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SPECIAL ISSUE/UNCERTAINTY

Uncertainty deconstructed: conceptual analysis and state-of-the-art review of the ERP correlates of risk and ambiguity in decision-making

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Abstract

Risk and uncertainty are central concepts of decision neuroscience. However, a comprehensive review of the literature shows that most studies define risk and uncertainty in an unclear fashion or use both terms interchangeably, which hinders the integration of the existing findings. We suggest uncertainty as an umbrella term that comprises scenarios characterized by outcome variance where relevant information about the type and likelihood of outcomes may be somewhat unavailable (ambiguity) and scenarios where the likelihood of outcomes is known (risk).

These conceptual issues are problematic for studies on the temporal neurodynamics of decision-making under risk and ambiguity, because they lead to heterogeneity in task design and the interpretation of the results. To assess this problem, we conducted a state-of-the-art review of ERP studies on risk and ambiguity in decision-making. By employing the above definitions to 16 reviewed studies, our results suggest that: (a) research has focused more on risk than ambiguity processing; (b) studies assessing decision-making under risk often implemented descriptive-based paradigms, whereas studies assessing ambiguity processing equally implemented descriptive- and experience-based tasks; (c) descriptive-based studies link risk processing to increased frontal negativities (e.g., N2, N400) and both risk and ambiguity to reduced parietal positivities (e.g., P2, P3); (d) experience-based studies link risk to increased P3 amplitudes and ambiguity to increased frontal negativities and the LPC component; (e) both risk and ambiguity processing seem to be related with cognitive control, conflict monitoring, and increased cognitive demand; (f) further research and improved tasks are needed to dissociate risk and ambiguity processing.

Keywords Decision-making · Uncertainty · Risk · Ambiguity · Event-related potentials

The present state-of-the-art review highlights what has been accomplished so far in the neuroeconomics literature of decision-making under uncertainty. We start by acknowledging the conceptual unclarity regarding the definitions of uncertainty, risk, and ambiguity, the implications for their operationalization, and ultimately for the neuroscientific research field. Thereafter, we analyze which conceptualizations best suit the neuroeconomic study of decision-making under uncertainty in an effort to guide future research on the matter. The second section focuses on the most frequently implemented paradigms, highlighting existing caveats that hinder the effective dissociation of risk and ambiguity processing. We briefly review neuroimaging literature on decision-making under uncertainty, explicitly focusing on the EEG/ERP literature. Here, it is noted that most research focuses on the feedback stages of the decision-making process, neglecting the choice evaluation stage. This has implications for understanding how the brain processes risk and ambiguity cues, as one cannot dissociate the effects of outcome processing from the former. Thus, we conducted a systematic review of the neural correlates of risk and ambiguity processing in the choice evaluation stage (with a focus on event-related potentials [ERPs]) to understand which processes are linked to each (or both) construct. In the final section, we emphasize what remains to be done in this field to better understand the decision-making process under uncertainty.

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Defining uncertainty

Risk and uncertainty are central concepts in the neuroscientific study of decision-making. Nonetheless, a comprehensive review of the use of these concepts in the literature shows that most studies define risk and uncertainty in an unclear fashion or use both terms interchangeably. This phenomenon is even more salient when comparing the conceptualizations of risk and uncertainty across scientific fields, with clinicians, psychologists, economists, and behavioral scientists frequently using the same terminology to refer to different phenomena (Fox et al., 2015; Huettel et al., 2006). This lack of consistency posits several constraints in the experimental operationalization of these variables, compromising our ability to advance with uniform measures, formulate testable hypotheses, and compare different studies within and across scientific fields (De Groot, 2020).

The concept of risk has been colloquially understood as involving potential harm. In fact, everyday vernacular

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considers risk as dreadful or poorly understood hazards, emphasizing the exposure to negative consequences (Schonberg et al., 2011; Trepel et al., 2005). Variations in risk, defined in this fashion, can be achieved by manipulating the probability of a negative consequence or the intensity of potential harm. Conversely, behavioral scientists operationalize risk as an unpredictable variation in the outcome of a given behavior with consequences for an organism's fitness and/or utility (Winterhalder et al., 1999). Therefore, the individual cannot optimally choose what action to follow (Huettel et al., 2006). Variations in risk are then coupled with variations in the probability of the outcome, either negative (e.g., losing money, physical harm) or positive (e.g., receiving monetary compensation).

Psychologists view risk as the probability of an undesired state or harm in a given scenario (Pidgeon & Beattie, 1997). In this context, risk is typically studied as risk-taking propensity, with most experimental designs assessing how participants engage in risk scenarios (e.g., gambling task), often complementing them with risk-taking self-report instruments (e.g., Domain-Specific Risk-taking Scale, DOSPERT; Weber et al., 2002).

For economists, risk reflects situations with outcome variance, where the decision-maker knows the probability of outcomes precisely (Fox et al., 2015; Knight, 1921), often operationalized in terms of rewards or losses (Huettel et al., 2006). As for behavioral scientists, variations in risk are achieved by manipulating the probability of the outcome, here defined in the form of a probability for a given outcome in a specific scenario (e.g., 20% probability of winning 10€ in a lottery).

Following economic and behavioral definitions of risk, neuroeconomics conceptualizes risk as the variability of the probability of the outcomes of a given choice (Weber et al., 2004; Platt & Huettel, 2008), assessed during predecision stages, with no emphasis on the actual outcome of a choice or preference. Contrarily, when people talk about risk, they are talking about their *risk perception*, which is deeply attached to what happens after the decision. In contrast, for conventional neuroeconomic operationalizations, the risk is not affected by the outcome of a particular choice or preference. Importantly, risk also is independent from other economic variables, such as expected value, operationalized as the sum of the value of each potential outcome multiplied by the probability of that outcome (Rustichini, 2009).

As shown above, conceptualizations of risk vary considerably, with uncertainty, exposure to danger, and hazard often used as synonyms for risk, involving a real or perceived chance for a potentially negative outcome (Mishra, 2014). Uncertainty terminology is more consensual, even though it is often labeled as ambiguity (Fox et al., 2015). Psychologists and economists understand uncertainty as a psychological state in which the decision-maker lacks knowledge about the outcomes of a choice (Platt & Huettel, 2008). Thus, uncertainty refers to situations where the decision-maker has not been given relevant information, which leads to a poor estimation of the probability of outcomes. This implies that acquiring information on the probability of the outcomes reduces the degree of uncertainty associated with a particular choice.

Even though uncertainty and risk have been classically understood as different components of decision-making (Ellsberg, 1961; Knight, 1921), the previous brief review of the concepts reveals that both terms are employed to reflect real or perceived outcome variance, as well as variations in knowledge on the probability of such outcomes (Mishra, 2014). One attempt to advance with a uniform definition for the concepts of risk and uncertainty suggests that uncertainty may represent a spectrum that translates the amount of information available to the decision-maker. Following this idea, Bach et al. (2011) distinguish first-order uncertainty (known probabilistic action-outcome associations, resembling risk) from second-order uncertainty (imprecise probabilistic action-outcome associations, resembling ambiguity). Wang et al. (2015) also conceptualize uncertainty in terms of scenarios where the likelihood of outcomes is unclear, in which the probability distribution of possible outcomes can be well-defined (e.g., risk) or unknown (e.g., ambiguity). Camerer and Weber (1992) view ambiguity as a subgenus of uncertainty, reflecting situations with outcome variance but with ill-defined probabilities for the outcomes of a given choice.

To provide a consistent terminology in the field, uncertainty may be best conceptualized as an umbrella term that comprises scenarios characterized by two continuous variables: risk, reflecting the outcome variance; and ambiguity, reflecting the knowledge about the type of outcomes and their probability distribution. As so, in ambiguous scenarios, the information about the likelihood of outcomes is to some extent unavailable/unknown or even unobtainable. Situations where the decision-maker does not know what outcomes will follow a decision (e.g., what happens after one decides to change sidewalks) are characterized by high ambiguity, independently of the probability associated with a specific outcome. Risk refers to variation in the outcome probability with no ambiguity, reflecting situations characterized by outcome variance but where the decision/maker knows the exact probabilities of each outcome (e.g., 50% chance of winning 10€ vs. 50% chance of winning nothing).

Decision-making paradigms

The conceptual imprecision in the definition of uncertainty may lead to erroneous conclusions and contribute to the heterogeneity of data reported in literature. As such, in the previous chapter, we presented a definition of uncertainty that varies along two axes: (1) knowledge of the type and probability of the outcome (ambiguity) and (2) the effective probability of the outcome (risk). Several studies address uncertainty in the literature. Tasks implemented in those studies present a considerable degree of variability in their experimental approaches. Considering this, in this section, we attempt to elucidate the conceptualization of uncertainty by reviewing the most commonly implemented tasks.

Neuroeconomics aims to identify and understand the neural processes underlying each stage of the decision-making process: option assessment, behavioral output, and feedback evaluation (Huettel, 2010; Lin et al., 2019). Neuropsychological data suggest that decision-making relies on numerous cognitive processes, such as executive control, reward anticipation, motivation, learning, cognitive conflict monitoring, perceptual processing, attention selection, and emotion (Berridge & Robinson, 2003; Bradley & Keil, 2012; Kropotov, 2016; Paulus et al., 2001; Poudel et al., 2017). Accordingly, Rangel et al. (2008) propose a five steps model of the computations involved in decision-making. The first step is to create a representation of the decision-making problem, entailing the decision-maker internal aspects, external states, and potential courses of action. Second, the different courses of action need to be assigned a value; this valuation process needs to be optimal to predict the benefits of a choice correctly. The third step is to compare the values of the different options, allowing the organism to choose. In the following step, the brain has to measure the desirability of the outcomes, which will ultimately lead to the fifth and final step: the updating of priors based on the feedback of a given choice to optimize future decisions. The latter relates to the ability of an organism to learn from past experiences. Understanding the neural underpinnings of each step is vital to a deeper understanding of the decision-making process as a whole and the decision-making process under uncertainty. Neuroimaging techniques with optimal temporal resolution (e.g., electroencephalography) may be of best use to capture these sequential and frequently overlapping processes that typically occur in tight timeframes (in the order of milliseconds). With such knowledge, it would be possible to unravel how the brain processes risk and ambiguity, as well as how it learns from such scenarios.

To unravel the cognitive and behavioral markers of the decision-making process, the implemented tasks often rely on subjects appraising the likelihood of outcomes, either by being informed about them beforehand or by having to learn them throughout the task. This distinction differentiates experimental tasks into descriptive- or experience-based (Hertwig et al., 2004; Mata et al., 2011; Wu et al., 2021). In descriptive-based tasks, participants are instructed on what will happen after a choice (type/likelihood of outcomes). This reflects explicit decision-making, as participants make an informed decision based on explicit rules (known odds—risk, or what cues are advantageous or disadvantageous—ambiguity). On the other hand, experience-based tasks are associated with implicit learning in decision-making as participants learn the type and likelihood of outcomes from experience, usually through trial and error. Their decisions are supported by a rough estimation of those probabilities based on the feedback provided over consecutive trials until they learn them. This means that participants decide under undetermined degrees of ambiguity at the beginning of the task (even in tasks that mainly manipulate risk).

Research suggests that decision-makers' behavior differs across descriptive- and experience-based tasks. One example of this relies on how well individual behavior in these decision-making tasks fits with the predictions of the Prospect Theory (Kahneman & Tversky, 2013). According to this theory, the value of an outcome depends on the decision weight that represents the impact of a relevant probability on the valuation of the outcome (Fox & Poldrack, 2009). As a result, individuals tend to overweight rare and underweight common events. Although this seems to be the case for descriptive-based tasks, the reverse tends to happen in experience-based tasks (Hertwig et al., 2004; Mata et al., 2011). This difference may be associated with the recency effect since in experience-based tasks subjects constantly update their outcome assessment (Bjork & Whitten, 1974), i.e., recently sampled outcomes will have a greater influence on outcomes' appraisal compared to older and infrequent ones.

Importantly for the context of the present review, both descriptive- and experience-based tasks can be further categorized based on how they relate to uncertainty, that is, based on the attainability of information about the outcomes—if the information is explicitly known (risk) or unavailable (ambiguity).

Descriptive-based tasks

Existing reviews of neuroeconomics studies show that most descriptive-based tasks (Table 1) assess risk (Hertwig et al., 2004; Wu et al., 2021). Typically, in these tasks, subjects must choose between two options: high risk vs. low risk, or risk vs. no risk, in which the probabilities are explicitly presented either numerically or visually (e.g., pie charts, frequency distributions). Table 1 reviews how these tasks relate to both risk and ambiguity processing.

Experience-based tasks

Even though experience-based tasks (Table 2) are frequently implemented in studies assessing decision-making under risk, as stated above, a closer examination of its characteristics reveals that, in some cases, participants face ambiguity in earlier trials, because they are not fully aware of the probability distribution of outcomes. Therefore, one cannot wholly dissociate risk from ambiguity, because it depends on the participants' learning curve. Furthermore, knowing the exact trial where the switch between ambiguity and risk occurs is complex. It requires not only large samples but also different approaches during data collection (e.g., self-report measures) to understand when participants understand the odds associated with each outcome entirely. This has important implications for the neuroeconomic study of risk and ambiguity processing (e.g., neglecting the influence of ambiguity in early risk trials).

The study of the neural correlates of uncertainty processing relies on both descriptive and experience-based tasks, several of them reviewed here. Although most tasks addressing risk provide parametric manipulations of risk (Preuschoff et al., 2006), the same is usually not valid for ambiguity. Tasks, such as the IGT, the BART, and the BIAS, rely on experienced-based learning, and variations in the degree of ambiguity are not directly measurable at a given trial (although these may be indirectly estimated through computational modelling). A parametric function whose variability in ambiguity can be implemented as a predictor of brain activation (e.g., ERP components, BOLD responses) would be of great value to understanding how the human brain processes ambiguity, how the involved brain mechanisms differ from those of risk processing, and how they dissociate from variables, such as expected value and utility.

Neural correlates of uncertainty

Extensive literature suggests that risk and ambiguity rely on shared neural circuits, as both are forms of uncertainty, and also nonshared ones (Lin et al., 2019; Wang et al., 2014). A recent meta-analysis on the neural processing of risk and ambiguity (Wu et al., 2021) demonstrated that risk and ambiguity processing overlap on the anterior insula, suggesting the important role of this area in the encoding of uncertainty. The authors also found that risk processing recruited the dorsomedial prefrontal cortex (dmPFC) and ventral striatum, whereas ambiguity processing relied on the inferior parietal lobe (IPL) and right anterior insula. The authors concluded that risk processing seems to be associated with reward-related regions and ambiguity with executive control and calculation.

Previous research has implicated the anterior cingulate cortex (ACC; Behrens et al., 2007; Bland & Schaefer, 2011; Krugel et al., 2009) in ambiguity processing, an area thought to be implicated in the assessment of the most likely changing rate of reward contingencies (associated with cognitive control processes). More recently, Blankenstein et al. (2017) found that risk-seeking attitudes in a gambling task were associated with increased activation in the medial and lateral orbitofrontal cortex (OFC), areas known to be involved in the coding of expected value. Ambiguity-seeking was linked to temporal cortex activation. Activations in the ACC, PPC, lateral PFC (lPFC), striatum, and insula were found for both types of uncertainty-seeking attitudes. Another study by Blankenstein and associates (2018) also found evidence for distinct risk and ambiguity neural mechanisms in adolescence, during a gambling task. Risk was associated with increased activation in the parietal cortex, whereas ambiguity was linked to increased activation in the dorsolateral and medial prefrontal cortex (PFC) during feedback processing. For the choice evaluation stage, the authors found greater activation in the bilateral precentral gyrus, right vlPFC, and PPC, for risky gambles, and increased activation in the left dlPFC, bilateral temporal lobe, inferior parietal cortex (angular gyrus) and precuneus activation for ambiguous gambles. A study by FeldmanHall and co-workers (2019) also found evidence for the role of lPFC in uncertainty processing—lesions in this area were positively associated with both risk- and ambiguity-seeking in a lottery task. The authors found a specific link between the mPFC and the amygdala with risk processing. Overall, their results suggest that the lPFC may help the regulatory response when it comes to decisions under uncertainty since individuals with lesions in this region were more risk- and ambiguity-seeking.

Wu et al. (2021) further hypothesized that risk and ambiguity processing could differ regarding the decision-making tasks, namely descriptive-based versus experience-based tasks. However, no evidence was found to support this hypothesis. The temporal resolution of the fMRI technique (implemented in the reviewed studies) may not be suitable for examining the learning influence on risk and ambiguity processing (Lin et al., 2019), because it may involve overlapped cognitive processes that also occur on time scales in the order of milliseconds. Implementing neuroimaging techniques with a more fine-grained temporal resolution, such as electroencephalography and Event-Related Potentials (ERPs), allows not only to test this hypothesis but also to understand the temporal dynamics of risk and ambiguity processing.

For the abovementioned reasons, ERPs are of great interest in the study of risk and ambiguity processing, because they accurately track the time course of neuronal responses to different stimuli, from early to late stages of stimuli processing (Harrewijn et al., 2017; Luck, 2014). The ERP technique uses scalp measurements of electrical brain activity related to specific events, making it possible to directly measure neurotransmission-mediated neural activity in very short time windows (in the order of milliseconds) (Luck, 2014; Warbrick, 2022). This allows studying the effects of specific stimuli on this activity, reflecting

Table 1 Descriptive-base decision-making tasks

Uncertainty	Task	Description
Risk	Devil's task (Slovic, 1966)	Participants must sequentially decide how many of seven treasure chests to open. They are informed about how many boxes contain a prize (n = 6) and how many contain a devil (n = 1; erases all potential gains accumulated on that trial). Because the likelihood of experiencing a loss increases with each trial, opening more boxes increases risk. As risk and expected value covary (opening more chests decreases expected value), deciding to cash out may be linked to less risk-taking propensity (measured by the average number of opened chests) and/or the reduction in expected value.
	Cambridge Gambling task (Rogers et al., 1999)	An arrangement of ten red and blue boxes is presented. Participants must guess where a token is hidden by choosing the color of the box. The ratio between box colors differs across trials. Risk covaries with the number of boxes of each color. Participants begin with 100 points and choose how many they will bet on their decision (5%, 25%, 50%, 75%, or 95%). Depending on the outcome, these points will be added or subtracted to their total score (Clark & Manes, 2004). The task measures the quality of decisions (percentage of trials where the participant chooses the color that has more boxes – optimal trials), the degree of risk-taking (average betting ratio on optimal trials), deliberation time (time between the beginning of the trial and betting), risk adjustment (the tendency to bet more when the odds are favorable), delay aversion/impulsivity (difference between average ascending and descending betting ratios), and overall proportion bet (average betting ratio across all trials) (Rogers et al., 1999; Romeu et al., 2020).
	Critchley et al. (2001)	On each trial, two cards are drawn without replacement from a deck containing ten cards (numbered from one to ten). After the first is presented, participants bet whether the next card will be higher or lower. After a delay period, the second one is drawn, providing feedback about their earlier decision. Participants are not informed about overall wins and losses during the task. Risk is maximal when the first card drawn is 5 or 6, and zero when the first card drawn is 10 or 1.
	The Cups task (Levin et al., 2007; Levin & Hart, 2003; Weller et al., 2007)	Participants must choose between a risky and safe option. In the risky option, two to five cups are presented, and only one contains a gain/loss outcome. In the safe option, one cup offers a sure gain/loss of 1 quarter. On each trial, an array of 2, 3, or 5 cups is shown on each side of the screen – one side is identified as the certain option of winning/losing 1 quarter for whichever cup was selected; the other is identified as the risky side where the selection of one cup leads to a designated number of quarters gained/lost and the remaining cups leads to no gain/loss. The expected value is matched in some trials and differs between the risk and safe option in others, not being dissociable from risk.
	The Game of Dice task (GDT; Brand et al., 2005)	In this computerized task, participants are instructed to maximize their earnings by playing 18 trials of throwing a single virtual dice. Before each trial, they bet on the throw's outcome: they can bet on one, two, three, or four digits out of six. The outcome of deciding to bet on one digit will be a 1,000 units win or a loss of 1,000 units. The expected value of betting in one digit is −666.67 units: (1/6 * 1000, win) – (5/6 * 1000, losing). The outcome of betting on two digits will be a 500 units win/loss with an expected value of −166.67. The outcome of betting on three digits will be a 200 units win/loss with an expected value of 0 units. The outcome of betting on four digits will be a 100 units win/loss with an expected value of 33.33 units. The potential gains are inversely correlated to the probability of winning and positively correlated with the expected value (risk and expected value are not dissociable).

Table 1 (continued)

Uncertainty	Task	Description
	The Columbia Card task (CCT; Figner et al., 2009)	In this computerized task, participants have to choose a number of cards to turn over from a virtual 32-card array, comprised by win and loss cards. They are informed about the number of points won/lost for turning a winning/loss card, and the number of loss cards in the trial (1, 2, or 3). In the "cold" CCT, participants specify at the beginning how many cards they want to turn, and the computer determines the trial's outcome. In the "hot" version, cards are turned one by one until participants voluntarily stop or turn a loss card; risk tolerance is underestimated since participants are forced to stop when facing a loss card, even if they are willing to keep playing. The in-between version—"warm CCT"—addresses this by allowing participants to select all the cards they want to turn at the start, and then feedback is given at the end of the trial (Huang et al., 2013). Moreover, because risk increases as participants choose to turn more cards in a given trial, comparing different levels of risk processing across participants is difficult as it depends on how many cards they turn and if they face a loss card at the earlier stages of the trial. Notwithstanding, one advantage of the CCT is that by independently varying the three informational parameters given to participants (the number of points won by turning a winning card, the number of points subtracted by turning a loss card, and the number of loss cards), it prevents risk and expected value from being confounded (de Groot & van Strien, 2019). Note that further adaptations of the task minimized risk and Expected value correlations (please see Van Duijvenvoorde et al., 2015).
	Christopoulos and colleagues' task (2009)	Participants decide between a risky and safe option on each trial. The risky option is a lottery with a 50-50 chance of different monetary outcomes, and the safe option offers a single amount with certainty (both with the same expected utility).
Ambiguity	The Ellsberg Paradox (Ellsberg, 1961)	Participants are presented with two urns, each containing 100 balls. Urn A contains 50 red and 50 black balls (odds known, risk), and urn B contains 100 grey balls, each representing a red or a black ball (odds unknown, ambiguity). Participants choose one of the urns to bet on the color of the ball drawn to win a monetary prize. Most choose urn A, even though this does not maximize expected utility; for example, if a participant chooses urn A and bets on the color red, she assumes that a red ball from urn B has a lower expected utility; this means that a black ball from urn B has a higher expected utility, being the optimal option. However, people tend to choose scenarios where the likelihood of outcomes is known, even if it leads to less profit, which explains why urn A is the most common choice (Eichberger & Pirner, 2018)—a phenomenon known as ambiguity aversion.
	Risky-Gain task (Paulus et al., 2003)	Participants are presented with three numbers in ascending order (20, 40, and 80). Each number is on the screen for 1 s. If participants press a button, then they receive the number of points displayed on the screen. They are instructed to respond rapidly to receive a small sure gain of 20 points or wait longer periods to receive more points (40 or 80). However, longer waiting times also lead to decreased winning probabilities/increased loss probabilities.

Table 1 (continued)

Uncertainty	Task	Description
	Preuschoff and colleagues' task (2006)	This task was adapted from Critchley et al. (2001), in which participants must bet on one of two options: "second card higher" or "second card lower" before seeing the first draw. Participants can double their earnings if they guess right or lose it all if they are wrong. In this design, the expected value is measured as a mathematical expectation of reward and increases linearly with the probability of reward (p). Although the bet placement is performed under a certain degree of ambiguity, the task mainly manipulates risk, measured as reward variance. As such, expected value and risk are orthogonal over the full range of probabilities. When placing a bet, the reward probability (p) is 0.5. Once card 1 is displayed, this probability changes, depending on whether the bet was the second card is higher or lower, and depending on the number of the card shown in draw 1, allowing the parametric dissociation of value and risk.
Risk and ambiguity	Levy and colleagues' task (2010)	This task distinguishes risk from ambiguity in terms of attitude (Levy et al., 2010). Participants have to choose between a reference lottery (50% chance of winning 5$) and a changing lottery with varying rewards and winning probabilities. In each trial, the changing lottery is depicted on the screen in the form of an "urn" painted partly red and partly blue. All urns contain 60 poker chips (blue and red); the percentages of each type of chip are disclosed by the red and blue areas of the urn. There are two types of changing lotteries: half of the trials are considered risky, in which winning probabilities are explicit; and the remaining are ambiguous (winning probabilities are to some extent unknown): part of the urn is hidden by a grey occlude, placed over the center of the image (covering 25%, 50%, or 75%). In half of the trials, participants are told that the red chips are associated with winning a positive amount and that the blue chips yield a zero amount. In the remaining, contingencies are reversed. These manipulations result in 60 unique trial types (3 ambiguity levels, 3 winning probabilities, 5 amounts, 2 colors). Other task versions have been implemented (Blankenstein et al., 2016; Tymula et al., 2012; van den Bos & Hertwig, 2017).

not only the information processing stages but also other cognitive processes such as perception, attention, emotion, memory, etc. (Bradley & Keil, 2012; Kropotov, 2016). When it comes to decision-making, as abovementioned, the processing of decision options incorporates perceptual processing, cognitive conflict monitoring, and attentional selection, some of these overlapping and occurring within milliseconds (Amodio et al., 2014; Lin et al., 2019).

However, most studies on the ERPs of decision-making under uncertainty focus on the feedback stages following a decision, ignoring how the human brain encodes other decision-making stages, such as option assessment and behavioral output (Blankenstein et al., 2017; Lin et al., 2019). Thus, data resulting from these studies reflect not only risk and ambiguity processing but also feedback processing. Studies focusing on the decision stage (i.e., ERPs locked to the stimulus presentation) are scarcer, especially when it comes to ambiguity processing. This, in addition to faulty operationalizations of risk and ambiguity, may contribute to the heterogeneity in this specific field, thus impairing conclusions on the putative neural mechanisms underlying risk and ambiguity processing.

To systematize the existing research, we conducted a state-of-the-art review on the ERP correlates of risk and ambiguity processing decision-making studies, specifically those reporting data for the option assessment stage. Our main goal was to better understand the temporal dynamics of risk and ambiguity processing, by applying a more consensual nomenclature both to the processes measured and to the experimental tasks implemented (i.e., categorizing the tasks according to descriptive- or experience-based and the manipulated construct: risk or ambiguity) in the retrieved articles.

Method

For the current state-of-the-art review, a systematic search was conducted accordingly to PRISMA recommendations (Page et al., 2021).

Table 2 Experience-based decision-making tasks

Uncertainty	Task	Description
Risk	Tobler and colleagues' task (Tobler et al., 2007)	Participants are presented with 12 circles of different colors and sizes, and distinct numbers inside, each associated with different reward magnitudes and probabilities. Before the decision stage, participants are trained to learn the likelihood distribution of the outcomes associated with each stimulus. Then, a stimulus appears in one of four screen quadrants and participants must select the quadrant where the stimulus appeared. Expected value is independent of magnitude and probability since different stimuli with the same expected value but different combinations of magnitude and probability are presented. By varying the risk levels across trials, it is possible to compare how individuals process different degrees of risk.
Risk and ambiguity	The Iowa Gambling task (IGT; Bechara et al., 1994)	Participants select a card from one of four decks – two are bad decks (higher rewards but also higher losses, resulting in lower overall gains); two are good decks (lower rewards and lower/less frequent losses, leading to higher overall gains). The nature of the decks is learned through trial-and-error with initial decisions being made under ambiguity. Usually, in trials 20 to 30, participants learn the distinct odds associated with each deck with some authors suggesting that, at this point, decisions are made under risk (Paixão, 2017). This task aims to mirror two kinds of daily situations - one where the subject is oblivious to the implications of the decision –ambiguity; and the other where the subject learned/knows the probability distribution of the outcomes – risk. The typical outcome measures of the IGT are the amount of money earned and the choice allocation score between the two types of decks (Koffarnus & Kaplan, 2018). The IGT does not parametrically differentiate between risk and ambiguity as it is not feasible to assess the degree of ambiguity at any given trial. It is also worth noting that, by relying both on learning and development of participant preferences and differences between participants, performances may be due to distinct learning curves or preferences for riskier options (Clark & Manes, 2004).
	The Behavioral Investment Allocation Strategy (BIAS; Kuhnen & Knutson, 2005)	It evaluates the propensity for irrationally choosing high-risk financial options (Shao & Lee, 2014). Participants choose between two stocks and one bond (a sure gain of 1€). After each choice, feedback on all stock options is given. At the beginning of each trial, one stock is randomly assigned as "good" (50% +10€; 25% +0€; 25% −10€) and the other as "bad" (25% +10€; 25% +0€; 50% −10€), with the good one dominating stochastically the bad one. Subjects know these distributions beforehand but are not told which stocks are good and which are bad. Thus, through trial-and-error, they learn the characteristics of the stocks, which reduces the level of ambiguity along the task. Risk-seeking is measured as the number of bad stocks chosen after learning the stock's rules (Mata et al., 2011).

Table 2 (continued)

Uncertainty	Task	Description
	The Balloon Analogue Risk-Taking task (BART; Lejuez et al., 2002)	In each trial, participants pump a simulated balloon without knowing when it will explode. Each pump increases the potential reward (5 cents) and the probability of explosion (which results in losing the gains from the trial). Participants decide when to stop pumping and collect the amount earned until that point (Canning et al., 2022). There are three types of balloons (orange, yellow, and blue), each with different explosion probabilities, unknown to the participants. Explosion probabilities are learned through trial and error. As such, participants face higher ambiguity in earlier trials relative to later trials. Because it is not known when the shift between ambiguity and risk occurs, it is unclear whether decisions are made under risk or ambiguity. This task measures risk-taking propensity, indexed as a higher mean number of pumps on unexploded balloons. One problem regarding this index is the statistical censoring, i.e., in trials where the balloon explodes, participants cannot take additional risk, resulting in and underestimation of their risk/ambiguity preference.

Search and study selection strategy

Studies were selected via PUBMED and Web of Knowledge databases by using the following search expressions limited to abstracts and topics: *Decision-making [Title/Abstract] AND (Uncertainty [Title/Abstract] OR Risk [Title/Abstract] OR Ambiguity [Title/Abstract]) AND (Neurophy*[Title/Abstract] OR "neuronal correlates" [Title/Abstract] OR "Evoked Potentials/physiology"[Mesh] OR "event-related potentials"[Title/Abstract] OR ERP[Title/Abstract]).* Mesh terms were used in PUBMED to optimize the search. Filters for language (English, Portuguese, Spanish) and species (Human) were applied. No filters for age or publication date were applied. The initial search was conducted in March 2022 and was updated in April 2023.

Initial screening of the articles was limited to title, abstract, and keywords. Two independent raters (CB and TOP) assessed the eligibility of studies by taking into account the following inclusion criteria: (1) empirical study—the study had to report empirical findings; (2) primary research—the study had to report original data; (3) economic decision-making—the study had to assess economic decision-making; (4) ERP—the study had to include analysis of ERPs (temporal-domain analysis) locked to the stimulus presentation; (5) uncertainty (risk and ambiguity) processing—the study had to include paradigms that varied risk and/or ambiguity parametrically or allowed to compare different degrees of risk and/or ambiguity. The interrater reliability was almost perfect (Fleiss' $\kappa = 0.96$; McHugh, 2012). All disagreements were examined by a third researcher (RP) and solved by consensus. All the included studies were analyzed for the following exclusion criteria: (6) repeated data—overlapping data across studies; (7) presence of psychological or neurologic disorders—studies, including samples with psychopathology or neurological disorder; (8) methodological issues—studies, including tasks with an inadequate design for ERP analysis (e.g., studies whose manipulation does not allow for a specific timing of the risk/ambiguity processing onset). No criteria for the ERPs time-windows and topography were imposed, as we followed what was stated in the original studies.

Data extraction

Two independent researchers extracted data regarding the studies characteristics (CC and CS) and conflicts were resolved between the two researchers and a third one (HG). Tasks were categorized into descriptive- or experience-based, depending on how the participant became aware of the probabilities of outcomes—either by giving that information during instructions or by having to learn them through trial and error, along the task. Tasks were further characterized regarding which type of uncertainty was being manipulated: risk or ambiguity. Stimuli were coded regarding the level of risk or ambiguity: high risk/ambiguity, low risk/ambiguity, or no risk/ambiguity. Rewards were categorized according to their dependence on participants performance: fixed (nondependent and defined at the beginning of the experiment) or performance-dependent (varying according to participants performance along the trials). Information regarding the sample (number, mean age, and percentage of females) and the ERPs extracted (time-window in milliseconds, latency, topography, and measure) were retrieved from the selected papers.

Results and discussion

Search results

A total of 250 nonduplicated studies were found (Figure 1). After the screening by title and abstract, 43 out-of-topic records were removed, and the remaining studies ($n = 195$) were assessed for eligibility criteria (abstract + full text). Twelve articles did not comply with criteria 1 (experimental study), 14 with criteria 2 (original data), 12 with criteria 3 (economic decision-making), 43 with criteria 4 (ERP), and 99 with criteria 5 (uncertainty processing). Sixteen articles were retained for the qualitative analysis (Figure 1; Table 3). Publication years ranged from 2007 to 2023, and no studies involved underaged or elderly samples.

Studies' characteristics

We reviewed 16 uncertainty processing studies, 11 assessing risk, 2 assessing ambiguity, and 3 assessing both. An attempt to apply a more homogeneous categorization of the implemented tasks revealed that most studies manipulating risk were descriptive-based ($n = 13$), and studies manipulating ambiguity relied both on descriptive- ($n = 4$) and experience-based paradigms ($n = 1$). Notably, risk processing has been more frequently studied, highlighting the need for more research on ambiguity processing—either by comparing ambiguous and risky cues or by parametrically comparing different ambiguity levels.

Note. *LPC* late positive complex, *FRN* feedback-related negativity, *LPP* late positive potential, *RewP* reward positivity, *ms* milliseconds.

Descriptive-based tasks

Risk Yang et al. (2007) employed a blackjack task in which participants had to decide if they wanted to draw a third card based on the sum of the two first cards (numbered from 1 to 10), to reach a total of 21. If the sum surpassed 21, participants lost, if it was inferior, they neither won nor lost the trial. The authors considered the sum 17 as a high-conflict/risk trial and 13 as a low-conflict/risk trial, based on behavioral results of the sample. It was found that N2 (220-320 ms) and N500 (500-600 ms) amplitudes were larger in high-risk conditions compared with low-risk conditions. The authors suggest that N2 plays a critical role in processing perceptual conflict, with the N500 being linked to response conflict during decision-making. Yang et al. (2010) applied the same task but considered the sum 16 as high-risk trials and the sum 13 as low-risk trials, once again based on behavioral results of the sample. The results demonstrated more negative N500 amplitudes (400-550 ms) in high-risk

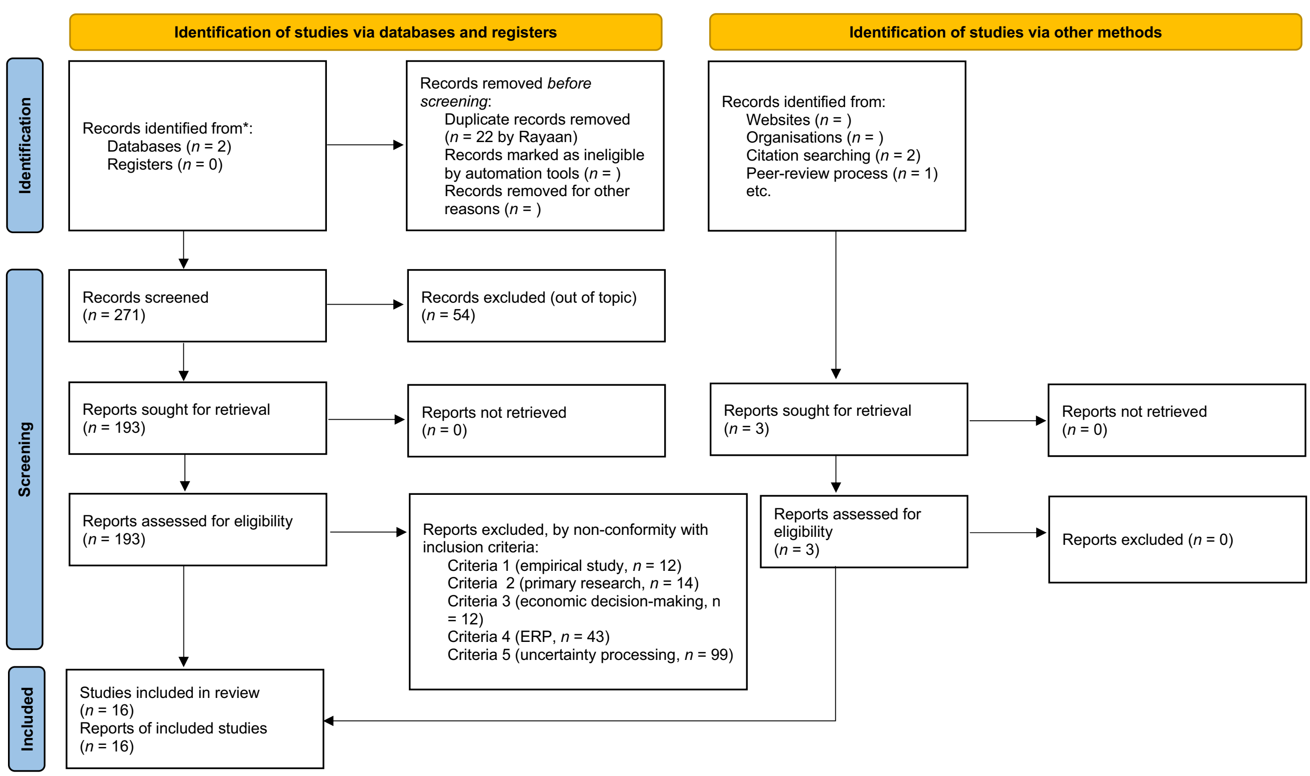

Fig. 1 PRISMA flow diagram

Table 3 Characteristics of the included studies

Study	Uncertainty	Decision-making	Task	n	Females (%)	Mean sample age	ERP	Time-windows (ms)	ERP latency	Topography	ERP measure	Reward type
Yang et al. (2007)	Risk	Descriptive-based	Blackjack	16	56.3	_	N2 N500	220-320 500-600	Long Long	All	Mean amplitude	Fixed
Yang et al. (2010)	Risk	Descriptive-based	Blackjack	28	60.7	21.4	N1 P2 Unnamed 300-400 N500 Unnamed 550-700	0-150 150-300 300-400 400-550 550-700	Short Mid Long Long Long	All Centro-parietal All All All All	Mean amplitude	Fixed
Bland and Schaefer (2011)	Ambiguity	Experience-based	Reward-based decision-making	31	58	24	N2 N400 LPC	200-350 350-500 500-800	Mid Long Long	Frontal	Mean amplitude	Performance-dependent
Yang et al. (2011)	Risk	Descriptive-based	Insertion card game	18	50	21.5	N400	300-500	Long	Frontocentro-parietal	Mean amplitude	Fixed
Deng et al. (2012)	Risk	Descriptive-based	Gambling	24	66.(6)	22.9	FRN	250-350	Long	Fronto-centro-parietal	Mean amplitude	Performance-dependent
Cui et al. (2013)	Risk	Experience-based	IGT	26	46.2	22.4	P3	300-500	Long	All	Mean amplitude	Performance-dependent
Wang et al. (2014) - Risk	Risk	Descriptive-based	Two primes – risk and ambiguous stimuli	13	38.5	22.4	P200 N200	170-220 210-260	Mid	Fronto-central	Mean amplitude	Performance-dependent
Wang et al. (2014) - Ambiguity	Ambiguity	Descriptive-based	Two primes – risk and ambiguous stimuli	13	38.5	22.4	P200 N200	170-220 210-260	Mid	Fronto-central	Mean amplitude	Performance-dependent
Wang et al. (2015) – Risk	Risk	Descriptive-based	Two primes – risk and ambiguous stimuli	12	41.7	22.6	P3	450-550	Long	All	Mean amplitude	Performance-dependent
Wang et al. (2015) – Ambiguity	Ambiguity	Descriptive-based	Two primes – risk and ambiguous stimuli	12	41.7	22.6	P3	450-550	Long	All	Mean amplitude	Performance-dependent
Kiat and Chiadle (2018)	Risk	Descriptive-based	Crocodile Dentist Game	26	76.9	20	LPP	592-736	Long	Central	Peak amplitude	Fixed
Meng and Xiu (2018)	Risk	Descriptive-based	Risk scenarios	18	50	_	N2	225-275	Long	All	Mean amplitude	_

Table 3 (continued)

Study	Uncertainty	Decision-making	Task	n	Females (%)	Mean sample age	ERP	Time-windows (ms)	ERP latency	Topography	ERP measure	Reward type
Chen et al. (2019)	Risk	Descriptive-based	Speed-Rewarded Go-NoGo	31	83.9	19.7	P2 P3b	180-250 420-800	Mid Long	Frontocentral Parietocentral	Mean amplitude	Performance-dependent
Lin et al. (2019) - Risk	Risk	Descriptive-based	Monetary Gambling	34	52.9	20.6	P1 N2	110-150 290-350	Mid Long	Occipital Frontal	Mean amplitude	Performance-dependent
Lin et al. (2019) - Ambiguity	Ambiguity	Descriptive-based	Monetary Gambling	34	52.9	20.6	P1 N2	110-150 290-350	Mid Long	Occipital Frontal	Mean amplitude	Performance-dependent
Sehrig et al. (2019)	Risk	Experience-based	BART	35	44	42.7	P3	200-400	Long	Centro-parietal	Peak amplitude	Performance-dependent
Zhu et al. (2019)	Ambiguity	Descriptive-based	Ambiguous choice task	25	48	_	P3	500-600	Long	Parietal	Mean amplitude	Performance-dependent
Lauffs et al. (2020)	Risk	Descriptive-based	Card game (Preuschoff et al., 2006)	20	50	23.5	P3 N2	460-800 199-288	Long Mid	Centro-parietal Central	Mean amplitude	Performance-dependent
Zheng et al. (2020)	Risk	Descriptive-based	Card Guessing	25	48	_	P3 RewP	400-650 302-342	Long Long	Parietal Fronto-central	Mean amplitude	Performance-dependent
Deng et al. (2023)	Risk	Descriptive-based	Wheel-of-fortune task	30	46.7	20.23	Cue-P3	400-520	Long	Centro-parietal	Mean amplitude	Performance-dependent
Deng et al. (2023)	Ambiguity	Descriptive-based	Wheel-of-fortune task	30	53.3	20.5	Cue-P3	400-520	Long	Centro-parietal	Mean amplitude	Performance-dependent

trials compared to low-risk ones. Both studies suggest that deciding under risk seems more difficult, as reflected by the N2 and N500, thought to be involved in conflict monitoring processes (Yang et al., 2007, 2010).

Yang and Zhang (2011) applied a blackjack task in which participants were randomly assigned 2 cards (numbered from 1 to 9) and had to decide whether they wanted a third one. If the face value of the third card was within the range of the two cards, they won 10 yuan, if not they lost the same amount. Trials with three numbered cards in-between the 2 initial cards were labeled as high-conflict[1] and if the number was 1 or 7, trials were labeled as high-risk and low-risk, respectively. The authors found that N400 amplitudes (300-500 ms) were more negative in the high-risk scenario, compared to low-risk ones (sure loss/gain), and in trials in which loss probability was higher, suggesting that this ERP may reflect the anticipation of a negative outcome.

Deng et al. (2012) used a gambling task in which participants were presented with four types of cues - one indicating 50% probability of monetary gain (2 or 0 yuan), one indicating 50% probability of monetary loss (2 or 0 yuan), one indicating a sure monetary gain (1 yuan), and another indicating a sure monetary loss (1 yuan). Participants distinguished these cues by their shape (square or circle) and color (grey or white). The results showed that the cue-FRN (250-350 ms) amplitudes were more negative for the risk cues compared to certain ones, only in the gain domain, with no differences in the loss domain. This ERP, thought to be generated in the ACC and medial prefrontal cortex (mPFC), may serve as a negative signal for possible negative outcomes associated with a risky option, preparing the evaluation system for such an event, which is in line with the results from the previous study regarding the N400 component. Moreover, considering that differences were only found in the gain domain, this evaluation system may process gain- and loss-related information differently.

A study by Kiat and colleagues (2018) administered the *crocodile dentist task*. In this task, participants engaged with a plastic crocodile prop with ten teeth that locked into place by being pressed down, stopping close to the participant's finger. Participants were instructed to pick the lowest unpressed number (1 to 10) in each trial. The authors analyzed the LPP (592-736 ms), a posterior ERP component associated with higher reactivity levels towards motivationally relevant stimuli. They found no differences between risk levels.

Meng and Xiu (2018) applied a decision-making task with high-risk (e.g., a screen displayed 3 blue cards and 3 red cards, and participants had to decide which color was drawn from those 6 cards) and low-risk scenarios (e.g., a screen displayed 5 blue cards and 1 red card and participants had to decide which color was drawn from those 6 cards). The authors found that N2 amplitudes were more negative in high-risk scenarios at frontocentral sites. This, again, suggests that decision-making under higher levels of risk is associated with higher levels of cognitive control and decision processing, as reflected by the N2 component.

More recently, Chen et al. (2019) applied a speed-rewarded Go/No-Go task, in which participants had to respond (Go) or not (No-Go), depending on the previous trial information period (a pie chart depicting the probability of winning and the bet amount). In it, a pie chart appeared, displaying the magnitude of the bet and Go probability (25% - low risk, 50% - high risk, 75% - low risk). They studied two ERP components—P2 and P3—implied in reward processing and value computations (processing predictive cues and decision outcomes). P2 is an early peaking component involved in emotional arousal and attention capturing (Carretié et al., 2001; Potts, 2004; Potts et al., 1996, 2006; Schutter et al., 2004). P3 can be divided into two components – P3a (peaking at ~350 ms) and P3b (peaking at ~450 ms). The first reflects stimulus-driven attention mechanisms, and the second context updating and stimulus-induced memory (Polich, 2007). The results showed a different pattern for these components; P2 amplitudes were higher in lower-risk scenarios (25% and 75% Go probability) compared with higher-risk scenarios (50% Go probability), whereas P3b amplitudes were higher for 75% Go probabilities (lower risk, higher probability of reward), compared with 25% and 50% probabilities. This suggests that reward and risk information may be reflected in the neural signal shortly after the cue is presented. However, contrarily to the linear increased P3 amplitudes across Go probabilities, P2 amplitudes revealed a nonlinear change, with the lowest amplitudes in the riskier scenario (50% Go probability). Thus, the authors argue that the two components reflect different information processing stages; P3b may reflect effortful control of task-relevant events toward a goal (reward). In contrast, the P2 may not only reflect affective and motivational salience linked to the cue information but also code information about the level of risk of a cue, as reflected by higher amplitudes for lower-risk cues.

In this line, Lauffs et al. (2020) applied the card game described in Table 1 (Preuschoff et al., 2006). They found increased P3b and less negative N2 amplitudes for certain trials (Card 1 either 1 or 10, in which the probability of winning is either 0 or 1), after Card 1 presentation, compared with high-risk trials (Card 1 either 4 or 5, in which the probability of winning is close to 0.5). The authors labeled

[1] The authors understand risk as higher probabilities of loss, whereas conflict as scenarios where outcomes have similar probabilities of occurring. This latter is in line with the conceptualization of risk adopted in this manuscript, and, thus we decided to consider high-conflict trials as high-risk trials, whereas low-risk loss and high-risk loss as low-risk trials (since the outcome variability is not maximal – i.e., 50%).

high-risk trials as low- prediction scenarios and low-risk trials as high-prediction scenarios.

One final study by Zheng et al. (2020) applied a card-guessing task in which participants were presented sequentially with two cards (from a deck of nine, numbered 1 to 9) and had to decide whether the second card was higher or lower than the first one. The risk levels, operationalized as reward variance, ranged from 0 (low risk) to 25 (high risk). Their results demonstrated that cue-P3 (400-650 ms) amplitudes were larger at parietal sites for low-risk scenarios (minimal gain and maximal gain) compared with high-risk trials (intermediate gain probabilities), which is in line with the previous study findings. This quadratic trend is aligned with research stating that P3 amplitudes are diminished in difficult discrimination trials (Polich, 1987; Senkowski & Herrmann, 2002; Zheng et al., 2020). One possible explanation lies in the triarchic model of P3 amplitude (Johnson, 1986), which states that P3 amplitude is proportional to the amount of information available to the participant; in high-risk trials, because each outcome has a 50% chance of occurring, the participant cannot tell which outcome will happen, whereas in low-risk trials (e.g., 20% of outcome A and 80% of outcome B), the participant knows that B is more likely to occur than A.

Ambiguity To our knowledge, only one study employed a descriptive-based task assessing ambiguity. Zhu et al. (2019) applied an ambiguous choice task in which participants were sequentially presented with two lotteries, with varying ambiguity and reward levels, and had to decide which one they preferred. The lotteries were presented as a pie chart with ten sections that were color-coded: sections painted in green indicated the probability of winning, sections in red represented the probability of losing, and sections in grey consisted of hidden information – thus, probabilities of the outcome were not fully known (the number of grey sections reflects the level of ambiguity). The authors found that P3 amplitudes (500-600 ms) at parietal sites were larger for low ambiguity cues and larger rewards. P3 has been suggested to reflect stimulus categorization and motivational salience (Polich, 2007; Polich & Kok, 1995) and has been associated with activation of the ventral striatum—a region linked to reward processing—during the evaluation process (Pfabigan et al., 2014). Thus, P3 may reflect the evaluation of reward and ambiguity processing and the encoding of the subjective value of ambiguous options.

Risk vs. ambiguity Wang et al. (2014) applied a decision-making task with two primes: risky stimuli (showing 50% of winning or losing money) and ambiguous stimuli (showing the amount of money without its probabilities). In each trial, participants were faced with risky or ambiguous stimuli and had to decide whether they wanted to bet. The results showed that P2 amplitudes (peak at ~190 ms) for the ambiguous condition were smaller than the risk condition. This component has been associated with early attention and perception, as well as attentional processes involved in the negativity bias (Carretié et al., 2001; Dennis & Chen, 2007), with studies finding smaller amplitudes in more negative contexts (Yuan et al., 2007). Therefore, the authors argued that smaller frontocentral P2 amplitudes in the ambiguous condition reflected a rapid feature of detection processes attending to the ambiguity context. Contrariwise, the N200 (210–260 ms) frontocentral amplitudes were higher for ambiguous stimuli compared with the risk stimuli. The N200 has been linked to cognitive control and conflict monitoring (Azizian et al., 2006; Nieuwenhuis et al., 2004). Hence, in ambiguous scenarios, participants may face higher perceptual conflict levels compared with the risk scenarios due to deciding with unknown probabilities. The authors further argue that decision-making under ambiguity may involve more complex cognitive and neural processes compared with decision-making under risk.

Wang's group conducted a subsequent study (Wang et al., 2015), with the same task, and found that P3 amplitudes were larger in risk scenarios compared with ambiguous ones. The authors suggest that, because the P3 component is inversely related to working memory load (Polich, 2007), in the stage assessment of decision-making under ambiguity, participants have a higher working memory load as they must mobilize past experiences (learning from previous trials) to calculate the expected value and reduce the cognitive effort, compared with risk trials.

Lin et al. (2019) applied a monetary gambling task in which participants had to accept or reject gambles; risk gambles showing the probability of each outcome and ambiguous gambles without such information. They found that the N2 (290–350 ms) and P3 (300-450 ms) amplitudes were larger in riskier scenarios compared with ambiguous ones, which may reflect that risk trials lead to more cognitive conflict and recruit more resources (e.g., sustained attention, memory updating). This result was unaffected by varying risk levels across trials. One possible explanation advanced by the authors is that, when deciding under risk, participants need to consider two different variables: the potential reward vs. its probability. In the ambiguous context, because participants are not informed about the probability of each outcome, such conflict does not arise, and the same calculations are not possible. Larger P3 amplitudes in risky trials also suggest that more cognitive resources are being recruited in weighting the potential risk in the risky context; as such, decision-making under risk seems to be more complicated than decision-making under ambiguity. The authors also found that gambles were more likely to be accepted in the small magnitude trials compared with the larger ones, and the same for risky trials compared with ambiguous ones.

This is in line with previous research showing that ambiguity aversion is stronger than risk aversion (Camerer & Weber, 1992; Glimcher, 2008).

Deng et al. (2023) also found increased cue-P3 amplitudes for risk scenarios compared with ambiguous ones. In this latter study, participants performed a wheel-of-fortune task where the outcome probabilities were either known (winning probability: low, medium, high) or unknown (ambiguity: low, medium, high). The authors also found that cue-P3 was maximal for riskier scenarios (medium probability of winning) and minimal for low-risk cues (low and high probability of winning). Inversely, cue-P3 was not sensitive to ambiguity-level. Once again, these results suggest that (a) cue-P3 may be a neuronal marker of risk evaluation as it is sensitive to risk level, and (b) risk cues mobilize more cognitive resources to make an informed decision (based on expected value computations), whereas the lack of information available in ambiguous scenarios may prevent participants from computing the expected value and, consequently, making an informed decision.

Summary of descriptive-based tasks Regarding risk processing, most studies implementing descriptive-based tasks found increased frontal negativities, namely the N2, N400, N500, and cue-FRN, in high-risk trials (Deng et al., 2012; Yang et al., 2007, 2010; Yang & Zhang, 2011). Contrarily, P2 and P3 amplitudes were diminished in high-risk scenarios (Chen et al., 2019; Lauffs et al., 2020; Zheng et al., 2020), whereas Deng et al. (2023) found the opposite, i.e., maximal cue-P3 amplitudes for high-risk cues and minimal for low-risk cues. Kiat and Chiadle (2018) found no risk relation with the LPP amplitudes modulation. Likewise, high ambiguity cues were related to diminished P3 amplitudes in a study by Zhu and colleagues (2019). Finally, studies comparing risk and ambiguous scenarios found reduced P2 and P3 amplitudes in ambiguous trials compared with risk ones (Deng et al., 2023; Lin et al., 2019; Wang et al., 2014; Wang et al., 2015). Conflicting results regarding the N2 component also were present. One study reported increased amplitudes for high ambiguity trials compared with risk ones (Wang et al., 2014); another reported the opposite (Lin et al., 2019). With the existing data, risk processing in descriptive-based tasks seems to be related to cognitive control and conflict processing, as reflected by higher frontal negativities. Regarding ambiguity, the existing literature is scarce and heterogeneous, emerging the need for more studies focusing on its processing.

Experience-based tasks

Experience-based tasks typically rely on participants' ability to learn from the cue-outcome pairing of the hidden probabilities of specific scenarios. With increasing trials, participants begin to learn the probabilities associated with each choice (e.g., IOWA Gambling task). As stated, it is expected that in such cases, early trials reflect ambiguity while later trials reflect risk. In order to aggregate existing results, we consider the studies where comparisons lead to nonsignificant differences between correlates of the early and later trials. In these cases, it is reasonable to assume that the average result would mainly reflect risk, notwithstanding the influence of ambiguity on early trials.

Risk Cui et al. (2013) applied a modified version of the IGT in which participants did not choose what deck to play in each trial. Instead, the computer selected a deck (from the four available: A, B, C, D), and participants had to decide whether they wanted to play or pass that card. They found larger P3 amplitudes for advantageous decks in the frontal left hemisphere and the opposite in the centroparietal right hemisphere—larger P3 amplitudes for disadvantageous decks; these results were not affected by the task period. P3 lateralization supports the emotional asymmetry hypothesis (Cunningham et al., 2005; Ohgami et al., 2006), in which positive emotions evoke more activity in the left hemisphere and negative ones in the right hemisphere. Past research has linked the right frontal hemisphere to punishment learning and negative situations and the left frontal hemisphere to reward learning and positive situations (Cunningham et al., 2005; Ohgami et al., 2006). Because the task period did not affect the results, the influence of ambiguity in earlier trials may be nonsignificant; thus, P3 amplitudes reflect the degree of risk across trials.

Similarly, Sehrig et al. (2019) applied a modified BART paradigm. Results demonstrated that P3 amplitudes were higher for high-risk trials compared with low-risk trials, reflecting effortful processing supported by recruiting more cognitive resources for difficult choices, in this case in high-risk scenarios (López-Caneda et al., 2012; Petit et al., 2014).

Ambiguity To our knowledge, only one study assessed ambiguity with an experience-based task. Bland and Schaefer (2011) applied a reward-based, decision-making task that manipulated two independent variables: volatility (the change rate of the stimulus-response-outcome rule—S-R-O rule: volatility relates to ambiguity as frequent changes the S-R-O rule do not allow for participants to learn the rules associated with the outcomes of the stimuli—participants have to decide without acquiring that information along the trials; thus, high volatility scenarios relate to high ambiguity and low volatility scenarios relate to low ambiguity), and feedback validity (the degree of correct predictions by the S-R-O rule). They found that N2 (200-350 ms) and N400 (350-500 ms) stimulus-locked potentials were more negative at frontal sites in the high-ambiguity context (in the high feedback validity context) compared with low-ambiguity scenarios. These results were not modulated by previous outcomes or the trial phase (earlier vs. later trials). These negativities, thought to be generated in the ACC, have been associated with cognitive control and conflict processing, i.e., with cognitive demands of scenarios that involve a high level of conflict between competing options (a habitual response that needs to be inhibited vs. an unhabitual adaptive response). Thus, the N2/N400 modulation by volatility may reflect the resolution of the conflict between competing options following a change in the S-R-O rule (higher ambiguity). Because this was exclusive to high feedback validity contexts, it shows that this conflict is enhanced in habitual scenarios, where unpredictable events are rare.

In the low feedback validity context, high ambiguity trials elicited higher frontal LPC amplitudes. This later positivity also has been associated with cognitive control, possibly involving processes, such as working memory, sustained attention, and long-term memory encoding (Donchin et al., 1997; Gevins, 1997; Otten et al., 2007). Therefore, this result suggests that high ambiguity in low-feedback validity scenarios increases working memory demands and the processing of encoding information in episodic memory, as reflected by higher LPC amplitudes in challenging decision-making contexts.

Summary of experience-based tasks As mentioned, few studies have implemented experience-based tasks regarding the neural correlates of the assessment stage in decision-making. Those assessing risk found increased P3 amplitudes for high-risk scenarios (Sehrig et al., 2019). One study restrained this finding to centroparietal sites in the right hemisphere and also found reduced P3 amplitudes at frontal sites in the left hemisphere for high-risk scenarios (Cui et al., 2013). Regarding ambiguity, frontal negativities (N2 and N400) and positivities (LPC) are increased for high ambiguity cues (Bland & Schaefer, 2011). These findings also relate ambiguity to conflict processing and cognitive demand, as did the findings regarding risk processing in descriptive-based tasks. Once again, the need for more studies implementing different types of paradigms (descriptive- vs. experience-based) to study both risk and ambiguity processing emerges.

Take-home message The present review reveals that the distinct cognitive processes linked to ambiguity and risk are difficult to infer from current literature. The underlying causes are twofold: (a) most studies failed to dissociate the neural correlates of risk from ambiguity processing; (b) most studies focus on the outcome assessment stage of the decision-making process, with the underlying assumption that differences in brain correlates of outcome processing would result from differences in the brain mechanisms of uncertainty processing. The former may hypothetically result from suboptimal experimental paradigms that do not control for econometrically relevant variables, such as expected value (Cui et al., 2013) and expected utility (Bland & Schaefer, 2011), and also do not include parametrical manipulations of both risk and ambiguity (Sehrig et al., 2019). The latter may be driven by the difficulty in the interpretation of ERP data; the high temporal variability of the EEG signal make it difficult to distinguish between specific cognitive processes that occur within a short timeframe. Specifically for ERP research, temporally precise events are essential for the of brain electrical responses, as well as experimental manipulations that dissociate distinct decision-related processes. In this regard, experimental protocols that dissociate between the perceptive stages of uncertainty processing and the cognitive and affective processes involved in decision-making are scarce. One exception is the protocol from Preuschoff et al. (2006), where the experimental manipulation of risk (defined as outcome variance) occurred after the decision-making, thus allowing the dissociation between decision-related and risk-processing brain mechanisms. For ambiguity, no such approach was found in the present review. As such, it would be highly speculative to advance with specific and precise cognitive functions for risk and/or ambiguity. Instead, we advance with the hypothesis that these notions would be testable under paradigms that manipulate risk and ambiguity in a temporally precise manner and disentangled from both decision-related and outcome processing mechanisms.

Implications, future directions, and concluding remarks

Uncertainty is present in nearly all human choices, because decision-making is rarely based on full knowledge about the outcomes that will follow. As such, how one copes with uncertainty influences the fitness of their decision-making and, consequently, their well-being (Wu et al., 2021). Understanding uncertainty and all its subgenera—risk and ambiguity—plays a significant role in comprehending how individuals make optimal decisions and what are the biomarkers of such processes (e.g., temporal dynamics of brain activity and its anatomical substrates). More importantly, learning how the human brain processes risk and ambiguity is essential for understanding how these processes may be altered in specific populations, such as neurodivergent populations (e.g., with Attention Deficit and Hyperactivity Disorder, known to have impaired decision-making skills) and populations facing addiction (e.g., alcohol and drug abuse), but also how intervention programs may be tailored to fit the specific characteristics of these individuals. Notably, a behavioral meta-analysis found evidence in favor of impaired decision-making under risk (e.g., substance users enrolling more in risky decision-making; Chen et al., 2020), whereas another did not find such results (Gowin et al., 2018). Regarding neurodivergent individuals, extensive literature suggests altered decision-making processes in adults and adolescents (for a comprehensive review, see Dekkers et al., 2022; Mowinckel et al., 2015).

Even though the existing literature is scarce and often heterogeneous, both risk and ambiguity processing have been related to increased frontal negativities, thus recruiting more cognitive resources and signaling conflict monitoring and cognitive control. Nevertheless, the heterogeneity found in this literature calls for more studies to assess risk and ambiguity processing in both descriptive- and experience-based paradigms. One common limitation of the ERP literature relies on the analysis of the ERPs that are typically employed. In fact, all reviewed studies rely on averaged ERPs to compare manipulations of risk and ambiguity. This approach loses two crucial sources of variability present in EEG data: time, as most studies measure features of interest in predefined time-windows; and trial-by-trial variability, as studies rely on averaged ERPs. Although signal-to-noise ratio is problematic for reliable ERP measurements, recent tools, such as LIMO (Pernet et al., 2011), offer linear modeling tools that model ERP responses in a hierarchical fashion, thus not losing either temporal or trial-by-trial variability. Future studies should rely on such modelling techniques to study the temporal dynamics of brain responses to risk and ambiguity.

The present review sheds light on the methodological consequences of ill-defined risk, ambiguity, and uncertainty concepts, identifies the most implemented and suitable tasks in decision-making research, and also enlightens the neural markers of risk and ambiguity processing (e.g., N2, N400, P3). Some concluding remarks emerge from the present review. First, the ill-definition of uncertainty, risk, and ambiguity concepts seems to lead to distinct experimental approaches further impairing comparability across studies. Second, existing experimental approaches, stemming from distinct conceptual bases to uncertainty, encompass distinct confounding variables that lead to multiple interpretations of the observed variations in brain activity. Examples of this are tasks with distinct difficulty levels, no experimental control of expected value and/or utility, and no parametric variations of risk and or ambiguity. Third, there is a need for experimental manipulations that parametrically and independently vary risk and ambiguity while controlling for possible confounds, such as task difficulty level, expected value, and expected utility. By providing a common taxonomy for the uncertainty, risk, and ambiguity concepts, the present review represents a first step to (and encourages) the development of such experimental approaches to shed further light on the neural mechanisms underlying decision-making under uncertainty.

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