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Learning from Novice Programmers' Metaphors of Generative Artificial Intelligence

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Abstract. Generative artificial intelligence (GenAI) tools are reshaping how students approach problem-solving in programming education. This study demonstrated the methodological value of metaphor analysis in examining students' perceptions of AI-supported learning. It explored how first-year students in an introductory Python programming module at a South African university conceptualize GenAI use during coding-related tasks. The context matters because many students from disadvantaged communities enter university with limited computing exposure. Guided by a framework of AI-mediated cognitive engagement, the study drew on 161 responses and used inductive-deductive metaphor analysis to examine how students position AI in relation to their thinking. Six dominant metaphorical framings emerged: tool, tutor, facilitator, specialist, liar, and threat. These metaphors revealed that students experienced AI in both constructive and cautionary ways, as a source of cognitive support and conceptual expansion, and as a potential source of reduced mental effort. The findings showed a systematic correspondence between metaphorical framings and reported cognitive experiences, including mind-mending, mind-stretching, mind-gaming, and mind-replacement. Chi-square and Fisher's exact tests strengthened the qualitative findings by confirming an association between metaphor roles and cognitive influence. The study contributes to research on AI in education by showing that metaphor offers a powerful lens for understanding how students interpret and regulate AI-supported learning. It argues that GenAI is a conditional cognitive mediator whose impact depends on student agency, epistemic trust, and the nature of engagement. The findings have implications for the design of programming curricula and educational practices, integrating AI responsibly while sustaining critical thinking and academic integrity.

Keywords: generative artificial intelligence (GenAI); metaphor analysis; novice programmers; Python; South Africa

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1. Introduction

At a South African university, Python is used as the programming language in an introductory programming module. The learning outcomes include: (i) the ability to implement basic structured programming principles; (ii) analyzing and defining programming-related problems; (iii) applying problem-solving skills to develop algorithms for small to medium-sized computational tasks; and (iv) demonstrating ethical responsibility in the use of computing technologies (du Plessis & Smit, 2026).

The emergence of generative artificial intelligence (GenAI) tools is rapidly transforming how these outcomes are pursued. What was recently considered a supportive enhancement in teaching and learning has increasingly become a baseline expectation (Kokina et al., 2025). Given that many GenAI tools are freely accessible, students' use of such technologies outside the classroom cannot be controlled. In the context of programming education, this raises important questions about how students engage with problem-solving when learning code and artificial intelligence (AI) tools are readily available to generate explanations, code and solutions.

This context is important because many students enter university from disadvantaged backgrounds and are often underresourced schools. In the South African context, educational inequalities are closely linked to the enduring effects of apartheid-era racial segregation, uneven school resourcing, and persistent socioeconomic disparities. These students may have limited exposure to digital technologies, requiring them to simultaneously learn programming concepts and navigate unfamiliar technological environments. For these novice programmers, the transition from school to a university requires developing new mental models for understanding abstract computational processes.

They often experience uncertainty and anxiety that are not merely behavioral but conceptual, reflecting how they position technology in relation to their own learning and identity (Chiramba & Ndofirepi, 2023; Wang et al., 2024). Student AI use is shaped by context, course rules, task design, and prior learning conditions (Lepp & Kaimre, 2025). A metaphor is useful in this context, as it provides a window into the underlying cognitive frameworks through which students understand complex and unfamiliar phenomena. Student metaphors may reflect not only perceptions of AI but also unequal access, limited prior computing exposure, and the pressure to use available digital support to compensate for educational disadvantage.

While a growing body of research examines the use of GenAI in education, relatively little is known about how students conceptually interact with AI while learning to code (Albrant et al., 2025; Güner & Er, 2025; Lepp & Kaimre, 2025; Nathaniel et al., 2025). Emerging studies suggest that metaphor analysis offers a powerful lens to explore these conceptual engagements, revealing how students interpret and internalize the role of AI in their learning processes (Beshlei, 2025; Karakitsou et al., 2025; Qiao et al., 2026). This study made sense, as we

investigated not only what students do with GenAI but also their thinking on GenAI and its role in the learning process.

Metaphors, understood as the process of “*understanding and experiencing one kind of thing in terms of another*” (Lakoff & Johnson, 1980), play a central role in shaping cognition. They provide a means of translating complex or abstract phenomena into more familiar terms, enabling individuals to construct meaning, organize experience, and guide behavior (Cornelissen et al., 2005). In this sense, metaphors do not merely describe experience; they actively structure how it is understood and enacted. Programming concepts are abstract, novice programmers form mental models, and GenAI introduces a new cognitive partner whose role is made visible through metaphorical framing (Pham & Morin, 2026).

Against this backdrop, this study investigated how novice programming students conceptualized their interactions with GenAI tools through metaphorical language. By examining these metaphorical framings, the study aimed to provide insight into how students positioned AI in relation to their own cognitive processes, particularly in problem-solving contexts. Emerging research presented by Almaiah et al. (2022) and Wang et al. (2023) suggests that students’ perceptions of AI are shaped by its perceived usefulness, as well as affective factors such as anxiety, trust and self-efficacy, leading to AI anxiety. Artificial intelligence anxiety is described as a lack of confidence and fear regarding the use of new technologies.

The central research question was as follows: To what extent and how do students in a South African higher education context use metaphors as cognitive tools to construct and express their understanding of GenAI during introductory Python coding tasks? To address this question, the study was guided by the following secondary research questions:

1. What metaphors do students use to conceptualize GenAI in novice Python coding tasks?
2. How do constructive and cautionary metaphors relate to students’ engagement in these tasks?
3. What implications do these metaphorical conceptualizations have for curriculum design and instructional strategies in South African AI-mediated programming education?

A deeper understanding of these conceptualizations offers important implications for curriculum design and instructional strategies in AI-mediated learning environments. The ethical dimension is also important because GenAI does not merely provide technical assistance; it mediates students’ access to knowledge and judgement. Analyzing metaphorical language directly addresses AI engagement because metaphors reveal not only use but also the cognitive, affective and epistemic positions from which students engage with GenAI (Pham & Morin, 2026). The paper is structured as follows. The next section outlines the theoretical framework, followed by the methodological approach to metaphor analysis. The findings are then presented and discussed. Finally, conclusions are drawn and recommendations are made.

2. Theoretical Framework: Towards a Model of AI-Mediated Cognitive Engagement

This study is grounded in the proposition that GenAI does not simply support learning tasks but actively reshapes the cognitive processes through which learning occurs. To capture this transformation, the framework integrates three complementary perspectives: metaphor as a cognitive structuring mechanism; GenAI as a participant in distributed cognition; and learning as a process of mediated and scaffolded engagement (Dong, 2026; Usman et al., 2025; Zhao & Yang, 2026). Together, these perspectives form a model of AI-mediated cognitive engagement through which students interpret, regulate, and negotiate their interactions with GenAI. Metaphor analysis is employed as the primary analytical lens, enabling access to students' implicit cognitive models of AI use in learning contexts.

2.1 Metaphor as a Cognitive Structuring Mechanism

The study of metaphors has evolved significantly, shifting from early analyses rooted primarily in linguistic theory to a broader recognition of metaphors as a central mechanism in cognition. Rather than serving merely as a stylistic or rhetorical device, metaphors are now understood as powerful tools for semantic enrichment and cognitive processing, including priming and conceptual framing (Lakoff & Johnson, 1980; MacCormac, 1990). The Lakoff and Johnson (1980) seminal contribution reframed metaphors as fundamental to human thought, demonstrating that individuals understand abstract phenomena by mapping them onto more familiar experiential domains. In this sense, metaphors function as cross-domain mappings that structure how people perceive, interpret, and act upon the world (Lakoff, 1993). This cognitive perspective highlights that meaning extends beyond the description of observed behavior; it encompasses the interpretation, justification and organization of experience, thereby shaping thought, action, and application of knowledge. As Cornelissen et al. (2005) argue, metaphors are generative: they do not merely reflect reality but actively participate in constructing it.

Within educational contexts, metaphors perform a dual function. First, they act as a cognitive bridge, enabling students to interpret unfamiliar or complex phenomena in relation to familiar roles or experiences. Secondly, they encode implicit assumptions about agency, knowledge, and trust, thereby shaping how students interact with and respond to these technologies (Cornelissen et al., 2005). In this way, a metaphor becomes both a lens for understanding and a mechanism that influences learning behavior. This study focused specifically on context-dependent metaphors, making them particularly valuable for uncovering how students make sense of complex phenomena within a coding environment (Schmitt, 2005; Wittink, 2011). First-year students enrolled in an introductory Python programming course participated in this research.

From this perspective, students' metaphorical framings of GenAI can be understood as cognitive representations of their learning relationships with AI, revealing how they position the system in relation to their own thinking processes (Ljadov et al., 2025). Given the black-box nature of GenAI, where the processes

through which outputs are generated are not fully visible to students, metaphorical language becomes especially useful for examining how they make sense of an opaque technological system. Metaphor analysis therefore provided a methodological pathway into the otherwise tacit mental models that shape AI-supported learning. This aligns with the argument of Malik (2025) that educational research must foreground student agency and actively promote forms of engagement that stimulate cognitive development. In future, these metaphors, utilized by lecturers, may be valuable in guiding the use of GenAI (Sanford et al., 2014).

2.2 Generative AI and Distributed Cognition

While metaphor theory explains how students conceptualize AI, it does not fully account for how AI participates in cognition. To address this, the study drew perspectives from distributed and extended cognition, which conceptualize thinking as a process that is not confined to the individual but distributed across tools, environments, and social actors. Hollan et al. (2000) argued for a reorientation of how to think about designing and supporting human-technology interaction. Unkelos-Shpigel et al. (2026) emphasize the need for structured educational frameworks to guide GenAI, inform metacognitive awareness training, and distinguish between GenAI-enhanced and -substituted thinking methodologies.

Generative AI can be understood as a cognitive artifact that participates in thinking processes by externalizing knowledge, generating alternatives, structuring problem-solving pathways, and augmenting memory and reasoning, holding both opportunities and challenges for pedagogical design. Scholars underscore the shifting role of AI from a passive resource to an active cognitive partner, contributing to what may be termed shared or hybrid cognition (Unkelos-Shpigel et al., 2026; Wilson & Burleigh, 2026). In such contexts, cognitive processes such as understanding, problem-solving, and decision-making are partially redistributed between a human and a system. However, this redistribution introduces critical tension. While AI can extend cognitive capacity (cognitive augmentation), it can also lead to cognitive offloading, where mental effort is reduced or displaced onto the system (Ljadov et al., 2025; Unkelos-Shpigel et al., 2026). This duality aligns with emerging research on AI in education, which highlights both its potential to support higher-order thinking and its risk of diminishing cognitive engagement when over-relied upon.

A metaphor can be seen as a distributed cognitive representation, since it shares understanding across people, language, artifacts and cultural praxis rather than residing solely in the mind of the individual (Sanford et al., 2014). Yet, in the context of GenAI, a metaphor may cloud as much as it discloses. Yes, the metaphor forms part of the distributed cognitive system, but the black-box nature of GenAI hinders our ability to affirm whether the metaphor accurately reflects the foundational processes (Ehsan & Riedl, 2024). Therefore, such shared understanding may be built upon representations that are of use pedagogically but correspond only in part to how GenAI operates (Kumarage & Saarela, 2026).

2.3 Learning as Mediated and Scaffolded Engagement

To understand how this distributed cognition unfolds within educational settings, the framework draws on socio-cultural learning theory, particularly the notion of mediation and scaffolding, referred to as “*complicated, qualitative transformations of one form of behavior into another*” (Hausfather, 1996). Learning is conceptualized not as an isolated cognitive act but as a mediated process shaped by tools, interactions, and cultural artifacts. A problem requires active resolutions to be resolved, thereby gaining new knowledge or experience. A problem posed to a student should generate motivation and cognitive activity, thus serving as a source of learning and development.

A problem may lack a clear method or means to achieve it, aligning with the development of students as critical thinkers and requiring students to apply creative and adaptive thinking (Dostál, 2015). The South African context is important for mediation as students’ engagement with GenAI occurs within conditions of uneven prior preparation, limited computing exposure and persistent educational inequality. For these novice programmers, GenAI may operate as an adaptive scaffold that supports access to explanations and problem-solving strategies. However, this mediation is conditional rather than neutral as it depends on students’ agency, epistemic trust, and ability to evaluate AI-generated outputs critically. From a sociocultural perspective, GenAI is therefore part of a wider mediated learning ecology.

Problem-solving involves three key components: known facts, a goal or desired outcome, and the actions needed to reach the goal. In traditional programming education, problem-solving is mostly human led, requiring students to interpret a problem, design an algorithm, implement a solution, and evaluate the output. GenAI introduces a different form of problem-solving in which some stages of cognition may be supported, augmented, or partially delegated to an AI system. In AI-assisted problem-solving, students must not only solve the problem itself but also evaluate AI-generated output and determine its accuracy, decide when to rely on it, and integrate it into their own reasoning.

The educational challenge therefore shifts from solving problems independently to managing an evolving relationship between human judgement and machine-generated assistance (Almaiah et al., 2022; Wang et al., 2023). Problems can be well-defined with clear goals and methods or ill-defined (more open-ended and complex) and solving them requires both declarative knowledge (knowing what) and procedural knowledge (knowing how), which work together in memory. Expert problem-solvers differ from novices by having deeper conceptual understanding, more automated skills, and effective domain-specific strategies. These attributes allow experts to solve problems more efficiently by focusing on complex aspects while relying on automated routines for basic tasks (Hardin, 2003).

When students begin their journey of learning to program in Python, their conceptual understanding of programming concepts involves both the knowledge of specific programming constructs and the mental frameworks or schemas that help them relate and organize these constructs in meaningful ways to accomplish a certain programming task. The content would include concepts such as basic syntax and semantics of Python; understanding keywords, indentation, operators and data types; core programming constructs such as variables, loops, functions and data structures. Algorithmic thinking - that is, the understanding of how to break down a problem into smaller, manageable steps, is an important skill (du Plessis & Smit, 2024).

According to Hardin's (2003) definition, students' conceptual understanding entails both content (what they understand) and structure (how they understand it). This means that students build a mental representation of how code executes line by line, and how data flow through a program. Students need to categorize groups of programming constructs into functional categories to enable loops, modularization, and an ordered collection of code. With a solid schema, students can transfer knowledge from one context to another. For instance, they realize that both for and while loops achieve repetition, but in different ways. In the context of Python, conceptual understanding is not just about memorizing syntax but about seeing patterns, understanding underlying principles, and being able to apply them flexibly across new problems (du Plessis & Smit, 2024). This deeper level of understanding supports better problem-solving, debugging, and long-term retention.

Talanker (2016) argues that problem-solving is based on a sequence of steps. In decision-making theory, a problem requires the problem-solver to consider multiple courses of action, of which more than one can lead to the desired outcome. The problem does not exist independently but is shaped by the way the student perceives it, and the lecturer defines and frames it. In decision-making theory, a problem is defined as a subjectively constructed gap between the current and desired states under uncertainty or conflicting objectives, existing only when a decision-maker recognizes the gap, has a goal, perceives alternatives, and requires further analysis to choose among them; its framing is shaped by individual, cultural and contextual factors and time constraints (Turpin & Marais, 2004).

Since the launch of ChatGPT in 2021, GenAI has entered the learning space as a form of adaptive, always-available scaffolding used during problem-solving and metacognitive reflection. However, unlike traditional scaffolding, GenAI is not fixed or pre-designed by the lecturer; it is dynamic, responsive, and mostly opaque. This introduces a shift from instructor-led mediation to student-managed mediation, where students must actively regulate how and when they engage with AI support. Cognitive load theory is not rejected but expanded in the AI era, as AI and educational neuroscience enable real-time measurement and dynamic adjustment of cognitive load, moving learning from static design principles to continuous, data-driven optimization (Gkintoni et al., 2025). It reveals that effective learning now hinges on AI's ability to personalize task difficulty, reduce

extraneous load, and align cognitive and emotional states, thereby shifting cognitive load theory from a prescriptive framework to an adaptive, intelligent system for maximizing learning efficacy. Bringing these perspectives together, this study conceptualized students' interaction with GenAI as a process of AI-mediated cognitive engagement. Within this model, metaphors functioned as surface expressions of deeper cognitive configurations, revealing how students positioned AI across these dimensions. The findings therefore position a metaphor as both an interpretive lens and an empirical indicator of how students experience AI as a cognitive presence in their learning.

3. Novice Programming Contextualized

Students were exposed to the use of GenAI through two assignments, and they were required to make use of the GenAI assistant of CodeGrade, a commercial educational technology platform used to auto-assess code scripts (Pyykkö, 2024). They had limited computing exposure upon starting their tertiary studies. Some students started their studies late due to financial pressures (Chiramba & Ndofirepi, 2023). This puts pressure on students to learn to code, which makes a GenAI tool an attractive learning partner. Credit-bearing interventions are conducted with the assistance of lecturers and assistants to deter students from using GenAI tools to generate code solutions and instead make sense of how to obtain a script solution. Formal assessments are conducted under strict invigilation, with GenAI usage resulting in disciplinary action.

At the same time, students were encouraged to use GenAI, and prompt engineering awareness was created during selected credit-bearing interventions. Mid-semester, an optional group project was launched where students were allowed to engage with GenAI without being monitored. Of the class of 272 students, only 82 students enrolled for the project, and a mere 26 students contributed to finalized projects. In future, offering these options as credit-bearing activities may encourage greater student participation. Since the launch of ChatGPT, students have become increasingly reliant on GenAI, and in 2026 students even engaged GenAI in calculating their participation marks, a new phenomenon, and an indication of their reliance on these tools.

4. Research Methodology

Guided by this integrated framework, the study examined how students construct and express their understanding of GenAI through metaphors and how these metaphorical framings relate to their cognitive experiences during introductory Python coding tasks. By linking metaphorical representations of what AI *is* with the cognitive implications of what AI *does* to thinking, this study sought to move beyond binary interpretations of AI as either beneficial or detrimental. Instead, it conceptualized AI as a context-dependent cognitive mediator whose role is actively negotiated by students. The study adopted a qualitative, deductive and inductive metaphor analysis approach to explore these dynamics within the context of first-year programming education. We recognize that the data collected only presents a snapshot of the student experience.

4.1 Metaphor Analysis

Inductive-deductive metaphor analysis is a hybrid analytical approach that combines data-driven and theory-driven processes. In the deductive stage, the students' responses were first examined using constructs from the theoretical framework, including metaphorical framing, cognitive mediation, scaffolding, student agency, epistemic trust and cognitive offloading. Thereafter, the metaphor categories were refined inductively from the students' own language. Through iterative cycles of interpretation and construct elicitation, the analysis generates new conceptual insights and simultaneously tests, refines, or extends existing frameworks, enabling a dynamic movement between empirical observation and theoretical explanation.

Metaphor analysis follows a systematic, bottom-up process comprising four interlinked steps: identification, classification, interpretation, and construct elicitation. First, we identified metaphors directly from the data without relying on predefined categories, allowing them to emerge naturally from participants' language (Cameron et al., 2009; Jacobs & Heracleous, 2006). Second, we classified the metaphors by coding vehicle terms, the metaphorical expressions, and grouping them into thematic clusters (Cameron, 2008; Schmitt, 2005). The third step was interpretation, where we analyzed the source domain and the metaphor function in discourse to uncover underlying meanings relevant to the research questions (Wittink, 2011). This step reflected the discourse dynamics perspective, where metaphors are understood within the evolving textual context (Cameron et al., 2009). Finally, construct elicitation involves identifying the broader concepts the metaphors represent by tracing how the vehicle-tenor interaction expresses participants' underlying thinking. This process enables researchers to label key constructs that capture shared patterns of thought (Schmitt, 2005).

4.2 Participants and Data Collection

The target group was first-year students at a public university. The 272 students in the introductory Python programming module, from which the participants were drawn, were from disadvantaged communities. This study did not rely on gender as a variable. An online survey was distributed via the university's learning management system. A total of 161 responses were received, representing a response rate of 59%. The dataset comprised both structured selections (e.g., predefined categories such as "mind-mending" or "mind-stretching") and open-ended survey responses, enabling a qualitative metaphor analysis supported by descriptive quantitative patterns. We elicited metaphors both directly and through identifying them from the qualitative responses.

5. Data Analysis

At its core, the use of GenAI is not merely a technological intervention but a cognitive one, subtly reshaping how students think, processing information and allocating mental effort. To understand the cognitive restructuring that occurs when students use AI tools, they were asked: "When you use GenAI as a resource to complete a coding task or assignment, how do you perceive its influence on your thinking?" We provided six mental models, as introduced by Malik (2025). Mind-mending describes the use of AI to repair and strengthen cognition through

error correction, clarification, and the filling of knowledge gaps. Mind-stretching reflects moments where AI expands cognitive capacity by enabling engagement with new or complex concepts. Mind-gaming describes how AI can shape or challenge thinking, sometimes influencing confidence, judgment, or decision-making. Mind-bending refers to encounters with outputs that disrupt conventional reasoning, introducing ideas that feel unfamiliar or difficult to interpret. Mind-storming represents a cognitive overload effect, where the rapid influx of AI-generated ideas overwhelms the student's ability to organize and prioritize thoughts. Lastly, mind-replacement denotes a shift in cognitive agency, where AI assumes much of the thinking and problem-solving, reducing the student's own mental effort.

Taken together, these mental models illuminate the multiple ways in which AI is reconfiguring cognitive engagement, from extending and stretching thinking to, in some cases, partially outsourcing it, thereby signaling a profound shift in how the brain interacts with knowledge and problem-solving. The distribution of metaphor categories reveals that students predominantly conceptualize AI as a cognitive support mechanism rather than as a replacement for their own thinking. Categories such as mind-mending, characterized by error correction and clarification, dominated the dataset. In Figure 1, the students' responses to cognitive restructuring are summarized.

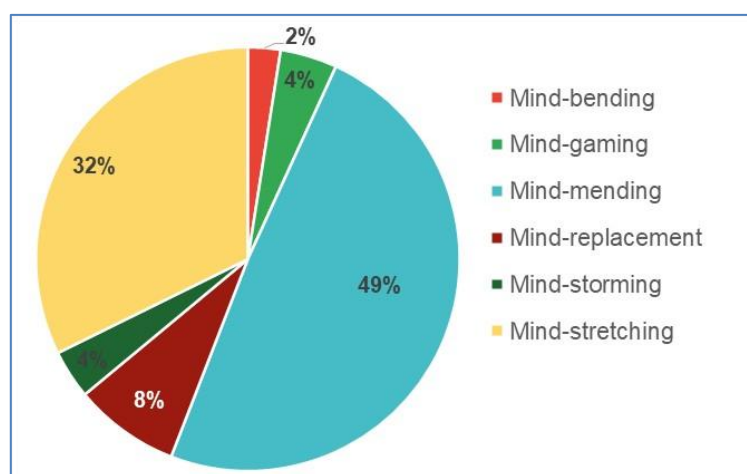


Figure 1: Students' responses to cognitive restructuring

The next step involved metaphor analysis. A qualitative coding framework was used where the vehicles (source domains of the metaphors) were identified. To enhance coding dependability, a second coder reviewed the responses independently, and discrepancies were resolved through discussion. The final step involved the classification of these metaphors through sub-codes and grouping them into thematic clusters. The sub-codes, as well as illustrative examples from the responses, are summarized in Table 1.

Table 1: Coding framework for student metaphors of GenAI

Metaphor	Sub-codes	Illustrative examples
Facilitator	Cognitive scaffolding; progress monitoring; guided discovery; concept simplification	<i>"...challenges me to think further"; "...AI will facilitate my work and correct me if I have forgotten something"; "helps break down complex tasks in a short period"; "helps me check if I'm on the right track"; "...simplifies concepts..."</i>
Liar	Misinformation risk; false confidence; lack of accountability	<i>"AI cannot be held accountable"; "...making me think I understand the work while I don't"; "...not always factual"; "more like fake news"; "... leads to a student not wanting to use their own brain."</i>
Threat	Cognitive offloading; dependency; reduced error detection	<i>"If I can use AI, I'm lazy to think"; "I can't even see mistakes"; "...puts me in an uncomfortable zone"; "decrease my self-belief that my answer is correct"; "It uses concepts that are not in the textbook sometimes."</i>
Specialist	Expert knowledge base; advanced capability; external authority	<i>"...contains ideas from many people..."; "...capabilities are way beyond my own"; "When I need a helping hand..."; "My source of knowledge"; "...correct me when I am wrong"; "...it almost never gets things wrong."</i>
Tool	Information tool; cognitive support; diagnostic tool; learning tool; productivity tool; metacognitive tool; structured system; constraint- compensation; bounded tool	<i>"...like a gardening tool..."; "I use it to get answers"; "helps correct mistakes"; "simplify tasks"; "tests my understanding"; "helps me learn new concepts"; "there to help people and not do their work"; "...tool to help"; "...correct and challenge me further"; "make my life more convenient..."</i>
Tutor	Concept explanation; adaptive instruction; practice support; feedback; skill development	<i>"...explains things better"; "AI helps me understand topics"; "step by step"; "explains to me like I'm a five-year-old"; "teach me so I don't repeat mistakes"; "guides me and helps me understand my work better"; "...help me know my strengths and weakness with regards to coding"; "...when I get stuck, there's no need of quitting or wait for another day to ask a lecturer"; "...I already have an idea of and I just want it to confirm if I am correct or not"; "identifies gaps and provides guidance..."</i>

The six dominant conceptual domains that emerged from the data are summarized in Figure 2.

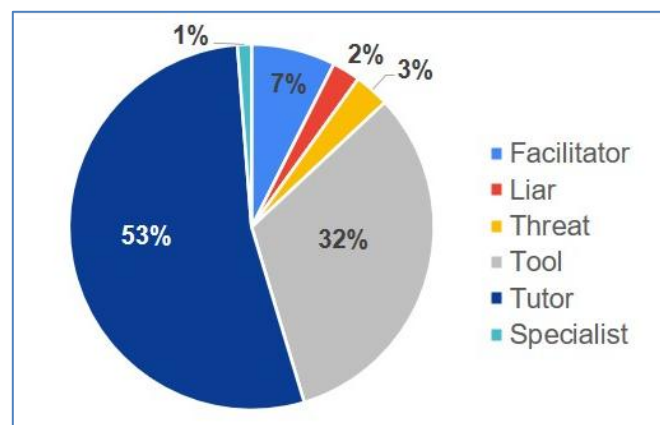


Figure 2: Students' responses on the use of AI through metaphor

6. Findings and Discussion

The analysis of students' responses revealed six dominant metaphorical framings of GenAI: *tool*, *tutor*, *facilitator*, *specialist*, *liar*, and *threat*. These metaphors do not merely describe usage but reflect distinct epistemic orientations, assumptions about agency and levels of trust in AI-supported learning. Overall, students' responses were constructive, with the majority positioning GenAI as a resource that enhanced learning. However, a smaller but significant subset of responses expressed critical or cautionary perspectives, highlighting concerns about reliability and cognitive dependency. This duality suggests that students experienced GenAI not as a single, uniform entity but as a dynamic and context-dependent learning partner.

6.1 AI as Cognitive Support

The metaphors *facilitator*, *tutor* and *tool* position AI as supporting learning, albeit in different ways. Generative AI as a *facilitator* simplifies concepts and "*challenges me to think further*". Generative AI is conceptualized as a process-supporting agent that scaffolds learning by structuring, guiding, or advancing thinking without fully taking over the task. Generative AI as a *tutor* refers to a teaching agent that explains, instructs and develops understanding, often substituting for or supplementing formal teaching. It makes support readily available: "*...when I get stuck, there's no need to quit or wait another day to ask a lecturer.*"

The *tool* metaphor reflects an instrumental orientation, where GenAI is used to perform specific functions such as accessing information, debugging code, or completing tasks more efficiently. Students emphasized control, often explicitly stating that AI should "*help, not do the work*". This framing suggests a relatively high degree of student agency, with AI functioning as an extension of the student's capabilities. In contrast, the *tutor* metaphor reflects a more pedagogical orientation, where GenAI assumes a teaching role. Students described AI as explaining concepts, providing step-by-step guidance, and helping them understand difficult material. Several responses positioned AI as compensating

for perceived gaps in formal teaching, suggesting that GenAI is beginning to function as an alternative or supplementary instructional resource.

The *facilitator* metaphor occupies a conceptual space between *tool* and *tutor*. Here, GenAI is not primarily a source of answers or explanations, but a scaffolding mechanism that structures thinking and supports problem-solving. Students highlighted how AI breaks down complex tasks and helps them stay “*on track*”, indicating a form of guided autonomy, where students remained cognitively involved while receiving structured support. Together, these three metaphors point to a spectrum of pedagogical roles, ranging from passive instrument (*tool*) to active teaching agent (*tutor*), with facilitation (*facilitator*) representing an intermediate, process-oriented role.

These metaphors indicate that the students perceived AI as facilitating cognitive scaffolding, enabling them to bridge gaps in understanding and improve coding performance without replacing their own effort. Students perceived GenAI as a metacognitive agent, one that not only supported task completion but also challenged understanding and promoted reflection. This finding contradicts dominant narratives of AI as a shortcut or cognitive crutch (du Plessis & Smit, 2024). Instead, for many students, GenAI appeared to function as a productive constraint, prompting deeper engagement with content.

6.2 AI as Authority or Expert

A smaller but notable group of responses conceptualized AI as an authority figure, a *specialist*. In this case, AI is perceived as possessing superior knowledge and providing definitive guidance. While this framing can enhance efficiency and confidence, it also implies a shift in epistemic control from student to system, from AI as a tool to AI as an authority, raising questions about dependency and critical engagement. Students recognized that GenAI aggregated knowledge from multiple sources and possessed capabilities beyond their own. Unlike the *tutor* metaphor, the *specialist* is not necessarily oriented towards teaching; rather, it serves as a reference point for expert insight. This distinction is significant: while the *tool* and *facilitator* metaphors preserve student control, the *specialist* metaphor reflects a shift towards reliance on external expertise, with potential implications for how students evaluate and internalize knowledge.

6.3 AI as Cognitive Risk or Threat

A critical counter-narrative emerges in metaphors that portray AI as a *threat* or *liar*. Students described AI as something that could make one “*lazy to think*”, create confusion, or provide incorrect information and could thus “*not be held accountable*”. GenAI as a *liar* is perceived as unreliable, misleading, or epistemically unsafe, producing outputs that may create false understanding. Generative AI is also perceived as a *threat*, diminishing cognitive effort, agency, or learning integrity, often associated with dependency or reduced thinking. The findings reveal that students did not hold a singular view of AI. Instead, they constructed multiple, often competing, metaphorical framings, positioning AI simultaneously as a supportive learning partner and a potential *threat* to independent thinking. This duality underscores the complexity of human-AI interaction in educational contexts and highlights the need for carefully designed

instructional strategies. Despite generally positive framings, the *liar* metaphor reveals important concerns about epistemic reliability. Some students explicitly noted that GenAI could produce incorrect or misleading information and may create a false sense of understanding. Unlike the *facilitator* or *tutor* metaphors, which emphasize support and growth, the *threat* metaphor reflects anxiety about cognitive offloading and the erosion of core academic skills.

The coexistence of *tool* and *threat* metaphors is particularly noteworthy: students simultaneously recognized AI as useful and potentially harmful, suggesting a tension between efficiency and intellectual development. This reflects a form of conditional trust, where students recognized the usefulness of AI but remained cautious about its outputs. Importantly, the issue is not only incorrect information but the illusion of competence, where students believed they understood a concept because AI had provided an answer, without fully engaging with the underlying reasoning. These metaphors foreground the ethical dimension of GenAI use.

There is a clear and systematic correspondence between the two datasets, cognitive models and AI utilization, as summarized in Table 2.

Table 2: Correspondence between cognitive models and AI utilization

Metaphor (What AI is)	Cognitive effect (What AI does)	Interpretation
Tool	Mind-mending	AI corrects, clarifies, stabilizes thinking
Tutor	Mind-mending/ Mind-stretching	AI explains and develops understanding
Facilitator	Mind-stretching	AI pushes deeper thinking and structuring
Specialist	Mind-stretching	AI expands knowledge through expertise
Threat	Mind-replacement	AI replaces student thinking
Liar	Mind-gaming	AI misleads or undermines confidence

This correlation confirms that the metaphors are not superficial or rhetorical but cognitively grounded. It also affirms that students' metaphorical language and their experience (mind effects) are internally consistent and strengthen construct validity. To strengthen analytical rigor, the study did not rely solely on interpretive metaphor analysis.

6.4 Relational Patterns

After the inductive coding, the mental and cognitive metaphors categories were cross tabulated to examine their relational patterning across cases. The original AI-cognitive effect categories were clustered into two broader sets: constructive cognitive influence, and disruptive (or delegating) influence. For the Chi-square analysis, mind-mending and mind-stretching were grouped as constructive influences because they reflected clarification, conceptual strengthening, and extended thinking. Mind-replacement, mind-gaming, mind-storming, and mind-bending were grouped as disruptive or delegating influences because they

indicated forms of AI-mediated engagement that could displace, unsettle, overload or redirect students' cognitive agency. Mind-storming and mind-bending were included because they reflected cognitive disruption rather than stable conceptual support. The use-of-AI metaphors were clustered into that of a supportive learning role versus a risk/negative role. The supportive learning role group includes *tutor*, *tool*, *facilitator* and *specialist*. The risk/negative role group includes *threat* and *liar*. All original values in the first two columns were successfully mapped into the collapsed categories. The collapsed table is presented below in Table 3.

Table 3: Correspondence between constructive cognitive influence and disruptive influence

Clustered datasets	Risk / negative role	Supportive learning role
Constructive cognitive influence	2	129
Disruptive or delegating influence	6	24

A Chi-square test and Fisher's exact test were performed to statistically determine whether there was evidence of a relationship between the cognitive influence of AI use and the role associated with AI during the completion of an assignment. The Chi-square test of independence showed a statistically significant association between the collapsed variables ($\chi^2[1, N = 161] = 13.95, p < .001$). Fisher's exact test confirmed this result, with an odds ratio of 0.06 and a two-sided p-value of 0.001 (rounded from 0.000568). The effect size was $\phi = 0.29$, indicating a small-to-moderate association between perceived cognitive influence of AI and the role assigned to AI in completing assignments. Substantively, the pattern suggests that students who viewed AI as cognitively constructive were far more likely to describe it as a supportive learning role, whereas those who viewed AI as disruptive or delegating were relatively more likely to assign it a risky or negative role.

In student learning terms, this indicated that AI was perceived not only as a technology but as a pedagogical presence whose educational value depended on whether students experienced it as supporting understanding or undermining independent thinking. The pattern therefore supports a nuanced interpretation of AI in learning: AI appears most educationally meaningful when students experience it as a form of guided support within the learning process, but it becomes problematic when it is seen as displacing effort, judgement, or trust.

7. Recommendations

Based on the finding that GenAI functions as a context-dependent cognitive mediator rather than a neutral tool, the following recommendations are proposed to support lecturers and curriculum designers and to highlight further research opportunities. The recommendations are grounded in the central finding that students do not experience GenAI as a neutral or merely technical tool but as a cognitive mediator, depending on how it is framed and used.

First, lecturers need professional development opportunities that focus on the pedagogical, cognitive and ethical implications of GenAI. Learning tasks should be designed in such a way that students are required to use GenAI as a scaffold rather than a substitute. Learning activities should encourage students to use GenAI for clarification, explanation, feedback and extension rather than for direct task completion. The findings show that when students frame AI as a tool, tutor or facilitator, it supports processes of mind-mending and mind-stretching. However, when AI is used to complete work on behalf of the student, it contributes to mind-replacement and reduced cognitive effort. It is recommended that lecturers structure tasks so that students first attempt the problem independently, identify areas of uncertainty, and then engage GenAI to clarify or extend their thinking. This may include requiring students to submit their own initial reasoning before using AI, compare their thinking with AI-generated responses, or explain how AI contributed to their understanding.

Second, AI literacy must be embedded in curricula. The use of GenAI is not only a technical skill but rather an epistemic and cognitive capability. If students see AI as a *liar* or *threat*, they may experience uncertainty and mistrust. If they see it only as a *facilitator* or *specialist*, they may over-rely on it. The metaphors, *liars* and *threats* can contribute to AI anxiety, epistemic trust, hallucination risk, and perceived loss of agency. It is recommended that AI literacy programmes help students understand both the affordances and limitations of GenAI, focusing on the critical evaluation of AI-generated output, prompt engineering, source verification, and an awareness of hallucinations and bias. Students must be aware of the difference between GenAI producing an answer and GenAI assisting learning to develop their own understanding. Higher education institutions should not assume that students will automatically regulate their use of GenAI in productive ways. Although some students in this study demonstrated emerging metacognitive awareness, such as checking AI responses or using AI only after attempting a task independently, this regulation was uneven and situational.

Third, students should be taught strategies for using GenAI, when to question it, and when to rely on their own reasoning. This includes helping students ask questions such as: What do I not understand? What am I asking AI to do? Am I using AI to help me think or to avoid thinking? How will I verify the response? Such metacognitive prompts can help students maintain agency in AI-supported learning environments. Python coding assignments should be redesigned to make students' thinking visible. If GenAI can produce polished answers, then assessment should not focus only on final products but also on the process through which understanding is developed. The findings suggest that a distinction must be made between performance as an outcome and understanding as part of the learning process. In disadvantaged communities, GenAI may bridge gaps by offering immediate support to students with limited prior computing exposure, but it may also widen gaps where access, AI literacy and verification skills are uneven. Therefore, AI-supported assignments should include explicit scaffolding, source-checking and critical reflection to ensure that GenAI strengthens rather than replaces student agency.

The study shows that the boundary between support and substitution is fluid. AI may reduce unnecessary cognitive load, but it may also displace core thinking processes if used uncritically. Conditional trust should be taught explicitly, with the understanding that GenAI can function as a tutor or support when students first attempt the task, verify outputs against course material, explain the logic in their own words, and retain responsibility for the final solution. However, it shifts towards a liar or threat when students accept outputs uncritically, use AI to replace their own reasoning, cannot detect errors, or become dependent on AI-generated code. At an institutional level, clear teaching and learning guidelines for the appropriate use of GenAI should be developed for both staff and students. Furthermore, based on the findings, institutional guidelines should avoid oversimplified binary positions such as “AI is good” or “AI is harmful”. Instead, guidelines should focus on the conditions under which AI supports, extends, or undermines learning.

As some students may frame AI as a *liar* or *threat*, and because AI may produce inaccurate or misleading responses, critical evaluation should be treated as a core learning outcome. Students should not be encouraged to accept AI-generated content at face value. It is recommended that lecturers create opportunities for students to evaluate AI responses against disciplinary knowledge, credible sources, course materials and their own reasoning. This can help students develop epistemic responsibility and reduce the risk of mind-gaming, where uncertainty and misinformation could negatively impact learning. The study also suggests that the use of GenAI is dependent on context. It may correct misunderstandings, extend thinking, or distort and replace cognitive engagement. These roles are not fixed; they depend on context, and therefore it is recommended that lecturers avoid one-size-fits-all approaches to AI integration. Decisions about AI use should be guided by the learning outcome, the type of task and the intended cognitive outcome.

To synthesize these relationships, a conceptual model is proposed and visually presented in Figure 3. This framework positions students’ metaphorical framings as the entry point to understanding AI-supported learning. The model shows how different ways of conceptualizing AI give rise to distinct cognitive processes, ranging from mind-mending and mind-stretching to mind-replacement and mind-gaming, which, in turn, produce varying learning outcomes. Crucially, these relationships are moderated by epistemic orientation, student agency and levels of trust, highlighting that the impact of AI is not inherent but contingent. The distinction between performance, as a learning outcome, and understanding, as part of the learning process, becomes especially important. In this framing, GenAI is best understood not as a static tool but as a context-dependent cognitive mediator embedded in a distributed system of learning. A model relating to how students frame GenAI metaphorically, its relation to how they use GenAI, and finally, the effect it has on how they navigate their learning is reflected in Figure 3.

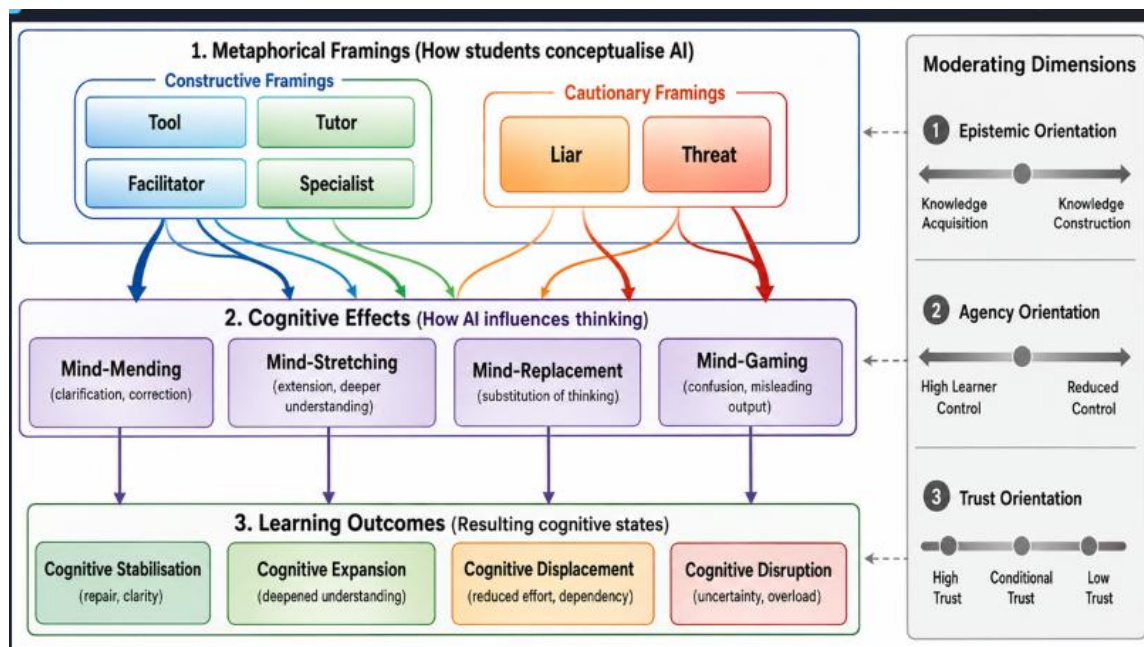


Figure 3: Generative AI as a conditional cognitive mediator in learning

This model illustrates how students' metaphorical framings of GenAI (layer 1) shape distinct cognitive effects (layer 2), which, in turn, produce different learning outcomes (layer 3). Constructive framings (e.g., *tool*, *tutor*, *facilitator*) are associated with processes of mind-mending and mind-stretching, whereas cautionary framings (e.g., *liar*, *threat*) relate to mind-replacement and mind-gaming. These relationships are not fixed but are mediated by epistemic orientation, student agency, and trust, indicating that the impact of AI depends on how students interact with and regulate its use. The model conceptualizes GenAI as a dynamic, conditional cognitive mediator within a distributed learning system.

Importantly, the findings show a consistent alignment between students' mental metaphorical framings and their reported cognitive experiences. Metaphors such as *tool* and *tutor* correspond to processes of mind-mending, while *facilitator* and *specialist* align with mind-stretching. Conversely, cautionary framings such as *liar* and *threat* reflect concerns related to mind-replacement and mind-gaming. This convergence suggests that metaphors do not simply describe AI but provide access to how students experience and regulate thinking in AI-mediated environments.

Future research should move beyond the broad question of whether GenAI improves or harms learning. The findings of this study suggest that the more important question to answer is: Under what conditions does AI support, extend or undermine critical thinking? Furthermore, future research could integrate observational or behavioral data to better understand how different modes of involvement with GenAI relate to student learning outcomes. Adding to the work of Albrant et al. (2025), more research on the inclusion of prompt engineering as a learning outcome would be meaningful in this context.

8. Limitations of the Study

This study has several limitations that should be considered when interpreting the findings. First, the research was conducted within a single institutional context, focusing on first-year students enrolled in an introductory Python programming module at a public South African university. As such, the findings are context-specific and may not be directly generalizable to other disciplines, institutions, or cultural settings. Students from different academic backgrounds or levels of experience may conceptualize their interactions with GenAI differently. Second, the study relies on self-reported data expressed through metaphorical language. While metaphor analysis provides rich access to students' conceptual and cognitive framing, such data captures perceptions rather than actual behavior. Third, the study provides a snapshot of students' conceptualizations at a particular moment in time.

Given the rapidly evolving nature of GenAI technologies, students' perceptions and practices may shift as they gain more experience or as tools become more sophisticated. Longitudinal research would be needed to capture these evolving dynamics. Finally, while the study draws on a theoretically informed framework of AI-mediated cognitive engagement, it does not directly measure cognitive processes such as cognitive load, depth of learning, or problem-solving performance. Despite these limitations, the study provides valuable insight into the conceptual and cognitive dimensions of AI use in programming education, offering a foundation for further empirical and theoretical development of cognitive learning.

9. Conclusion

This study demonstrates that GenAI can serve as an active cognitive partner that reshapes how learning unfolds. Through metaphors, students construct AI as an agent that can support, extend, or displace thinking, revealing that engagement with AI is fundamentally a process of negotiating cognitive responsibility rather than merely using a resource. A central insight is the coexistence of two competing cognitive framings: AI as scaffold, and AI as substitute. Rather than being resolved, this tension is dynamically managed by students themselves, many of whom demonstrate awareness of the boundary between productive support and overreliance. This positions students not as passive recipients of AI assistance but as metacognitively engaged agents navigating a distributed cognitive system.

This study makes three key contributions. Empirically, it reveals systematic patterns in how students conceptualize GenAI through metaphors, showing that these representations map onto distinct cognitive experiences of learning, including support, extension, substitution, and disruption. Theoretically, it advances an integrated account of AI-supported learning by linking metaphorical framing to cognitive experience, positioning GenAI as a dynamic cognitive mediator that redistributes effort, reshapes agency, and interacts with constructs such as scaffolding and cognitive load. Methodologically, it demonstrates the value of metaphor analysis as a rigorous approach for investigating AI in education, enabling researchers to capture the relationship between how students conceptualize technology and how they experience its effects on thinking. Taken

together, the study moves beyond binary debates about whether AI is beneficial or harmful. Instead, it proposes that the more consequential question is under what conditions AI supports, extends, or undermines thinking and how educational design can actively shape these conditions. GenAI changes not only what students do, but what learning means to them.

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