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Developing a Conceptual Cognitive GPS Matrix for Representational Learning and Assessment in STEM Subjects

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Abstract: *Representational competence (RC) is a cornerstone in developing 21st century skills, especially for effective scientific communication. However, research on representational competencies in science, technology, engineering, and mathematics (STEM) lacks a unified conceptual framework for a systematic and hierarchical development of these competencies. This hinders the efficiency of assessment for learning. However, the revised Bloom's taxonomy (RBT) can offer a good hierarchical structure to model representational competency progression. Thus, employing the antecedents, decisions, outcomes (ADO) model, the present study systematically mapped perceptual, conceptual, and meta-representational competencies to six (6) RBT cognitive levels to establish a conceptual framework for STEM subjects' learning and assessment designs. It involved the extraction of competency descriptors from synthesized research publications, the identification of cognitive process verbs, and analysis of exemplar STEM studies. The results include a 6×3 cognitive GPS matrix with 18 discrete and assessable competency-level intersections, a competency development trajectory map, and a competency integration framework at both lower-order and higher-order thinking levels. The framework's elements are also exemplified in different empirical STEM studies. Further, the framework has uncovered opportunities for using emerging technologies like intelligent tutoring systems (ITS), machine learning (ML), and Generative AI, for enhancing representational learning in STEM subjects. The developed conceptual framework significantly adds value to existing RC frameworks in STEM, as it presents a clear and hierarchical progression of representational competency from novice to expert. It is a valuable conceptual tool for STEM educators and researchers, particularly in the areas of representational learning and instructional planning.*

Keywords: *Assessment Designs, Cognitive GPS Matrix, Representational Competencies, Revised Bloom's Taxonomy (RBT), STEM Education*

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1. Introduction

Due to the importance of representational competence (RC) in 21st century skills, the extensive use of multiple external representations (MERs) in science, technology, engineering and mathematics (STEM) education has yielded wide research on students' representational competencies. Recent research indicates that using more than two MERs can improve performance, suggesting that diverse representations cater to various cognitive needs of students (Rexigel et al., 2024). Furthermore, multi-representational learning fosters deeper understanding, particularly in complex scientific concepts, although it may require more time compared to mono-representational approaches (Rolfes et al., 2022). However, the effectiveness of these representations in STEM is also influenced by students' representational competencies, which are crucial for effectively interpreting and utilizing visual information (Rau, 2017).

According to Van Meter et al. (2020), expert scientists can easily utilize MERs to enhance their understanding and practice within their respective disciplines, while STEM students may struggle with their representational abilities. As it is revealed by Rau and Wu (2015), students face challenges in spontaneously making connections between MERs and their mental rotation is limited. It is also argued that the spatial complexity of stimuli in MERs can affect students' performance and cognitive resource allocation (Sharma et al., 2019). Furthermore, it is asserted that STEM students with varying levels of prior knowledge require different types of representational-competency supports (Rau, 2022).

While existing studies have identified the importance of RC and documented various challenges students face when working with MERs in STEM, there is a limited research on how detailed and systematically structured representational competencies can be developed and assessed for reaching a complete RC. Some existing frameworks try to indicate how RC can be developed in STEM subjects, but do not provide detailed step-by-step progression in line with cognitive efforts that are required (Ainsworth, 2006; Kozma & Russell, 2005). This absence of a unified framework complicates the development of effective instructional strategies and assessment tools that leverage various types of representational competencies, as educators may not fully understand how to support students in navigating these representations (Rexigel et al., 2024).

However, the revised Bloom's Taxonomy (RBT) offers a promising theoretical lens for addressing this gap by providing a hierarchical framework for modeling the progression of students' representational competencies in STEM subjects. As it is described by Sudirtha et al. (2022), RBT categorizes cognitive processes into six levels as it can be depicted in Figure 1. Each level builds upon the previous one, fostering a comprehensive understanding of complex STEM concepts.

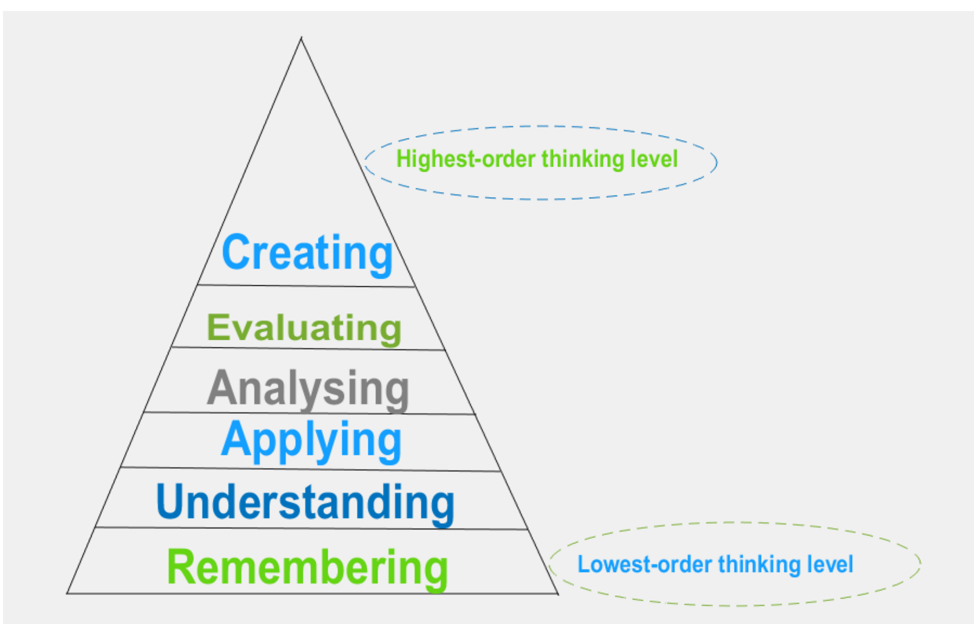

Figure 1: RBT Cognitive Levels
Source: (Sudirtha et al., 2022)

The present study aimed to map representational competencies to revised Bloom's taxonomy (RBT) for establishing a conceptual framework for STEM subjects' assessment designs. Specifically, the study intended to achieve the following objectives:

1. To develop a unified and hierarchical conceptual framework that systematically maps representational competencies to RBT cognitive levels for STEM subjects.
2. To establish a competency progression and integration framework for STEM subjects' instruction and assessment designs.

2. Literature Review

2.1 Theoretical Foundations

2.1.1 Educational Theories and Representational Learning

Representational learning and MERs in STEM subjects are supported by several educational theories, most notably those based on cognitive principles. Foremost, the cognitive load theory (CLT) is seen as foundational. According to Rexigel et al. (2024), CLT builds on managing the working memory load to optimize learning. In STEM learning, high cognitive load occurs when instructional materials are incoherent, discontinuous, or contains cognitive gaps (Maj, 2024). CLT is also the origin of Mayer's cognitive theory of multimedia learning (CTML), which focuses on multimedia learning principles in different learning environments (Çeken & Taşkın, 2022). CTML supports the combination of texts, pictures, and other representations for deeper understanding (Opfermann et al., 2017; Rexigel et al., 2024).

On the other hand, the DeFT framework (Ainsworth, 2006) models MERs-based STEM instruction by guiding the selection and sequencing of representations through design parameters, pedagogical functions (complement, constrain, construct), and cognitive tasks. This framework emphasizes on a three-step process (provoke, develop, predict), which promotes active learning and cognitive engagement, and enhances problem-solving skills through repeated exposure (Alkhatib & Rahmani, 2024). In learning chemistry, Kozma and Russell (2005) also developed a five-stages model which outlines students' progression from surface depiction to reflective, rhetorical representation use. In this model, surface depiction is the lowest level, followed by the symbolic skills. At the third and fourth levels, the syntactic and semantic use of representations are classified, whereas reflective and rhetoric use is considered as the expert-like RC in chemistry learning.

On the other hand, cognitive structures (schemas) which form in students' long-term memory, are developed through the human efforts to understand the complexity of their world through assimilation and accommodation using their perceptions and sensorimotor skills. This reflects the place of embodied cognition theory in representational learning in STEM (Putrawangsa & Hasanah, 2020). According to this description, students' cognitive development is not exclusively a mental affair, it is a complete interaction between perception, sensory experience and motoric experience, like interacting with science representations through touchscreen devices and using gestures (Soni et al., 2021).

As it is detailed by Ankiewicz (2024), constructivist learning theory is crucial in representational learning because its strategies focus on students' knowledge growth by adaptation from individual experiences (Piagetian). For example, a proper use of external representations is a good stimulus for situating a real STEM problem and activates all students' representational competencies through the working memory and long-term memory. Constructivism highlights the need to link new content to students' existing knowledge (Gavrilas & Kotsis, 2025).

2.1.2 The Revised Bloom's Taxonomy (RBT) in STEM Education

RBT serves as a vital framework for enhancing learning outcomes in STEM subjects by categorizing educational objectives into cognitive processes and types of knowledge. This structured approach aids educators in designing curricula that foster critical thinking and problem-solving skills, essential for STEM disciplines. RBT is comprised by six cognitive levels: remembering (C1), understanding (C2), applying (C3), analysing (C4), evaluating (C5), and creating (C6) (Sudirtha et al., 2022). These levels reflect the difference between learning objectives, in the cognitive domain, that an educator can set and guide students to achieve. Ramdhani et al. (2024) categorizes these levels in two groups including higher-order thinking skills (HOTS) and lower-order thinking skills (LOTS). LOTS includes the first three levels (C1→C3), whereas HOTS range in C4→C6.

In STEM education, RBT levels have been used for designing instructional activities and learning outcomes. For example, in the search for improving students' procedural activities and learning outcomes about the concepts of force and motion, learning activities and corresponding competencies were mapped to six cognitive levels (C1→C6) to improve students' activeness in learning, create learning experiences, and reflect on their learning progress (Adijaya et al., 2023). RBT has also been used in preparing exams for road engineering between 2020 and 2022 at Universidad Técnica Particular de la Lonaja in Equador (García-Ramírez, 2024). In these exams, it was observed that LOTS get higher grades compared to HOTS. RBT also helped to uncover students' HOTS for factual and conceptual knowledge in mathematical statistics at Al Asyariah Mandar University in Indonesia (Rahayu et al., 2021). According to these studies, the RBT is a flexible framework that may be used to connect learning objectives, assessment, and instructional design in order to encourage greater cognitive engagement in STEM education.

2.2 Representational Competence (RC) in STEM Subjects

RC is an extensively used concept in all STEM subjects. In science learning, RC is considered as the ability to successively understand, use and communicate about representations (Edelsbrunner et al., 2023). For engineers, RC entails visualization, transformation between static and dynamic MERs, generation of MERs, and modeling (Pande & Chandrasekharan, 2017). RC in mathematics is the ability to use representations meaningfully to understand and communicate mathematical ideas and to solve mathematical problems (Huinker, 2015). As it is indicated in all descriptions across STEM domains, RC is viewed as an integration individual representational abilities which are considered as representational competencies in STEM education.

In science domains, representational competencies manifest in different ways. For example, in chemistry learning, students must develop ability to link visual features in a representation with relevant concepts (conceptual competency) and intuitively process visual information and connect visual features across different types of representations (perceptual competency) (Talanquer, 2022). Additionally, using representations in quantum mechanics require students to evaluate the adequacy of various representations and judge their suitability for various tasks (meta-representational competency) (Wawro et al., 2020). Particularly for science subjects, representations serve to reveal phenomena from subatomic scale to celestial scale, requiring representational learning to minimize the distance between abstract and concrete concepts.

Through students' problem-solving techniques across various visual representations, representational competencies in engineering and technology education have been empirically studied. For example, the investigation of how engineering students handle representational translations in statics and digital logic has indicated that the way concepts are stored within representation features has a significant impact on students' capacity to access domain knowledge (Johnson-Glauch et al., 2020). Developing representational competencies should overcome students' difficulties in working with informationally incomplete representations that require coordination of multiple visual sources, failing to use concepts lacking perceptually salient features, and confuse concepts when representations use similar visual features, according to their cross-disciplinary study. The complexity of representational reasoning in engineering contexts is highlighted by the study's finding that RC in engineering goes beyond simple translation between representation types to include "hybrid translations", in which students integrate information from multiple representations simultaneously.

3. Methodology

3.1 Research Design

The present study employed a conceptual framework development approach through systematic theoretical synthesis and cross-mapping analysis. The research was designed as a qualitative, theory-building study that integrates established educational frameworks to generate a novel conceptual tool for STEM subjects' educators and researchers. This conceptual paper synthesizes existing theoretical constructs to create new knowledge through structured analytical reasoning.

3.2 Theoretical Synthesis with ADO Model

The theoretical synthesis has followed a systematic literature review using the Antecedents, Decision, Outcomes (ADO) model. ADO is among the highly-recommended models for framework-based reviews (Paul et al., 2021, p. 3). Figure 2 presents the procedural steps in using the model and key actions taken.

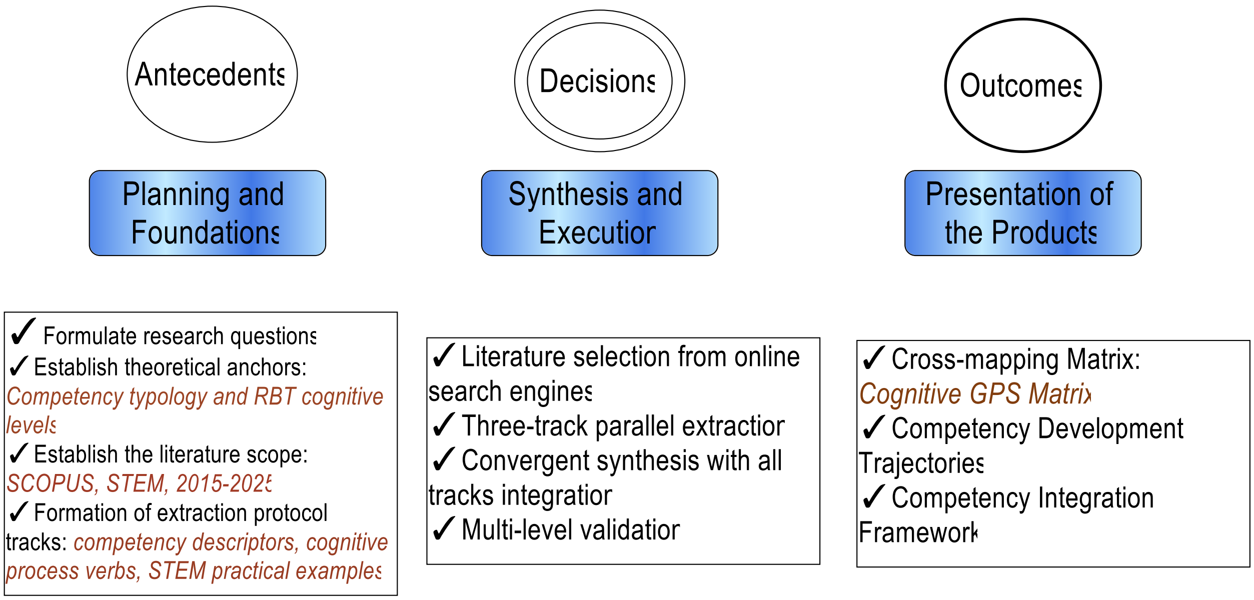

Figure 2: ADO Model for Literature Synthesis

3.2.1 Planning and Foundations

Phase 1 in the ADO model involved the formulation of research questions based on prescribed specific objectives: What are the defining characteristics of representational competencies (perceptual, conceptual, and meta-representational) in STEM? What are frequently used cognitive process verbs in STEM learning outcomes? How can these competencies be systematically aligned with RBT cognitive levels? What empirical evidence supports representational competency-cognitive level mappings?

The theoretical synthesis was also drawn upon two theoretical anchors. The representational competency typology in STEM by Rau (2017) and the Anderson and Krathwohl's 2001 RBT cognitive levels, operationalised through Sudirtha's (2022) application in STEM contexts. Moreover, a literature scope was established during planning. In this case, only SCOPUS-indexed journal publications were targeted. Publications whose focus was related to representational competencies or competence, the use of MERs or visual models in STEM and which were published between 2015 and 2025 were targeted. This phase was completed by forming the extraction protocol tracks including competency descriptors, cognitive process verbs, and exemplar STEM empirical studies.

3.2.2 Execution and Synthesis

The execution and synthesis were situated at phase 2 of the ADO model. At this phase, the literature selection was the first action. This was done through the screening of retrieved articles from online search engines (Google Scholar, Crossref, IEEE Xplore, ResearchGate, and Web of Science) based on predefined criteria. In total, 37 publications were included in the ADO model analysis (4 for cognitive process as the main focus, 5 for both representational competencies and cognitive process, and 28 for only representational competencies).

Literature selection was subsequently followed by a three-track parallel extraction of competency descriptors, cognitive process verbs, and exemplar STEM empirical studies. Further, all three tracks were integrated to form representational competency-cognitive level interactions. This has resulted into a 6×3 matrix, with 18 cells. Furthermore, this phase was concluded by multi-level validity check, with both vertical and horizontal validation.

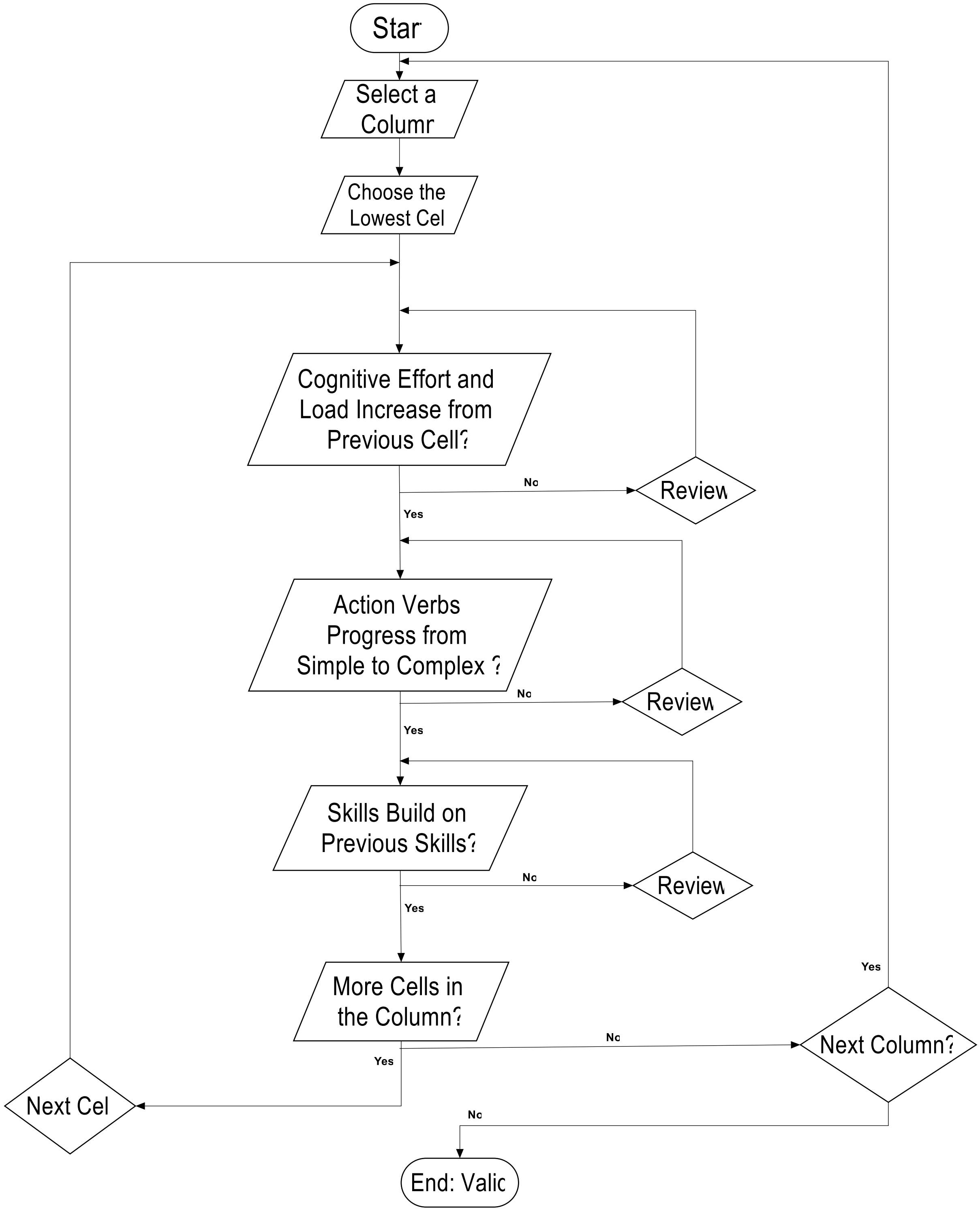

Figure 3: Internal Consistency Check (Vertical)

As it can be depicted from Figure 3, the vertical validation ensured progressive cognitive complexity from C1 to C6 through each competency column. This was carried out based on four dimensions including the cognitive effort, the complexity of the verb descriptors, the logical coherence in skills and the cognitive load.

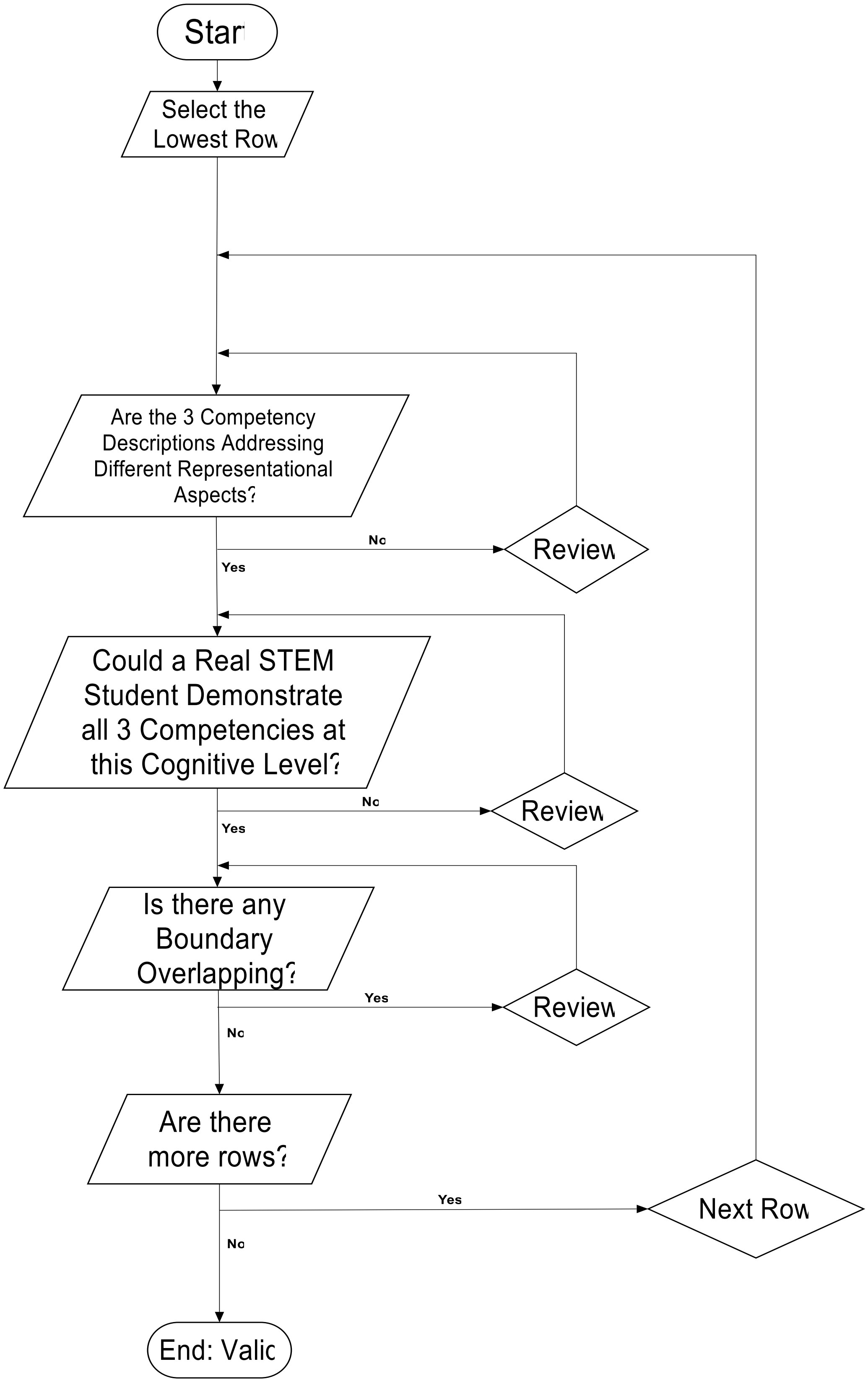

Figure 4: Cross-competency Alignment Check (Horizontal)

Figure 4 indicates the logical flow of how representational competency types were differentiated at each RBT cognitive level. Three themes guided this validation. The description of each representational competency must be unique but with complementarity among the three competency types. On the other hand, clear boundaries must be established for adequate use in STEM subjects teaching and learning.

3.2.3 Framework Products

The systematic literature synthesis by using the ADO model resulted in three key products addressing the issue of lack of unified conceptual framework for representational competencies assessment and development in STEM subjects. The cognitive GPS matrix was constructed with discrete representational competencies which are mapped to definite RBT cognitive levels across each competence type. Moreover, from the cognitive GPS matrix, the competency development trajectories and integration framework were established.

4. Results and Discussions

4.1 Results

4.1.1 Competency-cognitive Level Framework Overview

Table 1: The Cognitive GPS Matrix

RBT Cognitive Levels	Perceptual (P)	Conceptual (C)	Meta-Representational (M)
Remembering (C1)	To identify or recall or recognize individual features or elements of a representation. To extract or select sensory information from external representations. (Rau, 2017, p. 4)	To recall/name/ match the conceptual information depicted by various patterns in a given representation. (Gkitzia et al., 2020)	To name/recall/recognize/retrieve/ match the functions/purposes/ characteristics/properties/ affordances of various representations for discipline-specific contexts. (Eriksson, 2019, p. 4)
Understanding (C2)	To explain conventional rules and symbols in representations. To interpret different representational features or visual elements for the whole patterns. (Talanquer, 2022, p. 2665)	To connect/map /interpret features/patterns in a representation to domain-relevant concepts. (Eriksson, 2019, p. 4; Herder & Rau, 2022, p. 4)	To interpret or explain different purposes/functions/affordances of various representations in particular STEM contexts. (Zaqoot et al., 2019, p. 5)
Applying (C3)	To use/utilize/organize representational patterns for showing or visualizing or understanding a structure. (Herder & Rau, 2022, p. 3)	To use/utilize/organize/unpack a representation for explaining or interpreting a concept, a law, a theory or a principle in problem-solving tasks. (Talanquer, 2022, p. 2661)	To use/utilize/organize a representation as evidences in scientific discussions or in problem-solving tasks to support claims or to reflect on findings. (Nickel et al., 2025, p. 5)

Analysing (C4)	To compare/analyse /connect visual or sensory features within representations. (Nickel et al., 2025, p. 5; Talanquer, 2022, p. 2664)	To classify/analyse/compare conceptual information from different patterns of a representation. (Gkitzia et al., 2020, p. 3)	To analyse or compare the discipline-specific affordances of various representations. (Eriksson, 2019, p. 5)
Evaluating (C5)	To critique/judge the degree of abstraction of representational features or patterns for a given context. (Pande & Chandrasekharan, 2017)	To evaluate visual data against scientific principles. To critically evaluate relevant and irrelevant conceptual information from representations. (Rho et al., 2022, p. 70)	To select appropriate representations based on utility, contexts and task demands. To evaluate/critique the affordances and constraints of a given notation/representation in STEM context. (Zaqoot et al., 2019, p. 5)
Creating (C6)	To refine or add new sensory features or chunks or visual cues to an existing representation for modifying its degree of abstraction. (Nickel et al., 2025, p. 7)	To make annotations on an existing representation for making it conceptually rich. (Zheng et al., 2022, p. 5)	To invent or design new representations for specific STEM contexts. (Pande & Chandrasekharan, 2017, p. 17)

Table 1 presents the comprehensive cross-mapping matrix that systematically integrates representational competencies with RBT cognitive levels, from lower-level to higher-level cognitive capacity, for each competency category. This cognitive GPS matrix describes the progressive sophistication of cognitive tasks across eighteen (18) distinct competency-level interactions, each populated with empirically based descriptors and discipline-specific examples from STEM subjects.

Vertically, cognitive complexity increases systematically from C1 to C6, mapping a progression from foundational recognition to expert-level creative production. For example, perceptual competency evolves from basic feature identification (C1P) through pattern interpretation (C2P) to creative abstraction refinement (C6P). Each ascending level demands greater cognitive load, sophisticated verb descriptors, and enhanced metacognitive awareness. Horizontally, the matrix reveals competency differentiation at equivalent cognitive levels. For instance, at C6, distinctions emerge where C6P involves sensory-based modification, C6C emphasizes conceptual enrichment, while C6M pertains to holistic representational innovation, indicating technician-to-expert progression.

The diagonal progression, C1P→C6M, also indicates an important and complete developmental trajectory from novice to expert RC. Along this, C1P holds the threshold representational competencies for both dimensions (vertically and horizontally). On the other hand, C6M entails the overall required competencies to become an expert in representational communication in STEM subjects.

4.1.2 Competency Development Trajectories

The cognitive GPS matrix identifies distinct competency-cognitive level intersections, but an additional analysis of the representational skills dynamic progression across cognitive levels was necessary. This section breaks down the developmental paths for perceptual, conceptual, and meta-representational competency categories, showing how students in STEM disciplines progress methodically from basic recognition to expert-level proficiency (C1→C6).

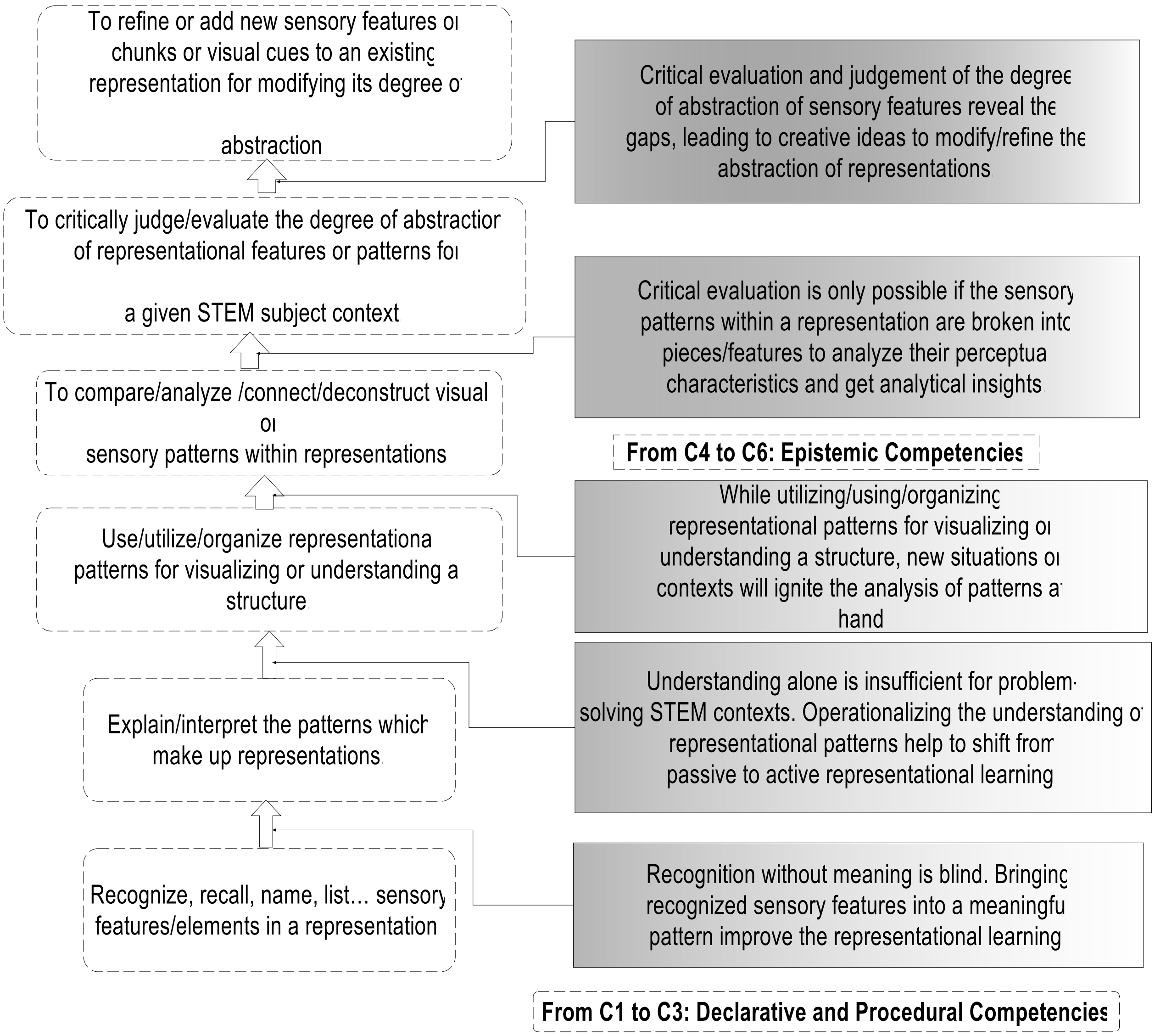

Figure 5: Perceptual Representational Competency Development from C1 to C6

Figure 5 illustrates perceptual representational competency development, showing progression from surface-level sensory recognition to sophisticated epistemic reasoning with visual-spatial information. This trajectory embodies a shift from passive consumption to active analytical interpretation of STEM representations. Development begins with declarative capabilities (C1→C2), establishing basic perceptual literacy. Cognitive abilities in C1 act as prerequisites to C2 ones. This progression is essential as recognition without meaning making obstructs learning. Further, deep understanding of sensory features is foundational using STEM representations in visualizing structures (C3).

Again, using various representations to visualize STEM structures ignites epistemic learning across from C4 to C6 RBT levels. At C4, analytical deconstruction enables pattern recognition and anomaly detection across representational forms. This progresses to critically evaluating abstraction levels (C5). The C4→C5 progression bridges representational learning, as judging abstraction requires understanding each element. Finally, C6 empowers students to modify representational abstraction through refining features and adjusting complexity for enhanced communicative effectiveness.

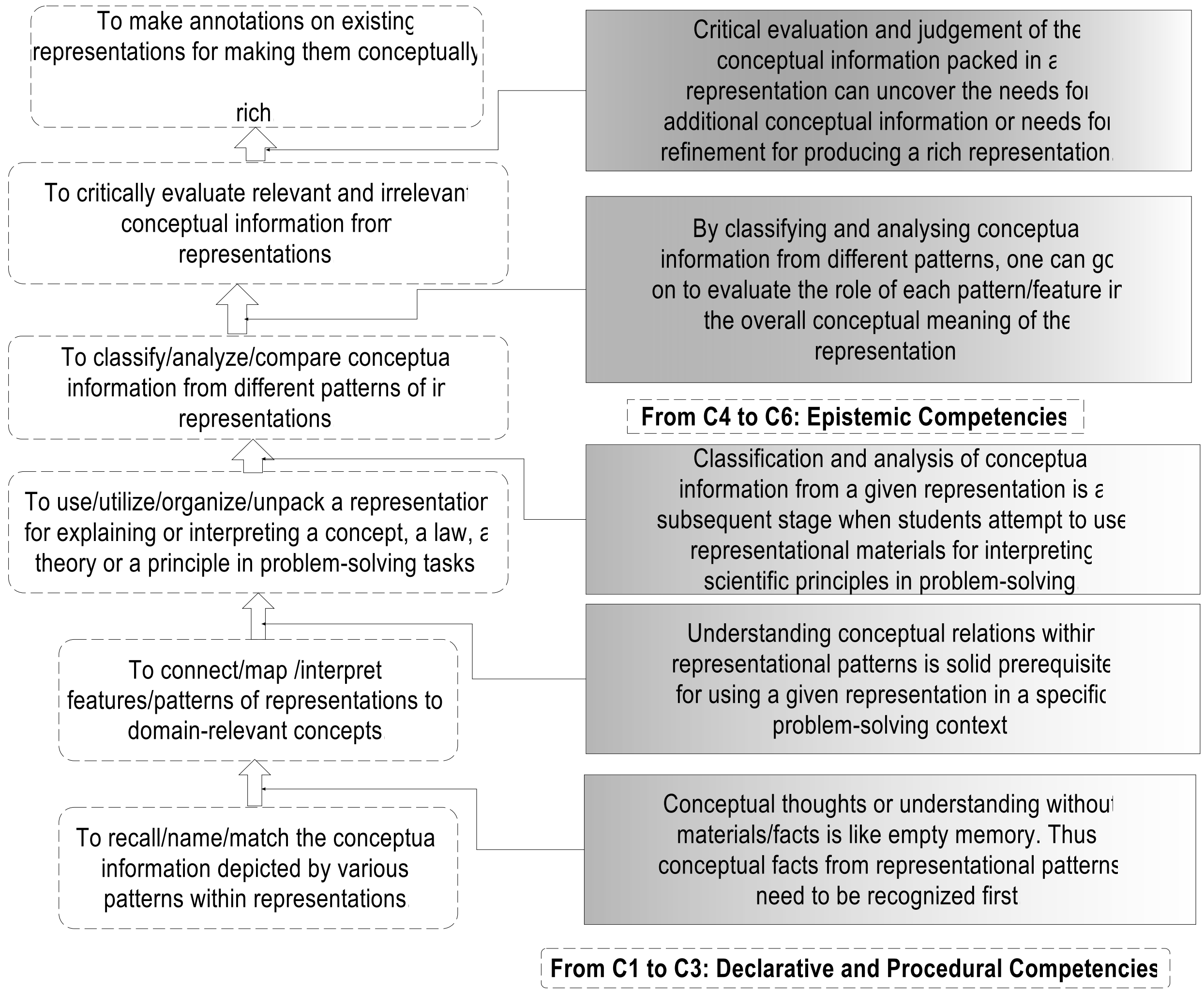

Figure 6: Conceptual representational Competency Development from C1 to C6

The competency development trajectory indicated in Figure 6 reflects on cognitive progression from surface-level domain-specific fact recognition to sophisticated conceptual reasoning and creative enrichment. Declarative competencies, C1→C2, establish conceptual grounding. At C1, students build conceptual vocabulary by recalling discipline-specific information from representational materials. This addresses the principle that conceptual thoughts without facts are empty, making C1 a prerequisite for C2, where students connect representational features to underlying concepts and interpret their relationships.

On the other hand, C3 involves procedural competencies, transitioning from comprehension to application. Students utilize representations to explain STEM concepts within problem-solving contexts (e.g., applying Newton's laws using free-body diagrams), generating practical experience for analytical insights. The epistemic phase, C4→C6, cultivates advanced reasoning. At C5, students become able to critically evaluate conceptual information embedded in STEM representations, requiring prior analytical classification and synthesis at C4. Further, evaluative capacity reveals representational inadequacies, creating cognitive demand for creatively annotating or modifying representations (C6) to enhance conceptual richness and explanatory power.

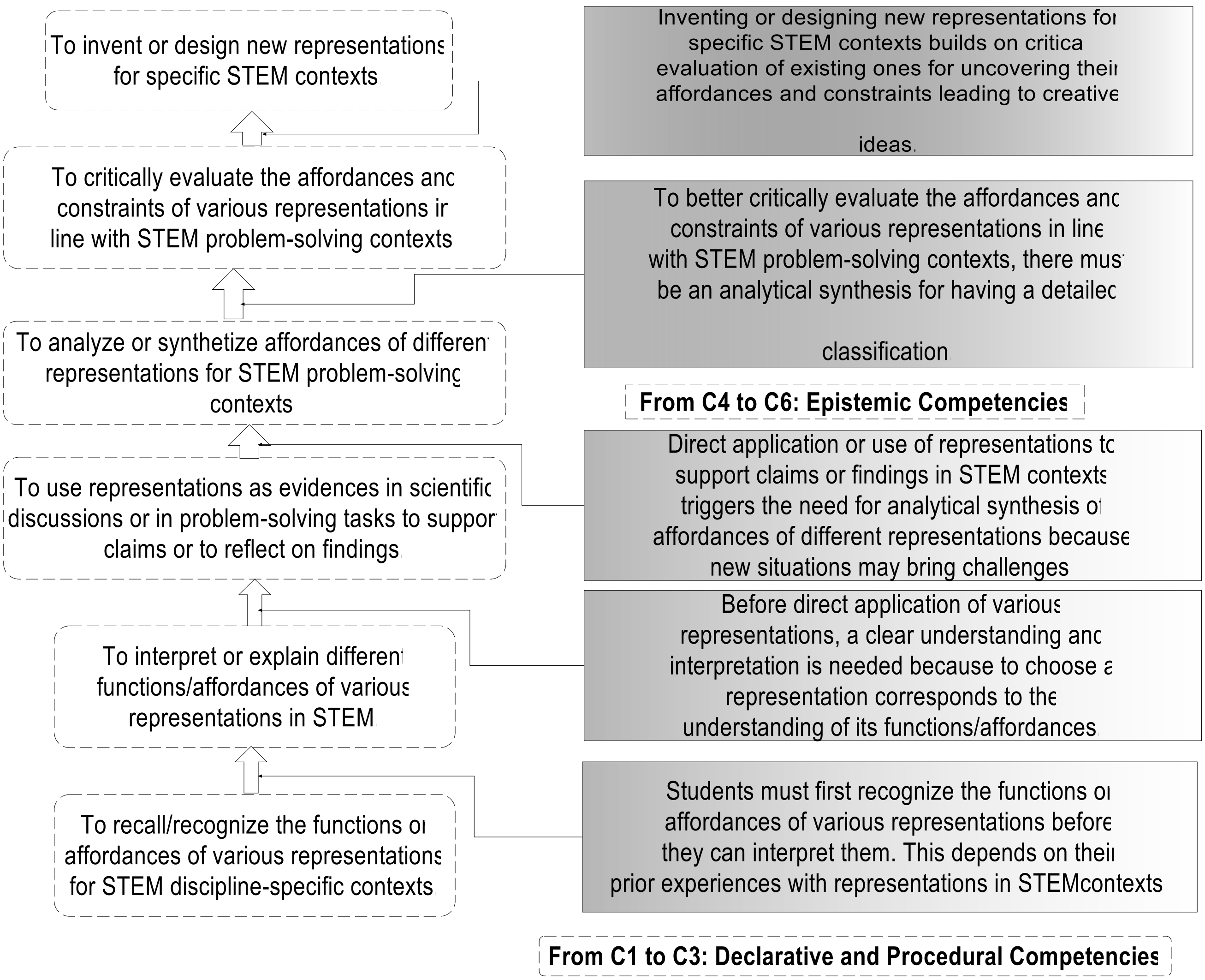

Figure 7: Meta-representational Competency Development from C1 to C6

The trajectory depicted in Figure 7 progresses from functional awareness to representational innovation, the highest expertise level. At basic cognitive levels, learning begins with recognizing and recalling representational functions and qualities (C1). This foundational recognition is crucial, as students must first identify these functions and affordances before deepening why specific representations are employed in particular STEM contextual problems. This deep understanding of functions and affordances of various representations augments engagement in real STEM problem-solving tasks, which triggers a strategic use of these representations as evidence in scientific argumentation (C3), supporting claims or reflecting on findings.

At advanced cognitive levels (C4→C6), meta-representational competency develops analytical and creative skills. Students learn to interpret and synthesize representation functions in STEM (C4), applying them to support claims. This triggers analytical synthesis of affordances, leading to critical evaluation of representations' strengths and constraints in problem-solving contexts (C5). Ultimately, this evaluation enables students to invent new representations for specific STEM applications (C6), building creatively on existing understanding.

4.1.3 Competency Integration and Framework Implementation

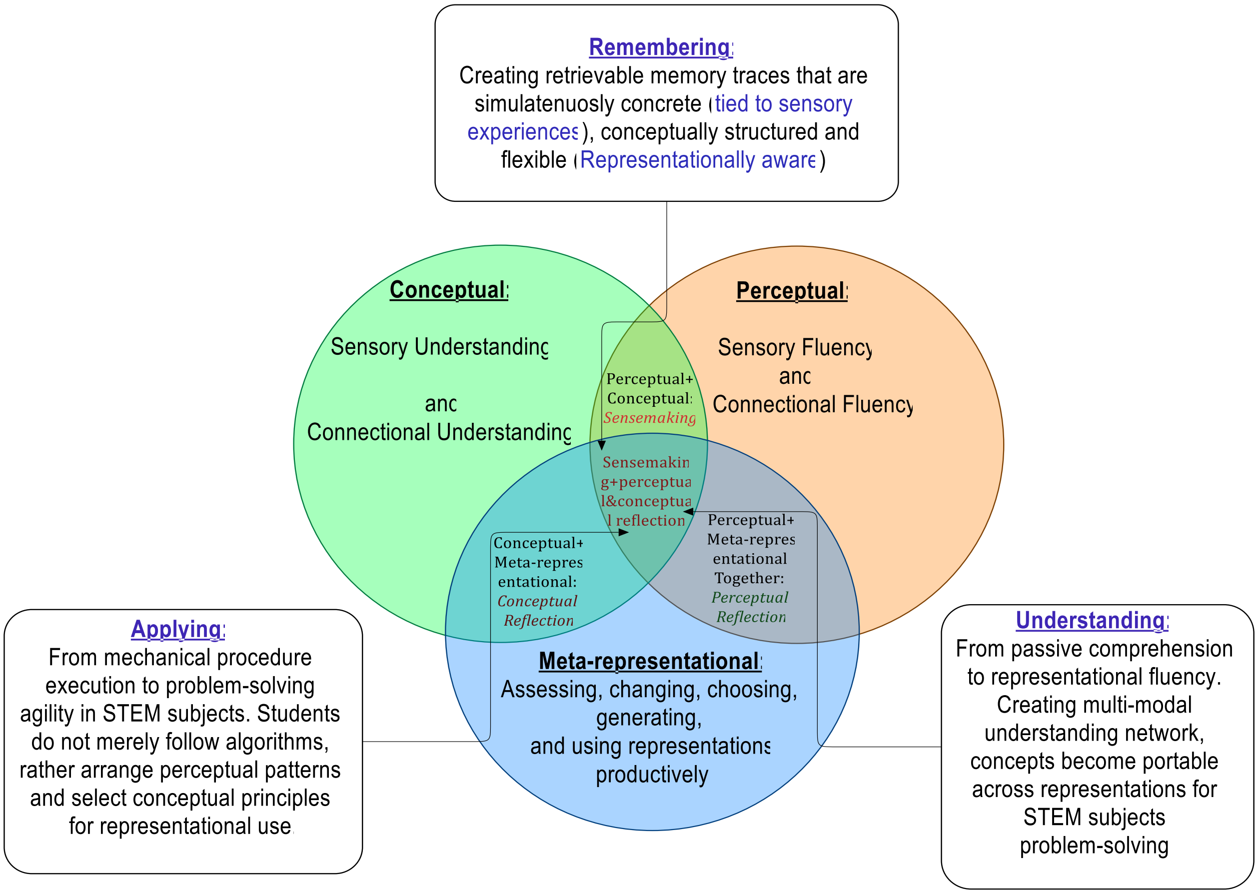

Figure 8: Competency integration at lower-order thinking levels

Figure 8 illustrates the synergistic integration of perceptual, conceptual, and meta-representational competencies within lower-order cognitive levels (C1→C3). As it can be observed, foundational cognitive operations also require coordinated deployment of all three representational competency categories. At C1, the competency integration demonstrates that effective recognition transcends rote memorization, requiring the formation of multi-dimensional memory traces. There must be perceptually concrete memory traces and organized around STEM domain-specific concepts and relationships (conceptually structured). Further, functions and affordances awareness must be a complement to the other two. For example, recalling a molecular structure, in chemistry, could involve remembering its visual configuration (perceptual), its chemical properties (conceptual), and its utility in depicting bonding patterns (meta-representational). This integration at C1 indicates that, in representational learning, memory should not be merely photographic, but also conceptually meaningful and contextually situated.

At C2, the competency integration relates to the capacity of fluidly translating meaning across representational forms while maintaining conceptual coherence (representational fluency). In this case, the focus on developing multi-modal understanding networks where sensory pattern understanding combines with conceptual mapping and interpretation to enable sense-making, with deep awareness of STEM representations' contextual functions and affordances. Ultimately at C3, the competency integration supports adaptive problem-solving agility rather than mechanical procedure execution. Here, students orchestrate perceptual arrangement, select relevant conceptual principles, and make strategic representational choices for use in real STEM problem-solving contexts.

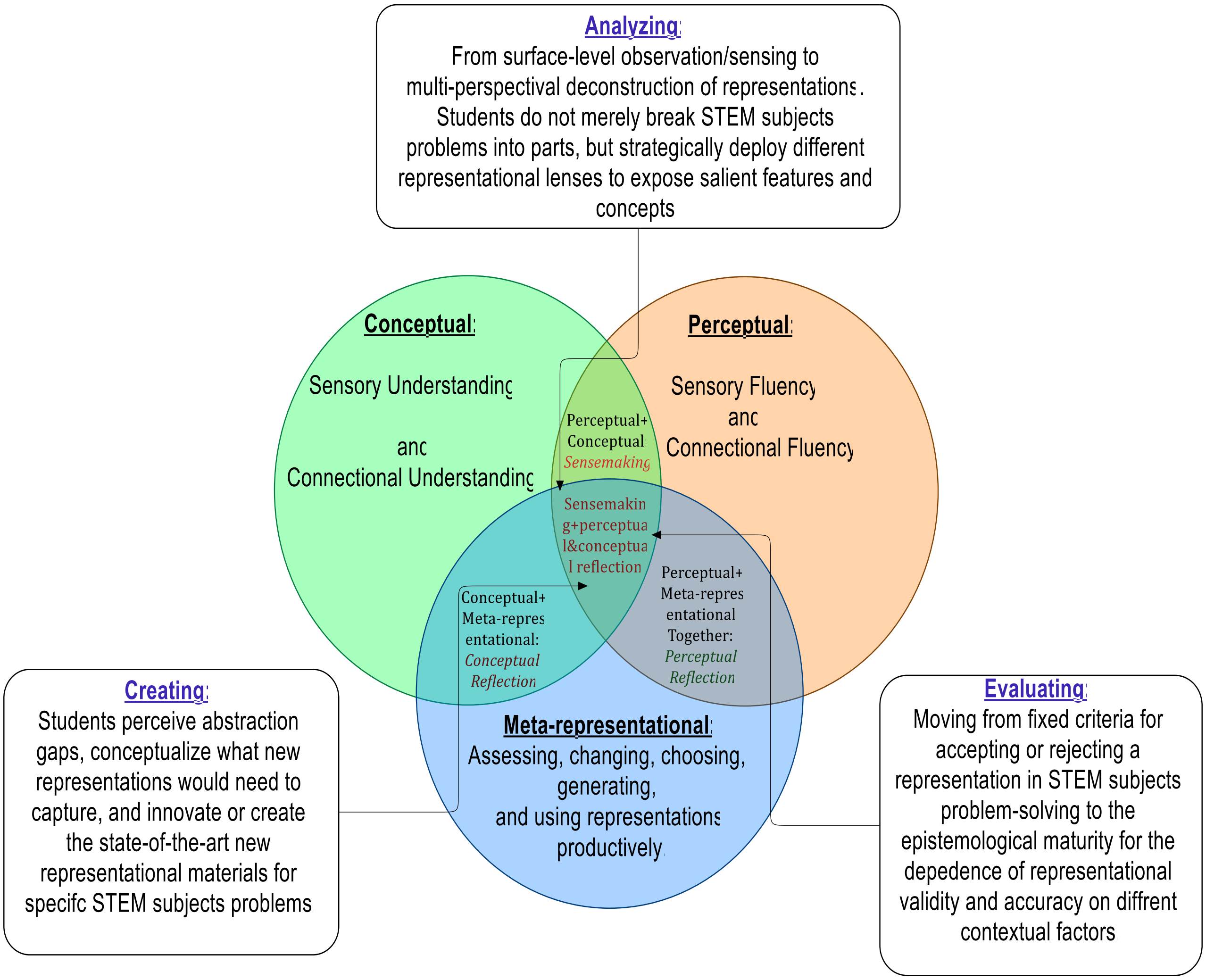

Figure 9: Competency integration at higher-order thinking levels

Figure 9 explains the representational competency integration as students engage with higher-order thinking levels within RBT (C4→C6) STEM. It demonstrates how the three representational competency types coalesce into expert-level STEM reasoning and reveals increasing interdependence and complexity as cognitive demands escalates, directly informing the development of advanced STEM assessment designs. At the analytical level (C4), the process moves beyond surface-level observation to a multi-perspectival deconstruction of representations. Here, students strategically deploy various representational lenses for exposing salient features, underlying concepts and corresponding representational characteristics and affordances. This involves analytical deconstruction of representational sensory patterns into constituent elements, conceptually parsing the relationships these elements encode, and reflecting on analytical insights from the representational forms.

Progressing to C5, the framework highlights a shift from fixed criteria for accepting or rejecting representations to an epistemological maturity that acknowledges the dependence of representational validity and accuracy on different contextual factors rather than being absolute. This integration framework involves a critical assessment of how well representations serve their purpose, integrating perceptual interpretation, conceptual understanding, and meta-representational judgment of their appropriateness. In this case, students must assess if a representation accurately convey relevant sensory information, faithfully represent underlying domain-specific STEM concepts and relationships, and if it serves its intended purpose in the defined context. This multi-dimensional evaluation overcomes the traditional one of right/wrong judgments, promoting the understanding that various representations possess different strengths and limitations depending on task demands, audience expertize, and communicative goals.

Finally, competency integration culminates in innovative synthesis at C6. This is where a holistic understanding and detection of representational gaps occurs for generating novel, effective representational solutions for complex STEM problems. As it is revealed in Figure 9, students perceive abstraction gaps in existing representations, conceptually envisioning the requirements for new representational forms, and innovate or design new state-of-the-art representations for specific STEM problems, addressing identified limitations. Learning at this level focuses on developing representational creativity for developing new notations, new visualization techniques, or hybrid systems that advance STEM disciplinary knowledge communication.

4.2 Discussions

4.2.1 Theoretical Relevance

Mapping representational competencies to RBT cognitive levels has successively developed a conceptual framework that can be used in domain-specific STEM assessment instructional designs. The established 6×3 cross-mapping matrix in Table 1 and the representational competency integration framework in Figure 8 and 9 make a significant theoretical contribution in STEM education by supporting the proposal of non-generalization of RC by Daniel (2018, pp. 229–230). The established framework operationalizes the general notion of RC into eighteen discrete, assessable competency-level interactions, each characterized by specific cognitive demands and observable behaviours. Pedagogically, this discretization can enable educators to diagnose students' current competency levels in their domain-specific STEM subjects and design targeted interventions. This is why the designed cross-mapping matrix functions as a "**cognitive GPS matrix**" for representational learning.

Additionally, the competency development trajectory represented in Figures 5−7 aligns with both Piaget's constructivist learning theory of cognitive development and Sweller's cognitive load theory (CLT) (Gavrilas & Kotsis, 2025, pp. 12–13). The competency progression from declarative and procedural to epistemic competencies highlights a well-structured and hierarchical cognitive development with more sophisticated cognitive demands building on simpler ones, fitting in Piaget's ideas. On the other hand, for real domain-specific STEM problem-solving, the well-defined representational cognitive tasks for each RBT level promote the Sweller's ideas of step-by-step learning and reducing extraneous load for proper cognitive load management. Moreover, the use of cognitive GPS matrix in this context brings the idea of "Zone of Proximal Development" (ZPD), used by Gavrilas and Kotsis (2025, p. 12). From Table 1, it is clear that students' representational difficulties can be located at some points of representational learning conceptual space in comparison with the targeted learning achievement. This can help STEM educators to design scaffolding intervention based on what students can do without help and what they cannot do.

Table 1 and Figures 8 and 9 reveal a critical connection between representational learning in STEM and learning theories of embodied cognition and CTML. According to Pande and Chandrasekharan (2017, p. 33), learning science and engineering is strongly based on the interaction with dynamic models. This shows how the present conceptual framework is an important addition in STEM learning. The competency integration (perceptual, conceptual and meta-representational) aligns with the embodied cognition theory where it promotes the sensorimotor experiences to develop cognitive capabilities in representational learning. When students interact with dynamic representations, their sensory perceptions are paired with conceptual connections and contextual reflections. On the other hand, the horizontal differentiation of competency types goes hand-in-hand with CTML's dual-channel assumption, as it is explained by Çeken and Taşkın (2022, p. 5). In this case, perceptual competencies engage visual-spatial channel, conceptual competencies draw upon both visual and verbal channels to construct integrated mental models, while meta-representational competencies employ metacognitive monitoring for both channels.

In another perspective, the present framework addresses complementary aspects of learning with MERs in STEM education. While DeFT identifies design parameters, pedagogical functions (complement, constrain and construct), and cognitive tasks undertaken when students interact with MERs (Ainsworth, 2006, p. 184), it does not provide structured competency progression from novice to expert. Moreover, the RC's five levels model by Kozma and Russell (2005, pp. 11–12) describes a clear and hierarchical developmental progression from using representation as depiction to a reflective and rhetoric use in chemistry, but it does not systematically map the representational skills to cognitive levels, which may challenge in designing assessments and instructional tasks. The cognitive GPS matrix adds to both frameworks by 18 assessable competency-level intersections that operationalize three representational competencies (perceptual, conceptual, and meta-representational) across six RBT cognitive levels. This bi-dimensional structure transforms broad development stages into granular, discrete competencies with explicit descriptors applicable across all STEM disciplines.

4.2.2 Mathematics Education Application Relevance

As it is argued by Daniel (2018, p. 229), RC is highly context-specific and the individual's level of competence can vary significantly depending on the specific content or domain of the representation. Although this argument can hold some empirical evidence, the present conceptual framework has provided detailed perspectives that worth discussion for different STEM domains. As mathematics considered as fundamental for both science and engineering, the discussion needs to start with representational competencies in mathematics.

According to Mainali (2020, p. 1), the cornerstone representational skill in mathematics learning is to be able to fluidly translate between representational modes. This makes one a mathematically proficient person, but it can wrongly be understood as a single representational competency. No, the developed conceptual framework can help to understand its detailed representational tasks in mathematics learning. As it can be figured out from the study by Mainali (2020), students need to generate, select and utilize representations to articulate mathematical concepts and relationship, to solve mathematical problems, or to model and interpret physical, social or mathematical phenomena. However, the current developed conceptual framework aligns with the translation processes in terms of step-by-step cognitive tasks (Mainali, 2020, pp. 14–15). For example, to translate from formulae to verbal description, there is parameter recognition, which is at C1. Another example is to translate from graph to formulae, where there is a task of curve fitting (C6). Moreover, there is a translation from graph to verbal description which requires interpretation skills combining analytical competency (C4), understanding (C2) and surface-level detection (C1).

The representational competency integration (perceptual, conceptual and meta-representational), developed in the current conceptual framework, aligns closely with suggestions in the study by Pedersen et al. (2021, p. 21) for activating students' critical thinking by encouraging them to investigate the strengths and weaknesses of mathematical representations. According to the developed cognitive GPS matrix, critical thinking competencies can be tracked through C5P, C5C and C5M. However, mathematics educators should note that critical thinking skills are developed progressively from lower-order thinking skills (C1→C3) and that critical thinking is very much connected to analytical skills (C4P, C4C and C4M), which precede. This marks a great contribution to assessment designs for representational learning in mathematics and mathematics educators can systematically prepare tailored instructions for the desired competency achievements. Nevertheless, representational learning in mathematics presents a unique nature: mathematical objects cannot be directly accessed like physical phenomena do in science, engineering and technology (Pedersen et al., 2021, p. 3). This is why mathematical representations can only be accessed through semiotic representations (linguistic, symbolic, figurative, and graphic), which dictates representational learning in mathematics to focus on these four semiotic representation registers.

4.2.3 Science Education Application Relevance

The created conceptual framework addresses students' difficulties navigating numerous representations in biology, chemistry, and physics, which have important consequences for science education. The "triplet relationship" of chemical thinking requires students to coordinate symbolic notations, submicroscopic models, and macroscopic observations (Talanquer, 2022, p. 2660). In order to address this, the developed cognitive GPS matrix defines representational skills at various cognitive levels. While selecting suitable representations, students at C1→C2 gain the ability to remember, decipher, and relate symbols to molecular structures. Inadequate integration of these competencies results in translation challenges. Through the development of annotated molecular diagrams that enhance conceptual understanding (C6C) and the mapping of progress from simple symbol recognition to sophisticated comparison of representational affordances (C4M), this approach can support representational fluency in chemistry.

The framework integrates perceptual and conceptual representational competencies to solve the issues identified by Eriksson (2019, p. 14) in astronomy, where students must read the sky by connecting theory and observation. This is especially important in physics education, where spatial-temporal reasoning is crucial. In line with this, Figures 5–7 show the competency trajectories, which show how students can progress from identifying diagram features (C1P) to analysing vectors and graphs (C2P, C2C) and assessing the sufficiency of representations (C5P, C5C, C5M), which can improve graph literacy as it was seen by Uwayezu and Yadav (2023). In other fields like quantum physics and electromagnetism, where exact images are essential to abstract concepts, this development is crucial as well. For example, Edelsbrunner and Hofer (2023) found that there is a positive relationship between representational competencies and content knowledge in electromagnetism.

As it is detailed in the study carried out by Flores-Camacho et al. (2021), students must understand, create, and employ many representational forms in a connected manner to convey their learning in order to gain RC in biology. According to this study, students learn Mendelian genetics in five different ways, ranging from simple observable features to complex model integration. This learning perspective aligns with the developed conceptual framework as expert-like RC is seen as an integration of progressive RBT-based cognitive level competencies and the integration of perceptual, conceptual, and meta-representational competencies. Importantly, rather than just obtaining more detail, representational refinement entails integrating knowledge across organisational levels and establishing causal links between macroscopic observations and microscopic mechanisms.

4.2.4 Engineering and Technology Education Application Relevance

In engineering education contexts, the developed framework directly parallels the cognitive development identified between novice students (those who are struggling to access information from visual representations) and expert-like representation manipulators (those who spontaneously and fluidly translate between representations in problem-solving tasks) (Johnson-Glauch et al., 2020). According to this work, some engineering students may confuse concepts which share similar visual features in their representations. Although this is a common treat in STEM education, the present study adds another dimension in representational learning by integrating perceptual, conceptual and meta-representational recognition and understanding (at C1→C2), which pertains to declarative representational competencies. The meta-representational competency dimension helps engineering students to reflect on their recognition about representational features and corresponding domain-specific conceptual connections.

As engineering students must progressively work with increasingly complex visualizations (Rho et al., 2025, p. 21), the developed framework addresses a pressing issue of integrating perceptual and conceptual representational competencies. In this sense, it is described that electrical engineering students critically require dual competencies to successfully process visual representations from simple time-domain graphs and phasors to complex vector addition diagrams. The discretization of representational competencies in the present framework has the power to systematically guide engineering educators in designing instructional activities for achieving merit students' abilities to work with complex visual representations. However, the study by Ortega-Alvarez et al. (2018, pp. 4–5) strongly indicates a well-structured representational learning in engineering for developing conceptual understanding.

Representational competencies in engineering and technology education are not just learning outcomes, but rather, these are real workplace demands. Real-world engineering problems require designing, building, and maintaining various materials, systems, and processes, relying heavily on iterative generation and use of MERs. A particular nature for technology or engineering representations is that they are highly open-ended compared to science subjects and mathematics (Pande & Chandrasekharan, 2017, p. 29). The developed cognitive GPS matrix provides a systematic assessment and scaffolding traces in line with this complexity by acknowledging that engineering representations do not merely encode information but constitute thinking and learning devices that augment cognition through sensorimotor interactions. Moreover, the framework's competency development trajectories align with the Miller's pyramid for competency-based assessment (CBA) designs in technical and vocational education and training (TVET) (Zamri & Mohamad, 2023, pp. 4–6).

4.2.5 Pressing Need for using Emerging Technologies

A solid theoretical foundation for leveraging emerging technologies to improve representational learning in STEM is offered by the competency integration framework and the cognitive GPS matrix. In order to provide adaptive learning, identify students' representational levels, and offer focused interventions, Intelligent Tutoring Systems (ITS) can utilize the cognitive GPS matrix. For example, electrical engineering students can construct a phase-domain visual by identifying important features of a sinusoid, find a corresponding type of visual representation depicting a sinusoid, and construct a phase-domain sinusoid visual with an interactive tool (Rho et al., 2022, p. 69). In line with the developed conceptual framework, ITS can be used to design assessment and learning paths by incorporating the cognitive GPS matrix to overcome the traditional practices which may not detect competency gaps on time.

Additionally, the framework calls for the integration of virtual reality (VR), augmented reality (AR) and virtual experiments. According to Sanfilippo (2022), multi-sensory learning with haptic technologies enhance both sensorimotor and perceptual experiences. This aligns with the developed conceptual framework's competency integration, which also can help in fostering mathematical sensemaking for STEM students (Uwayezu et al., 2024). On the other hand, machine learning (ML) algorithms can be developed for automatic assessment of student-drawn models and their corresponding verbal descriptions (Zhai et al., 2022), where the algorithms can be developed based on discrete representational competencies from the cognitive GPS matrix. Moreover, Cao et al. (2023) indicated that Generative AI can be used in transforming complex principles into visual metaphors in mathematics and physics. These technologies collectively enable precise, scalable interventions that align with the framework's emphasis on systematic competency development across representational modes.

4.2.6 Limitations

The present study acknowledges some limitations. At first, the developed conceptual framework is theoretically tested and validated. This indicates that empirical testing in various STEM situations and academic levels can discover practical points for refining the framework. Although the cognitive GPS matrix and correspond tools are developed, additional automated scoring algorithms, validated rubrics, and standardised measurement instruments were not developed in the present study. Employment of the framework for technology integration (ITS, VR/AR, ML) for individualised representational learning pathways in STEM should be operationalised through methodical research.

5. Conclusion and Recommendations

5.1 Conclusion

A unified and hierarchical conceptual framework that methodically maps representational competencies to RBT cognitive levels for STEM subjects' learning and assessment is developed in the present study. The cognitive GPS matrix and subsequent tools give STEM teachers conceptually supported tools for creating competency-based instructions and assessments by operationalising 18 distinct, assessable competency-level crossings. This framework advances the theoretical understanding and practical application of representational learning across STEM disciplines by integrating perceptual, conceptual, and meta-representational competencies within a hierarchical cognitive structure. It also lays the groundwork for utilizing emerging technologies including intelligent tutoring systems (ITS), virtual reality and augmented reality (VR/AR), machine learning (ML), and Generative AI technologies for meaningful STEM education.

5.2 Recommendations

Based on the outcome of the present study, future studies can focus on creating automated scoring algorithms and standardised assessment tools based on the presented cognitive GPS matrix and corresponding representational competency progression and integration. Further, situation-based empirical validations across a range of STEM contexts and educational levels are required for increasing the practical relevance of the framework. Furthermore, methodically operationalising technology integration for customised representational learning pathways can be an instrumental research focus in the future.

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