Facets of Metacognition and Their Impact on Associative Learning

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Competing Interests

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics and Consent

The study was reviewed and approved by the Comité de Ética Institucional en Investigación at the Universidad del Desarrollo. All participants provided their written informed consent to participate in the study.

Author Contributions

MB and GR contributed to the study concept and design. MB collected and analysed the data. JS provided feedback throughout the project. All authors wrote the manuscript and approved it for submission.

Data and Code Availability

The datasets and code used in this study can be found at https://osf.io/kqsr7/

Abstract

Metacognition refers to the monitoring and control of one's own cognitive processes. The positive impact of metacognition on learning and academic performance has been extensively studied. However, metacognition is not a unitary construct; it is composed of interrelated facets, such as knowledge about one's cognitive processes and products (metacognitive knowledge), the real-time monitoring of these processes (metacognitive experiences), and the ability to regulate them (metacognitive skills). Few studies have explored how these three components and their interrelations relate to learning. To investigate this issue, we assessed 73 undergraduate students using two self-report questionnaires and two behavioural tasks designed to evaluate facets of metacognition and associative learning. We also collected data on participants' academic performance. The results show that associative learning is primarily related to metacognitive experiences, while academic performance is associated with all facets. Additionally, we found evidence of how the facets of metacognition jointly relate to learning. First, mediation analysis revealed that the impact of metacognitive knowledge on learning is fully mediated by metacognitive experiences. Second, moderation analysis demonstrated that the use of metacognitive skills strengthens the relationship between metacognitive experiences and learning. Our findings underscore the differential roles of metacognition facets in associative learning and academic performance.

Keywords: metacognitive knowledge; metacognitive experiences; metacognitive skills; associative learning; academic performance.

Introduction

Metacognition, defined as the monitoring and regulation of one's own cognitive processes and products (Flavell, 1976), is recognized as a higher-order psychological process integral to numerous cognitive functions, including problem-solving, decision-making, and self-regulation. Conceptual models of metacognition typically identify three main facets: knowledge about one's own cognitive processes, ongoing monitoring, and regulation of these processes (Dunlosky & Metcalfe, 2009; Efklides, 2008). While early work often treated metacognition as a general, unitary capacity (e.g., Schraw & Dennison, 1994), more recent research has emphasized its multifaceted nature. Contemporary models distinguish between metacognitive knowledge, monitoring experiences, and control processes as functionally distinct but interrelated components (Efklides, 2008, 2014; Nelson & Narens, 1990; Dinsmore et al., 2008). Due to its impact on learning and academic achievement, metacognition has become a prominent focus within educational and cognitive psychological research (Norman et al., 2019), with growing interest in understanding how each of these components contributes to the learning process (Fleur et al., 2021). Previous research indicates that individuals with better metacognitive ability demonstrate better academic performance and, overall, tend to be more effective learners than their peers (Clerc & Clément, 2016; Wang et al., 1990).

Building on this theoretical distinction, it is essential to examine how each facet contributes to learning in practice. A significant body of theoretical and empirical research supports the role of metacognition in both simple learning tasks, such as associative learning (Cf., Hainguerlot et al., 2018), and more complex learning tasks involving critical thinking or problem-solving skills (Greiff et al., 2014; Magno, 2010). However, existing studies often treat metacognition as a one-dimensional construct or rely on a single task to assess it, overlooking its multifaceted nature (Dinsmore et al., 2008; Tarricone, 2011; van Loon & Roebers, 2024). Consequently, despite the established link between metacognition and learning, it remains unclear how the individual facets of metacognition and their interactions impact learning outcomes, highlighting a need for further investigation. Despite this recognition, there is not enough research aimed at addressing these questions. Empirical studies exploring how these facets relate to each other and how they interact with learning-related processes are limited (Jacobse & Harskamp, 2012; Jang et al., 2020; Zepeda & Nokes-Malach, 2023), with the main sources that document this issue being meta-analyses comparing research using different instruments to study the different facets of metacognition in relation to learning and academic performance (Dent & Koenka, 2016; Muncer et al., 2022; Ohtani & Hisasaka, 2018). This is problematic given evidence suggesting that these facets are not always interrelated (Lehmann et al., 2022; Sarac & Karakelle, 2012; Terneusen et al., 2024) and that not all metacognitive activities are beneficial to the individual (Desender & Sasanguie, 2021; Norman, 2020).

Based on the above, the main goal of this study is to explore the role of the facets of metacognition and their interactions in both simple and complex learning-related tasks. However, before examining their impact on learning, it is important to first understand each metacognitive facet individually. By doing so, we can better elucidate how each facet contributes to the learning process and their potential interrelationships.

The Facets of Metacognition

Metacognition encompasses two main functions: *monitoring*, which is the awareness of the use of one's own cognitive skills, and *control*, which is the ability to regulate these skills (Nelson & Narens, 1990). Conceptual models decompose these functions into three interrelated facets (Dunlosky & Metcalfe, 2009; Efklides, 2008): *metacognitive knowledge* (MK), *metacognitive experiences* (ME), and *metacognitive skills* (MS).

Metacognitive Knowledge (MK) is the offline aspect of metacognitive monitoring and refers to the declarative knowledge that a learner holds about their abilities, the tasks they engage in, and the strategies they use (Flavell, 1979). This knowledge is shaped by feedback derived from individual experiences of self-monitoring (Efklides, 2008) and also through cultural learning and social interactions (Heyes et al., 2020). MK is studied through self-report questionnaires which ask students to recall and reflect on their use of metacognitive learning strategies (Craig et al., 2020; Dent & Koenka, 2016). Due to the ease of application of these instruments, MK has been extensively researched in natural learning environments, especially by educational psychologists (Harrison & Vallin, 2018; Veenman, 2011). On the other hand, Metacognitive Experiences (ME) are the online aspect of metacognitive monitoring and involve the feelings and judgments that emerge while a learner is actively performing and processing a task (Flavell, 1979). While metacognitive knowledge involves reflection on past cognition, ME entails real-time monitoring of cognition (Dunlosky & Metcalfe, 2009). Experiences such as the feeling of knowing, judgments of learning, tip-of-the-tongue states, and confidence judgments are examples of this facet (Fleming & Lau, 2014; Jang et al., 2020; Norman et al., 2016; Schwartz, 2006). Metacognitive experiences are influenced by both emotional (Culot et al., 2021; Reyes et al., 2015) and social factors (Gajdos et al., 2019), as well as by metacognitive knowledge itself (Efklides, 2008; Lehmann et al., 2022). ME have been studied commonly by cognitive psychologists in experimental settings, using online methods such as behavioural tasks designed to prompt students to reflect on their ongoing mental activity during the task (Lai, 2011). Finally, Metacognitive Skills (MS) refer to a learner's abilities to exert deliberate metacognitive control over their cognitive processes and to use cognitive and metacognitive strategies in pursuit of a learning goal (Efklides, 2008; Tarricone, 2011). These skills are often associated with executive functioning (Fleur et al., 2021; Marulis et al., 2020; Roebers, 2017), though the exact nature of their relationship is still debated (Bryce et al., 2015). The deployment of MS depends on metacognitive monitoring, as MK provides strategy and task-specific knowledge, and ME provides the input that triggers their use (Chen & Son, 2024; Efklides, 2008, 2009; Metcalfe, 2009). MS has been the subject of research in both educational and cognitive psychology, often using online methods such as observation protocols and behavioural tasks to analyse the use of strategies in real-time (Pintrich et al., 2000; Undorf et al., 2021).

In the present study, we adopt an integrative approach that explicitly combines both trait-based and task-specific perspectives on metacognition, articulated within a theoretical framework primarily based on Efklides (2008, 2014). We conceptualize metacognitive monitoring as encompassing both offline components —assessed through selected subscales of the Awareness of Independent Learning Inventory (AILI), specifically targeting participants' awareness of strategies and self-evaluation of learning— and online components, assessed via retrospective confidence judgments, reflecting real-time, task-specific monitoring processes during a memory recognition task. This distinction allows us to capture general beliefs and knowledge (offline monitoring) as well as moment-to-moment self-assessment of performance (online monitoring), both theorized to interact dynamically in guiding behavior. In contrast, metacognitive skills (MS) are defined strictly as regulation strategies dependent on prior monitoring, conceptualizing them as control processes rather than monitoring processes. This theoretical distinction is crucial for understanding how each component distinctly contributes to the learning process and is intended to bridge conceptual insights from educational and cognitive psychology research traditions (Efklides, 2008, 2014; Fleming & Lau, 2014; Maniscalco & Lau, 2012).

How do Metacognition Facets Relate to the Learning Process?

Literature agrees on the association between metacognition and learning. Indeed, current research covers a wide range of phenomena related to the learning process, both simple, such as associative learning, and complex, such as academic performance. Associative learning represents a simple cognitive process, involving the ability to learn the relationship between stimuli, and is directly influenced by metacognitive experiences, such as judgements of learning or confidence judgements (Dunlosky et al., 2003; Hainguerlot et al., 2018). In contrast, academic performance reflects a more complex outcome, encompassing the deployment of a wide array of cognitive, metacognitive, and motivational processes over time, and has been associated with both aspects of metacognitive monitoring and metacognitive control (Dent & Koenka, 2016; Ohtani & Hisasaka, 2018).

Regarding the role of metacognition facets in the learning process, the effect is nuanced by lack of knowledge and several methodological issues. For instance, a meta-analysis by Ohtani and Hisasaka (2018) found that the type of instrument used to measure metacognition acts as a moderator in the relationship between metacognitive monitoring and academic performance. Specifically, using online methods revealed larger effect sizes than using offline methods. This pattern was consistent even after controlling for participants' intelligence. These findings are supported by other meta-analyses and studies (Dent & Koenka, 2016; Muncer et al., 2021; Veenman & van Cleef, 2019). Although not directly tested, it is plausible that these differences come from the specific metacognition facets being assessed -metacognitive knowledge for offline measures and metacognitive experiences for online measures-, rather than the methodology itself, hinting that different facets could play distinct roles in the learning process.

Current research on the interrelation between metacognitive monitoring and control often relies on experimental paradigms such as "opting out" and "asking for help," where participants are given the opportunity to engage in these strategies during task performance (Chen & Son, 2024; Sidi & Ackerman, 2024; Undorf et al., 2021). In line with this literature, the tasks and paradigms used in the present study were selected based on established approaches to metacognitive assessment. Confidence-based recognition tasks are widely used to evaluate metacognitive sensitivity, as they allow researchers to quantify how well confidence ratings discriminate between correct and incorrect responses, independent of task performance (Fleming & Lau, 2014; Maniscalco & Lau, 2012). This approach, grounded in signal detection theory, is particularly well-suited to recognition-based learning contexts like the one employed in our study. Additionally, we incorporated two paradigms that are widely recognized as ecologically valid indicators of metacognitive control: "opting out" and "asking for help." The opt-out paradigm allows participants to decline a difficult trial when uncertain, opting instead for a smaller but guaranteed outcome (Watson, 2024). Empirical studies further support this paradigm as a robust indicator of metacognitive control across species, including dolphins, rhesus monkeys, and even honeybees (Schwartz et al., 2023; Smith et al., 1995; Perry & Barron, 2013). In parallel, the "ask for help" paradigm captures the strategic use of assistance in response to internal uncertainty. For example, Goupil et al. (2016) showed that 20-month-old infants selectively request help when they recognize that they lack sufficient knowledge to make a confident decision, demonstrating an early-emerging form of adaptive control. Together, these paradigms provide a comprehensive and developmentally grounded framework for assessing how individuals monitor and regulate their cognition in learning contexts.

Evidence points out that the implementation of these strategies—particularly help-seeking—depends on various cognitive and affective factors, and that uncertainty monitoring and judgments of solvability play a key role in deciding whether or not to engage with them (Law et al., 2022). Specifically, withholding an answer or asking for help requires self- and task-monitoring in order to assess the effectiveness of one's own cognitive resources based on expected outcomes, maximising performance, and reducing resource costs (Goldsmith, 2016). In summary, the facets of metacognition seem to play distinct roles during the learning process. Theoretical models suggest that both metacognitive knowledge (MK) and experiences (ME) operate by monitoring the use of metacognitive strategies during the performance of a certain cognitive task (Terneusen et al., 2024). The deployment of these two facets would not occur in parallel, but rather there is evidence pointing to a sequential process, with MK informing ME, regarding past experiences and known criteria against which to compare current performance (Jang et al., 2020; Lehmann et al., 2022). In turn, metacognitive skills (MS) are theorised to operate after metacognitive monitoring, once it informs and elicits the use of the various strategies required to complete the task at hand. The results obtained in this will inform the MK, which will allow the MK to feed back to the ME and MS in a loop (Efklides, 2014). However, despite the knowledge about the interrelationships of these facets, there is still an insufficient amount of empirical research addressing the role they play in the learning process.

Whereas research has often viewed metacognition as a singular, one-dimensional construct, current research recognizes its multifaceted nature and the need to distinguish between its components. In this study, we aim to address this gap by investigating how the distinct facets of metacognition, that is, MK, ME, and MS, influence learning efficiency. For this, we conducted a within-participant study with university students. Participants completed two self-report questionnaires meant to operationalize their MK and reported their Grade Point Average (GPA) as an index of their academic success. We engaged participants in a first laboratory task where we measured their metacognitive experiences (ME) using retrospective confidence judgments and their metacognitive skills (MS) through an ask-for-help (AFH) procedure. In a second laboratory task, we assessed learning efficiency using an associative recognition paradigm, where participants were shown two-word pairs—one previously studied and one re-paired—and asked to select the pair that had been presented during the study phase. This two-alternative forced choice (2AFC) format allowed for a controlled and objective measure of associative learning. In addition to performance on this task, we also collected participants' GPA to examine how the facets of metacognition operate across different levels of task complexity, from specific memory-based learning to broader academic achievement.

Building on the theoretical frameworks of Efklides (2008, 2014), Dunlosky and Metcalfe (2009), and Nelson and Narens (1990), we propose that the facets of metacognition play distinct but interconnected roles in the learning process. These models conceptualize metacognitive knowledge (MK) as a foundational structure, shaped by prior learning and cultural experiences, which informs real-time metacognitive experiences (ME), such as confidence or judgments of knowing. In turn, ME guides the deployment of metacognitive skills (MS), understood as control mechanisms that optimize task performance. This sequential structure—MK → ME → MS—is supported by empirical work (e.g., Lehmann et al., 2022; Jang et al., 2020; Chen & Son, 2024). Based on this framework, we hypothesize the following: (Hypotheses A) Associative learning will be primarily related to ME, given its reliance on real-time monitoring rather than strategic planning (Hainguerlot et al., 2018); (Hypotheses B) Higher MK will lead to better learning outcomes through its influence on ME, as knowledge structures shape monitoring accuracy (Lehmann et al., 2022; Efklides, 2008); (Hypotheses C) The relationship between MK/ME and learning will be enhanced by MS, which act as regulatory tools triggered by monitoring signals (Efklides, 2009; Undorf et al., 2021).

Whereas traditional approaches have often treated metacognition as a global or undifferentiated construct—typically assessed via broad self-report inventories (e.g., Schraw & Dennison, 1994; Dinsmore et al., 2008)—recent frameworks emphasize the importance of distinguishing between multiple components. These traditional views tend to conceptualize metacognition as a stable trait, overlooking its dynamic, task-dependent, and functionally distinct facets (Fleur et al., 2021; Koriat, 1997). In contrast, our approach builds on recent integrative models (Efklides, 2008, 2014; Nelson & Narens, 1990; Dunlosky & Metcalfe, 2009) that differentiate between metacognitive knowledge, experiences, and skills. This framework allows us to formulate specific hypotheses about how these components interact in the learning process.

Methods

Participants

73 Chilean undergraduate students (63% women) ages 18 through 42 (*M* = 22.2 years, *SD* = 3.6 years) were recruited for the study from several universities in Santiago, Chile, through a non-probability self-selection sampling method. An a priori power analysis was conducted using G*Power v.3.1.9.7 (Faul et al., 2007), assuming a two-tailed correlation test with a small effect size ($r = 0.30$), $\alpha = .05$, and power $(1 - \beta) = 0.80$. The analysis indicated that a minimum sample of $N = 43$ participants was required to detect such an effect. Our final sample of $N = 73$ exceeded this requirement. Inclusion criteria required that all participants had normal or corrected-to-normal vision and were native Spanish speakers. Participants received a compensation of CLP$10,000 (~ USD$11) after completing all tasks.

The ethics committee of Universidad del Desarrollo approved the study. All participants gave written informed consent to participate in the study.

Procedure

Undergraduate students were invited to participate through posters and flyers distributed across several universities. The study consisted of two sessions scheduled approximately one week apart (*M* = 7.8 days). The first session was conducted online, where participants were asked to complete two self-report questionnaires designed to assess their metacognitive knowledge and collect information about their educational background. Participants accessed the questionnaires through a Google Forms link sent via email by a research assistant. In the second session, participants were invited to a laboratory, where they performed two behavioural tasks: a metacognition task and an associative learning task. Both tasks were coded in Psychopy v2022.2.1 (Peirce et al., 2019) and completed on a laptop in a quiet, dimly lit room. The order of the questionnaires and tasks was counterbalanced across participants to control for order effects.

Materials and Measurements

Metacognitive Knowledge (MK). For the evaluation of participants' knowledge and beliefs about their monitoring and self-regulation strategies, we used the Awareness of Independent Learning Inventory (AILI). This component corresponds to what Efklides (2008, 2014) conceptualizes as metacognitive experiences. The AILI was designed for higher education students and evaluates their metacognitive knowledge over a broad range of topics relevant for learning and studying (Meijer et al., 2013). While other questionnaires are based on two-factor models of metacognition, the AILI is based on a three-factor model that comprises knowledge and beliefs about one’s own metacognitive knowledge, metacognitive responsiveness (i.e., experiences), and metacognitive regulation (i.e, skills). These components are evaluated through 45 items with Likert-type responses ranging from 1 (*Absolutely false*) to 7 (*Absolutely true*), and we utilized the Spanish-translated version by Pérez-Acuña et al. (2020). Reliability analyses showed good internal reliability for the AILI (Cronbach’s α = .832) and acceptable reliability for its subscales (Cronbach’s α = 0.618, 0.639, and 0.663, respectively). Metacognitive knowledge scores were calculated based on the AILI total score as well as its three subscales: metacognitive knowledge, metacognitive responsiveness, and metacognitive regulation. In this study, we analyzed both the global score and the subscale scores individually (see Table I), with particular emphasis on those subscales most closely aligned with metacognitive knowledge (e.g., awareness of learning strategies, self-evaluation of performance). This dual approach allowed us to capture a broad measure of metacognitive knowledge while also more precisely isolating the specific knowledge-related components consistent with theoretical models (Efklides, 2008).

Metacognitive Experiences and Skills’ Task (ME & MS). This task combined elements designed by McCurdy et al. (2013) and Undorf et al. (2021) to evaluate metacognitive experiences, through confidence ratings during a memory task, and metacognitive skills, giving participants the option to ask for help to improve their performance in said task. The main memory task consisted of four blocks, each containing 50 trials. The first two blocks included a memorization phase and a test phase, while the last two blocks added a ‘help’ phase (see Fig. 1a). In the memorization phase, participants were shown 50 Spanish words displayed in a 10 x 5 array and asked to memorize as many as possible within 60 seconds. The words were generated from the Spanish lexical database EsPal (Duchon et al., 2013), ranging from four to six letters in length, with one to three syllables, a familiarity rating from 5.0 to 7.0, and had no diacritical marks (e.g., accents, tildes, or umlauts). In the test phase, participants were presented with two words and had to identify which one was present in the studied array. One word was randomly selected from the array, while the other was a distractor generated from the same database under the same criteria. Each distractor was a novel word, not previously presented to participants. After selecting a word, participants rated their confidence in their decision on a discrete scale from 1 (*I chose randomly*) to 5 (*I am sure of my answer*). In the third and fourth blocks, after participants had reported their confidence, they could either submit their response and move on to the next trial or choose to ask for help. If they chose the latter, they were shown a response—allegedly from a previous high-performing participant—for two seconds. They were informed that the help had an 80% chance of being correct, but they were unaware that it was actually randomly generated. After receiving the help, participants were asked to repeat the test phase, selecting a word again and providing a new confidence rating. Importantly, the third and fourth blocks introduced a performance-based scoring system to encourage the strategic use of the help. Participants earned two points for each correct answer but lost two points for each incorrect answer. Additionally, asking for help incurred a one-point penalty. After each trial, participants were informed of their score to motivate strategic decision-making.

Based on this task, we evaluated metacognitive experiences using two metrics grounded in signal detection theory: meta-d’ (Maniscalco & Lau, 2012) and meta-d’/d’ (Fleming & Lau, 2014). Judgments in decision-making can be divided into first-order and second-order levels. First-order judgments refer to task performance—in this case, discriminating between studied and non-studied words—while second-order judgments involve evaluating one’s own first-order decisions through confidence ratings. Meta-d’ quantifies metacognitive sensitivity, that is, how well confidence ratings discriminate between correct and incorrect responses. Meta-d’/d’, or metacognitive efficiency, expresses this sensitivity relative to the individual's first-order task performance (d’). In summary, we distinguish between first-order and second-order performance. First-order judgments refer to participants' primary task performance—deciding whether each item was previously studied or not. Second-order judgments involve participants' confidence ratings about their first-order decisions and are used to assess metacognitive monitoring.

Thus, high metacognitive sensitivity means an individual is confident when correct and unconfident when incorrect, indicating an ability to monitor their own performance accurately. Meta-d’/d’ measures metacognitive efficiency, that is metacognitive sensitivity adjusted for individual differences in first-order performance (d’). This results in a purer measure of metacognitive ability that accounts for confidence-related changes based on individual performance. For these calculations, we employed Matt Craddock's R implementation of Maniscalco and Lau’s MATLAB functions (Craddock, 2021). Finally, we measured metacognitive skills through two metrics. First, we evaluated the improvement in performance on the main memory task attributable to the help provided. Specifically, for each trial where the help was selected, we compared accuracy on the decision after and the decision before the help to determine whether participants used the help in order to enhance their performance in the task. Second, we measured the efficiency with which participants used the help provided (AFH efficiency) by dividing the performance improvement by the total number of times each participant requested help.

Associative Learning Task. Associative learning was assessed using an associative recognition task with an experimenter-paced, five-block design. Each block consisted of 24 trials using cue–response word pairs, selected from the EsPal Database (Duchon et al., 2013) according to the same criteria applied in the metacognition task (e.g., word length, familiarity, and absence of diacritical marks). From an initial pool of 45-word pairs, 24 were chosen based on low semantic, phonological, and perceptual similarity to minimizing associative bias (see Supplementary Material 1). None of the words used overlapped with those in the metacognition task. In each trial, participants were shown a cue word at the top of the screen and two possible responses at the bottom: the correct word previously paired with the cue and a distractor. This constitutes a two-alternative forced choice (2AFC) recognition format. The display remained on screen for five seconds, during which participants selected the word they believed had been associated with the cue. They were encouraged to guess if unsure. After the selection, immediate feedback (correct/incorrect) was provided for one second. Although the same 24 cue–response pairs were used across all five blocks, the distractors varied across trials to prevent learning by elimination (see Fig. 1b).

An individual learning score was calculated by determining the area under each participant's accuracy curve across the five blocks. Since participants were responding randomly in the first block, this initial accuracy score (acc_0) was used as a baseline for measuring learning progression across subsequent blocks. We calculated the area under the learning curve by summing the trapezoids defined by changes in accuracy between blocks. The area between ground level (acc = 0) and the baseline (acc_0) was subtracted from all blocks. Finally, the scores were standardised by dividing the area by the maximum achievable area for each participant. Using this approach, the learning score was calculated as follows (1):

$$Learning = \frac{\sum_{i=1}^{n}\left(\frac{acc_i+acc_{i-1}}{2}\right)-n*acc_0}{n(1-acc_0)} \quad (1)$$

where acc_i represents the accuracy on the *i*-th block and *n* is the number of blocks (in this case, $n = 5$). Information regarding learning curves for all participants is provided in Supplementary Material 1.

Sociodemographic questionnaire. We administered a sociodemographic questionnaire, which included questions about participants' education, such as their university affiliation and years of education. Participants were also asked to report their GPA, which they provided on a 1-5 interval scale, with higher scores reflecting better academic performance.

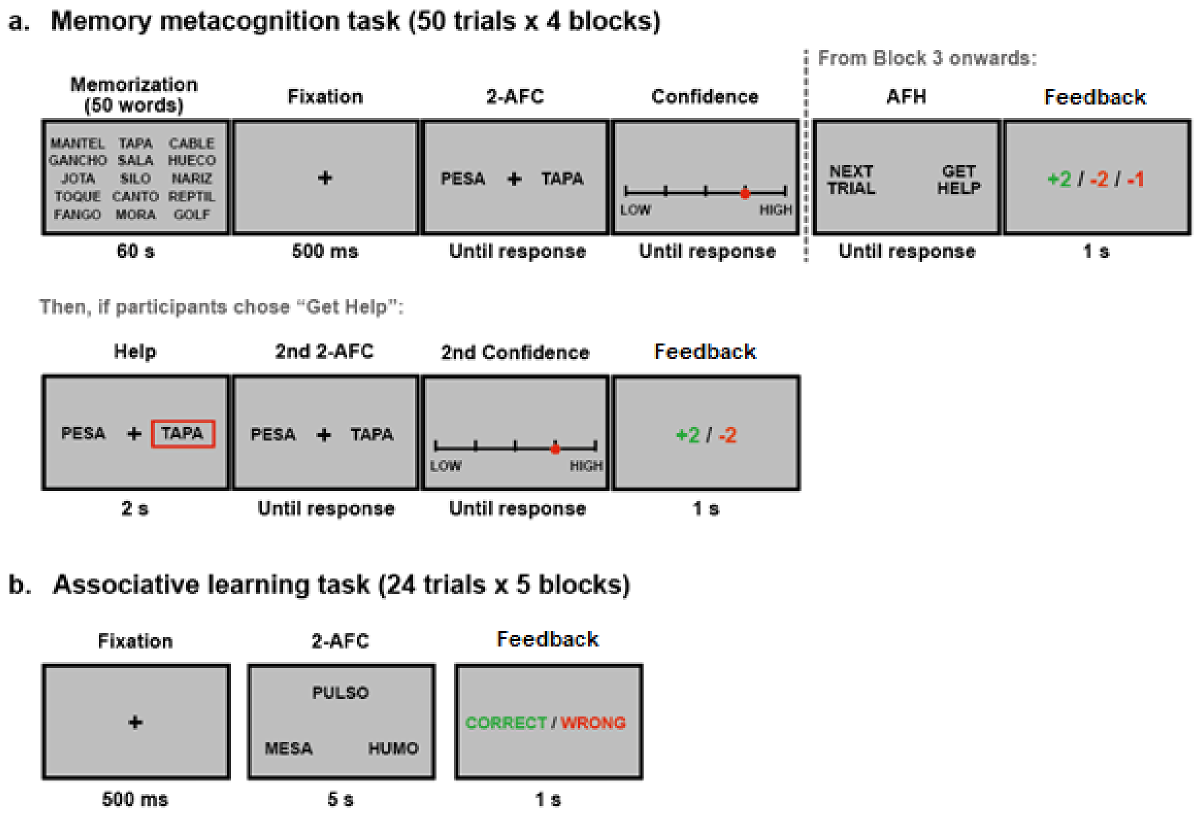

Fig. 1. (a) illustrates the structure of the metacognition task. Participants were asked to memorise as many words as possible. After the stimuli presentation, they completed 50 two-alternative forced choice (2AFC) trials with confidence ratings, where they indicated which word was part of the previously memorised set and rated their confidence in their choice. Starting from the third block, two new rules were introduced. First, participants had the option to "Get Help" before proceeding with the next trial. If they chose to get help, they were shown "the response of a previous participant" and had to repeat the trial. The help had an 80% chance of being correct. Second, a scoring system was implemented: participants earned 2 points for each correct response, lost 2 points for each incorrect one, and had 1 point deducted each time they requested help. (b) illustrates the structure of the associative learning task. Participants were required to identify which word in the lower half of the screen was associated with the cue shown in the upper half. The associations between words and cues were arbitrary. After making their selection, participants received immediate feedback indicating whether their response was correct or incorrect. The task consisted of 120 trials, divided into five blocks.

Statistical Analysis

Seven participants were excluded from further analyses due to technical and/or human errors during data collection. We assessed the normality of all continuous variables prior to analysis. All statistical analyses were conducted using JASP v.0.17.2.1 (JASP Team, 2023) and R v.4.3.1 (R Core Team, 2023). First, we evaluated the relationship between each metacognition facet and learning. Next, we performed statistical analyses to assess the combined impact of the three metacognition facets on learning. Since GPA was coded as an ordinal variable, Kendall's tau (τ) correlations were used to evaluate the relationship between each metacognition facet and GPA. Finally, response times (RTs were recorded to assess cognitive task adjustments across conditions but were not used as direct indicators of metacognitive processes.

Results

Preliminary analyses. Tables 1 and 2 present the descriptive statistics for AILI, the associative learning task, and the memory task. No significant differences were found when comparing the variables by students' sex (all *ps* > .080) or career (all *ps* > .214). Additionally, there were no significant correlations between the variables studied and years of education (all *ps* > .110), nor with the time lag between sessions (all *ps* > .124).

Then, we examined changes in first- and second-order performance between blocks 1-2 and blocks 3-4 (see Table 2). Since blocks 3-4 of the memory task introduced feedback and the option to ask for help, we considered it important to check for unexpected changes in cognitive monitoring, i.e., metacognitive experiences. To explore the effect of feedback, we calculated the changes in first- and second-order scores for blocks 3-4 (before help) compared to blocks 1-2. We found a statistically significant decrease in response times ($t(65) = -3.03$, $p = .004$, *Cohen's d* = -0.37), and a significant increase in both first-order sensitivity ($t(65) = 2.12$, $p = .038$, $d = 0.26$), and confidence scores ($t(65) = 7.32$, $p < .001$, $d = 0.90$). No other significant differences were observed (all *ps* > .053). Next, to explore the effect of getting help, we calculated the changes in blocks 3-4 after and before getting help. A significant improvement in accuracy was observed ($t(65) = 2.21$, $p = .031$, $d = 0.27$), along with a reduction in response times ($t(65) = -4.96$, $p < .001$, $d = -0.61$), and metacognitive efficiency ($t(65) = -3.09$, $p = .003$, $d = -0.38$). No other variables showed significant differences between post- and pre-AFH (all *ps* > .093). Based on the observed differences in first- and second-order performance due to the introduction of feedback and the option to ask for help, we used ME scores from blocks 1-2 of the metacognition task for subsequent analyses.

Table 1. Descriptives for the questionnaire scores and the associative learning task ($n = 66$).

Variable	*M* (*SD*)
Age	22.26 (3.71)
Scholarity (in years)	15.36 (2.36)
AILI	179.15 (21.86)
Knowledge	64.38 (7.61)
Responsiveness	52.29 (7.79)
Regulation	62.49 (10.41)
Associative Learning	.61 (.16)

Associative learning is predicted by ME (Hypothesis A). We then evaluated how metacognition facets related to associative learning and academic performance, respectively. Firstly, we started with associative learning. When comparing with MK, we found no significant correlations between the AILI scores and the learning measure (all *ps* > .06). In contrast, regarding ME, we observed a weak but positive correlation with both confidence ($r = .37$, $p = .002$) and metacognitive sensitivity ($r = .39$, $p = .001$). Finally, for MS, there was no significant correlation between our MS measures and the associative learning score (all *ps* < .065). In summary, only the two ME measures demonstrated a statistically significant correlation with associative learning. Since both confidence and metacognitive sensitivity are susceptible to performance bias, we conducted a multiple regression analysis to determine whether these relationships remained significant after controlling for first-order sensitivity (*d'*). The results indicated that both confidence ($\beta = .30$, $p = .034$) and metacognitive sensitivity ($\beta = .34$, $p = .021$) remained significant predictors of learning, even after accounting for first-order performance bias. Subsequently, we assessed how metacognition facets related to academic performance. When comparing MK to GPA, we observed positive correlations between GPA and total AILI ($\tau = .21$, $p = .028$), in addition to the AILI's subscales *metacognitive responsiveness* ($\tau = .19$, $p = .046$) and *metacognitive regulation* ($\tau = .19$, $p = .048$). Regarding ME, we found a weak and positive correlation with metacognitive efficiency ($\tau = .19$, $p = .045$). Finally, while comparing to MS, we found a negative relation between AFH efficiency and GPA ($\tau = -.21$, $p = .049$). That is, participants with better grades demonstrated lower efficiency in asking for help, indicating that their improvement in accuracy relative to the frequency of asking for help was less than those with lower grades. In summary and opposed to what we found when comparing metacognition facets and associative learning, all three of them were related to self-reported GPA.

Table 2. Descriptives and change between blocks and after the AFH option for the metacognition task ($n = 66$).

Variable	Blocks 1-2 *M* (*SD*)	Blocks 3-4 (Pre AFH) *M* (*SD*)	Blocks 3-4 (Post AFH) *M* (*SD*)	$B_{3\text{-}4} - B_{1\text{-}2}$ ΔM	$B_{3\text{-}4\ Post} - B_{3\text{-}4\ Pre}$ ΔM
First-order performance					
Accuracy (acc)	.77 (.07)	.79 (.07)	.80 (.06)	.02	.01*
Response time (rt)	2.43 (0.67)	2.26 (0.64)	2.11 (0.57)	-0.17**	-0.16***
Sensitivity (d')	1.34 (0.39)	1.45 (0.40)	1.51 (0.36)	0.11*	0.06
Metacognitive experiences					
Confidence	3.52 (0.47)	3.88 (0.49)	3.90 (0.51)	0.36***	.02
Metacognitive sensitivity (meta-d')	1.31 (0.48)	1.35 (0.51)	1.30 (0.49)	0.04	-0.05
Metacognitive efficiency (meta-d' / d')	1.01 (0.35)	0.95 (0.34)	0.87 (0.30)	-0.06	-0.08**
Metacognitive skills					
Performance improvement[1]	-	-	.02 (.02)	-	-
AFH efficiency[1]	-	-	.31 (.41)	-	-

Statistical significance: * $p < .05$, ** $p < .01$, *** $p < .001$.

[1] Excluding 10 participants that never used the AFH option (n = 56).

MK predicts learning via ME (Hypothesis B). Next, we tested two statistical models combining both forms of monitoring—MK and ME—with associative learning and GPA, respectively. Given the established role of MK as a source of information and bias for ME (Efklides, 2008; Lehmann et al., 2022) and following methodological recommendations by Agler & De Boeck (2017), we explored mediation models with associative learning as the outcome, MK as the predictor, and metacognitive sensitivity as the mediator (see Fig. 2a). Our analysis revealed an indirect effect of the metacognitive knowledge subscale of the AILI on learning, mediated by metacognitive sensitivity ($\beta = .112$, 95% CI [.01, .24]). In other words, an individual's knowledge or beliefs about their own cognitive processing and problem-solving abilities (i.e., MK) predicted how accurately they monitored their own cognitive performance (i.e., ME), which, in turn, predicted their learning outcomes. No significant effects were found when evaluating the other AILI subscales. When assessing the same model with GPA as the dependent variable, we found no statistically significant mediation (all ps > .186).

MS moderates the effect of ME on learning (Hypothesis C). Finally, we aimed to evaluate the role that MS played in the relation between metacognitive monitoring - MK and ME- and learning. Given that MS measures showed no relationship with associative learning and considering that several participants never used the AFH option during the metacognition task, we decided to investigate the differences between participants who asked for help and those who did not (for more details on AFH use, see Supplementary Material 1). Specifically, we tested whether the relationship between metacognitive sensitivity and learning changed depending on AFH use (categorised as 0 = never asked for help, 1 = asked for help at least once). To explore this, we performed a hierarchical multiple regression analysis. In the first step, three variables were included: metacognitive sensitivity, first-order sensitivity (to control for performance bias), and use of AFH. These three variables accounted for a significant amount of variance in learning ($R^2 = .21$, $F(3, 62) = 5.39$, $p = .002$). In the second step, the interaction term between metacognitive sensitivity and AFH use was added. This model significantly improved over the initial model ($\Delta R^2 = .11$, $\Delta F(1, 61) = 10.18$, $p = .002$), with metacognitive sensitivity ($b = .41$, $t = 3.94$, $p < .001$), AFH use ($b = .56$, $t = 3.65$, $p < .001$), and their interaction ($b = -.36$, $t = -3.19$, $p = .002$), as significant predictors of associative learning. The interaction plot (Fig. 2b) reveals a shallower slope for participants who asked for help compared to those who did not. At lower levels of metacognitive sensitivity, participants who asked for help exhibited better learning outcomes than those who did not. However, this trend disappears at higher metacognitive sensitivity scores, where learning outcomes were similar regardless of AFH use.

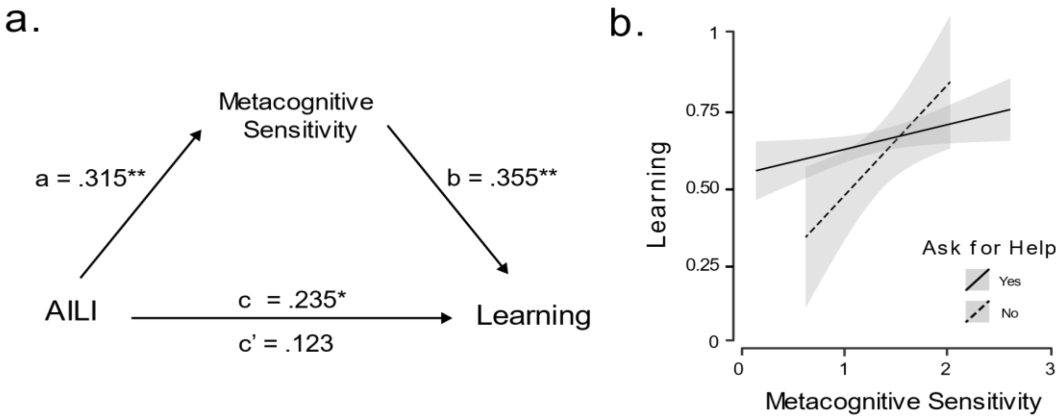

Fig. 2. (a) shows the indirect effect of the AILI's subscale *metacognitive knowledge* on associative learning, fully mediated by metacognitive sensitivity. Figure (b) shows the regression of metacognitive sensitivity on associative learning using the AFH option. $n = 66$

Discussion

The aim of this study was to examine how different facets of metacognition —metacognitive knowledge (MK), metacognitive experiences (ME), and metacognitive skills (MS)— are related to learning, both independently and in combination. In line with established models in cognitive and educational psychology, we operationalized MK as beliefs and knowledge about one's own mental processes, measured through two self-report questionnaires. ME was assessed via confidence judgments reflecting task-based self-monitoring, and MS was measured through participants' use of an ask-for-help (AFH) procedure, representing strategic control over performance. Our results revealed a differentiated pattern: while ME was directly associated with learning outcomes, MK and MS were not. However, when analyzed together, MK predicted learning indirectly via ME, and MS moderated the relationship between ME and performance. These findings can be interpreted within the framework proposed by Efklides (2008, 2014), who conceptualizes metacognition as a dynamic interaction between knowledge, experience, and control. This perspective helps explain the pathways we observed and supports the idea that effective regulation is contingent on the quality and accuracy of preceding monitoring processes.

More specifically, regarding how the facets of metacognition are related to learning individually, our results show that only ME are significantly associated with learning. Specifically, we found a positive relationship between participants' metacognitive sensitivity and their performance on the learning task. In other words, individuals who monitor their performance most effectively through confidence judgments also tend to be the best learners. Confidence judgments —and their accuracy— are critical components of the self-regulated learning process, as they enable learners to allocate cognitive resources more efficiently to the tasks at hand (Mengelkamp & Bannert, 2012). Notably, unlike most studies that assess ME through judgments of learning or feelings of knowing within the learning context (Jang et al., 2020; Schwartz, 2008), our study evaluated participants' ME outside of the learning task, suggesting a relationship between general monitoring skills and the learning process. On the other hand, when comparing learning with MK and MS, we did not find significant correlations. Although this contradicts previous findings in the literature (e.g., Aghaie & Zhang, 2012; Desoete et al., 2003), we believe that our results could be attributed to the nature of the task used to assess learning, which may primarily activate low-level associative mechanisms where participants' knowledge about and use of strategies play a minimal role. Previous research has shown that both MK and MS are particularly beneficial when learners transfer knowledge from familiar to novel contexts (Bransford et al., 1999). Thus, our learning task may not have sufficiently engaged the types of cognitive processes required to activate these facets of metacognition. Future research should explore whether the cognitive complexity of a learning task influences which facets of metacognition become engaged in the learning process.

When evaluating the collective role of metacognition facets on learning, two important findings emerge. First, we observed a mediation effect between MK and learning through ME. In other words, an individual's beliefs and knowledge about their metacognitive abilities predict their cognitive self-monitoring capacity, which, in turn, predicts their learning outcomes. This finding aligns with the work of Jang et al. (2020) and the theory proposed by Efklides (2008), suggesting that an individual's beliefs shape their ability to monitor their cognitive processes. Consistent with Lehmann et al. (2022), it could be argued that MK serves as a foundational level—or bias—for constructing ME, such as confidence judgments. In turn, ME has been proposed as the link between subjective learning experiences and actual learning outcomes (Winne & Hadwin, 1998). Learners need to reconcile their knowledge and beliefs about the learning process with their real-world experiences to effectively use that knowledge in learning contexts. Second, we found that the relationship between ME and learning is moderated by the use of the AFH option during the task. Specifically, participants who used the AFH option showed more stable learning outcomes with less variation across different levels of ME. In contrast, participants who did not use the AFH option displayed a steeper slope: lower learning outcomes when their ME was low and similar learning outcomes to others when their ME was high. This suggests that using strategies like asking for help allows students with less developed monitoring skills to achieve learning outcomes comparable to learners with greater metacognitive abilities. Although our associative learning task did not include an AFH option, this result might reflect the use of other self-regulatory strategies or changes in self-monitoring beyond confidence judgments (Undorf et al., 2021). These results indicate a potential differential role of both monitoring and control aspects of metacognition in learning, with control processes acting as a complementary system that enhances performance, particularly for learners with lower monitoring abilities.

Finally, we also asked participants for their GPA as a proxy measure of learning and academic achievement, which we compared with all facets of metacognition. We found that the self-reported GPA score was related to all three facets of metacognition. In line with the literature (Abdelrahman, 2020; Young & Fry, 2008), we found a positive relationship between different measures of MK and academic performance, meaning that individuals who believe they are good learners indeed have better grades than their peers. We also found a positive relationship between ME and academic performance, indicating that individuals who are better at monitoring their own performance tend to have higher grades. Unlike the learning task results, we found evidence of a similar role of both an individual's knowledge and beliefs, as well as their cognitive self-monitoring, on academic performance. We propose that since academic performance depends on multiple factors, such as beliefs, motivation, and social elements—not just learning skills (Gębka, 2013; Hidayatullah & Csíkos, 2023)—it is more broadly related to various aspects of metacognitive ability.

In contrast, associative learning is restricted to ME alone. Consistent with previous findings, it is crucial to investigate the effect of task complexity on the metacognitive processes employed. Lastly, and contrary to our expectations, we observed a negative relationship between one of our MS measures and academic performance. Specifically, we found that participants who used the ask-for-help option more efficiently had lower grades. Additional studies are necessary to better understand the relevance of this finding.

This study demonstrated that the three facets of metacognition—knowledge, experience, and skills—contribute to learning and academic performance in distinct yet complementary ways. Their interaction appears especially relevant for shaping students' outcomes, lending support to theoretical models that emphasize dynamic self-regulation grounded in accurate monitoring. However, these findings must be interpreted with caution due to several methodological limitations. A central concern is the use of different instruments to assess each metacognitive component, which may have introduced measurement variability unrelated to the constructs themselves. In particular, metacognitive experience was measured using retrospective confidence judgments, rather than prospective judgments such as Judgments of Learning (JOLs) or Feelings of Knowing (FOKs). Confidence ratings are well suited to recognition tasks and are compatible with the signal detection framework that informs our analyses (Fleming & Lau, 2014; Maniscalco & Lau, 2012). Still, they tap into different cognitive processes than prospective measures, and the generalizability of our findings to other types of monitoring remains uncertain. As Koriat (1997) emphasized, these measures are not interchangeable. Future research should systematically examine how different operationalizations of metacognition—especially those using integrated, task-embedded designs—shape observed relationships with learning outcomes. Such efforts are essential not only for refining our theoretical understanding of metacognitive processes, but also for enhancing the practical relevance of metacognitive interventions in educational settings. Clarifying the distinct contributions and boundaries of each facet will enable more targeted, effective approaches to fostering self-regulated learning.

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Supplementary Material A. Learning Task

A.1. Selection of cue-stimulus pairs.

The list of words used was generated from the EsPal database (Duchon et al., 2013; https://www.bcbl.eu/databases/espal/), considering the phonology of Latin American Spanish. Words were four to six letters long, with one to three syllables, a familiarity rating from 5.0 to 7.0. Subsequently, words with diacritical marks (tildes, accents and/or umlauts) were excluded from the list. The result was a list with 865 words, from which 60 cue-stimulus pairs were randomly formed.

To rule out pairs of words that could facilitate the association between the words during the task, the 60 pairs were evaluated by a sample of 14 Chileans native Spanish-speaking participants. The evaluation criteria were phonological similarity (“How similar are the sounds of both words?”), semantic similarity (“How close are the meanings of both words?”) and perceived similarity (“How related do you consider that the two words are in relation to each other?”). The scores for each criterion were averaged, which yielded a total similarity score for each pair of words. From this, the 24-word pairs with the lowest total similarity score were selected. Descriptives of the 24 pairs can be seen in Table S1.

The distractors used in the task were randomly selected in each trial from a subsample of the original list of 865 words. This subsample was randomly created so that the words used in this task and in the metacognition task could not be repeated.

A.2. Learning task

We decided to calculate an individual learning score based on the area under the learning curve of each participant in order to reduce the impact of the ceiling effect on task performance. For this same purpose, different configurations of the task were tested seeking to increase the variability in the results. Based on a pilot study carried out on a sample of 26 participants (77% women), we decided to cut the task at 5 blocks (Figure S1A), because after that point no significant differences were observed between blocks in the performance of the tasks (*p*s > .106). Figure S1B shows the learning curves for participants in the study.

Table S1. Descriptives of the three similarity criteria and familiarity scores for the 24 cue-stimulus pairs used in the learning task.

Cue - Stimulus	Phonological similarity *M* (*SD*)	Semantic similarity *M* (*SD*)	Perceived similarity *M* (*SD*)	Total similarity *M* (*SD*)	Familiarity *M* (*SD*)
Firma - Tira	1.50 (0.73)	1.00 (-)	1.14 (0.35)	1.21 (0.21)	5.71 (0.01)
Pulso - Mesa	1.29 (0.45)	1.00 (-)	1.00 (-)	1.10 (0.14)	5.81 (0.77)
Mantel - Recado	1.00 (-)	1.00 (-)	1.00 (-)	1.00 (-)	5.84 (0.47)
Bronce - Folio	1.00 (-)	1.00 (-)	1.00 (-)	1.00 (-)	5.85 (0.76)
Sirena - Regla	1.07 (0.26)	1.07 (0.26)	1.00 (-)	1.05 (0.03)	6.00 (0.26)
Jersey - Colmo	1.00 (-)	1.00 (-)	1.00 (-)	1.00 (-)	6.06 (0.38)
Edad - Feria	1.00 (-)	1.07 (0.26)	1.00 (-)	1.02 (0.03)	6.29 (0.63)
Fuego - Chicle	1.00 (-)	1.07 (0.26)	1.00 (-)	1.02 (0.03)	6.62 (0.14)
Premio - Umbral	1.07 (0.26)	1.14 (0.35)	1.07 (0.26)	1.10 (0.03)	5.63 (0.62)
Viaje - Jefe	3.07 (0.88)	1.93 (0.80)	1.64 (0.72)	2.21 (0.62)	6.37 (0.17)
Luna - Lucha	3.57 (0.82)	1.00 (-)	2.00 (0.76)	2.19 (1.06)	5.63 (0.33)
Piloto - Salida	1.14 (0.52)	1.64 (0.89)	1.57 (0.73)	1.45 (0.22)	5.91 (0.72)
Portal - Seguro	1.00 (-)	1.00 (-)	1.00 (-)	1.00 (-)	6.05 (0.07)
Juerga - Anillo	1.00 (-)	1.21 (0.41)	1.14 (0.35)	1.12 (0.09)	5.94 (0.19)
Trampa - Cubo	1.00 (-)	1.36 (0.61)	1.14 (0.35)	1.17 (0.15)	6.10 (0.14)
Novio - Centro	1.07 (0.26)	1.21 (0.56)	1.07 (0.26)	1.12 (0.07)	6.41 (0.28)
Grito - Cuadro	1.00 (-)	2.29 (1.28)	1.93 (1.16)	1.74 (0.54)	6.07 (0.25)
Huevo - Nivel	1.07 (0.26)	1.14 (0.35)	1.00 (-)	1.07 (0.06)	6.35 (0.09)
Rasgo - Mezcla	1.14 (0.35)	1.14 (0.35)	1.21 (0.41)	1.17 (0.03)	5.02 (0.00)
Frasco - Olvido	1.00 (-)	1.14 (0.35)	1.14 (0.35)	1.10 (0.07)	5.68 (0.33)
Llave - Llama	3.50 (0.91)	1.07 (0.26)	1.57 (0.73)	2.05 (1.05)	5.90 (0.83)
Reptil - Tenis	1.36 (0.48)	1.14 (0.35)	1.43 (0.49)	1.31 (0.12)	6.01 (0.14)
Fuente - Gusto	1.00 (-)	1.21 (0.41)	1.07 (0.26)	1.10 (0.09)	5.86 (0.48)
Chisme - Crimen	1.07 (0.26)	1.14 (0.35)	1.07 (0.26)	1.10 (0.03)	5.16 (0.02)

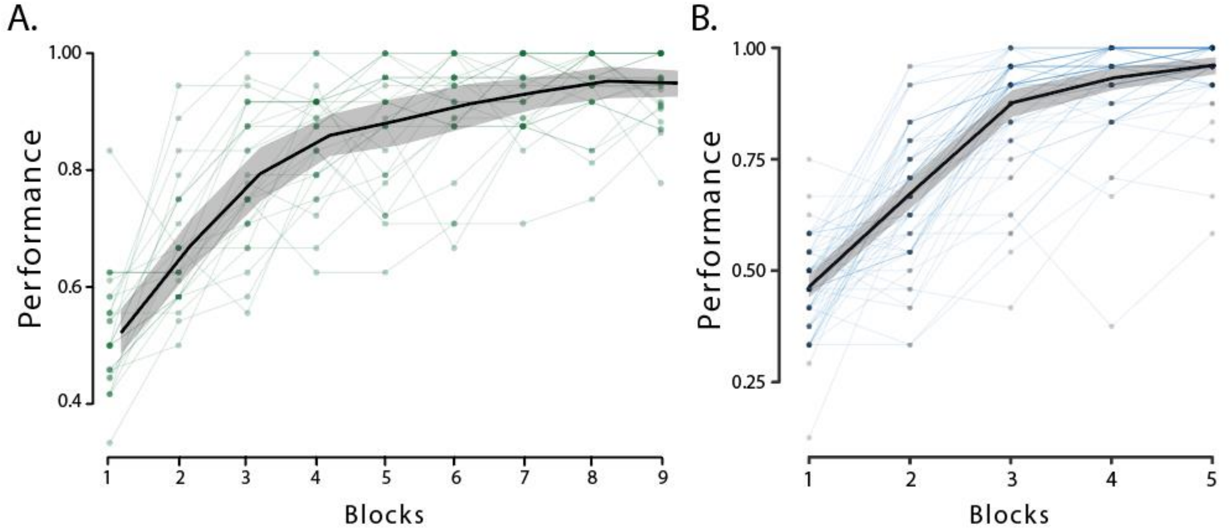

Figure S1. A) Learning curve of the pilot study (*n* = 26). B) Learning curves of the study participants (*n* = 66).

Supplementary Material B. Ask for Help analyses.

Based on the data obtained in the metacognition task, we decided to explore the factors that may explain the decision of the participants to ask for help or not in a given trial. Given the impossibility of determining why they did not use this option, we decided to exclude from these analyses the 10 participants who never asked for help with the task. Our sample was 56 students (*M* = 21.79 years, *SD* = 2.76, 55% female), who asked for help 403 times in total (*M* = 7.20, *SD* = 8.14). We decided to consider three factors that might influence an individual's decision to ask for help or not on a given trial (Goupil et al., 2015; Undorf et al, 2021): the difficulty of that trial, the reported confidence in that trial, and the accuracy with which an individual monitors their performance on the trial, which we evaluated via the metacognitive efficiency in blocks 1-2.

We used logistic regression to determine the effect that difficulty in memorising each stimulus (operationalized as one minus the average performance of all participants on that stimulus) has on the probability of asking for help on a trial. We found that the difficulty of the trial does have an effect on the probability of asking for help (*OR* = 2.89, 95% *CI* [1.35, 6.18], *p* = .006). Since the difficulty of a trial is an objective parameter to which the participant does not have explicit access during the course of the task, we decided to test how a subjective parameter (i.e., their confidence report) affects their probability of asking for help. Using logistic regression, we found that individual confidence (reported on a discrete scale of 1 to 5) does have an effect on whether or not to ask for help (Figure S2A). Specifically, participants have 72.5% less odds of asking for help on a trial with confidence equal to 2 than on a trial with confidence equal to 1. While, on trials with confidence equal to 3, 4, or 5, the odds of asking for help drop by 88.6%, 95.4%, and 99.6%, respectively (Table S2). Next, we decided to assess how participants' metacognitive efficiency influences the likelihood of asking for help. Using logistic regression, we found that the odds of asking for help on a given trial increase 106% for each 1-point increase in participants' metacognitive efficiency (*OR* = 2.06, 95% *CI* [1.56, 2.72], *p* < .001, Figure S2B), suggesting that individuals who are better at monitoring their mental states are more likely to ask for help during the task.

Table S2. Logistic regression of the probability of asking for help in a trial with confidence in that trial as a predictor(*n* = 56).

Coefficients	B	S.E.	Exp(B) with 95% CI
Confidence (2)	-1.29	0.14	0.275*** (0.209 - 0.362)
Confidence (3)	-2.18	0.17	0.114*** (0.082 - 0.158)
Confidence (4)	-3.07	0.20	0.046*** (0.031 - 0.069)
Confidence (5)	-5.48	0.35	0.004*** (0.002 - 0.008)

Statistical significance: *** p < .001

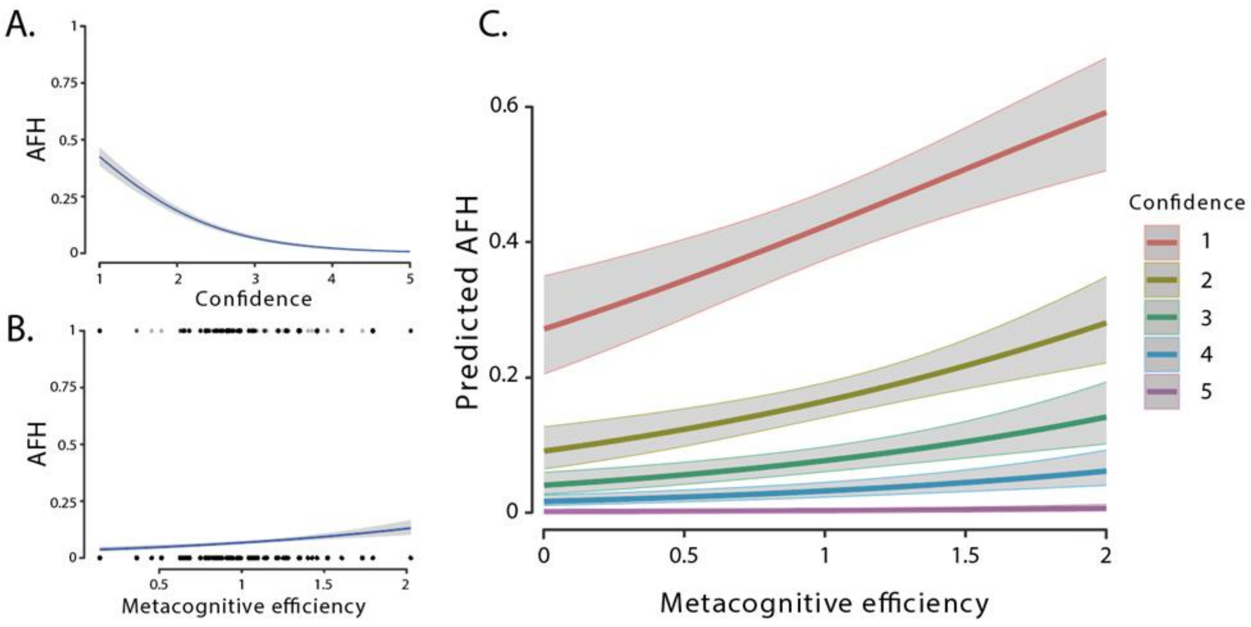

Figure S2. (A) shows the probability of asking for help in a single trial with confidence in that trial as a predictor. Figure (B) shows the probability of asking for help in a single trial with metacognitive efficiency as a predictor. Figure (C) shows the probability of asking for help in a single trial with confidence and metacognitive efficiency as predictors. (*n* = 56).

Finally, we decided to assess the joint effect that both variables (confidence and metacognitive efficiency) have on the probability of asking for help in a trial. We performed a multiple logistic regression on the probability of asking for help with confidence and metacognitive efficiency as predictors. We found that participants have 73.1% less odds of asking for help on a trial with confidence equal to 2 than on a trial with confidence equal to 1. While, on trials with confidence equal to 3, 4, or 5, the odds of asking for help drop by 88.7%, 95.5%, and 99.6%, respectively. In turn, the odds of asking for help increase by 97.4% for each 1-point of increase in the metacognitive efficiency of the participants (Table S3). In figure S2C, we can see that the odds of asking for help are higher in trials with low confidence, but they increase when those who report such confidence are participants with high metacognitive efficiency.

Table S3. Logistic regression of the probability of asking for help in a trial with confidence in said trial and the participant's metacognitive efficiency as predictors. (*n* = 56).

Coefficients	B	S.E.	Exp(B) with 95% CI
Confidence (2)	-1.32	0.14	0.269*** (0.203 - 0.354)
Confidence (3)	-2.18	0.17	0.113*** (0.081 - 0.157)
Confidence (4)	-3.10	0.20	0.045*** (0.030 - 0.067)
Confidence (5)	-5.47	0.35	0.004*** (0.002 - 0.008)
Metacognitive efficiency	0.68	0.15	1.974*** (1.474 - 2.644)

Statistical significance: *** p < .001