It's like "X": How Engineering Faculty Metaphors Construct (and Constrain) AI Understanding in Engineering Education

Mitchell Gerhardt, Virginia Polytechnic Institute and State University

Mitchell Gerhardt is a Ph.D. candidate in Engineering Education at Virginia Tech. He earned his B.S. in Electrical Engineering from Virginia Tech and worked as a software engineer for General Motors in Detroit, Michigan, before returning to graduate school. Mitch's research focuses on engineering expertise and generative artificial intelligence (GAI); in particular, how GAI is transforming the way engineering expertise is developed, displayed, recognized, and trusted. His current research examines the use of GAI for qualitative research methods, STEM graduate students' GAI use and norms, and how STEM instructors negotiate personal, professional, and student GAI applications in higher education.

Kylee Shiekh, Virginia Polytechnic Institute and State University

Kylee Shiekh is a Ph.D. student in Engineering Education at Virginia Tech. She has a degree in Computational Applied Mathematics and Data Science and a Masters in Quantum Engineering.

Dr. Andrew Katz, Virginia Polytechnic Institute and State University

Andrew Katz is an assistant professor in the Department of Engineering Education at Virginia Tech. He leads the Improving Decisions in Engineering Education Agents and Systems (IDEEAS) Lab.

Benjamin Edward Chaback, Virginia Polytechnic Institute and State University

Benjamin (Ben) Chaback is a Ph.D. student in engineering education at Virginia Tech. He uses modeling and systems architecture to investigate undergraduate engineering education and is working towards creating sustainable systems for student success. Ben is a member of the American Society for Engineering Education, the Council on Undergraduate Research and is a facilitator for the Safe Zone Project and the Center for the Improvement of Mentored Experiences in Research. He is passionate about student success and finding ways to use research experiences to promote student growth, learning, and support.

It’s like “X”: How Engineering Instructors Metaphors Construct (and Constrain) AI Understanding in Engineering Education

Introduction

Generative artificial intelligence (GAI) is generally described as a type of artificial intelligence (AI) that creates new content including text, images, video, and code. This is not, however, how everyone would describe GAI. How would you? Perhaps you would focus on *types* of GAI systems or the audience, such as large language models (LLMs), focus on the algorithmic process, or even liken GAI to an assistant or advanced student. Regardless, we cannot help but understand GAI through figurative language [1], [2], [3], [4], [5], [6]. The ways “we both think and act, is fundamentally metaphorical in nature” [7, p. 3]. In everyday and professional life, metaphors draw together objects and compare them: recognizing and evaluating their features and properties. For example, comparing GAI to a “mirror,” suggests it reflects our biases, assumptions, norms, and weaknesses [8], [9]. We might relate it to a “crutch” or “drug”, where students’ misuse has potential for cognitive offloading and intellectual degradation [10]. Importantly, these metaphors are more than descriptors, but central elements of how understanding is achieved: “the way we think, what we experience, and what we do every day is very much a matter of metaphor” [7, p. 454]. Figurative language, therefore, *surrounds* our understanding of reality and of GAI systems.The figurative language used by instructors to describe GAI provides insight into collective understandings of these systems during a time of rapid technological adoption.

Investigations of figurative language regarding GAI in educational settings has focused on students, to a wide assortment of results It naturally reveals multiple aspects of students’ interactions with GAI, such as chatbot-like interfaces, the societal and ecological impacts of GAI systems, and students’ relationships with GAI [8], [10], [11], [12]. For instance, postgraduate international students in the UK described GAI as “high-heeled shoes” because systems like ChatGPT can polish their writing, correct grammar, and modify their style like fashionable clothing [8]. Among younger students, Demir and Güraksin [11] found that Turkish 7th and 8th graders frequently compared GAI to humans, using metaphors about the brain, smartness, creativity, mimicry, or learning. While these studies provide valuable insight into students’ conceptualizations of GAI, instructors play a significant role in facilitating students’ understanding through their pedagogy and practice [13], [14], [15], [16]; however, less is known about their figurative language and how it affects students’ GAI understanding and literacy [17]. In engineering in particular, figurative language is instrumental for conceptual understanding [18], [19], [20]. Without a documented shared understanding of GAI, developing training programs and facilitative pedagogical discussions becomes increasingly difficult. Understanding instructors’ conceptualizations and descriptions of GAI supports progress towards these endeavours. Illustrating this, the term “artificial intelligence” arises from a 1956 Dartmouth conference [21], [22], but is understood today to represent a number of different systems, including financial optimization algorithms, music recommenders, self-driving vehicles, traffic-based navigation systems, chess solvers, and creative technologies. This breadth and integratedness challenge descriptions of GAI and other computing systems because they exist as integrations into other technologies and tasks [23]. Common metaphors for LLMs–the “models” powering many text-based GAI systems–showcase this variety, with discourse including terms like “copiers/stochastic parrots,” “simulators,” “crowds/zeitgeist,” “gods,” “shoggoths,” “e-bikes,” and “drop-in remote workers” [24], [25], [26]. Consequently, designing a faculty development program or facilitating discussions within departments can be compromised due to a lack of shared language between stakeholders. Evaluating the range of this language used by instructors can provide a bearing in an otherwise discursive sea of meaning-making.

Current investigations of instructors’ perceptions about GAI systems reveal quite heterogeneous effects, with faculty divided in terms of their awareness and knowledge of GAI systems, integration of them into their research and teaching, and engagement with others about GAI. A sample of 122 German higher education faculty members found four profiles of perceptions about GAI systems for teaching and learning using LCA: optimistic (33.5%), critical (27.3%), critically reflected (33.9%), and neutral (5.3%) [27]. Optimistic faculty recognize more benefits than challenges, and Critical ones see the opposite. Critically reflected recognize both equally, and neutral faculty members saw little of either. These results likely carry consequences for the figurative language faculty use; for example, an optimistic portrayal might be more likely among those who embrace GAI systems in their personal and professional workflows, leading to language about “assistants” or “collaborators.” Suggesting this, Karakitsou et al.’s [17] categorized visual metaphors used during faculty focus groups: anthropomorphic vs. non-anthropomorphic and positives vs. concerns/challenges. These distinctions were contentious, with results “reflecting the competing visions of GAI as either an intelligent entity or a functional tool” [17, p. 31]. Positive perceptions in both studies include features like improved task performance, time savings, personalized learning, and amplifying human potential, while ethical challenges (e.g., misuse and exploitation), need for institutional support, and overdependence/loss of control concerning faculty and contributing to contrasting language. Lucas and Lioy [28] call out this dilemma, recognizing the problematic forces pulling on instructors in their review of 18 AI literacy frameworks. Across them, the most common depiction of instructors is that of a GAI designer and guide, harnessing GAI capabilities to create innovative pedagogical experiences for their students, facilitating learning of GAI and disciplinary content simultaneously. Yet, few faculty have the pedagogical knowledge, time, and resources to continuously learn about GAI developments, appraise their current material, and change it where appropriate [29], [30], [31]. Therefore, incoherence between institutional and faculty language regarding GAI systems complicates efforts to sustain educational initiatives about GAI for students, develop effective training programs, and facilitate productive adoption discussions because it collapses the nuance between GAI systems themselves and their use. Ultimately, more research is needed to understand these nuances to texture educator and researcher understanding of GAI system integration in higher education and support institutional initiatives.

Toward such efforts, this study investigates the figurative language used by higher education engineering instructors to describe “GAI.” Deductive and inductive analysis evaluated excerpts collected from 57 semi-structured interviews with engineering instructors at various institutions. Initial codes derived from pre-existing literature served as a starting point to review instructors’ descriptions of: (1) the ontology of GAI, (2) the epistemology of GAI, (3) GAI’s operation, (4) our relationships to GAI, and (5) the power and capabilities of GAI. By mapping out the conceptual terrain engineering instructors occupy, we hope to ennoble efforts anticipating, assessing, and intervening in how GAI systems operate in engineering education.

Methods

Study Design and Data Collection

This study utilized data collected from a larger, multi-institutional investigation exploring higher education engineering instructors' mental models of GAI and its effects on teaching, learning, and assessment. Instructors were directly contacted via email and participated in an hour-long interview that utilized a semi-structured protocol [32]. This protocol was iteratively developed by the research team, with particular attention to instructors' descriptions of the state, form, function, and purpose of GAI, as well as how these features relate to their GAI use, student learning, teaching and assessment practices, and state of higher education. While this scope touches on many aspects of GAI, this study focused on instructors' responses to one question in the protocol: "If you had to think of an analogy or metaphor to describe GAI to someone, what would you say?" Where necessary, the interviewers probed instructors further, but only their responses to this question were used in this analysis. Given this exclusive focus on one interview question, our current work seeks to expand this study's analysis, exploring the figurative language instructors employed during the entire interview using custom LLM-based workflows [33], [34], [35]. Thus far, nearly 170 instructors from 18 different universities have shared their perspectives, but this study evaluates 57 of them collected in Spring 2025. Despite the focused sample, these 57 instructors come from 17 different disciplines across seven universities, as shown in the **Appendix**, **Table I**.

Data Analysis

Informed by metaphor analysis, figurative language identification and evaluation comprised two phases: (1) literature gathering and initial metaphor gathering, and (2) deductive and inductive content analysis [36], [37]. This process identified common figurative language across instructors' responses, comparing it with documented language found in existing literature, and recognizing new language instructors employed. Following Pitterson et al. [18], we first defined "figurative language" as both metaphors and analogies, where "analogies represent explicit measures whereby the learner is encouraged to make connections between or across two specific domains. A metaphor, on the other hand, is an implicit comparison where the basis of the comparison must be created by the concept to which it is applied" [18, p. 3]. An analogy for GAI, therefore, might trace the comparison: "GAI is like a calculator for writing because it helps with text generation similar to how calculators help with math calculations." By contrast, the metaphor "GAI is a writing partner" requires inferring what "partnership" means [36]. Using these definitions and in the first phase of analysis, (1), we consolidated a compendium of GAI figurative language from existing literature, focusing on metaphors and analogies with GAI as the target concept [1], [2], [3], [6], [8], [9], [10], [11], [20], [24], [25], [26], [28], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48]. An unsystematic, snowballing approach was used to collect these sources until saturation was reached, which was possible given the topic's recency and limited publications, particularly in educational settings [14], [36]. To organize the terms, we leveraged Maas'[1] five-dimensional taxonomy of GAI figurative language because it spotlights shared features among common framings, such as the essence, operation, relation, function, and impact of GAI systems [36]. Essence focuses on what GAI *is*, operation about how GAI works “under the hood,” relation about how individuals relate to GAI, function is how GAI systems are used in society, and impact are the risks, benefits, or effects of GAI. Using this taxonomy, we categorized the initial list of 68 metaphors and analogies about GAI, which we then applied as an initial codebook to deductively code instructors’ responses. That is, the literature-gathered terms provided provisional codes for the first round of data analysis, allowing us to find parallels between instructors’ conceptualizations and others’ while permitting new codes to inductively emerge that were not already described.

We refer to this initial list of 68 items as the “Version 1” codebook, which was iteratively refined during phase (2) through three coding passes. During these passes, codes were applied to responses wherever matches were found and created whenever the existing codes were insufficient [37]. Following each pass, the research team reflected on the codebook, member-checking to confirm accurate code assignment, deliberating about code coverage, and refining the codebook [49]. This process is described in depth in the **Appendix**, producing a final codebook with five “continua” to capture the recurring dimensions of GAI systems and use across instructors’ responses. The continua share similarities with Maas’ initial taxonomy dimensions; however, rather than discrete phrases, we demarcate three “positions” along each continuum to capture the continuous, interwoven, and multifaceted conceptual spaces of instructors’ mental models of GAI that failed to reduce into neat stances [50]. Put another way, the final codebook captures the non-discrete mental architectures structuring the responses, achieving greater code parsimony without overlap [37].

Results and Discussion

The engineering instructors do not hold a unified mental model of GAI. Instead, their understanding of GAI operates across multiple dimensions, interlaced and distinguished through personal experiences, typical use cases, professional backgrounds, and diverse student relationships. Instructors within the same departments, same semesters, and same institutional policies can construct fundamentally different understandings of what GAI “is” and “means” for them and engineering education. None inherently “correct,” but shaped by their realities and experiences. This section explores the five-continuum codebook shown in **Figure 1** and described in **Appendix, Table II**, which locates the instructors’ perspectives into the dimensions: Ontology, Epistemology, Operation, Relationship, and Power/Capability, each with three contrasting positions to represent instructors’ different perspectives along the same theme. While not every instructor touched on all these dimensions in their responses, their varying positions underscore how different conceptualizations about the state, form, function, and purpose of GAI systems are shaped by instructors’ unique contexts and experiences. As such, they are instructive for self-reflection and faculty development initiatives, functioning as guidepoints to evaluate the role of these technologies for ourselves, others, and organizations [51]. When describing the positions below, percentages describe their occurrence frequency relative to the total responses coded *for the same dimension*, not relative to all the dimensions. This accounts for instructors who did not describe a particular dimension in their responses (e.g., Given 55 total occurrences for X dimension, 18 in position X_1, then $X_1 = 18/55 * 100\% = 32.7\%$). We also include references to existing literature that describe shared figurative language among other populations, showcasing common conceptualizations across research inquiries. The concluding section synthesizes these trends and observations for faculty developers.

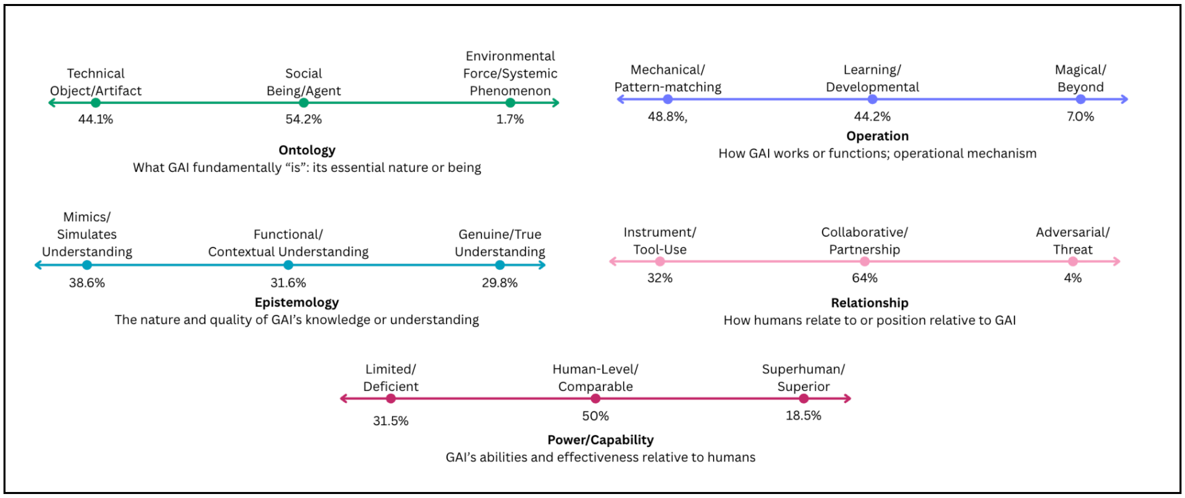

Fig. 1. Five-dimensional taxonomy of instructors' figurative language, shown with continuum-specific percentage distributions

Ontology – What "is" GAI?

Overwhelmingly, instructors regarded "GAI" as an object or entity [9], [11], [17]. Most often, a "**Social Being/Agent**" (54.2%), resembling a living, social organism. Sometimes this was an animal, such as "stochastic parrots" [52] or spiders, "going out, weaving [information] together into a response" [53]. However, instructors most frequently conceptualized GAI as having human-like qualities, which Nerlich [38] calls "Ur-metaphors" from the German "ur" meaning primal. Ur-metaphors describe technical features of GAI through terms like "reasoning," "intelligence," and "learning" that liken GAI to human cognition [36], [54]. Instructors employed these terms routinely, using explicit and implicit language to suggest GAI possesses human-like agentic and relational qualities. For example, one instructor subtly noted GAI "thinking," saying, "[GAI] doesn't just give you an answer, it shows its thought process," while another explicitly compared GAI to "a person with deep knowledge who thinks far faster than I do." Aligning with this description, nearly 75% of the "Social Being/Agent" co- occurrences (i.e., joined positions along different continuum) came from the codes "Collaborative/ Partnership" (Relationship), "Human-Level/Comparable" (Power/Capability), "Genuine/True Understanding" (Epistemology), and "Learning/Developmental" (Operation). In this frame, GAI *is* a human-like assistant or collaborator, learning and developing over time through its training and interactions with users, and possessing forms of agency enabling it, with some variance, to independently act. This metaphor is particularly evident through instructors' use of pronouns (e.g., he, she, they) and descriptions of GAI as "a PhD student," "assistant," and "person."

Juxtaposing the "Social Being/Agent" framing, the second-most common interpretation of GAI was as a "**Technical Object/Artifact**" (44.1%), which mainly co-occurred with "Mimics/ Simulates Understanding" (Epistemology), "Mechanical/Pattern-Matching" (Operation), "Instrument/Tool-Use" (Relationship), and "Limited/ Deficient" (Power/Capability). This set encapsulates one of the most prevalent descriptions of GAI: as a non-living, non-cognitive, engineered entity trained on "data" [55] to produce coherent, 'good-sounding' answers to user queries in a non-agentic, tool-like manner. As one instructor said, "It's a program that's going to get your input and based on pre-learned information, output the data." Often, instructors likened GAI to information-retrieval devices that specialize in breaking down queries, finding relevant information and returning that to users: "I probably would describe it [as] similar to a search engine that is really efficient at identify[ing] words out of large data sets." While such descriptions capture properties of GAI systems, particularly GAI-enhanced browsers (e.g., ChatGPT Atlas, Microsoft Edge, Perplexity), they inaccurately position GAI as retrieving pre-existing information. In fact, GAI does not "search" for information or "retrieve" it from a knowledge base, but algorithmically generates plausible continuations of tokens based on probabilistic patterns garnered from curated data [56], [57], [58]. These implications are explored more in the section on GAI operation, but here demonstrate that instructors map GAI to familiar, existing technologies mirroring their applications and relationships, but not the underlying processes [5]. Instructors focused more on what GAI *does* than what GAI "knows," "says," or "is," with the latter ideas often implicit.

The final and least occurring position on the Ontology continuum is "**Environmental Force/ Systemic Phenomenon**," seen across only 1.7% of the Ontology responses. Despite wide recognition of the impacts GAI presents across multiple industries, higher education, and geopolitics, few instructors called attention to GAI as a force, a tsunami crashing into the shoreline, an iceberg with more under the surface, electricity- or internet-like reach, an international race between countries and technology companies, or a system with multifaceted, distributed impacts [9], [38], [39], [40]. One likened GAI to "photography" in that, despite early criticism, GAI will open creative opportunities [59], while another called GAI a "paradigm shift" that does not "mean the field of greater science is going to completely go away," but presents a "disruptive impact" [60], [61], [62]. Thus, while scholarly language and discourse forefront concerns of GAI's widespread usage and effects, the instructors in this study rarely included such considerations in their responses. Failing to do so can hide the massive computational infrastructure required to effectuate GAI, minimize the human labor involved in training data creation and training processes, the corporate interests shaping GAI systems, and their environmental costs [21], [63], [64]. However, instructors did speak of such topics throughout the broader interview, suggesting that development approaches that feature these perspectives could be important for their mental model construction and student communication.

Epistemology - What is the nature of GAI "knowledge" or "understanding"?

Ur-metaphors can deceive because comparing GAI to humans masks the underlying complexity within instructors' responses. Whereas some might describe GAI "reasoning" and explicit personhood references, others strongly avoided and even called out such language. Instructors distinguished between GAI as a social, living being with "Genuine Understanding" (29.8%) from an organism with "Functional/Contextual Understanding" (31.6%), and from non-living "Mimics/Simulates Understanding" (38.6%). "**Genuine Understanding**" is reflected through language that does not distinguish between human and artificial cognition, as shown in the previous examples of "intelligence," "learned," and "thinking" verbiage. By contrast, "**Functional/ Contextual Understanding**," acknowledges weaknesses, blind-spots, hallucinations, and other "gaps" in what GAI "knows." For example, one instructor described GAI as: "Someone who knows a lot across many domains but lacks deep specialization. [GAI] performs better than me on certain tasks, but doesn't have the same depth of expertise as a human professional." GAI with functional understanding might not have expertise in certain topics, but it maintains a developmental quality: "It can follow instructions reasonably well. It is very confident even when it shouldn't be, and [is] not very good at knowing what it doesn't know, but if you break down [tasks] into very simple steps, it does them quite well." Both genuine and functional understanding, therefore, recognize GAI as possessing a valid, albeit different, interpretation of reality based on its prior knowledge and experience. These portrayals sometimes had the effect of *technomorphically* relating GAI to human subjective experience and knowledge construction [65], [66]. As one described: "[GAI] understands high-level patterns – like how humans perceive media – without analyz[ing] every individual data point. It grasps the essence, the context. Its behavior is remarkably similar to how humans learn: by experience, feedback, and pattern recognition." For these instructors, GAI is like another mind: with experiences, abilities, and biases, but different in what it knows and how it knows. However, no instructors used the words "conscious" or "consciousness," despite 61.4% of the responses being coded as either genuine or functional understanding. Perhaps their metaphorical weight resists lackadaisical application [67].

"Functional/Contextual Understanding" encapsulated an assortment of such responses from those who recognized a few inabilities to nearly compromised understanding. However, "**Mimics/Simulates Understanding**" does not regard GAI as possessing any degree of cognition, subjective experience, or knowledge construction processes. Sometimes these relied on technical, programmatic, or math-based descriptions of how GAI operates: "I think of it as an optimization problem. There's a cost function, and you vary the parameters to improve the match to the training data." Others related these descriptions to how GAI can create the appearance of understanding: "What goes into it is a lot of data and what comes out of it is something that sounds good. It isn't necessarily intelligence or reasoning. What comes out is designed [to] sound good." 38.6% of the responses were identified as containing the "Mimics/Simulates Understanding" code, with common references including "stochastic" processes, "copiers," "emulating" cognition, or "cobbling" together information without genuine comprehension. Most of those who described GAI as mimicking understanding also viewed GAI as a "Technical Object/Artifact" (Ontology), reinforcing the model of GAI as a non-living, engineered entity.

Operation – How does GAI work?

The Operation of GAI continuum describes how GAI *functions*. Like popping the car hood to inspect the engine, how do instructors describe the processes driving GAI systems? Within this continuum lie three positions: "Mechanical/Pattern-matching," "Learning/ Developmental," and "Magical/Beyond" with observed frequencies of 48.8%, 44.2%, and 7.0%, respectively. The least common of these, "**Magical/Beyond**" co-occurred with a variety of other positions, but most often treating GAI as a living, social organism. For some instructors, this took mystic forms: "Like a magician getting a rabbit out of his hat. You don't know what's coming, but somehow it manages to do it." Another likened GAI to the Oracles at Delphi: "With thousands of oracles woven together for each response." Not all, however, related the magic of GAI's operation to human-like qualities, with one noting that GAI gives the illusion of intelligence: "A mathematical trick…[M]achine learning is a way to decipher very weak or very detailed and nuanced correlations at the level that even humans cannot perceive." Notably, only one instructor referenced the popular "black box" metaphor to describe GAI systems, which treats them as opaque, inscrutable input-output systems at the expense of current explainability research [8], [9], [38], [68]. Despite capturing an essential quality of GAI systems and widespread use in popular media, the lack of black box metaphor might suggest the metaphor fails to illuminate anything substantial for instructors; not a means of understanding, but an end. If GAI is a "black box," why investigate it? Additional research is needed to explore this possibility, but the magical qualities assigned to GAI should concern program developers making GAI systems accessible [69].

"**Learning/Developmental**," the second-most common position, also shares parallels with GAI as a "Social Being/Agent" (Ontology) in its treatment of GAI as "learning" from training data, "developing" in its abilities over time, and subject to "change." Demonstrating this, one instructor described how GAI systems: "Learn from vast amounts of data, refine their understanding, and become better at predicting relevant information. Over time, they improve just like how human expertise develops through continuous learning and experience." However, instructors distinguish little between GAI training methods (e.g., one-time processes on fixed datasets, fine-tuning on specific, task-specific datasets, and reinforcement learning with human feedback based on conversation histories). For example, one tentatively remarked, "Isn't it supposed to be like a human? [GAI] takes in information and then does something with that afterwards." While both humans and GAI systems improve from prior examples of a task [70], neither this depiction nor the previous demarcates the precise "learning" training methods. However, instructors' understanding of GAI training systems should not be restricted to this study's single interview question, but must also include additional context, capturing their awareness of GAI system designs, training processes, and operations.

The "**Mechanical/Pattern-matching**" position recognizes GAI as based on statistical models implemented through algorithmic, programmatic implementations, but sometimes involves glossing over technical details in a similar fashion to "Learning/Developmental." As one commented, "I understand the basics: how language is broken down into tokens and how probabilistic processes generate new text." While this view is factually correct, it does not distinguish between the systems finding patterns in training data and those for generating new data. This smoothing is again found in another description of GAI models as a "set of data points and then extrapolat[ing] from those." While partially correct for some training approaches, this portrayal fails to recognize the complex array of processes currently employed [71]. Another described GAI as a "JPEG picture compression for the entire universe of knowledge," noting how both JPEG image compression and GAI training are lossy by design. Lossy means the original data used cannot be fully reconstructed, despite system outputs looking like them [72], [73]. However, such a layered comparison requires technical understanding of both technologies, while also ignoring that GAI systems are complex, distributed infrastructures requiring immense commercial and regulatory organization for their use by users. By contrast, JPEG algorithms are open-source and easily implemented programmatically [74], while GAI necessitates a vast corpus of largely stolen information, outsourced human labor, and robust technical and reflexive know-how [21], [63], [75].

Relationship – How do we relate to GAI?

Nearly all instructors positioned GAI relative to themselves or others, with 87.7% participants describing human-GAI relationships across the responses. Of these roughly 88% of responses, 64% fell into the "**Collaborative/Partnership**" position, representing a depiction of GAI systems as a developing social entity that can learn, grow, and collaborate. Within this position, however, instructors described very different relationships with GAI [10]. Some are alleviated because GAI "frees up" cognition and time to focus on other tasks, as one described: "[GAI has been] like a colleague for me. It gives me some ideas of how to improve, quotes, or humorous thing[s] I can include in my teaching. So it's kind of like a colleague who is providing input." Others emphasized how GAI can extend their thinking like an e-bike: augmenting capabilities, but requiring instructors "steer" and "balance" to gain additional power [24]: "Imagine your brain was the entire internet [with] everything available as well as all of your own lived experiences. You're able to pull and connect that information to improve your responses." However, few instructors described GAI as helping regulate their learning, and even fewer that their thinking is hybrid – a co-construction with GAI [10].

The second-most common position treated GAI as an "**Instrument/Tool**" (32%). As mentioned, this code co-occurred highly with "Technical Object/Artifact" (Ontology), "Mechanical/ Pattern-matching" (Operation), and "Mimics/Simulates Understanding" (Epistemology), reinforcing the model of GAI as a technical artifact that performs poorly, producing unreliable outputs that require constant monitoring and correction. Most framed GAI as an instrument, whether a library, database, search engine, or "tool" that they could use for specific tasks to save time. A few noted this as "scary" and caution their students about GAI systems' limitations [76], [77], [78], [79], [80]. Also near this position is a unique analogy specifically described the sequential, path-dependent inference process (i.e., using a trained model) in ways that broach the "Collaborative/ Partnership" position, but without ascribing GAI agency: "Like a mountain range where you put in the prompt [at] the top the more prompts you put in, it cascades down in a certain direction. To start a different conversation, you would go back and start over." This sophisticated, multi- dimensional conceptualization showcases how instructors' descriptions do not cleanly fall into categorical positions: acknowledging power and capability (vast terrain) within limits (bounded mountain range), lacking anthropomorphism, featuring a way people interact with GAI, and drawing attention to aspects of its operation. Meanwhile, the analogy obscures plate tectonics (i.e., model training), simplifies probabilistic sampling by comparing it to gravity "pulling down," and minimizes the shifting representational space with context. Regardless, whether "I use it for X" or "I work with it for Y," these findings align with suggestions about the insufficiency of the "calculator" treatment of GAI because of the diversity in GAI-instructor collaboration practices described [10].

The least-frequent relationship (4%) portrayed GAI systems in adversarial or threatening terms: "**Adversarial/Threat**." Few instructors explicitly called out GAI as a powerful external force entering the educational space; neither colleague nor tool, but an invasive phenomenon that challenges existing practices and requires controls. While other parts of the interview protocol touched on these topics, their absence from instructors' metaphors suggests that this relationship is not immediately apparent.

Power/Capability – What can GAI do?

When instructors drew attention to what GAI can *do* for them, they did so partially in terms of how they relate to GAI, as captured by the Relationship continua. An additional quality of these relationships considers the "muscle-power," or the effectiveness and utility GAI presents for various tasks. The second-most common position (31.5%) frames GAI as "**Limited/Deficient**," building on the previous descriptions of codes it co-occurs with frequently: "Technical Object/Artifact" (Ontology), "Mimics/Simulated Understanding" (Epistemology), "Mechanical/ Pattern-matching" (Operation), and "Instrument/Tool-Use" (Relationship). Through this lens, GAI is unreliable and inadequate across tasks, requiring constant human intervention or outright rejection. As one described: "They're text predictors. It's just a function, you give it some input, it does some calculation and gives you an output. It's not a mind, it doesn't think, and I have to warn my students [that] they can't solve your logic problems. They don't know how to reason, they just predict text." A few similarly cautioned against placing undue confidence in GAI outputs, with one calling GAI "a really good bluffer," and another advising users "understand what they're focused on before using [GAI]." Instructors with this perspective might still use GAI, but consider its "understanding" limited across domains and tasks.

The most prevalent view positioned GAI at a roughly "**Human-Level/Comparable**" capability (50%), with instructors again expressing nuanced views about GAI's capability in certain tasks. Although this position more strongly references human-comparable performance or compares GAI to employees, the descriptions used vary between GAI as having "Functional/Contextual" and "Genuine/True" understanding. The latter saw GAI as possessing human-like expertise that could improve or replace conventional functions of occupations, and uncover hidden connections and possibilities: "One time I used it as a therapist and it's actually really, really good. I can be like, 'No, that's terrible, I don't want to hear that,' [but] you would never say that to a therapist. It was very strangely affirming." Others recognized GAI limitations similarly to human limitations and of different types of expertise [62], [81], [82]; that is, GAI with "Functional/ Contextual Understanding." One instructor discussed work augmentation, saying, GAI is: "Like an intern working for you. Interns can be very innovative, creative, break some new frontiers, [but] at the same time they don't know everything about your work environment, so you need to keep an eye on that." Monitoring GAI during use was discussed by multiple instructors, another of whom noted that "[GAI] is very good at learning about past experiences, but that kind of prediction is never 100%, so there's always an uncertainty." Such views largely regard GAI as providing human-like returns on meaningful tasks for their lives but requiring oversight to account for its limitations.

The other "end-point" on the spectrum, and least common among the instructors (18.5%), is the view that GAI exceeds human capabilities: "**Superhuman/Superior**." This comparison is not inherently "artificial general intelligence" (i.e., AGI or ACI), but recognition that GAI can perform tasks better than humans. Co-occurring most with "Collaborative/Partnership," "Social Agent/Being," and "Learning From Examples," this position is likely to hold ontological anthropomorphic views of GAI, as shown by the remark, "[GAI] is, however, a better artist than I am or the undergraduates are." Instructors' comments were narrowly directed at particular tasks in this regard: "If you have to create a literature review, there's only X number of papers that you can read over the next three days. And you [will] only have a 3% or 10% of that access of information in that time, where [GAI] might be able to cover 80% more because they have more access to a lot more data so they can provide you with a summary with a lot more information and content." These instances rarely moved beyond this task-performance-based metric to encompass truly supernatural descriptions, though one described GAI as an "alien child" learning from humans. These remarks related more strongly to other dimensions of the taxonomy, as opposed to considering GAI as possessing supernatural powers beyond those of humans. However, instructors recognize how GAI capabilities may be more-or-less impactful for different tasks. Several responses allude to the reconfigured networks and forms of expertise required to navigate and meaningfully integrate GAI into existing interaction-based professional routines [83]. As one instructor said, "The way we perform computer science and the way we teach computer science, also figuring out what skills come before and after. Learning to use [GAI] is a discussion we need to have."

Implications for Faculty Development

This five-dimensional taxonomy presents several opportunities for faculty developers working with engineering instructors.

Ontologically and Epistemologically, the prevalence of "Social Being/Agent" (54.2%) suggests training should help instructors recognize when *functional* anthropomorphism becomes *ontological* anthropomorphism [5], [17], [44], [84]. Conveying that GAI systems are fully-fledged humans may not be instructors' genuine belief, yet employing such ontological anthropomorphism in the classroom rather than a more tactful, functional version may unintentionally engender student misconceptions. Further, what counts as understanding varies, making it a worthwhile discussion prompt for engaging instructors about why different legitimate answers are rooted in assumptions about the nature, construction, and function of knowledge and knowing [10], [85], [86]. GAI, then, can prompt learning about learning.

Operationally, all three positions suggest limited instructor understanding of GAI functionality, aligning with recognition that: (1) GAI operations are difficult to parse for non-programmers, (2) existing resources inadequately distinguish between different GAI systems, and (3) keeping up with GAI development is challenging. Developers should weigh the benefits of training about the specifics of GAI system operation against instructors' other GAI training needs, while providing information about basic architectural and system differences, such as the data and privacy difference between commercial ecosystems like ChatGPT and university GAI resources [63].

Relationally, the dominance of "Collaborative/Partnership" (64%) reformulates notions of tool use educators convey to students [5], [17], [84], with instructors describing human-GAI relationships that exceed the mere instrumental application of calculators [10, p. 118]. Instructors could benefit from training about reflexive GAI use to check understanding, remaining mindful that treating these systems as knowledgeable colleagues can reduce the propensity for verification [14], [26], [41]. Developers should also help instructors recognize why mappings between GAI systems and other technologies may have surface plausibility, but contribute to misunderstandings about reliability and verification. Lastly, given active concerns about bias [87], [88], [89], developers should specifically address "Adversary/Threat" (4%) perspectives, given their low occurrence, to promote awareness of the heterogeneously distributed origins and effects of GAI systems.

Capably, developers should remain sensitive to the “jagged edge” of technological development enabling task performance advances in some areas and not others [90]. Encouraging skepticism and active monitoring can build from instructors with amenable views, and examples of local, ongoing GAI integration can signal areas where support is most needed [91], [92].

These integrated dimensions demand efforts to bridge between GAI vocabularies rather than enforce standardized language [17], [93]. Doing so means reaching instructors from all disciplines and creeds, not just early adopters or those “speaking the same language” as coordinators [27]. Faculty training is needed exploring these different conceptualizations of GAI and how they affect our interactions with others and GAI systems [94], [95], [96]. Using this taxonomy as a conversation-starter, instructors and faculty developers can identify their positions and consider their beliefs about GAI capabilities and expectations for student use.

Limitations

Notably, responses to the other interview questions were *not* included in the analysis. However, ongoing work is expanding this analysis to the figurative language used to describe GAI throughout the entirety of the interview and across 170 instructors at 18 different universities using GAI-assisted qualitative methods [34]. Additionally, exceptions, such as instructors who struggled to find analogies, were not described given space constraints, but should be investigated in future studies to explore their justifications and alternatives. Future work could also delve into the degree of subjective experience credited to GAI, and compare the figurative language between instructors of different disciplines.

Conclusion

This study presents preliminary findings about the figurative language employed by higher education engineering instructors to describe GAI, which vary widely across five dimensions capturing the ontology of GAI, the epistemology of GAI, GAI operation, human-GAI relationships, and the capabilities of GAI. This variance suggests the need for greater exploration into instructors’ mental models about GAI, expanding analysis to their broader figurative language and use of GAI in everyday interactions and settings. Incommensurable views challenge institutional policy roll-out and coherence, requiring bridge building efforts between GAI interpretations. It requires us to ask, “How do I describe GAI?”

References

[1] M. M. Maas, "AI is Like… A Literature Review of AI Metaphors and Why They Matter for Policy," Oct. 25, 2023, *Social Science Research Network, Rochester, NY*: 4612468. doi: 10.2139/ssrn.4612468.

[2] M. Mitchell, "The metaphors of artificial intelligence," *Science*, vol. 386, no. 6723, p. eadt6140, Nov. 2024, doi: 10.1126/science.adt6140.

[3] E. Mollick, "On-boarding your AI Intern," One Useful Thing. Accessed: Jan. 18, 2026. [Online]. Available: https://www.oneusefulthing.org/p/on-boarding-your-ai-intern

[4] M. Blythe, S. Lindley, and D. Murray-Rust, "Artificial Intelligence and other Speculative Metaphors," in *Proceedings of the 2025 ACM Designing Interactive Systems Conference*, in DIS '25. New York, NY, USA: Association for Computing Machinery, Jul. 2025, pp. 347–356. doi: 10.1145/3715336.3735714.

[5] L. McKnight and C. Shipp, "'Just a tool'? Troubling language and power in generative AI writing," *English Teaching: Practice & Critique*, vol. 23, no. 1, pp. 23–35, Apr. 2024, doi: 10.1108/ETPC-08-2023-0092.

[6] M. Shanahan, "Talking about Large Language Models," *Commun. ACM*, vol. 67, no. 2, pp. 68–79, Feb. 2024, doi: 10.1145/3624724.

[7] G. Lakoff and M. Johnson, "Conceptual Metaphor in Everyday Language," *The Journal of Philosophy*, vol. 77, no. 8, pp. 453–486, 1980, doi: 10.2307/2025464.

[8] F. Jin, L. Sun, Y. Pan, and C.-H. Lin, "High heels, compass, spider-man, or drug? Metaphor analysis of generative artificial intelligence in academic writing," *Computers & Education*, vol. 228, p. 105248, Apr. 2025, doi: 10.1016/j.compedu.2025.105248.

[9] L. Furze, "AI Metaphors We Live By: The Language of Artificial Intelligence," Leon Furze. Accessed: Oct. 08, 2025. [Online]. Available: https://leonfurze.com/2024/07/19/ai-metaphors-we-live-by-the-language-of-artificial-intelligence/

[10] J. M. Lodge, S. Yang, L. Furze, and P. Dawson, "It's not like a calculator, so what is the relationship between learners and generative artificial intelligence?," *Learning: Research and Practice*, vol. 9, no. 2, pp. 117–124, Jul. 2023, doi: 10.1080/23735082.2023.2261106.

[11] K. Demir and G. E. Güraksın, "Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis," *PER*, vol. 9, no. 2, pp. 297–312, Mar. 2022, doi: 10.17275/per.22.41.9.2.

[12] M. Zirenko, I. A. Machura, S. Fabriz, L. Schulze-Vorberg, and H. Horz, "AI and Learning with AI: University Students' Metaphorical Conceptualizations | Journal of Interactive Media in Education," Mar. 2025, doi: 10.5334/jime.994.

[13] K. R. Muis, G. Trevors, and M. Chevrier, "Epistemic climate for epistemic change," in *Handbook of Epistemic Cognition*, Routledge, 2016.

[14] G. Ferreira, E. Costello, R. Farrow, and K. Lee, "Metaphors of AI in Education: Discourses, Histories and Practices," *Journal of Interactive Media in Education*, vol. 2025, no. 1, Aug. 2025, Accessed: Oct. 10, 2025. [Online]. Available: https://oro.open.ac.uk/105789/

[15] T. G. Amin, "Conceptual Metaphor and the Study of Conceptual Change: Research synthesis and future directions," *International Journal of Science Education*, vol. 37, no. 5–6, pp. 966–991, Apr. 2015, doi: 10.1080/09500693.2015.1025313.

[16] M. Koc, "Student teachers' conceptions of technology: A metaphor analysis," *Computers & Education*, vol. 68, pp. 1–8, Oct. 2013, doi: 10.1016/j.compedu.2013.04.024.

[17] C. Karakitsou, I. Karayianni, K. Leftheriotis, A. Logotheti, and M. D. Avgerinou, "Planets, cars, and personas: Toward an understanding of faculty perceptions of artificial intelligence through visual metaphors and projective techniques," *Journal of Visual Literacy*, vol. 44, no. 3, pp. 272–306, Jul. 2025, doi: 10.1080/1051144X.2025.2538256.

[18] N. Pitterson, N. Perova-Mello, and R. Streveler, "Engineering students' use of analogies and metaphors: Implications for educators," *International Journal of Engineering Education*, vol. 35, pp. 2–14, Jan. 2018.

[19] A. Hamilton, "Metaphor in theory and practice: the influence of metaphors on expectations," *ACM J. Comput. Doc.*, vol. 24, no. 4, pp. 237–253, Nov. 2000, doi: 10.1145/353927.353935.

[20] P. Khadpe, R. Krishna, L. Fei-Fei, J. T. Hancock, and M. S. Bernstein, "Conceptual Metaphors Impact Perceptions of Human-AI Collaboration," *Proc. ACM Hum.-Comput. Interact.*, vol. 4, no. CSCW2, p. 163:1-163:26, Oct. 2020, doi: 10.1145/3415234.

[21] M. Mitchell, *Artificial intelligence: a guide for thinking humans*, First Picador paperback edition, 2020. New York: Picador, 2020.

[22] D. Crevier, *AI: the tumultuous history of the search for artificial intelligence*. New York, NY: Basic Books, 1993.

[23] T. Haigh and P. E. Ceruzzi, *A new history of modern computing*. in History of computing. Cambridge [Massachusetts]: The MIT Press, 2021.

[24] G. Skorburg, "Models of Models," Moving Things Around. Accessed: Oct. 06, 2025. [Online]. Available: https://substack.com/inbox/post/173854966

[25] S. Trott, "What we talk about when we talk about LLMs," The Counterfactual. Accessed: Oct. 06, 2025. [Online]. Available: https://seantrott.substack.com/p/what-we-talk-about-when-we-talk-about

[26] E. M. Bender, E. Costello, K. Lee, R. Farrow, and G. Ferreira, "Unsafe AI for Education: A Conversation on Stochastic Parrots and Other Learning Metaphors ⚠️ | Journal of Interactive Media in Education," *Journal of Interactive Media in Education*, vol. 2025, no. 1, p. 10, Mar. 2025, doi: 10.5334/jime.1079.

[27] D.-K. Mah and N. Groß, "Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs," *Int J Educ Technol High Educ*, vol. 21, no. 1, p. 58, Oct. 2024, doi: 10.1186/s41239-024-00490-1.

[28] K. A. Lucas and A. Lioy, "Mapping AI Literacy Frameworks: An Analysis of the Evolving Metaphorical Relationships between Students, Teachers, and AI | Journal of Interactive Media in Education," Mar. 2025, doi: 10.5334/jime.974.

[29] S. J. Baldwin, Y.-H. Ching, and N. Friesen, "Online Course Design and Development among College and University Instructors: An Analysis using Grounded Theory," *OLJ*, vol. 22, no. 2, Jun. 2018, doi: 10.24059/olj.v22i2.1212.

[30] A. H. Eichen, "Do classroom AI policies work? Examining the relationship between syllabus restrictions and academic performance in higher education," Dissertation, 2025. [Online]. Available: http://login.ezproxy.lib.vt.edu/login?url=https://www.proquest.com/dissertations-theses/do-classroom-ai-policies-work-examining/docview/3215574475/se-2

[31] A. Ghimire, J. Prather, and J. Edwards, "Generative AI in Education: A Study of Educators' Awareness, Sentiments, and Influencing Factors," Mar. 22, 2024, *arXiv*: arXiv:2403.15586. doi: 10.48550/arXiv.2403.15586.

[32] J. W. Creswell, *Research design: Qualitative, quantitative, and mixed methods approaches, 3rd ed*. in Research design: Qualitative, quantitative, and mixed methods approaches, 3rd ed. Thousand Oaks, CA, US: Sage Publications, Inc, 2009, pp. xxix, 260.
[33] R. Chew, J. Bollenbacher, M. Wenger, J. Speer, and A. Kim, "LLM-Assisted Content Analysis: Using Large Language Models to Support Deductive Coding," Jun. 23, 2023, *arXiv*: arXiv:2306.14924. doi: 10.48550/arXiv.2306.14924.
[34] M. Nicmanis and H. Spurrier, "Getting Started with Artificial Intelligence Assisted Qualitative Analysis: An Introductory Guide to Qualitative Research Approaches with Exploratory Examples from Reflexive Content Analysis," *International Journal of Qualitative Methods*, vol. 24, p. 16094069251354863, Sep. 2025, doi: 10.1177/16094069251354863.
[35] A. Katz, G. C. Fleming, and J. B. Main, "Thematic analysis with open-source generative AI and machine learning: a new method for inductive qualitative codebook development," *Humanit Soc Sci Commun*, vol. 13, no. 1, p. 209, Jan. 2026, doi: 10.1057/s41599-026-06508-5.
[36] R. Schmitt, "Systematic Metaphor Analysis as a Method of Qualitative Research," *The Qualitative Report*, vol. 10, no. 2, pp. 358–394, Jun. 2005, doi: 10.46743/2160-3715/2005.1854.
[37] M. Nicmanis, "Reflexive Content Analysis: An Approach to Qualitative Data Analysis, Reduction, and Description," *International Journal of Qualitative Methods*, vol. 23, p. 16094069241236603, Nov. 2024, doi: 10.1177/16094069241236603.
[38] B. Nerlich, "Hunting for AI metaphors," Making Science Public. Accessed: Oct. 08, 2025. [Online]. Available: https://blogs.nottingham.ac.uk/makingsciencepublic/2024/04/12/hunting-for-ai-metaphors/
[39] B. Nerlich, "AI, LLMs and an explosion of metaphors," Making Science Public. Accessed: Oct. 08, 2025. [Online]. Available: https://blogs.nottingham.ac.uk/makingsciencepublic/2024/08/30/ai-llms-and-an-explosion-of-metaphors/
[40] E. M. Lim, "Metaphor analysis on pre-service early childhood teachers' conception of AI (Artificial Intelligence) education for young children," *Thinking Skills and Creativity*, vol. 51, p. 101455, Mar. 2024, doi: 10.1016/j.tsc.2023.101455.
[41] M. Shanahan, "Still 'Talking About Large Language Models': Some Clarifications," Dec. 13, 2024, *arXiv*: arXiv:2412.10291. doi: 10.48550/arXiv.2412.10291.
[42] B. D. Heinsfeld and G. Veletsianos, "The Language on GenAI: A Critical Exploration of Personification Metaphors in UNESCO's Guidance for Generative AI in Education and Research," *Journal of Interactive Media in Education*, vol. 2025, no. 1, 2025, Accessed: Oct. 10, 2025. [Online]. Available: https://eric.ed.gov/?id=EJ1483348
[43] C. Vallis, S. Wilson, and A. Casey, "Fear and Awe: Making Sense of Generative AI Through Metaphor," *Journal of Interactive Media in Education*, vol. 2025, no. 1, p. 14, Aug. 2025, doi: 10.5334/jime.972.
[44] A. Konstantinidis, "A Metaphor for Rethinking Artificial Intelligence in/and Education," *Journal of Interactive Media in Education*, vol. 2025, no. 1, Aug. 2025, doi: 10.5334/jime.981.
[45] Z. Ye and J. Li, "Artificial Intelligence Through the Lens of Metaphor: Analyzing the EU AIA," *International Journal of Digital Law and Governance*, vol. 1, no. 2, pp. 361–381, Oct. 2024, doi: 10.1515/ijdlg-2024-0016.

[46] R. M. Hogervorst, “Metaphors for AI | A braindump of unfinished ideas that are just not there yet.” Accessed: Oct. 08, 2025. [Online]. Available: https://notes.rmhogervorst.nl/post/2023/06/04/metaphors-for-ai/

[47] D. Murray-Rust, I. Nicenboim, and D. Lockton, “Metaphors for designers working with AI,” *DRS2022: Bilbao*, Jun. 2022, Accessed: Oct. 08, 2025. [Online]. Available: https://doi.org/10.21606/drs.2022.667

[48] L. Ouchchy, A. Coin, and V. Dubljević, “AI in the headlines: the portrayal of the ethical issues of artificial intelligence in the media,” *AI & Soc*, vol. 35, no. 4, pp. 927–936, Dec. 2020, doi: 10.1007/s00146-020-00965-5.

[49] S. J. Tracy, “Qualitative Quality: Eight ‘Big-Tent’ Criteria for Excellent Qualitative Research,” *Qualitative Inquiry*, vol. 16, no. 10, pp. 837–851, Dec. 2010, doi: 10.1177/1077800410383121.

[50] N. A. Jones, H. Ross, T. Lynam, P. Perez, and A. Leitch, “Mental Models: An Interdisciplinary Synthesis of Theory and Methods,” *Ecology and Society*, vol. 16, no. 1, 2011, Accessed: Jul. 16, 2024. [Online]. Available: https://www.jstor.org.ezproxy.lib.vt.edu/stable/26268859

[51] O. Almatrafi, A. Johri, and H. Lee, “A systematic review of AI literacy conceptualization, constructs, and implementation and assessment efforts (2019–2023),” *Computers and Education Open*, vol. 6, p. 100173, Jun. 2024, doi: 10.1016/j.caeo.2024.100173.

[52] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, “On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜,” in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, in FAccT ’21. New York, NY, USA: Association for Computing Machinery, Mar. 2021, pp. 610–623. doi: 10.1145/3442188.3445922.

[53] A. Gupta, Y. Atef, A. Mills, and M. Bali, “Assistant, Parrot, or Colonizing Loudspeaker? ChatGPT Metaphors for Developing Critical AI Literacies | Open Praxis,” Feb. 2024, doi: 10.55982/openpraxis.16.1.631.

[54] J. (Joey) Ji, “Demystify ChatGPT: Anthropomorphism around generative AI,” *GRACE: Global Review of AI Community Ethics*, vol. 2, no. 1, Jan. 2024, doi: 10.60690/cee03e53.

[55] K. Charmaz, “Grounded Theory in Global Perspective: Reviews by International Researchers,” *Qualitative Inquiry*, vol. 20, no. 9, pp. 1074–1084, Nov. 2014, doi: 10.1177/1077800414545235.

[56] A. Cho *et al.*, “Transformer Explainer: Interactive Learning of Text-Generative Models,” Aug. 08, 2024, *arXiv*: arXiv:2408.04619. doi: 10.48550/arXiv.2408.04619.

[57] S. Raieli, *Building AI Agents with LLMs, RAG, and Knowledge Graphs: A practical guide to autonomous and modern AI agents*, 1st ed. Birmingham: Packt Publishing Limited, 2025.

[58] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever, “Language Models are Unsupervised Multitask Learners,” 2019. Accessed: Aug. 08, 2024. [Online]. Available: https://www.semanticscholar.org/paper/Language-Models-are-Unsupervised-Multitask-Learners-Radford-Wu/9405cc0d6169988371b2755e573cc28650d14dfe

[59] L. Larson, “Photography was historically considered ‘art’s most mortal enemy.’ Is AI?,” Medium. Accessed: Jan. 19, 2026. [Online]. Available: https://medium.com/@elarson39/photography-was-historically-considered-arts-most-mortal-enemy-is-ai-69a2dc2f43ef

[60] M. Suleyman and M. Bhaskar, *The coming wave: Technology, Power, and the Twenty-First Century's Greatest Dilemma*. New York: Crown, 2023.
[61] P. Denny *et al.*, "Computing Education in the Era of Generative AI," Jun. 05, 2023, *arXiv*: arXiv:2306.02608. doi: 10.48550/arXiv.2306.02608.
[62] E. Mollick, *Co-intelligence: living and working with AI*. New York: Portfolio/Penguin, 2024.
[63] E. M. Bender and A. Hanna, *The AI Con: how to fight big tech's hype and create the future we want*, First edition. New York: HarperCollins, 2025.
[64] K. Crawford, *Atlas of AI: power, politics, and the planetary costs of artificial intelligence*. New Haven: Yale University Press, 2021.
[65] J. Bhalla, "Technomorphic Mental Tools," Surprising Science. [Online]. Available: https://bigthink.com/surprising-science/technomorphic-mental-tools/
[66] J. Vertesi, "Seeing like a Rover: Visualization, embodiment, and interaction on the Mars Exploration Rover Mission," *Soc Stud Sci*, vol. 42, no. 3, pp. 393–414, Jun. 2012, doi: 10.1177/0306312712444645.
[67] A. Frank, M. Gleiser, and E. Thompson, *The blind spot: why science cannot ignore human experience*. Cambridge, Massachusetts: The MIT Press, 2024.
[68] B. Fresz, E. Dubovitskaya, D. Brajovic, M. F. Huber, and C. Horz, "How Should AI Decisions Be Explained? Requirements for Explanations from the Perspective of European Law," in *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, Oct. 2024, pp. 438–450. doi: 10.1609/aies.v7i1.31648.
[69] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, "Conceptualizing AI literacy: An exploratory review," *Computers and Education: Artificial Intelligence*, vol. 2, p. 100041, Jan. 2021, doi: 10.1016/j.caeai.2021.100041.
[70] J. E. (Hans) Korteling, G. C. van de Boer-Visschedijk, R. a. M. Blankendaal, R. C. Boonekamp, and A. R. Eikelboom, "Human- versus Artificial Intelligence," *Front. Artif. Intell.*, vol. 4, Mar. 2021, doi: 10.3389/frai.2021.622364.
[71] X. Chen, C. Gao, C. Chen, G. Zhang, and Y. Liu, "An Empirical Study on Challenges for LLM Application Developers," Feb. 18, 2025, *arXiv*: arXiv:2408.05002. doi: 10.48550/arXiv.2408.05002.
[72] N. Carlini, D. Ippolito, M. Jagielski, K. Lee, F. Tramer, and C. Zhang, "Quantifying Memorization Across Neural Language Models," presented at the The Eleventh International Conference on Learning Representations, Sep. 2022. Accessed: Jan. 17, 2026. [Online]. Available: https://openreview.net/forum?id=TatRHT_1cK
[73] H. Brown, K. Lee, F. Mireshghallah, R. Shokri, and F. Tramèr, "What Does it Mean for a Language Model to Preserve Privacy?," in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, in FAccT '22. New York, NY, USA: Association for Computing Machinery, Jun. 2022, pp. 2280–2292. doi: 10.1145/3531146.3534642.
[74] G. Hudson, A. Léger, B. Niss, I. Sebestyén, and J. Vaaben, "JPEG-1 standard 25 years: past, present, and future reasons for a success," *JEI*, vol. 27, no. 4, p. 040901, Aug. 2018, doi: 10.1117/1.JEI.27.4.040901.
[75] C. Huyen, *AI engineering: building applications with foundation models*, First edition. Sebastopol,CA: O'Reilly, 2025.
[76] C. S. Kay, "Why you shouldn't trust data collected on MTurk," *Behav Res*, vol. 57, no. 12, p. 340, Nov. 2025, doi: 10.3758/s13428-025-02852-7.

[77] H. Schroeder, M. A. L. Quéré, C. Randazzo, D. Mimno, and S. Schoenebeck, "Large Language Models in Qualitative Research: Uses, Tensions, and Intentions," Feb. 27, 2025, *arXiv*: arXiv:2410.07362. doi: 10.48550/arXiv.2410.07362.

[78] S. Atreja, J. Ashkinaze, L. Li, J. Mendelsohn, and L. Hemphill, "Prompt Design Matters for Computational Social Science Tasks but in Unpredictable Ways," *ICWSM*, vol. 19, pp. 122–145, Jun. 2025, doi: 10.1609/icwsm.v19i1.35807.

[79] D. Reeping, C. Hampton, and D. Özkan, "Interrogating the Use of Large Language Models in Qualitative Research Using the Qualifying Qualitative Research Quality Framework," *Studies in Engineering Education*, vol. 6, no. 2, Jul. 2025, doi: 10.21061/see.174.

[80] T. Jowsey, V. Braun, V. Clarke, D. Lupton, and M. Fine, "We reject the use of generative artificial intelligence for reflexive qualitative research," Oct. 20, 2025, *Social Science Research Network, Rochester, NY*: 5676462. doi: 10.2139/ssrn.5676462.

[81] P. E. Tetlock, *Expert political judgment: how good is it? How can we know?*, New edition. Princeton: Princeton University Press, 2006.

[82] G. Eyal, "For a Sociology of Expertise: The Social Origins of the Autism Epidemic," *American Journal of Sociology*, vol. 118, no. 4, pp. 863–907, 2013, doi: 10.1086/668448.

[83] J. He, "Redefining human Go experts in the post-AI era: a perspective from sociology of professions," 2024. [Online]. Available: https://jiuhenghe.com/assets/pdf/Redefining%20human%20Go%20experts%20in%20the%20post-AI%20era.pdf

[84] M. Alwaqdani, "Investigating teachers' perceptions of artificial intelligence tools in education: potential and difficulties," *Educ Inf Technol*, vol. 30, no. 3, pp. 2737–2755, Feb. 2025, doi: 10.1007/s10639-024-12903-9.

[85] P. E. Doolittle, "Vygotsky's Zone of Proximal Development as a Theoretical Foundation for Cooperative Learning," *Journal on Excellence in College Teaching*, vol. 8, no. 1, pp. 83–103, 1997.

[86] D. S. Fleur, B. Bredeweg, and W. van den Bos, "Metacognition: ideas and insights from neuro- and educational sciences," *npj Sci. Learn.*, vol. 6, no. 1, pp. 1–11, Jun. 2021, doi: 10.1038/s41539-021-00089-5.

[87] A. T. Kalai, O. Nachum, S. S. Vempala, and E. Zhang, "Why Language Models Hallucinate," Sep. 04, 2025, *arXiv*: arXiv:2509.04664. doi: 10.48550/arXiv.2509.04664.

[88] Z. Ji *et al.*, "Survey of Hallucination in Natural Language Generation," *ACM Comput. Surv.*, vol. 55, no. 12, pp. 1–38, Dec. 2023, doi: 10.1145/3571730.

[89] R. Mao, Q. Liu, K. He, W. Li, and E. Cambria, "The Biases of Pre-Trained Language Models: An Empirical Study on Prompt-Based Sentiment Analysis and Emotion Detection," *IEEE Transactions on Affective Computing*, vol. 14, no. 3, pp. 1743–1753, Jul. 2023, doi: 10.1109/TAFFC.2022.3204972.

[90] F. Dell'Acqua *et al.*, "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality," Harvard Business School, Cambridge, MA, Working Paper 24–013, Spet 2023. [Online]. Available: https://www.hbs.edu/ris/Publication%20Files/24-013_d9b45b68-9e74-42d6-a1c6-c72fb70c7282.pdf

[91] J. Jiao, S. Afroogh, K. Chen, D. Atkinson, and A. Dhurandhar, "The global landscape of academic guidelines for generative AI and LLMs," *Nat Hum Behav*, pp. 1–5, Mar. 2025, doi: 10.1038/s41562-025-02124-6.

[92] U. Dewan, A. Hingle, N. McDonald, and A. Johri, “Engineering Educators’ Perspectives on the Impact of Generative AI in Higher Education,” in *2025 IEEE Global Engineering Education Conference (EDUCON)*, Apr. 2025, pp. 1–10. doi: 10.1109/EDUCON62633.2025.11016518.
[93] S. Bødker, C. Dindler, O. S. Iversen, and R. C. Smith, “What Is Participatory Design?,” in *Participatory Design*, in Synthesis Lectures on Human-Centered Informatics. , Cham: Springer International Publishing, 2022, pp. 5–13. doi: 10.1007/978-3-031-02235-7_2.
[94] K. E. Olson, M. A. O’Brien, W. A. Rogers, and N. Charness, “Diffusion of Technology: Frequency of use for Younger and Older Adults,” *Ageing Int*, vol. 36, no. 1, pp. 123–145, Mar. 2011, doi: 10.1007/s12126-010-9077-9.
[95] “Artificial Intelligence and Future of Teaching and Learning: Insights and Recommendations,” U.S. Department of Education, Office of Educational Technology, Washington, DC, 2023.
[96] K. Charmaz, S. R. Harris, and L. Irvine, *The social self and everyday life: understanding the world through symbolic interactionism*. Hoboken, New Jersey Oxford, UK: Wiley Blackwell, 2019.

Appendix

Detailed Data Analysis

After collecting and organizing the initial codebook, the Version 1 codes were applied to the sample of 57 instructor responses using the MAXQDA qualitative analysis software. During this first-pass coding, we identified the analogy/metaphor types and assigned relevant content codes from the Version 1 list to each response segment. This evaluation allowed for new codes to emerge inductively when instructor language did not align with existing categories, while also noting areas of overlap and redundancy between existing items. Multiple codes were applied to each response as needed, since instructors often employed several metaphors or addressed multiple dimensions of GAI understanding within a single response. Similar to Pitterson et al.'s [18] analysis of engineering students' analogies and metaphors in circuits problems, we examined figurative language through object relationships. Direct comparisons relate GAI to familiar concrete things (e.g., "GAI is like a calculator"). Structure comparisons focus on specific attributes or operational characteristics shared between GAI and the base concept (e.g., comparing how GAI processes information to how a brain processes information). Bridge analogies chain intermediate concepts to connect GAI to more distant domains (e.g., "GAI is like photography, photography takes practice to learn, so GAI takes practice"). We also identified imaginative metaphors that helped visualize abstract GAI concepts (e.g., "black box," "neural network," "prompt/context engineering") and affective metaphors that bridged cognitive understanding with emotional responses (e.g., "collaborative partner," "magician," "threat").

Following this first-pass, a second version codebook (Version 2) was created by revising the initial 68-item list to accommodate newly identified themes and consolidate similar or overlapping codes. In addition, the first-pass revealed areas requiring more-or-less granularity, which were also addressed in Version 2. For example, Version 1 included the codes "Probabilistic text generator" and "Template applier." The first references how text-based GAI systems generate text using the probabilistic distribution of possible word sequences calculated during training. The second is the notion that GAI systems "copy" patterns in their training data that they "paste" into new situations [25]. While these metaphors, and others like "copier" and "stochastic parrot," capture different features of GAI operation, there was little discernment between them in instructors' responses. To address this, Version 2 introduced the code "Pattern-matching machine/template application/math problem" for responses portraying GAI operation as advanced pattern-recognition performed on training data, applying learned templates to new situations, and generally focusing on the technical process of pattern recognition and application. Similar analyses were used for the other Version 1 codes, resulting in a Version 2 codebook that retained Maas' five-dimensional taxonomy and contained 48 total metaphors and analogies.

A second pass applied these revised codes to all 57 responses, resulting in 417 total coded segments. We then calculated descriptive statistics, including code frequencies, co-occurrence patterns, and distributional trends across Maas' [1] dimensions to identify dominant themes and tensions in how engineering instructors conceptualize GAI. These themes and occurrences informed the final Version 3 codebook, which reduced overlapping codes and better captured how instructors described GAI versus those metaphors/analogies found in regulatory discourse. For example, several Version 2 codes relate to an anthropomorphic portrayal of GAI that required delineating, including “Person,” “Brain/Neural Structure,” “Collaborative Partner,” and “Learning From Examples.”

The final Version 3 codebook transitioned to dimensional categories, rather than metaphor/analogy “types.” This reduced the overlap between co-occurring codes, again, while also capturing better the intended target object. For example, the “Power/Capability” continuum includes, “Limited/Deficient,” “Human-Level/ Comparable,” and “Superhuman/Superior.” These positions collapse several previously overlapping codes, such as consolidating “Person,” “Brain/Neural Structure,” and “Collaborative partner” aspects of GAI capability to “Human-Level/Comparable.” “Limited/Deficient” included the Version 2 codes “Calculator, Mimicking understanding,” and “Dependency” relating to GAI being unable to adequately meet the task requests and expectations of their users.

Tables

Table I
Participant Demographic Information

	Percentage	**Count**
Sex		
Man	61.4%	35
Woman	15.8%	9
Prefer not to answer	22.8%	13
University Affiliation		
Southeast-Metro-Large	3.5%	2
Midwest-LandGrant-B	8.8%	5
Midwest-LandGrant-C	10.5%	6
Southeast-LandGrant-A	12.3%	7
Southwest-LandGrant-A	19.3%	11
Midwest-LandGrant-A	21.1%	12
Northeast-LandGrant-A	24.6%	14
Discipline		
Engineering Education	1.8%	1
Mining Engineering	1.8%	1
Communication	1.8%	1
Engineering Design	1.8%	1
Architectural Engineering	1.8%	1
Multidisciplinary Engineering	3.5%	2

Engineering Technology	5.3%	3
Mechanical Engineering	5.3%	3
Chemical Engineering	5.3%	3
Engineering Science and Mechanics	5.3%	3
Material Science and Engineering	5.3%	3
Industrial Systems Engineering	5.3%	3
Civil Engineering	7.0%	4
Aerospace Engineering	8.8%	5
Biomedical Engineering	8.8%	5
Computer Science	15.8%	9
Electrical and Computer Engineering	15.8%	9
Race/Ethnicity (can select more than one)		
Hispanic or Latino	3.5%	2
Middle Eastern or North African	5.3%	3
East Asian (e.g., Chinese, Korean, Japanese)	12.3%	7
South Asian (e.g., Indian, Pakistani, Bangladeshi, Sri Lankan)	14.0%	8
Prefer not to answer	29.8%	17
White or Caucasian	36.8%	21

Table II
Five-Dimensional Codebook for Understanding Instructors' GAI Figurative Language

Category	Code	Description	Indicators	Examples	Notes
Ontology *What GAI fundamentally "is": its essential nature or being*	Technical Object/Artifact	Conceptualized as a non-living thing, machine, or technical system with no inherent agency or personhood	References to tools, software, mechanisms, calculators, machines, boxes	Black box, calculator, software, imperfect copier, pattern-matching machine	No developmental arc; static unless modified

	Social Being/Agent	Conceptualized as having person-like qualities, agency, or developmental potential; occupying social roles	References to people, roles, learning entities, beings that develop or mature	Graduate student; colleague; partner; baby-to-mature; assistant; apprentice	Implies some form of agency, social competence, or developmental trajectory
	Environmental Force/Systemic Phenomenon	Conceptualized as a large-scale force or phenomenon beyond individual control; neither object nor agent but something that happens to the field or society	References to natural forces, historical movements, pervasive conditions	Wave, tsunami, electricity, manifest destiny, everywhere, inevitable, disruption	Transcends human-tool or human-agent frameworks; systemic scale
Epistemology *The nature and quality of GAI's knowledge or understanding*	Mimics/ Simulates Understanding	Appears to understand but lacks genuine comprehension; produces plausible outputs without meaning	References to mimicking, parroting, hand-waving, bullshit, surface-level, appearance without substance	Stochastic parrot, bullshit machine, hand-waving, imperfect copier, plausible response machine	Emphasizes gap between appearance and reality; outputs without genuine comprehension
	Functional/ Contextual Understanding	Has task-specific or domain-limited understanding; can "know" within bounds but	References to context-dependent capability, domain expertise, learned patterns that work	Pattern recognition that works, knows what it was trained on, understands in limited domains/does not have	Acknowledges both capability and limitation; pragmatic stance on understanding

		not universally		expert knowledge	
	Genuine/True Understanding	Possesses real comprehension, knowledge, or reasoning comparable to human understanding	References to actual knowledge, real understanding, genuine reasoning, comprehension	Truly understands, has knowledge; reasons, thinks (non-metaphorically)	Attributes full cognitive or epistemic status to GAI
Operation *How GAI works or functions; operational mechanism*	Mechanical/Pattern-matching	Operates through deterministic or statistical processes; token prediction, pattern recognition, algorithmic assembly	References to copying, matching, predicting, assembling, statistical processes	Copier, stochastic parrot, pattern-matching machine, magnet attracting tokens	Emphasizes technical, explainable processes; no genuine learning or understanding
	Learning/Developmental	Operates through processes analogous to learning, training, or development; improves through experience	References to training, learning from examples, improving, developing skills	Learning from examples; trained on data; improves with feedback; neural network (for learning)	Implies capacity for change and adaptation, though mechanism may remain unclear
	Magical/Beyond	Operates through unknown, mysterious, or supernatural processes that exceed human	References to magic, mystery, incomprehensibility, divine power, alien processes	Black box, magic, god-like, alien intelligence, shoggoth, incomprehensible	Emphasizes unknowability rather than specific mechanism; may indicate awe or fear

		comprehension			
Relationship *How humans relate to or position relative to GAI*	Instrument/ Tool-Use	Relationship of user to instrument; GAI serves human purposes, under human control and direction	References to using, applying, directing, controlling; GAI as means to human ends	Tool, calculator, software, resource, assistant (purely instrumental)	Human agency primary; GAI passive means; unidirectional control
	Collaborative/ Partnership	Relationship of mutual engagement; GAI and human work together with some reciprocity	References to collaboration, partnership, co-creation, working with, mutual benefit	Partner, colleague, co-pilot, collaborator, graduate student (mutual learning)	Implies bidirectional interaction; some degree of GAI agency; emotional investment
	Adversarial/ Threat	Relationship of opposition or defense; GAI poses threat that must be resisted, controlled, or guarded against	References to threat, danger, invasion, replacement, need for boundaries or control	Enemy, threat, poison, invasion, must be policed, taboo, petrified	Human in defensive posture; GAI as external threat; fear-based relationship
Power/Capability *GAI's abilities and effectiveness relative to humans*	Limited/ Deficient	Inadequate, unreliable, or inferior to human capabilities; needs constant correction	References to failure, inadequacy, unreliability, errors, limitations, deficiency	Broken tool, dumb, cannot create, unreliable, inadequate, not creative, needs constant checking	Emphasizes failures and need for human oversight/ correction

	Human-Level/ Comparable	Capabilities roughly equivalent to human abilities in relevant domains; neither clearly superior nor inferior	References to human-comparable performance, similar abilities, complementary strengths	Like a junior colleague, comparable to an entry-level worker, like a human assistant	Pragmatic assessment of similar capability levels; may vary by domain
	Superhuman/ Superior	Exceeds human capabilities; possesses abilities beyond human limits	References to superior performance, overwhelming power, god-like abilities, exceeding human limits	God, superhuman intelligence, can do what humans cannot: superior	Emphasizes GAI's advantages over human capability; may inspire awe or fear