Title
Impulsivity Shapes Metacognitive Accuracy in Domain-General Ways

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 48(0)

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Publication Date
2026

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Abstract

Although inaccurate metacognition impairs decision-making, its sources are still debated. Early theories suggest a hierarchical metacognitive structure where a domain-general system shapes domain-specific metacognitive processes. Recent theory attributes metacognitive inaccuracy to systematic errors in the computation of decision-making confidence. The present study combines these two theories to examine the extent to which general and specific systems affect decision-making confidence, and therefore metacognitive accuracy. The results show evidence for domain-general and domain-specific sources of metacognitive accuracy. Impulsivity has domain-general effects on decision-making confidence and metacognitive accuracy, while the tendency to consider suboptimal choices has domain-specific effects.

Keywords: metacognition; risky decision-making; confidence; mouse-cursor tracking

Introduction

Why do some people excel at making good decisions while others struggle? Metacognition is the ability to evaluate your own thought processes and can improve decision-making when accurate. For example, students with high metacognitive accuracy choose efficient study strategies, resulting in higher academic achievement, and experience better mental health outcomes (Abdelrahman, 2020; Cai et al., 2019; Mwangi et al., 2024; Seow et al., 2021). Hence, research in metacognition is concerned with identifying sources of metacognitive accuracy and determining if these sources affect metacognition across a wide (domain-general) or narrow (domain-specific) range of decision-making contexts. To address this concern, we take inspiration from two theories: hierarchical metacognition (Nelson, 1990) and a recent push for the study of systematic errors in the computation of confidence judgments (Shekhar & Rahnev, 2021).

Metacognitive Hierarchy

Early theory suggests a hierarchical organization of metacognition in which domain-general systems shape domain-specific processes. Domain-general systems involve beliefs people have about their own abilities and behaviors, while domain-specific systems involve the confidence felt for individual decisions that encourage cognitive control or gathering more evidence before committing to a decision (Desender et al., 2018; Seow et al., 2021).

Behavioral and neuroimaging data further support this hierarchy. For example, behavioral data showing that metacognitive accuracy in a perceptual task is related to metacognitive accuracy in a memory task (McCurdy et al., 2013) alludes to a domain-general source of metacognitive accuracy. Neuroimaging studies, however, suggest that perceptual and memorial metacognitive accuracy are guided by distinct brain-region activity. Medial frontal regions support domain-general signals of accuracy and confidence, while anterior PFC activity differs depending on the domain: memory or perception (Morales et al., 2018). The evidence suggesting that relations between metacognitive accuracy for two distinct cognitive tasks are guided by distinct brain-region activity not only supports a hierarchical organization of metacognition but also implies that there are domain-general and domain-specific sources of metacognitive accuracy. Still, the functional influence of these systems on metacognitive accuracy remains poorly understood (Seow et al., 2021).

When considering domain-general influences on metacognitive accuracy, we turn to *impulsivity* and *maladaptive metacognitive beliefs* (Elliott et al., 2023; Leontyev & Yamauchi, 2025; Wells & Cartwright-Hatton, 2004). Impulsivity is often regarded as the tendency to act rash, without “thinking things through", while maladaptive metacognitive beliefs (henceforth “maladaptive beliefs") are characterized by extreme overthinking and excessive worry. In either case, greater impulsivity or maladaptive beliefs may introduce errors in how people evaluate their thoughts, thereby reducing metacognitive accuracy. Indeed, there is evidence that greater impulsivity is associated with substance use disorders and increases in maladaptive beliefs in clinical samples (Mansueto et al., 2024; Turiaco et al., 2022) and cognitive awareness in non-clinical samples (Ermis & Icellioglu, 2016). Furthermore, these errors likely operate at the domain-general level because they are concerned with general behavior and abilities rather than confidence for specific decisions. Hence, the present study measures self-reported impulsivity and maladaptive beliefs to examine how increases in either construct affect metacognitive accuracy in three domains.

Metacognitive Accuracy

In a laboratory setting, metacognitive accuracy is assessed by the trial-by-trial agreement between one’s confidence in making the correct choice and their observed accuracy. Signal detection theory quantifies this trial-by-trial agreement using

In G. Boleda, I. Dautriche, M. Maldonado, C. Saldana and T. Torrent (Eds.), *Proceedings of the 48th Annual Conference of the Cognitive Science Society*

Meta-*d’* - an index of how well confidence ratings distinguish correct from incorrect responses. Higher values of Meta-*d’* indicate that an individuals confidence judgments can reliably differentiate when they have likely made a correct or incorrect choice. Thus, people who are more confident when correct (and less confident when incorrect) demonstrate greater metacognitive accuracy (Fleming & Lau, 2014; Maniscalco & Lau, 2012). While both traditional *d’* and Meta-*d’* rely on *Hit Rates* and *False Alarm Rates*, Meta-*d’* differs in that *Hits* and *False Alarms* are defined as correct and incorrect choices made with high confidence (Table 1). Thus, we estimate Meta-*d’* for tasks with correct or incorrect choices.

Table 1: Meta-*d’* Matrix

	High Confidence	Low Confidence
Correct	Hit	Miss
Incorrect	False Alarm	Correct Rejection

However, similar to accuracy or response time, Meta-*d’* describes the outcome of a decision-making process, not the process itself. To better understand sources of metacognitive accuracy, we consider the extent to which these sources operate through specific decision-making processes. Mouse-cursor tracking offers a novel way to observe decision-making processes unfold in real-time given its ties to evidence accumulation, response competition, and changes-of-mind (Freeman, 2018; Leontyev & Yamauchi, 2019; Song & Nakayama, 2009; Spivey, 2008; Stone et al., 2022).

Mouse-cursor Tracking

Mouse-cursor tracking quantifies how choice preferences are formed based on how people move their cursors in computerized decision-making tasks (Wulff et al., 2025). For example, Area Under Curve (AUC) quantifies how much preference was given to a *non-chosen* option (“Left" in Figure 1) based on how much the cursor deviates *away* from the ultimately chosen option. In the present study, we use AUC measures to investigate whether preferences for the choices people *do not* commit to later affect their confidence judgment and metacognitive accuracy (Yamauchi et al., 2019; Yamauchi & Xiao, 2018).

Experiment

The present study consisted of two phases: a cognitive task phase and a self-report phase (Figure 2). During the cognitive task phase, participants completed a Risky Decision-making Task (RiskyDM; Verbruggen et al., 2017), an Attention Network Task (ANT; Fan et al., 2009; Yamauchi and Wang, 2025), and a Random Dot Kinematogram Task (RDK; (Zehetleitner & Rausch, 2013)). Across all cognitive task trials, participants chose one of two options. In the RiskyDM, participants subjectively chose the best of two gambles. In the ANT and RDK, participants were instructed to choose the objectively correct choice. During the choice-phase of

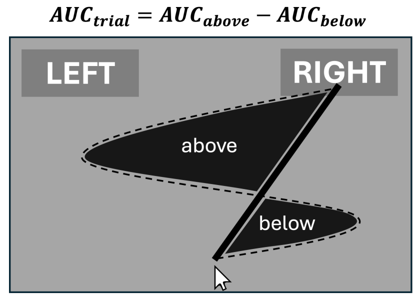

Figure 1: Measuring AUC: solid lines represents ideal trajectories (the shortest straight line drawn from the cursor’s starting point to the chosen option), dashed lines represent observed trajectories.

each task, we recorded mouse-cursor coordinates to obtain AUC values for non-chosen *suboptimal* choices (i.e., “risky" or “incorrect" choices). Here, these AUC values represent how much participants tended to consider a risky or incorrect choice before committing to the safer or correct choice. After every choice, participants reported their confidence in having made the best (or correct) choice, on a scale of “Not Confident" to “Very Confident". In the RiskyDM we use“best", instead of “correct choice" to account for the task’s subjective nature. In the self-report phase, participants completed the Urgency-Premeditation-Perseverance-Sensation Seeking-Positive Urgency Impulsive Behavior Scale (UPPS-P; Lynam et al., 2006) and the Metacognitions Questionnaire (MCQ-30; Wells and Cartwright-Hatton, 2004). We predict that higher self-reported impulsivity and maladaptive beliefs will negatively affect metacognitive accuracy across all domains. Furthermore, we expect these effects to be partially driven by preferences for non-chosen *suboptimal* choices, suggesting domain-general sources of metacognitive accuracy affect people’s ability to confidently avoid suboptimal choices.

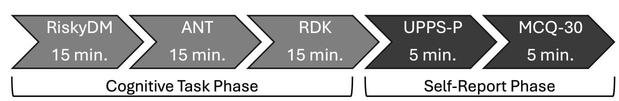

Figure 2: Study overview and approximate completion times.

Method

Participants Participants were recruited from an undergraduate Introduction to Psychology course (N = 99). After excluding participants who made zero risky choices (N = 1) or had a mean confidence of zero for any risky choices they did make (N = 1), we analyzed a final sample of 97 participants (33 = Male, M_{age} = 18.83, SD = 0.83, $Range$ = 18 − 22).

Apparatus All cognitive tasks and questionnaires were administered in PsychoPy v2023.2.3 using a 64-bit Windows 11 computer with an Intzel(R) Core(TM) i9-9900 CPU with a

60Hz refresh rate. Mouse-tracking trajectories were captured using an HP USB 2-Button Optical Scroll Mouse where the mouse pointer speed" was set to 10/20 and “enhanced pointer precision" activated. All analyses were completed using R v2024.09.0+375. The“mousetrap” (Kieslich & Henninger, 2017) and “mediation” (Tingley et al., 2014) packages were used to analyze mouse-cursor data and conduct mediation analyses. A percentile-based nonparametric bootstrap with 5000 simulations (per mediation) was used to calculate the confidence intervals for the indirect effects. Indirect effects were considered significant if the confidence intervals did not contain zero.

Risky Decision-Making To investigate metacognitive accuracy for subjective decisions, we used a Risky Decision-Making task in which participants were shown a pair of green pie charts on each trial, some of which were partially shaded red, against a gray background. Each pie chart was associated with a point value, with the probability of winning those points proportional to the green-shaded area and the probability of winning zero points proportional to the red-shaded area (Figure 3).

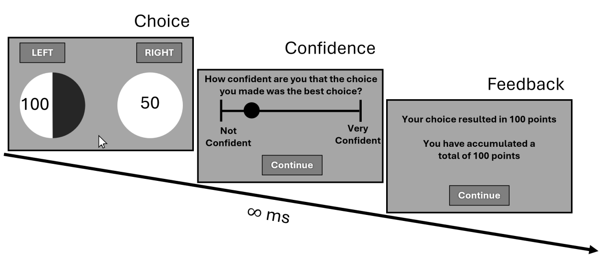

Figure 3: RiskyDM example trial. The left pie chart represents a 50% chance of winning 100 points while the right represents a 100% chance of winning 50 points.

Point values and probabilities were chosen to yield expected values of 20 or 50 points (Verbruggen et al., 2017); see Table 2). Participants were shown all *unique* point-value pairs, such that they never chose between two pie charts with the same point value. This resulted in 90 trials (45 unique pairs presented twice and counterbalanced), among which 66 were classified as *risky*, meaning one option offered more points at a lower probability of success compared to the other. Only risky trials were analyzed. The pie charts remained visible until participants made their choice, after which they had unlimited time to report their confidence in having made the best choice before reviewing the outcome and beginning the next trial.

Attention Network Task We used a mouse-tracking version of the Attention Network Task (ANT; Fan et al., 2009; Rompilla et al., 2026; Yamauchi and Wang, 2025; see Figure 4A) to examine metacognition in contexts where accuracy requires more attentional control. Here, a 5-arrow sequence (e.g. “> > < > >”) is presented within a rectangular box

Table 2: RiskyDM Probabilities

Win Prob.	EV 20	EV 50
1.00	20	50
0.66	30	75
0.50	40	100
0.33	60	150
0.25	80	200

left or right of a fixation cross. Participants are instructed to quickly and accurately identify the direction of the center arrow by clicking the corresponding “LEFT" or “RIGHT" button (Rompilla et al., 2026; Yamauchi & Wang, 2025); see Figure 4A).

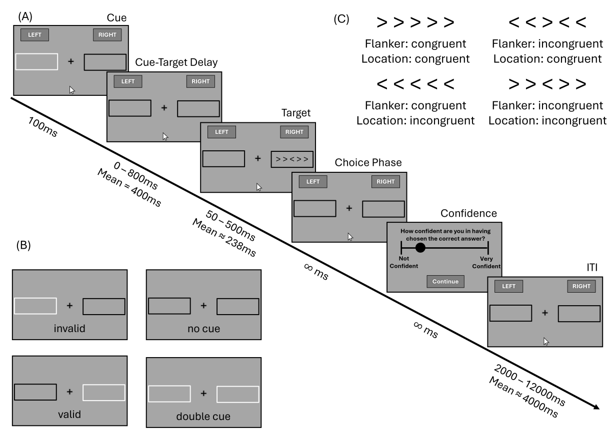

Figure 4: (A) Six phases of an ANT trial. (B) Cues. (C) Flanker and Location classifications depending on the direction of center arrow. Here, location congruence is relative to the arrows presented right of fixation.

Participants first saw two black rectangular boxes, one on each side of a constant black fixation cross, against a gray background. These boxes sometimes flashed white to serve as cues that may or may not have helped classify the center arrow. All cues were presented for 100ms after which there was a variable cue-to-target delay(0, 400, 800ms) where each delay had eight trials for each cue type (four where the correct answer is “LEFT" and four where the correct answer is “RIGHT"; Figure 4B). This resulted in 32 trials per cue-to-target delay and a total of 96 trials for the task. Target arrows are then presented for a variable duration (50, 150, 250, 500ms). Each duration of arrow presentation occurred 24 times, dispersed randomly throughout all trials. Afterwards participants had unlimited time to indicate the direction of the center arrow and report their confidence in having made the correct choice before experiencing a variable inter-trial interval (2000 - 12000ms).

Random Dot Kinematogram To investigate perceptual metacognitive accuracy, we used a mouse-tracking version the Random Dot Kinematogram (RDK). Participants were

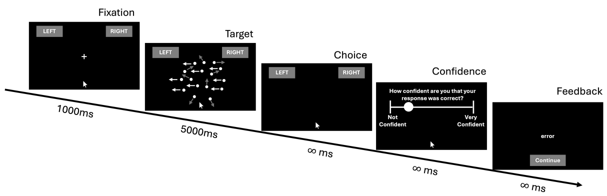

Figure 5: RDK example trial with leftward coherent motion.

first presented with a 1000ms white fixation cross against a black background. After which, white dots appeared for 5000ms within a centered black circular aperture. These dots traveled in straight lines but in random directions across the aperture. A small subset (0.7%, 1.3%, 2.7%, 5.3%, 10.7%, 21.3%, or 42.7%) of the total dots moved horizontally (left or right) across the aperture. This horizontal movement is the trial's "coherent motion". Each level of coherent motion was presented 10 times (five with leftward and five with rightward coherent motion) for a total of 70 trials. Participants indicated the direction of coherent motion by clicking the "LEFT" or "RIGHT" buttons. Afterwards, they would have unlimited time to report their confidence in having chosen the correct answer. Unlike the ANT, participants received feedback on the accuracy of their choices in the RDK. If they chose incorrectly, the word "error" appeared on their screen (Figure 5) before the start of the next fixation. If they chose correctly, no words would appear before the next fixation.

Mouse-cursor Tracking - Cognitive Tasks For each trial in the cognitive task phase, mouse-cursor coordinates were recorded every frame (~16.67ms) in PsychoPy "height" units, where the full screen height is 1.0, spanning -0.5 to 0.5, and the width spanning -0.8 to 0.8. Every trial, cursors were positioned at the bottom-center of the screen ([0.0, -0.3]) and participants clicked on "LEFT" ([-0.6, 0.4]) or "RIGHT" ([0.6, 0.4]) buttons to make their choice. These practices ensure that participants' start and end positions are comparable for future analysis (Wulff et al., 2025). Across all tasks, we excluded individual trials with response times greater than 15 seconds and anomalous trajectories greater than three standard deviations from prototypes recognized by the mousetrap package.

Across all tasks, we calculated AUC values (Figure 1) that represent preference, but not commitment, for "risky" or "incorrect" choices. Doing so allows us to examine how consideration for these suboptimal choices relates to errors in confidence judgments that affect metacognitive accuracy. Thus, Risky Choice AUC quantifies how much participants tended towards the risky option, before committing to the safer option. Similarly, ANT Incorrect AUC and RDK Incorrect AUC (3 quantify how much participants tended towards the incorrect choice before committing to the correct choice (Figure 1). We predict that people who deviate more towards "risky" and "incorrect" choices will demonstrate lower metacognitive accuracy in part because excessive consideration for these suboptimal choices may increase confidence later assigned to "risky" and "incorrect" choices (i.e., increase false alarms; Table 1).

Self-Report Participants completed the UPPS-P and the MCQ-30 in the self-report phase. The **UPPS-P** captures five dimensions of trait-like impulsivity (Negative Urgency, Lack of Premeditation, Lack of Perseverance, Sensation Seeking, Positive Urgency). After reverse scoring, higher scores indicate greater impulsive tendencies. The **MCQ-30** captures five dimensions of metacognitive beliefs (Cognitive Self-Consciousness, Cognitive Confidence, Positive Beliefs about Worry, Negative Beliefs about Worry, and Need to Control Thoughts). Higher scores indicate greater maladaptive beliefs about one's own cognition. Thus, we hypothesize that higher scores in both questionnaires would predict a decrease in metacognitive accuracy across all tasks.

Design

We calculated Meta-*d'* using an R-adapted version of the original MATLAB code (Rausch et al., 2015). Though Meta-*d'* cannot be estimated for the RiskyDM due to the subjective nature of choosing between gambles, we examine the mean confidence participants have in their risky choices. This substitute is informed by research showing that people who are more confident in their risky choices tend to take excessive risks (Hoven et al., 2023). Mediation analyses informed the extent to which domain-general impulsivity and maladaptive beliefs promote excessive consideration for suboptimal choices, thus impairing confidence judgments and metacognitive accuracy.

Results

Domain-general Effects on Metacognition

Across all tasks, maladaptive beliefs (Total MCQ-30 scores) were not correlated with metacognitive accuracy. In contrast, impulsivity (Total UPPS-P scores) correlated with metacognitive accuracy in the RiskyDM, ANT, and RDK (Table 3). Impulsivity also correlated with confidence assigned to risky choices in the RiskyDM, and with confidence assigned to incorrect choices made in the ANT and marginally in the RDK, suggesting that reductions in Meta-*d'* were driven by increases in false alarms (Table 1). Recall that metacognitive accuracy in the RiskyDM is not quantified with Meta-*d'* because there is no objectively correct choice to make on a given risk trial. One could consider classifying whether participants chose the option with the highest utility as the rationally correct choice (Navarro-Martinez et al., 2018). Yet, the RiskyDM contains trials in which both options have the same expected utility but differ in probability. Hence "risky" choices were classified as trials in which participants chose the pie chart with the lowest probability of success or highest payoff. If, however, we consider "risky" choices as "incorrect" choices, then high confidence in one's risky choices may serve as a proxy for Meta-*d'* because one would be highly confident in a more uncertain outcome. This remains consistent with what we observed in ANT and RDK because it implies

Table 3: Correlations

Variable	1	2	3	4	5	6	7	8	9	10
1. Impulsivity (Total UPPS-P)	–									
2. Maladaptive Meta-beliefs (Total MCQ-30)	.07	–								
3. Risky Choice AUC	.22*	.00	–							
4. Risky Choice Confidence	.27**	−.03	.26*	–						
5. ANT Incorrect AUC	.13	−.11	.55***	.12	–					
6. ANT Incorrect Confidence	.21*	−.05	.24*	.36***	.28**	–				
7. ANT Meta-*d*'	−.25*	−.04	−.22*	.00	−.30**	−.58***	–			
8. RDK Incorrect AUC	.09	−.12	.33**	−.01	.27**	.16	−.11	–		
9. RDK Incorrect Confidence	$.19^{M}$	−.12	.15	.38***	.24*	.52***	−.13	.16	–	
10. RDK Meta-*d*'	−.23*	−.05	.10	−.03	.06	.02	.01	.16	−.03	–

Note. N = 98. AUC = Area Under the Curve; ANT = Attention Network Task; RDK = Random Dot Kinematogram.
^{M} $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

that highly confident risky choices yield more "false alarms" thereby reducing RiskyDM metacognitive accuracy. Interestingly, confidence for risky and incorrect choices (in both ANT and RDK) positively correlate with each other (Table 3) suggesting some domain-general general source of confidence judgments consistent with brain imaging research (Rouault et al., 2023). However, metacognitive accuracy between the ANT and RDK did not correlate with each other (Table 3). Although we suspect this is partially due to differences in task difficulty, we argue that impulsivity might tailor general confidence in domain-specific ways. Thus, impulsivity is likely involved in a domain-general source of metacognitive accuracy as it negatively relates to metacognitive accuracy across all tasks. Specifically, this domain-general source may concern how confidence is assigned to risky and incorrect (suboptimal) choices, rather than risk-averse and correct (optimal) choices.

Suboptimal Choice Preference Affects Metacognitive Accuracy

To further probe how impulsivity affects metacognitive accuracy, we used mouse-cursor tracking to examine the extent to which preference, but not commitment, for risky choices in the RiskyDM and incorrect choices in the ANT and RDK relate to confidence later assigned to those choices. In the ANT and RDK, increases in impulsivity did not correlate with mouse-cursor deviations toward the non-chosen incorrect choice. This suggests that impulsivity does *not* decrease metacognitive accuracy for objective decisions by increasing the consideration given to incorrect choices (Figure 6B and C). In contrast, impulsivity scores correlated with greater mouse-cursor deviations toward the risky option before participants committed to the safer choice. This suggests that increases in impulsivity may affect our preference for risky options, even in times when we do not commit to them. This preference for non-chosen risky options is later correlated with confidence assigned to risky choices (Figure 6A), suggesting that confidence in risky choices is informed (and increased) by the preferences felt for the risky choices we did not commit to.

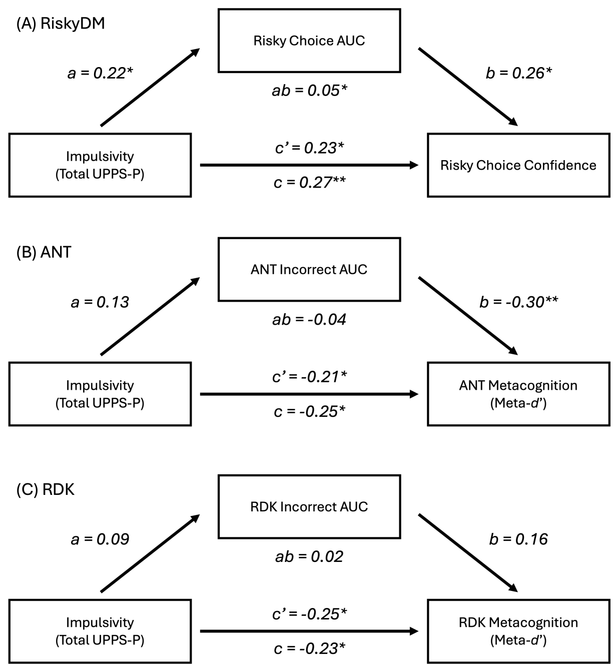

Figure 6: Mediations where suboptimal choice tendency serves to explain how impulsivity affects metacognitive accuracy. Only (A) RiskyDM shows significance. Risky Choice AUC = Tendency towards non-chosen risky option. Incorrect AUC = Tendency towards non-chosen incorrect option.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Discussion

Early theories of metacognition proposed a hierarchical organization in which domain-general beliefs about one's own abilities influence domain-specific metacognitive accuracy. Recent theories suggest that errors in the way decision-making confidence is computed are systematic sources of metacognitive accuracy. The present study combines these two theories to examine the extent to which impulsivity and maladaptive beliefs affect metacognitive accuracy across risky, attention, and perceptual decision-making tasks.

Maladaptive beliefs (Total MCQ-30) did not correlate with any metacognitive accuracy measure. One explanation for this is that people with poor metacognition likely misrepresent their own abilities. Therefore, low MCQ-30 scores could consist of people who honestly report having good metacognition and people who overestimate their metacognitive abilities.

In contrast, there is evidence that impulsivity has a domain-general effect on metacognitive accuracy. This effect may be driven by increasing confidence for risky and incorrect choices, while leaving confidence for safer and correct choices in tact. Additionally, impulsivity may increase our preference or tendency to consider risky choices, even for decisions where we do not commit to the risky choice. This consideration for non-chosen options seems to influence the confidence judgment, and therefore metacognitive accuracy, of future decisions, particularly for risky decisions. Future research on the sources of metacognitive accuracy would benefit from distinguishing the circumstances in which confidence for "correct" choices is computed differently than confidence for "incorrect" choices. Doing so provides a better understanding of how errors involved in the computation of confidence judgments affect metacognitive accuracy across decision-making contexts.

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