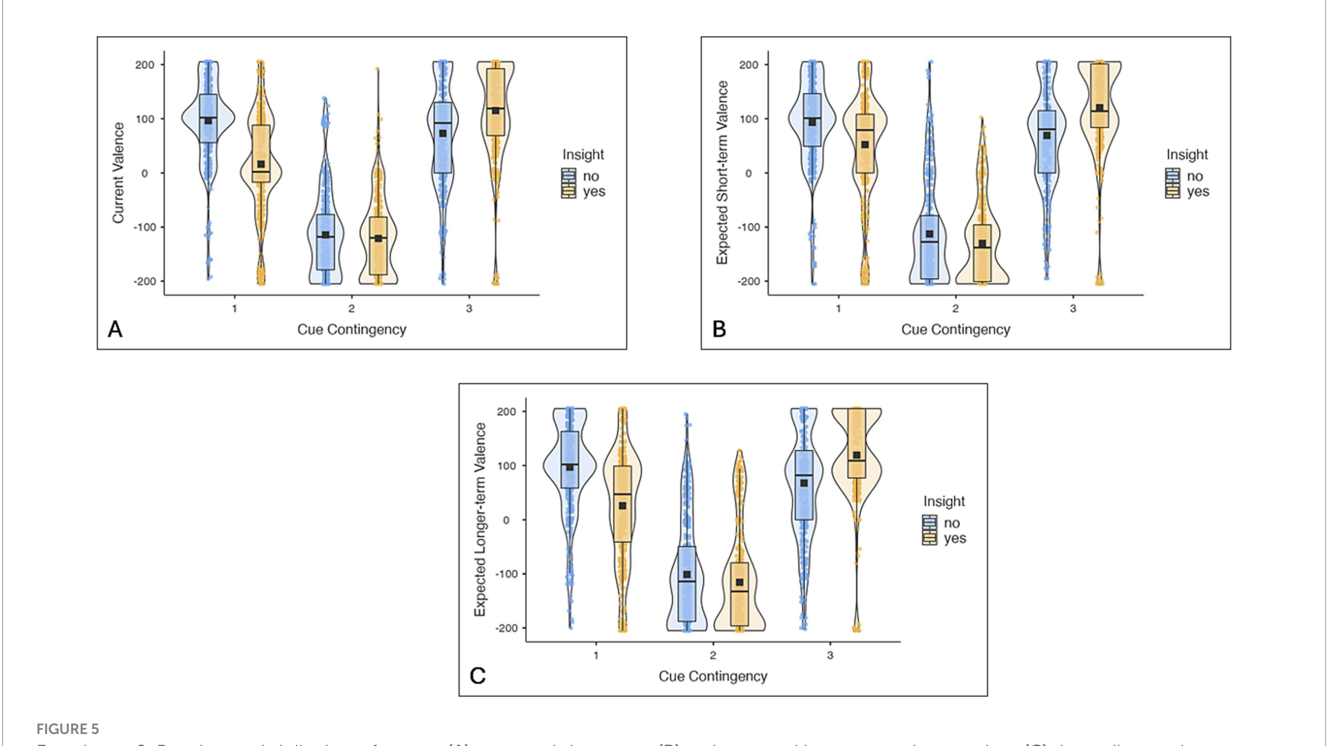


FIGURE 5
Experiment 2: Boxplots and violinplots of current **(A)**, expected short-term **(B)** and expected long-term valence ratings **(C)** depending on the cue contingency of the symbol (CC1, CC2, CC3) and whether participants had insight into the task structure. Black squares represent the mean, the black line in the box the median. More details and statistical tests can be found in the Supplementary materials.

TABLE 2 Generalized linear mixed effect estimates of the choice prediction model of Experiment 2.

Predictors	Response		
	Exp(B)	CI	*p*
(Intercept)	2.159	1.054–4.423	**0.035**
Long-term expected valence	5.955	2.609–13.593	**< 0.001**
Short-term expected valence	1.660	0.960–2.869	0.069
Current valence	3.840	1.704–8.656	**0.001**
Insight	0.258	0.186–0.359	**<0.001**
Insight × Current valence	2.791	1.544–5.046	**<0.001**
Insight × Short-term expected valence	0.395	0.190–0.821	**0.013**
Insight × Long-term expected valence	2.273	1.158–4.462	**0.017**
Random components			
Groups		Variance	ICC
Subject ID	(Intercept)	4.29	0.566
Long-term expected valence		3.84	
Current valence		3.63	
Short-term expected valence		0.63	
Residuals		1.00	

Fixed Effects: Estimates, Confidence Intervals (CI), and *p*-values. Random Effects: Variance Estimates for the random intercepts of subjects and random slopes for Long-term Expected Valence, Current Valance, and Short-Term Expected Valence; ICC = proportion of variance explained by between-person differences; significant results are printed in bold.

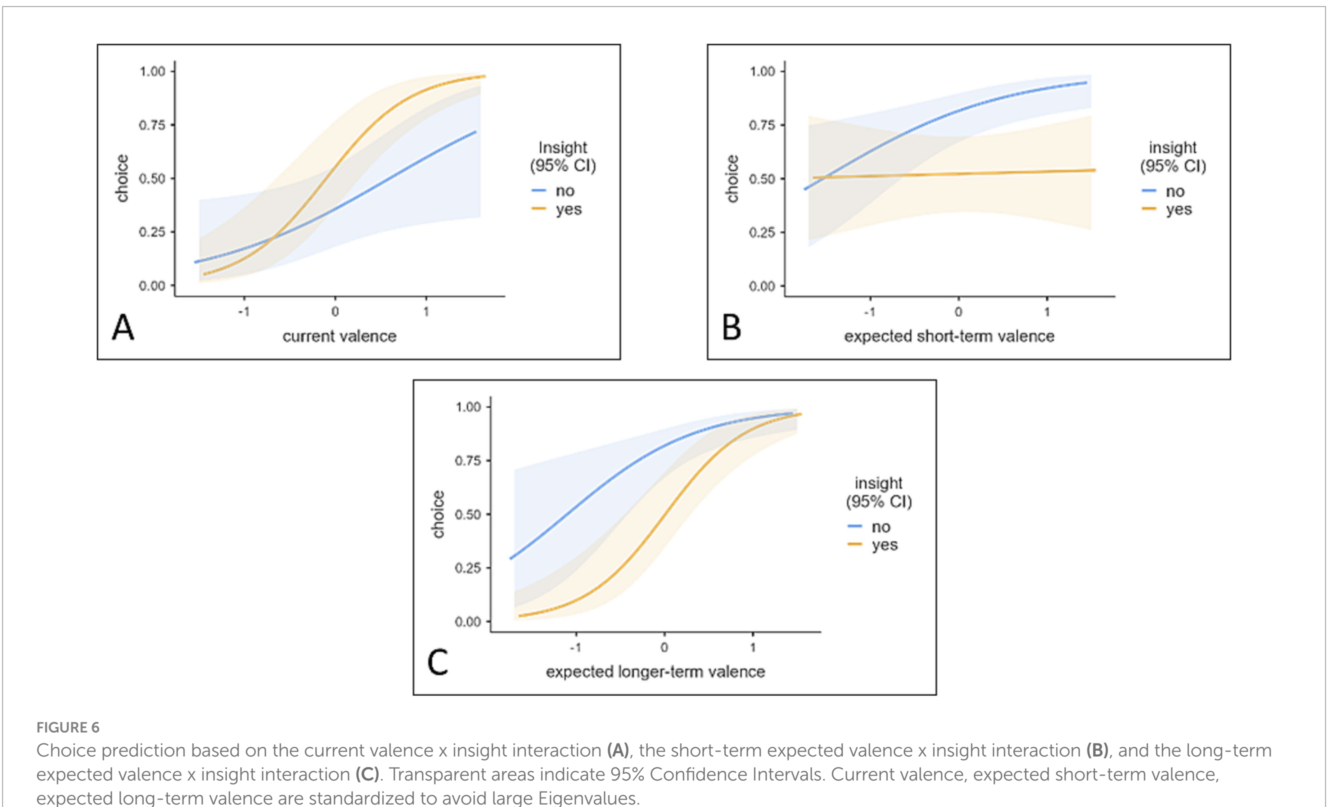


FIGURE 6
Choice prediction based on the current valence x insight interaction **(A)**, the short-term expected valence x insight interaction **(B)**, and the long-term expected valence x insight interaction **(C)**. Transparent areas indicate 95% Confidence Intervals. Current valence, expected short-term valence, expected long-term valence are standardized to avoid large Eigenvalues.

CURRENT VALENCE (0.96), EXPECTED LONG-TERM VALENCE (1.00), and INSIGHT (1.00), as well as for the interaction between CURRENT VALENCE and INSIGHT (0.85). Moderate power was observed for the interactions of EXPECTED SHORT-TERM VALENCE with INSIGHT (0.56) and EXPECTED LONG-TERM VALENCE with INSIGHT (0.59). In contrast, power was low for EXPECTED SHORT-TERM VALENCE (0.08) and the INTERCEPT (0.33). These findings suggest the model had sufficient sensitivity to detect main effects and key interactions but limited power for certain predictors, particularly for EXPECTED SHORT-TERM VALENCE and its interaction with INSIGHT.

We applied the same Bayesian model comparison approach as in Experiment 1 to assess the contribution of EXPECTED SHORT-TERM VALENCE in Experiment 2. Specifically, we compared a full model to a reduced model that excluded only the main effect of EXPECTED SHORT-TERM VALENCE. The resulting Bayes factor ($BF_{10} = 0.32$) indicates moderate evidence in favor of the null model, suggesting that EXPECTED SHORT-TERM VALENCE does not meaningfully contribute to explaining choice behavior in this experiment.

Discussion

In Experiment 2, we wanted to replicate the findings of Experiment 1 in a point-omission context. Hence, we designed Experiment 2 to examine short-term and long-term expectations by manipulating presentation probabilities of the symbols depending on choices participants made. Thus, participants had to omit points to maximize their outcome over the whole course of the experiment. In contrast to Experiment 1, positive short-term expectations and negative long-term expectations were attached to the same symbol. Participants performed the same gabling task twice; however, at first, they had no insight into the previously mentioned task structure. Only in the second round, they were given insight into the task structure.

In short, the manipulation worked as planned. Participants adapted their choices in the second round to the instruction. Moreover, self-rated valence expectations changed as expected. Most importantly, long-term valence expectations for the manipulated symbol were rated more positively after participants gained insight into the task structure. Last, participants adapted their choices in the questionnaire blocks. After they had had insight into the task structure, they omitted points for the manipulated symbol more often to maximize their overall outcomes. All in all, results remained stable: We found main effects for current and long-term expected valence, and interaction effects for current valence and short-term expected valence with insight into the task structure. Nevertheless, there were also some findings contrary to our hypotheses. We did not find a main effect of expected valence on gambling choice and long-term expected valence showed an interaction effect with insight into the task-structure in a point omission context.

One reason that we did not find a main effect for expected valence could be loss aversion. It relates to expected emotions and is present in contexts of immediate experience of realized gains and losses (Sokol-Hessner and Rutledge, 2019). Hence, loss aversion might have been more prominent in the first experiment, which lead to a stronger reliance on short-term expected valence, even after participants got

insight into the task structure in Experiment 1. However, in Experiment 2, short-term expectations did no longer influence choices participants made after participants got insight into the task structure. In Experiment 1 the influence of expected valence diminished but was still present despite insight into the task structure, which might mean that it was easier for participants to omit points than to accept a loss of points. The framing of losing points seems to trigger a stronger reliance on short-term expectations, while the framing of omitting points for a long-term goal seems to eradicate the reliance on short-term expectations. This further adds to the framing effect literature (see also Nabi et al., 2020).

Moreover, we found an interaction effect for long-term expected valence and insight as we originally expected in the hypotheses of Experiment 1. Again, loss aversion is a reasonable explanation for this discrepancy. In both experiments, we found a main effect for long-term expected valence. In Experiment 2, the influence on choice of long-term expected valence even became stronger after participants got insight into the task structure. However, in Experiment 1, a similar effect could not be observed, as participants had to accept losses. This might have hampered a stronger reliance on long-term expectations. We will discuss this in further detail in the general discussion section.

General discussion

In two experiments, we could show that the human subjective feeling system is capable of adapting to different choice situations. Current valence, short-term valence expectations and long-term valence expectations were significant predictors in different choice contexts. Our findings clearly show that the predictive value of each emotional variable depends on the choice situation. Looking at the random effects of our models shows that the predictive power of each construct is highly dependent on individual differences between participants. Furthermore, changing the choice situation by providing information on the task structure changes the predictive value of the valence constructs depending on the context (losing points, Experiment 1 vs. omitting points, Experiment 2). After getting insight into the task structure, losing points opposed to omitting points seems to make a reliance on short-term expectations more likely. Omitting points increases the reliance on long-term expectations after insight into the task structure. For both contexts, the predictive power of current valence increased after participants got insight. One reason could be that the instruction proposed a counterintuitive, optimal gambling strategy which generated uncertainty. Although participants knew the optimal gambling strategy, it was discordant with their intuition. This resulted in a cognitive dissonance, which makes automatic processes like current feelings more accessible. In previous experiments a similar pattern emerged after instructions were changed (see Jäger et al., 2022).

Overall, our findings align with prior research on the influence of emotional valence on risky decision-making, while expanding on previous work by incorporating both current and expected emotional states. Charpentier et al. (2016) demonstrated that expected valence—how positively participants anticipated feeling after the decision—was a strong predictor of gambling behavior, with higher expectations of positive emotion leading to increased gambling. Mellers et al. (1997) found similar results, reinforcing the role of expected emotions, though neither study investigated the role of current valence (emotions felt at the moment of decision-making). Building on this, Schlösser et al. (2013) examined the role of immediate emotions, in contrast to anticipated emotions. Their findings support the risk-as-feelings hypothesis, which argues that many risky decisions are influenced not only by anticipated emotions but also by the "hot" visceral feelings individuals experience in the moment of decision-making. Schlösser et al. (2013) found that these immediate emotions predicted decisions beyond anticipated emotions or subjective probabilities. In other words, decisions were driven by how participants felt about the decision options themselves, rather than solely by their predictions of future emotional outcomes or the perceived probabilities of those outcomes. This emphasizes the powerful influence of current emotional states on risky choices, a finding that resonates with our results, which also show that both current and expected valence significantly predict gambling behavior. Jäger et al. (2022) further supported this by showing that current and expected valence interact to predict choices, underscoring the dynamic relationship between current feelings and future emotional expectations in decision-making. Our findings add to the literature in showing that expected emotional states can be differentiated in those occurring immediately after a recurrent decision is made and in long-term expected emotional states. We could also demonstrate that both time perspectives differ regarding their influence on decision making, and that their effect depends on the structure of the decision task.

To expand on this, our results resonate with Seth (2013) model of interoceptive inference, which proposes that emotions arise from the brain's predictive modeling of internal bodily states. According to this framework, subjective feeling states (such as current valence) reflect the brain's top-down predictions about interoceptive input, which are updated through prediction errors. This predictive model suggests that uncertainty or dissonance—such as the tension between intuitive and instructed strategies in our task—may enhance the salience of interoceptive signals, thereby increasing the impact of current feelings on decision-making.

Our findings are in line with the work by Schneider et al. (2016), who showed that past emotional experiences, such as a series of losses or gains, affect future risk-taking behavior. Their work suggests that emotional outcomes shift reference points, influencing future decisions—a concept that ties into how current and expected valence can shape gambling choices in our study. Prietzel (2020) reviewed the impact of emotions on decision-making through the lens of Prospect Theory, finding that positively valenced emotions generally lead to increased risk-taking in the gain domain. Prietzel (2020) also emphasized the complexity of negatively valenced emotions, which exhibit varied effects depending on the context. The review emphasized the distinction between integral emotions (emotions directly tied to the decision) and incidental emotions (unrelated to the decision). Integral emotions tend to lead to decisions that deviate more from the predictions of Prospect Theory, with greater independence from scope and probability. Hence, our findings suggest that the subjective valuation system is highly adaptable to various choice situations. The interplay between current and expected valence in predicting decisions highlights the flexibility of emotional influences on risky decision-making. Future research should focus on identifying the conditions under which different emotional states interact and how task structures and contexts shape these

dynamics. These factors hold great potential for advancing our understanding of emotion-driven choices.

In light of our findings, it is also important to consider the role of language and internal bodily states in shaping emotional experiences and their impact on decision-making. Brooks et al. (2017) demonstrated that the presence of emotion words can modulate neural activity during emotional processing by enhancing the activation of semantic brain regions (e.g., inferior frontal and temporal cortices) and reducing amygdala responses. This suggests that the conceptualization of emotion through language—such as labeling a symbol as "good" or "bad"—may influence how emotional information is accessed and used in decision-making. In our study, participants were given structured verbal instructions that framed the task in emotionally salient ways (e.g., "losing" vs. "omitting" points), which likely affected how they conceptualized and subsequently integrated their emotional experiences. The increased influence of current valence after instruction could thus reflect a language-mediated process in which emotional states became more accessible and actionable through verbal categorization.

One limitation of our study is that, while we conducted a power analysis, it is possible that our experiments were underpowered to detect smaller effects. Nevertheless, our post-hoc power analysis reached sufficient power for most effects. Significant effects with a post-hoc power below 0.75 should be interpreted with caution. It is also possible that our self-report measures captured verbal evaluations of the reward contingencies rather than participants' true subjective feelings. While self-report offers the advantage of directly accessing participants' conscious reflections and is relatively easy to administer, it is prone to biases such as demand characteristics and may not fully capture unconscious or more automatic emotional responses. In contrast, physiological measures or behavioral proxies could offer more objective insight into emotional processing but often lack the specificity of self-report when it comes to understanding how participants consciously interpret their emotional states. Despite these limitations, we believe that self-report still provides meaningful data. Relatedly, we did not assess participants' arousal levels, focusing exclusively on valence judgments. This decision was based on findings from previous work (Jäger et al., 2020, 2022) and pilot testing, which indicated that self-reported arousal did not systematically influence participants' choices. To reduce task complexity and participant burden, we chose to omit arousal ratings. However, we acknowledge that arousal may play a relevant role in other contexts or populations, and future studies should consider its inclusion to provide a more comprehensive picture of emotional processing. Lastly, we were unable to fit the maximal random-effects structure in our regression models, which may increase the risk of anticonservative results (Barr et al., 2013). While we included relevant random slopes where possible, future research should aim for a more comprehensive random-effects structure to minimize the likelihood of Type 1 errors. Additionally, one potential limitation concerns the influence of handedness on valence judgments. Prior research (Casasanto, 2009; Milhau et al., 2013, 2015) has shown that individuals often associate positive concepts with their dominant side, suggesting that handedness can systematically shape emotional-laterality associations. While we did not explicitly assess handedness, we accounted for individual variability—such as motor fluency or dominant hand—by including participant identity as a random effect in our models. This statistical approach captures stable individual response patterns, potentially including those related to handedness. Nonetheless, the absence of a direct handedness measure means we cannot disentangle its specific contribution. Future research could benefit from incorporating handedness as an explicit variable to examine its role more precisely. Finally, the generalizability of our findings is limited by the use of a laboratory-based gambling task and a homogeneous student sample. While this allowed for tight experimental control, it may not fully reflect the complexity of real-world decision-making or emotional processes in more diverse populations. Future research should test whether our results replicate in ecologically valid contexts and with more heterogeneous samples.

In conclusion, our study demonstrates that the subjective feeling system adapts to different choice situations, with current valence, short-term, and long-term valence expectations significantly predicting risky decisions. The predictive power of these emotional variables is context-dependent, influenced by task structure and individual differences. Our findings highlight the flexibility of emotional influences in decision-making and emphasize the importance of understanding how various contexts shape the interaction between current and expected emotions. Future research should continue to explore these dynamics to further deepen our understanding of emotion-driven choices.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://osf.io/ypc7v/.

Ethics statement

The studies involving humans were approved by Ethics committee of the University of Bamberg. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

DJ: Conceptualization, Data curation, Formal analysis, Investigation, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing. JR: Conceptualization, Data curation, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2025.1570369/full#supplementary-material

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