EXPLORING THE IMPACT OF COGNITIVE, AFFECTIVE, AND PERSONALITY DIFFERENCES ON LEARNING PROCESSES

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Abstract

Individual differences play a critical role in shaping how learners engage with and internalize new information during various stages of the learning process. This study investigates the extent to which cognitive, affective, and personality-related individual differences predict distinct learning processes—namely encoding, rehearsal, elaboration, and metacognitive regulation. Employing a mixed-methods design, 180 undergraduate participants completed standardized measures of working memory capacity, cognitive style, learning motivation, and trait anxiety. Quantitative data were analyzed using structural equation modeling to examine direct and indirect effects of individual differences on learning outcomes. Complementing this, think-aloud protocols from a purposive subsample of 30 students were thematically coded to identify strategy use during problem-solving tasks. Results reveal that (a) higher working memory capacity and reflective cognitive styles are positively associated with deeper elaboration strategies, (b) intrinsic motivation and low anxiety levels predict more frequent metacognitive monitoring and regulation, and (c) personality traits linked to conscientiousness moderate the relationship between cognitive style and rehearsal strategies. Qualitative themes illustrate how learners adapt their study tactics in real time, confirming and extending the quantitative model. These findings underscore the necessity of tailoring instructional design to accommodate multidimensional individual differences, suggesting that adaptive scaffolding and metacognitive prompts can enhance learning efficiency. Implications for educators include integrating diagnostic assessments of learner profiles and embedding process-oriented interventions to foster self-regulated learning.

Keywords: *individual differences, learning processes, cognitive style, metacognition, self-regulated learning, working memory capacity*

Introduction

Over the past several decades, educational researchers and cognitive scientists have increasingly recognized that learners are not interchangeable vessels into which knowledge can be poured, but rather complex individuals whose unique profiles of cognitive capacities, affective dispositions, and personality traits profoundly shape how they engage with, process, and ultimately internalize new information. In traditional instructional paradigms, pedagogical design has often assumed a “one-size-fits-all” approach, overlooking the reality that factors such as working memory capacity, information-processing speed, intrinsic motivation, trait anxiety, and Big Five personality dimensions each contribute to variability in how students encode, rehearse, elaborate upon, and regulate their learning. Individual differences thus represent a critical frontier for optimizing educational outcomes, since tailoring instruction to the diverse needs of learners has been shown to improve engagement, enhance knowledge retention, and foster deeper conceptual understanding. Despite this clear significance, the field has been hampered by a fragmentation of research efforts: cognitive, affective, and personality factors are frequently studied in isolation, and when they are examined in concert, the focus often remains on static outcome measures (e.g., test scores) rather than on the dynamic learning processes—the stages of encoding, rehearsal, elaboration, retrieval, and metacognitive monitoring—that mediate the pathway from instruction to performance.

To clarify our terms, we define cognitive individual differences as relatively stable capacities and preferences in information processing (e.g., working memory span, cognitive style), affective individual differences as emotional and motivational states or traits (e.g., intrinsic versus extrinsic motivation, anxiety levels), and personality individual differences as enduring dispositional traits (e.g., conscientiousness, openness to experience). We conceptualize learning processes as the sequence of mental operations and self-regulated strategies that learners employ: from the initial encoding of new material into working memory, to the rehearsal and practice that consolidate information, to the elaboration techniques that integrate new knowledge with existing schemas, and finally to metacognitive regulation, whereby learners monitor their comprehension, evaluate task performance, and adapt strategies as needed. Although each of these stages has been examined independently—cognitive style linked to elaboration strategies, motivation associated with persistence, and metacognitive awareness correlated with achievement—their interrelations within a unified, process-oriented framework remain underexplored.

This gap is significant for both theory and practice. Theoretically, without an integrated model that maps how multidimensional individual differences feed into specific processing stages, our understanding of learning remains compartmentalized and unable to predict when and why certain learners struggle or excel under different instructional conditions. Practically, educators lack clear guidance on how to design adaptive scaffolding interventions that seamlessly align with learner profiles at each stage of the processing continuum. Indeed, extant studies often report inconsistent findings—for example, some research indicates that reflective cognitive styles enhance elaboration, while other work finds negligible effects; similarly, motivation has been linked to both improved metacognitive monitoring and, paradoxically, heightened anxiety that undermines self-regulated learning. These contradictory results underscore the need for a comprehensive investigation that systematically examines multiple dimensions of individual differences in relation to discrete learning processes, using both quantitative and qualitative methodologies to capture the richness of learner experiences.

Accordingly, the present study sets out to address two primary research questions: (1) How do distinct cognitive styles—specifically, reflective versus impulsive processing preferences—relate to information-processing strategies such as encoding depth, rehearsal frequency, and elaboration complexity? and (2) To what extent do motivational profiles, characterized by intrinsic motivation and trait anxiety levels, predict learners' metacognitive regulation behaviors, including planning, monitoring, and strategy adjustment? By integrating standardized psychometric assessments with think-aloud protocol analyses, we aim to illuminate not only the statistical associations between individual difference dimensions and learning process metrics but also the nuanced, context-sensitive ways that learners adapt their study strategies in real time. In doing so, we aspire to construct an empirically grounded, process-oriented framework that can guide the development of targeted, adaptive instructional designs—scaffolds that dynamically respond to learner profiles at each stage of the processing timeline, thereby enhancing both efficiency and depth of learning. This investigation promises to advance theoretical models of self-regulated learning and to furnish educators with actionable insights for fostering personalized, process-driven pedagogy.

Literature review

Research into individual differences has long emphasized three broad domains—cognitive, affective, and personality factors—that contribute uniquely to variability in learning outcomes. Within the **cognitive** domain, two constructs have received particularly extensive investigation: working memory capacity and processing speed. Working memory, defined as the system responsible for the temporary storage and manipulation of information, has emerged as a robust predictor of complex cognitive tasks such as reading comprehension and problem solving[1]. Individuals with higher working memory spans are better able to maintain and integrate multiple sources of information during learning, supporting deeper encoding and elaboration. Processing speed—the rate at which simple cognitive operations can be performed—also influences learning, particularly in tasks requiring rapid retrieval and rehearsal; slower processors may experience bottlenecks during encoding, leading to less efficient consolidation[2]. In the affective realm, motivation and anxiety stand out as key determinants of how learners approach and sustain engagement with academic

[1] Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, 4(11), 417–423.

[2] Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, 103(3),403–428.; Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, 84(1), 1–66.

materials. Self-Determination Theory distinguishes intrinsic motivation—engaging in an activity for its own sake—from extrinsic motivation—driven by external rewards—and demonstrates that intrinsic orientation fosters greater persistence, deeper processing, and enhanced self-regulated strategies. Conversely, anxiety, particularly test anxiety or math anxiety, can tax attentional resources and working memory, thereby undermining encoding and retrieval processes. Pekrun and colleagues have further shown that negative achievement emotions correlate with avoidant study behaviors, whereas enjoyment and pride support metacognitive monitoring[3].

Finally, personality traits—most commonly operationalized via the Big Five framework—have been linked to differential learning behaviors. Conscientiousness, characterized by organization, diligence, and goal-directed persistence, consistently predicts academic achievement and effective study habits, including systematic rehearsal and time management. Openness to experience, reflecting intellectual curiosity and imagination, correlates with the use of elaboration strategies and conceptual integration. Neuroticism, overlapping with anxiety constructs, may impede self-regulated learning through increased worry and negative self-evaluation[4]. Together, these multidimensional individual differences shape learners' approach to the mental operations central to acquiring and applying new knowledge.

The study of learning processes has been guided by several overarching theoretical models. Behaviorist perspectives, epitomized by Skinner's operant conditioning framework, focus on how external reinforcement shapes stimulus–response associations, emphasizing repetition and feedback as drivers of behavioral change. Cognitive models, in contrast, conceive learning as internal information processing; the Atkinson and Shiffrin multi-store model delineates distinct stages—encoding (sensory input transformed into memory traces), storage (maintenance in short- and long-term stores), and retrieval (accessing stored information). Constructivist theories, drawing on Piaget and Vygotsky, highlight the active role of learners in constructing knowledge through assimilation, accommodation, and social

Building on these models, contemporary research often adopts a process-oriented view in which learning unfolds through sequential and self-regulated stages. Encoding involves attentional selection and elaboration of new material; deeper encoding—linking new information to existing schemas—predicts stronger retention[5]. Rehearsal, through repeated practice or rehearsal loops, supports consolidation into long-term memory but may be shallow if limited to rote repetition. Elaboration

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strategies, such as generating examples or analogies, foster integration with prior knowledge and facilitate transfer. Finally, metacognitive regulation—encompassing planning, monitoring, and evaluating one's cognitive activities—enables learners to adjust strategies in response to task demands[6]. Winne and Hadwin's[7] model of self-regulated learning further emphasizes recursive cycles of task analysis, goal setting, strategy enactment, and adaptive modification, underscoring the dynamic interplay between cognitive processes and motivational-affective regulation.

Despite rich literatures on both individual differences and learning processes, relatively few studies have systematically integrated multidimensional IDs with dynamic process stages. Cognitive research often controls for affective and personality factors rather than examining their interactive effects; likewise, motivation and metacognition studies frequently treat working memory and processing speed as background variables[8]. When multiple domains are considered concurrently, the focus tends to remain on static outcome measures—such as final test scores—rather than on how different learner profiles preferentially engage in encoding, rehearsal, elaboration, or self-regulatory loops during task performance. This compartmentalization limits our ability to predict which combinations of cognitive, affective, and personality factors give rise to adaptive versus maladaptive processing patterns under varying instructional conditions.

Moreover, inconsistencies in operational definitions and measurement approaches have yielded conflicting findings. For example, while some studies find a positive link between reflective cognitive styles and elaboration complexity, others report negligible or context-dependent effects. Similarly, research on test anxiety demonstrates both direct impairments on working memory and moderated impacts via metacognitive control[9], suggesting that motivational profiles may have complex, stage-specific influences. Without a unified, process-oriented investigation, practitioners lack concrete guidance on how to tailor pedagogical scaffolds—such as metacognitive prompts or adaptive rehearsal schedules—to the nuanced profiles of individual learners.

Addressing this gap requires a mixed-methods approach that couples quantitative modeling of cognitive–affective–personality predictors with qualitative analyses of strategy enactment (e.g., think-aloud protocols). By mapping

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[7] Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in Educational Theory and Practice* (pp. 277–304). Erlbaum.

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multidimensional individual differences onto discrete processing stages—encoding depth, rehearsal frequency, elaboration quality, and metacognitive regulation—researchers can develop an integrative framework that informs targeted, adaptive instructional designs. Such a framework would allow educators and instructional technologists to deploy diagnostic assessments and dynamic scaffolds that respond to real-time learner behaviors, ultimately enhancing both the efficiency and depth of learning across diverse educational contexts.

Theoretical Framework

Integrating the classic Information-Processing (IP) model with contemporary Self-Regulated Learning (SRL) theory yields a comprehensive framework in which individual differences (IDs) serve as antecedents that shape each stage of cognitive processing and regulatory control. In this model, the three core IP stages—encoding, storage, and retrieval[10] —are embedded within Zimmerman's cyclical SRL phases of forethought, performance, and self-reflection. In the forethought phase, cognitive IDs such as working memory capacity and processing speed determine the depth and selectivity of initial encoding: learners with higher spans allocate attentional resources more effectively, enabling elaborative encoding strategies, whereas those with slower processing speeds may rely on shallower, rehearsal-based approaches. Simultaneously, affective IDs—intrinsic motivation and anxiety—moderate goal-setting and task-analysis activities; highly motivated learners proactively plan elaboration tasks, while anxious learners may overemphasize rote rehearsal to mitigate uncertainty. During the performance or monitoring phase, personality traits such as conscientiousness and openness to experience influence the selection and sustained use of encoding and rehearsal strategies[11]. Conscientious individuals systematically implement spaced rehearsal schedules, enhancing consolidation in the storage stage, whereas open learners favor integrative elaboration, forging richer associative networks. Metacognitive monitoring—central to SRL—relies on both cognitive IDs (e.g., reflective versus impulsive processing styles) and affective states; reflective processors engage in continuous self-questioning and adaptive strategy shifts, while learners experiencing high anxiety may struggle to accurately appraise their comprehension. This dynamic interplay ensures that storage processes are not passive but are continually evaluated and adjusted according to real-time feedback. In the self-reflection or retrieval stage, IDs again exert differential influences: working memory capacity supports the reconstruction of complex schemas, whereas learners with strong metacognitive awareness evaluate retrieval success against learning goals and revise

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[11] O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, 43(5), 971–990.

future forethought strategies[12]. Personality facets such as neuroticism can lead to negative self-evaluations, prompting avoidant study behaviors, while conscientious learners interpret retrieval failures as diagnostic cues for adjusting rehearsal intensity. Importantly, motivational and affective IDs dictate whether reflection leads to constructive strategy refinement or disengagement; intrinsically motivated students view errors as opportunities for growth, reinforcing adaptive encoding–storage–retrieval cycles. By mapping IDs onto specific SRL/IP stages, this integrative framework illustrates how multidimensional learner profiles drive the selection, enactment, and adaptation of cognitive and metacognitive processes. It underscores that effective instruction must diagnose these IDs—through assessments of working memory, cognitive style, motivation, anxiety, and personality—and deploy targeted scaffolds (e.g., metacognitive prompts, adaptive rehearsal schedules) aligned with each processing phase. Such an approach promises to optimize individual learning trajectories by ensuring that instructional interventions resonate with both the cognitive capacities and motivational-affective orientations of diverse learners.

Methodology

Building on the convergent mixed-methods framework, this study further incorporated a preliminary pilot phase to refine instruments and protocols. In the pilot, 20 undergraduates completed the full survey battery and engaged in a brief think-aloud session; feedback informed minor wording adjustments and estimated administration times. The main study then proceeded with parallel quantitative and qualitative strands, merging results through a joint display[13]. A target sample of **N = 180** was determined via an a priori power analysis for SEM. Stratified random sampling across three faculties (Psychology, Engineering, Business) ensured representation of diverse academic profiles and cognitive demands. We verified demographic balance post hoc: 112 female, 68 male; ages 18–24 ($M = 20.4$, $SD = 1.8$). The purposive qualitative subsample was drawn to capture contrasts in working memory capacity. All participants received a small gift voucher for participation. The Metacognitive Awareness Inventory provided subscale scores for planning, monitoring, and evaluation. For the think-aloud protocols, we developed a coding manual following Miles, Huberman, detailing 12 codes mapped to encoding, rehearsal, elaboration, and regulation. Two doctoral-level coders underwent a 10-hour calibration workshop, coding three practice transcripts collaboratively before independently coding the study data; interrater reliability (ICC) exceeded .85 across all codes[14]. All procedures were conducted over a four-week period in Spring 2025. Participants first completed online

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surveys via Qualtrics in a supervised computer lab, ensuring data integrity[15]. Survey completion took 40–50 minutes. Within one week, the qualitative subsample attended lab sessions for two 20-minute think-aloud tasks (text comprehension and quantitative reasoning). Sessions were audio-recorded with Olympus digital recorders, then transcribed verbatim using transcription conventions. All data—survey responses, OSPAN logs, transcripts—were stored on encrypted university servers, with participant IDs replacing names.

Quantitative: Data screening included Little's MCAR test for missingness[16] and inspection of univariate skew/kurtosis. Missing survey items (<2%) were handled via full information maximum likelihood in AMOS 27. SEM tested a three-factor ID latent variable (cognitive, affective, personality) predicting four process latent variables (encoding, rehearsal, elaboration, metacognition). Model modification followed Byrne's guidelines, retaining paths with $p < .05$ and ensuring theoretical plausibility. Multi-group SEM assessed invariance across gender and academic discipline[17].

Qualitative: Transcripts were imported into NVivo 12 for coding. After initial deductive coding using our manual, an inductive phase allowed emergence of subthemes, such as "strategy switching under time pressure."

Results and discussion

The findings of this study demonstrate that learners' cognitive capacities, affective states, and personality traits each play distinct yet interrelated roles in shaping how they engage with, process, and regulate their learning, with important implications for instruction and future research. Specifically, students with higher working memory capacity—reflecting the ability to hold and manipulate information in mind—consistently employed deeper elaboration strategies, such as generating analogies and examples, which align with depth-of-processing principles[18]. Reflective thinkers—those who naturally pause to analyze information—were more likely than impulsive processors to integrate new material through elaborative techniques, confirming links between cognitive style and conceptual integration[19]. In the affective domain, intrinsically motivated students—who engage in learning for its inherent satisfaction—demonstrated more frequent and effective metacognitive monitoring and evaluation behaviors, supporting Deci and Ryan's assertion that self-determination fosters self-

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regulated learning. Conversely, students with high trait anxiety experienced difficulties in the planning phase, often bypassing goal setting and proceeding directly to rote review; this pattern reflects attentional control theory, which posits that anxiety depletes working memory resources and undermines strategic planning[20]. Personality traits further moderated these processes: conscientious learners, characterized by organization and diligence, maintained regular rehearsal schedules and systematically reviewed material (O'Connor & Paunonen, 2007), while highly open individuals devoted additional effort to linking new concepts to prior knowledge, consistent with findings on openness and elaborative learning.

Qualitative insights from think-aloud protocols enriched these quantitative patterns by revealing three dominant strategy clusters—Adaptive Elaboration, Regulated Monitoring, and Stress-Driven Rehearsal—through real-time verbalizations of problem-solving processes[21]. High-capacity and reflective participants predominantly exhibited Adaptive Elaboration and Regulated Monitoring, whereas lower-capacity or anxious learners often defaulted to repetitive rote rehearsal ("I just repeated it until it stuck") under time pressure, illustrating how stress interacts with individual differences to shape strategy selection. Notably, a subset of learners combining high anxiety with strong intrinsic motivation nevertheless engaged in proactive metacognitive checks, suggesting that motivational orientation can buffer the adverse impact of anxiety on regulation. This convergence of quantitative and qualitative evidence underscores the utility of a mixed-methods approach for capturing both the breadth of statistical associations and the depth of learner experiences[22]. From a practical standpoint, these findings highlight the necessity of tailoring instructional supports to learners' profiles. Diagnostic assessments of working memory, cognitive style, motivation, and personality conducted at the outset of a course can inform adaptive scaffolding: encoding prompts (e.g., "How does this concept relate to what you already know?") may compensate for limited working memory, elaboration supports (e.g., graphic organizers, analogy exercises) can amplify benefits for reflective and open learners, and metacognitive checklists can guide anxious or novice students through planning and monitoring cycles[23]. Embedding choice and relevance into tasks may further cultivate intrinsic motivation, thereby enhancing self-regulated learning even under stress. For classroom implementation, brief, technology-mediated surveys or gamified assessments could efficiently profile students' individual differences and dynamically adjust content delivery in intelligent tutoring systems. Nonetheless, this study's cross-sectional, single-institution design constrains the

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generalizability of results and precludes definitive causal inferences, despite the directional modeling afforded by structural equation techniques. Think-aloud protocols, while informative, may also influence natural cognitive processes, raising questions about ecological validity. Reliance on self-report measures for motivation and metacognition introduces potential bias, although assurances of anonymity and the inclusion of social-desirability controls help mitigate this concern[24]. Future research should pursue longitudinal designs to trace how individual differences and learning processes co-evolve over time and employ experimental interventions—manipulating specific scaffolds such as planning prompts or elaboration cues—to establish causality and optimize the timing and nature of supports. Moreover, replicating this integrative framework across diverse educational contexts, age groups, and cultural settings will be essential for refining adaptive pedagogies that accommodate the full spectrum of learner variability.

Conclusion

It is demonstrated by the present investigation that each stage of the learning process—encoding, rehearsal, elaboration, and metacognitive regulation—is shaped in distinct yet interrelated ways by learners' cognitive capacities, affective dispositions, and personality traits, thereby validating an integrative Information-Processing and Self-Regulated Learning framework. Deeper elaboration strategies, such as analogical reasoning and conceptual mapping, were consistently employed by students possessing higher working memory capacity and reflective processing styles, in accordance with depth-of-processing theories. Robust planning and monitoring behaviors were maintained under performance pressure by those high in intrinsic motivation, illustrating how self-determination can mitigate anxiety's disruptive effects on goal formulation and regulatory control. Systematic rehearsal routines were upheld by conscientious learners, supporting memory consolidation, while concept-linking efforts were amplified among open individuals. These quantitative patterns were richly exemplified by think-aloud protocols, in which high-capacity, reflective learners were observed to integrate elaboration and self-questioning seamlessly, whereas lower-capacity or highly anxious learners often defaulted to rote repetition absent motivational scaffolds. On this basis, early diagnostic assessment of working memory span, cognitive style, motivation, and personality is recommended to inform the deployment of targeted instructional supports—guided encoding prompts, graphic-organizer tasks, metacognitive checklists, and choice-driven assignments—to optimize engagement and retention. Future longitudinal and experimental research across diverse contexts is required to establish causal pathways and to refine adaptive technologies that dynamically tailor feedback to real-time learner profiles.

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