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When AI Use Is Not Simply Generation: The GOPA Framework as a Shared Vocabulary for Human-Centered AI in Education

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Abstract

Generative artificial intelligence (AI) is rapidly reshaping educational practice by enabling the production of instructional materials, assessments, feedback, explanations, and learning supports with unprecedented speed. However, discussions of AI in education often rely on broad labels such as “AI-generated” or “AI-assisted,” which can obscure important differences in how cognitive and epistemic responsibilities are distributed between humans and AI systems. This paper introduces the GOPA Framework; Generation, Organization, Personalization, and Analysis as a shared vocabulary for distinguishing AI-Centered Production from Human-Centered Augmentation in educational contexts. Grounded in Human-in-the-Loop perspectives, the Curated Authorship Model, cognitive offloading research, epistemic cognition, and Human–AI augmentation, the framework examines where responsibility for interpretation, adaptation, evaluation, and judgment resides within AI-supported work. Generation describes uses in which AI assumes primary responsibility for producing content and meaning, while Organization, Personalization, and Analysis describe forms of AI use that support human thinking while preserving human responsibility for meaning making. The paper argues that educationally meaningful AI use should not be evaluated only by efficiency or output quality, but by whether learners and educators remain active drivers in constructing, adapting, evaluating, and interpreting knowledge. By prioritizing agency, authorship, accountability, epistemic authority, and productive cognitive friction, the GOPA Framework offers educators a practical language for examining AI use in teaching, learning, writing, and knowledge construction.

Keywords: Generative Artificial Intelligence, Human-in-the-Loop, Human–AI Augmentation, Cognitive Friction, AI Literacy

Introduction

Generative artificial intelligence (AI) has rapidly emerged as one of the most influential technological developments in contemporary education. Yet broader scholarship on AI in education cautions that expectations surrounding educational AI are frequently shaped by misunderstandings of current technical possibilities and narrow assumptions about the purposes of education (Holmes & Tuomi, 2022). Recent evidence suggests that ChatGPT can positively influence learning achievement, although the evidence base remains relatively early and context-dependent (Doo & Park, 2026). AI systems now support content generation, feedback, assessment, explanation, analysis, and conversational learning, raising important questions about how they should be integrated into educational practice (Dogan, 2025; Sabzalieva & Valentini, 2023). Advocates of educational AI emphasize its potential to personalize learning, increase access to resources, reduce routine workload, support instructional design, and provide scalable learner support (Dogan, 2025; Price & Grover, 2025). Educators increasingly use AI for lesson planning, assessment design, feedback, and instructional development, while learners use AI to explore concepts, receive explanations, generate study materials, and support academic tasks, suggesting considerable potential for improving efficiency, accessibility, and responsiveness within educational environments (Dogan, 2025; Sabzalieva & Valentini, 2023; Weaver & Lewitzky, 2025).

At the same time, researchers have raised concerns regarding the implications of AI for learning, cognition, and intellectual development (Price & Grover, 2025; Weaver & Lewitzky, 2025). Generative AI can support tasks associated with higher-order learning, including explanation, synthesis, argument development, analysis, and problem solving (Sanchez Munoz, Flores-Erana, Silva-Campos, Chavira-Quintero, & Olais-Govea, 2025). As a result, learners and educators may increasingly engage with completed outputs rather than the intellectual processes through which understanding develops. Concerns regarding cognitive offloading, reduced opportunities for effortful engagement, diminished critical reflection, and altered processes of knowledge construction therefore remain central to educational discussions of AI (Atchley, Pannell, Wofford, Hopkins, & Atchley, 2024; Weaver & Lewitzky, 2025).

This tension reveals a distinctive challenge for education. In many domains, technological advancement is evaluated by the extent to which effort can be reduced, tasks automated, and productivity increased. Education, however, differs because learning often depends upon intentional engagement. Research on desirable difficulties and productive failure suggests that cognitive effort, struggle, and delayed support can be necessary for durable learning, transfer, and understanding (Bjork & Bjork, 2011; de Bruin, 2023; Kapur, 2008). The educational question then is not simply whether AI can reduce effort, but whether it reduces the right kinds of effort. AI may be valuable when it reduces unnecessary barriers to participation, but problematic when it replaces the evaluative, interpretive, reflective, and justificative work through which learning occurs.

A related challenge is the absence of a shared vocabulary for describing different forms of human–AI interaction in educational contexts. This problem reflects broader concerns in higher education scholarship, where AI is often vaguely defined and entangled with shifting questions of authority, agency, and accountability (Bearman, Ryan, & Ajjawi, 2023). Existing literature suggests that human–AI interaction can range from AI-generated outputs with minimal human contribution to collaborative processes involving substantial human oversight, adaptation, evaluation, and refinement (Dogan, 2025; Schonewille, 2026). Yet these diverse forms of interaction are frequently grouped under broad labels such as "AI-generated" or "AI-assisted," obscuring important differences between situations in which AI performs the majority of cognitive and epistemic work and situations in which AI supports humans while they remain active participants in meaning making.

This distinction matters because educationally meaningful AI use may depend less on what AI produces than on how cognitive and epistemic responsibilities are distributed between humans and intelligent systems. When AI assumes primary responsibility for producing content and interpretive direction, concerns regarding cognitive replacement and epistemic offloading become more pronounced (Atchley, Pannell, Wofford, Hopkins, & Atchley, 2024; Weaver & Lewitzky, 2025). Conversely, when AI supports humans in organizing information, adapting learning experiences, refining ideas, and analyzing evidence, opportunities for human judgment, reflection, interpretation, and learning may be preserved (Dogan, 2025; Schonewille, 2026).

To address this gap, this paper introduces the GOPA Framework as a shared vocabulary for examining where responsibility for interpretation, adaptation, evaluation, and judgement resides within AI-supported educational activity. The framework is grounded in applied Human-in-the-loop and Human-Machine Augmented Intelligence perspectives (Kakon, Kamoun, Fenniri, & Lisimachio, 2025), the Curated Authorship Model (Schonewille, 2026), research on cognitive offloading and distributed cognition (Atchley, Pannell, Wofford, Hopkins & Achtley, 2024; Weaver & Lewitzky, 2025), and scholarship examining epistemic agency, epistemic awareness, and AI literacy context (Wu, Lee, Chai, & Tsai, 2025).

Rather than classifying AI use simply as "AI-generated," GOPA distinguishes between Generation, where AI assumes primary responsibility for producing content and meaning, and Organization, Personalization, and Analysis, where AI supports human thinking while preserving human responsibility for meaning making. The central argument of this paper is that the educational value of AI depends not on how much work it removes, but on how effectively it augments human thinking while preserving agency, authorship, accountability, epistemic authority, and the productive cognitive friction through which meaningful learning occurs.

Literature Review

Generative AI in Education: Beyond Content Generation

AI in higher education has long been associated with applications such as profiling and prediction, assessment and evaluation, adaptive systems, personalization, and intelligent tutoring systems (Zawacki-Richter, Marin, Bond, & Gouverneur, 2019). More recently, generative AI has expanded this landscape by enabling conversational interaction, synthesis, content generation, explanation, and forms of cognitive and instructional support (Dogan, 2025; Holmes & Tuomi, 2022; Price & Grover, 2025). These capabilities have contributed to growing interest in AI for instructional design, personalized learning, learner support, assessment development, and curriculum planning.

Educational researchers have identified several potential benefits associated with generative AI integration, including personalization, expanded access to resources, reduced administrative workload, instructional planning support, and scalable feedback (Dogan, 2025; Price & Grover, 2025). Learners similarly use AI to explore concepts, receive explanations, generate study materials, and participate in conversational learning experiences (Weaver & Lewitzky, 2025). These uses demonstrate the practical appeal of AI within educational environments, particularly where efficiency, accessibility, and responsiveness are valued.

However, much public and institutional discourse has centered on AI's ability to produce content. Essays, lesson plans, assessments, discussion prompts, feedback, instructional materials, and other educational resources can now be generated through natural language interaction with unprecedented speed (Dogan, 2025; Price & Grover, 2025). Early guidance on AI in higher education often introduced these tools through examples of the outputs they could produce, contributing to a view of generative AI primarily as a content-generation technology (Sabzalieva & Valentini, 2023). While content generation is an important and visible application of AI, this framing risks obscuring how humans participate in AI-supported work.

Educational uses of AI increasingly extend beyond finished artifacts. AI systems are also used to organize information, synthesize research, adapt learning experiences, support instructional planning, identify patterns in educational data, facilitate reflection, and assist with decision making (Dogan, 2025; Holmes & Tuomi, 2022; Price & Grover, 2025; Sabzalieva & Valentini, 2023). In these cases, AI may function less as an independent producer of content and more as a tool that supports human thinking, professional judgment, and epistemic agency (Dogan, 2025; Wu, Lee, Chai, & Tsai, 2025).

This distinction matters because different forms of human–AI interaction distribute cognitive and epistemic responsibilities in different ways. In some interactions, AI assumes primary responsibility for producing content, structuring meaning, and presenting conclusions. In others, AI supports humans as they organize ideas, refine arguments, adapt materials, interpret evidence, and make decisions. Although both forms involve AI, they may have substantially different implications for learning, agency, authorship, accountability, and epistemic authority.

Recent scholarship on human–AI collaboration emphasizes that the educational implications of AI are shaped not only by technological capability but also by how responsibility is distributed between humans and intelligent systems (Wu, Lee, Chai, & Tsai, 2025). Human-in-the-Loop perspectives similarly argue that humans should remain responsible for interpretation, evaluation, and decision making even when AI contributes substantially to a task (Kakon, Kamoun, Fenniri, & Lisimachio, 2025; Shneiderman, 2020). Despite these developments, educational discussions often collapse diverse forms of AI use into broad categories such as “AI-generated” or “AI-assisted” work, reflecting broader concerns that AI in higher education is frequently defined in vague or overly general terms (Bearman, Ryan, & Ajjawi, 2023; Sabzalieva & Valentini, 2023). Such language may obscure important differences between situations in which AI performs the majority of cognitive and epistemic work and situations in which AI supports humans as they develop, organize, refine, adapt, or interpret their own ideas. As AI becomes increasingly integrated into educational practice, educators need more precise language for describing how AI participates in cognitive work and where responsibility for meaning making resides.

Human Responsibility, Authorship, and Human–AI Collaboration

As artificial intelligence systems become increasingly capable of performing complex cognitive tasks, researchers and designers have emphasized the importance of maintaining meaningful human involvement in AI-supported processes (Gomez, Cho, Ke, Huang, & Unberath, 2024; Shneiderman, 2020). Human-Centered AI and Human-in-the-Loop perspectives position AI not as an autonomous replacement for human expertise, but as a tool that supports human judgment, interpretation, and decision making (Shneiderman, 2020). Within such systems, AI may contribute information processing, pattern recognition, content generation, analytical support, or recommendations, while humans retain responsibility for evaluating outputs, determining relevance, exercising judgment, and making consequential decisions (Gomez, Cho, Ke, Huang, & Unberath, 2024; Wu, Lee, Chai, & Tsai, 2025).

The central premise of Human-Centered AI and Human-in-the-Loop design is that reasoning, contextual understanding, ethical consideration, and accountability remain fundamentally human responsibilities (Shneiderman, 2020). AI systems can process information at significant scale and speed, but they do not possess the contextual awareness, professional expertise, lived experience, or value-based judgment required to assume full responsibility for many educational decisions. This balance is especially important in education because learning depends upon active participation in cognitive and epistemic processes. Learners and educators must evaluate information, interpret evidence, justify conclusions, reflect upon understanding, and make informed judgments; these activities are central mechanisms through which knowledge is constructed and expertise develops (Greene, Sandoval, & Braten, 2016; Wu, Lee, Chai, & Tsai, 2025).

Questions of responsibility are closely connected to questions of authorship. The emergence of generative AI has renewed debate regarding intellectual contribution, ownership, authority, and authorship within human–AI interaction (Bearman, Ryan, & Ajjawi, 2023; Schonewille, 2026). Traditional understandings of authorship often emphasize direct human production as a defining feature of intellectual work. As AI systems increasingly contribute to idea generation, drafting, revision, and content production, questions arise regarding whether meaningful human authorship can be preserved when intelligent systems participate in content creation (Schonewille, 2026).

The Curated Authorship Model (CAM) provides a useful educational perspective for addressing this concern. CAM proposes that authorship is not determined solely by direct production, but also by the human decisions that shape, evaluate, contextualize, and refine content. Within this perspective, authorship emerges through selection, interpretation, revision, and meaning making rather than through production alone. Generative AI may contribute drafts, suggestions, alternative perspectives, organizational structures, summaries, or analytical insights. However, when humans remain responsible for determining relevance, selecting among alternatives, adapting content to context, refining ideas, and establishing meaning, the intellectual direction of the work remains fundamentally human (Schonewille, 2026).

Together, Human-Centered AI perspectives and the Curated Authorship Model suggest that educationally meaningful AI use does not require excluding AI from intellectual work. Rather, it requires preserving human responsibility for shaping, interpreting, evaluating, and determining meaning (Schonewille, 2026; Shneiderman, 2020). These perspectives provide an important foundation for the GOPA Framework because they connect Human-Centered Augmentation to agency, accountability, and authorship.

Cognitive and Epistemic Responsibility in AI-Mediated Learning

One of the most significant concerns surrounding generative AI involves its potential to facilitate cognitive offloading. Cognitive offloading refers to the use of external tools, technologies, or systems to reduce the cognitive demands associated with memory, reasoning, problem solving, information management, or decision making (Risko & Gilbert, 2016). Humans have long relied on technologies such as writing systems, calculators, search engines, note-taking tools, and digital databases to extend cognitive capabilities beyond individual memory and processing capacity. Generative AI, however, introduces new possibilities for delegating more complex forms of cognitive work, including explanation, synthesis, argument construction, analysis, and problem solving (Atchley, Pannell, Wofford, Hopkins, & Atchley, 2024; Sanchez Munoz, Flores-Erana, Silva-Campos, Chavira-Quintero, & Olais-Govea, 2025).

Not all cognitive offloading is educationally problematic. External tools can support learning by reducing unnecessary cognitive demands and enabling learners to direct attention toward higher-order intellectual activities (Atchley, Pannell, Wofford, Hopkins, & Atchley, 2024; Risko & Gilbert, 2016; Sweller, 1988). From this perspective, the central issue is not whether AI reduces cognitive effort, but what kind of effort it reduces. In this paper, this distinction is described as the difference between unproductive and productive cognitive friction. Unproductive friction refers to effort that creates unnecessary barriers to learning, such as locating scattered resources, navigating inefficient systems, managing repetitive administrative tasks, or overcoming avoidable procedural complexity. Productive cognitive friction refers to intellectual effort that contributes to learning, including interpretation, evaluation, reflection, synthesis, justification, and meaning making (Bjork & Bjork, 2011; Chi, 2009; de Bruin, 2023; Kapur, 2008). The educational challenge is therefore to reduce unproductive friction while preserving opportunities for productive cognitive friction.

Generative AI complicates this balance because it can perform tasks traditionally associated with higher-order cognition. Unlike tools that primarily store, retrieve, or organize information, generative AI can explain concepts, synthesize information, construct arguments, generate analyses, and produce solutions to complex problems. As a result, the distinction between cognitive support and cognitive substitution becomes more difficult to identify. Recent research suggests that learners may offload substantial portions of their cognitive labor when they accept AI outputs without critical evaluation or independent reasoning (Harkki, Thorstrom, Leino, Vartiainen, & Tedre, 2025). Similarly, Knowledge Building scholarship cautions that AI support must be balanced with students' epistemic agency so that learners remain active participants in inquiry and knowledge creation rather than over-relying on AI-generated outputs (Cacciamani & Khanlari, 2025). Cognitive offloading becomes educationally concerning when responsibility for meaning making, judgment, and intellectual engagement shifts from the human participant to the technology itself.

These concerns extend beyond cognitive effort and raise broader epistemic questions regarding knowledge, authority, justification, and truth. Generative AI systems can produce responses that appear coherent, authoritative, and confident regardless of factual accuracy, creating challenges for learners who must evaluate the reliability and validity of AI-generated information. Unlike traditional educational resources, which often include identifiable authorship, citation structures, and institutional credibility markers, AI-generated outputs may obscure the origins of information and complicate verification. The fluency and confidence of AI-generated responses can therefore shape how learners assign epistemic authority, leading them to accept claims without fully examining their evidentiary basis, assumptions, or limitations (Harkki, Thorstrom, Leino, Vartiainen, & Tedre, 2025; Wu, Lee, Chai, & Tsai, 2025).

These concerns intersect with research on epistemic cognition, which examines how individuals understand knowledge, evidence, justification, certainty, and truth

(Greene, Sandoval, & Braten, 2016). Epistemic cognition plays a critical role in critical thinking, information literacy, and knowledge construction because it influences how learners evaluate competing claims, assess evidence, and determine what constitutes credible knowledge. The educational challenge therefore extends beyond determining whether AI-generated information is accurate. Learners and educators must also determine how knowledge claims are justified, what evidence supports those claims, and how alternative perspectives should be evaluated. Developing these capabilities requires what Sanchez Munoz, Flores-Erana, Silva-Campos, Chavira-Quintero, and Olais-Govea (2025) describe as epistemic vigilance, or the capacity to critically reflect upon, validate, and evaluate information generated by AI systems.

Within AI-mediated learning environments, questions of epistemic authority become particularly significant. In this paper, epistemic authority refers to responsibility for determining what information is meaningful, how evidence should be interpreted, what conclusions are justified, and how knowledge claims should be evaluated. This understanding builds on scholarship emphasizing epistemic agency in Knowledge Building and human responsibility in AI-mediated authorship (Cacciamani & Khanlari, 2025; Schonewille, 2026). When learners rely primarily on AI-generated outputs without critically evaluating the reasoning, assumptions, or evidence underlying those outputs, epistemic authority may gradually shift from the learner to the system. Educational technologies have long supported learning by extending cognitive capabilities and expanding access to information. The critical question is whether learners and educators remain responsible for evaluating, interpreting, adapting, and justifying knowledge claims.

Theoretical Foundations

Human Responsibility and Cognitive Friction

The literature reviewed thus far suggests that meaningful educational AI use depends on preserving human responsibility for cognitive and epistemic work. Human-Centered AI and Human-in-the-Loop perspectives emphasize human judgment and accountability within AI-supported processes (Price & Grover, 2025; Shneiderman, 2020). The Curated Authorship Model highlights the role of human participation in shaping, refining, and determining meaning within human–AI collaboration (Schonewille, 2026). Research on epistemic cognition and epistemic agency further suggests that learners and educators must remain responsible for evaluating evidence, interpreting information, and justifying knowledge claims (Greene, Sandoval, & Braten, 2016; Wu, Lee, Chai, & Tsai, 2025). Together, these perspectives point toward a central claim: the educational value of AI depends not only on what AI can produce, but on what humans continue to do.

This paper uses cognitive friction to describe the intellectual effort involved in evaluating information, interpreting meaning, resolving uncertainty, justifying decisions, constructing understanding, and developing expertise. Although friction is often viewed negatively because it increases difficulty or slows performance, educational research shows that some forms of difficulty contribute directly to learning. Research on desirable difficulties and productive failure demonstrates that effort, struggle, and delayed support can strengthen durable learning and transfer (Bjork & Bjork, 2011; de Bruin, 2023; Kapur, 2008). Similarly, scholarship on inquiry-based learning, metacognitive reflection, and active knowledge construction shows that learning often emerges through effortful engagement with challenging ideas rather than through frictionless access to information (Chi, 2009; Hmelo-Silver, Duncan, & Chinn, 2007).

From this perspective, cognitive friction can be understood as an educational resource rather than merely an obstacle. When learners compare competing explanations, identify weaknesses in arguments, reconcile contradictions, interpret evidence, evaluate alternative perspectives, or reflect upon their reasoning, they engage in processes that strengthen conceptual understanding and support long-term knowledge development (Chi, 2009; Greene, Sandoval, & Braten, 2016). However, cognitive friction is not synonymous with unnecessary difficulty. Consistent with cognitive load theory, instructional design should reduce unnecessary burdens so learners can direct effort toward learning-relevant processes (Sweller, 1988). Productive cognitive friction contributes to learning and knowledge construction; unproductive friction creates unnecessary barriers, such as navigating complex interfaces, locating scattered resources, managing repetitive administrative tasks, or overcoming avoidable procedural complexity.

This distinction provides a critical foundation for educational AI integration: the goal should not be to eliminate all friction, but to reduce unproductive friction while preserving productive friction. Learning is not strengthened when opportunities for thinking, interpretation, reflection, justification, and judgment are removed. It is strengthened when unnecessary barriers are reduced so that intellectual effort can be directed toward the cognitive and epistemic activities that matter most (Bjork & Bjork, 2011; Chi, 2009; de Bruin, 2023; Kapur, 2008; Sweller, 1988).

Within human–AI interactions, cognitive friction emerges through the human engagement that happens before, during and after the AI output. When learners and educators critically evaluate AI-generated ideas, compare alternative interpretations, revise assumptions, contextualize information, and determine what is meaningful, they remain active participants in learning. Conversely, when AI-generated outputs are accepted without evaluation, interpretation, or justification, opportunities for productive cognitive friction may be diminished (Harkki, Thorstrom, Leino, Vartiainen, & Tedre, 2025; Wu, Lee, Chai, & Tsai, 2025).

In Figure 1, the GOPA Framework emerges from this theoretical foundation as a practical model for distinguishing AI uses that replace cognitive and epistemic engagement from those that augment and support it. The figure maps AI-supported educational work across two dimensions: the extent of the AI role in producing output and the extent of human responsibility for meaning making. Uses in which AI produces the main content while the human role is limited to acceptance, submission, or light editing are positioned as Generation as Replacement. In contrast, uses involving Organization, Personalization, and Analysis are positioned as forms of augmentation when AI supports organizing, adapting, feedback, and analysis while humans retain judgment, interpretation, accountability, and epistemic authority.

At its core, the framework is guided by a single principle: educational AI should reduce unproductive friction while preserving human responsibility for the productive cognitive and epistemic work through which learning occurs. Building on this principle, effective AI literacy requires educators to recognize whether AI is functioning as a collaborator, working with humans through iterative exchange; a scaffold, providing temporary support for thinking and learning; a shortcut, reducing time or effort in ways that may be helpful or harmful; or a substitute, taking over cognitive or epistemic work that should remain human. Rather than evaluating AI according to how much work it can perform independently, GOPA evaluates AI according to how effectively it supports humans in constructing, refining, adapting, evaluating, and interpreting knowledge.

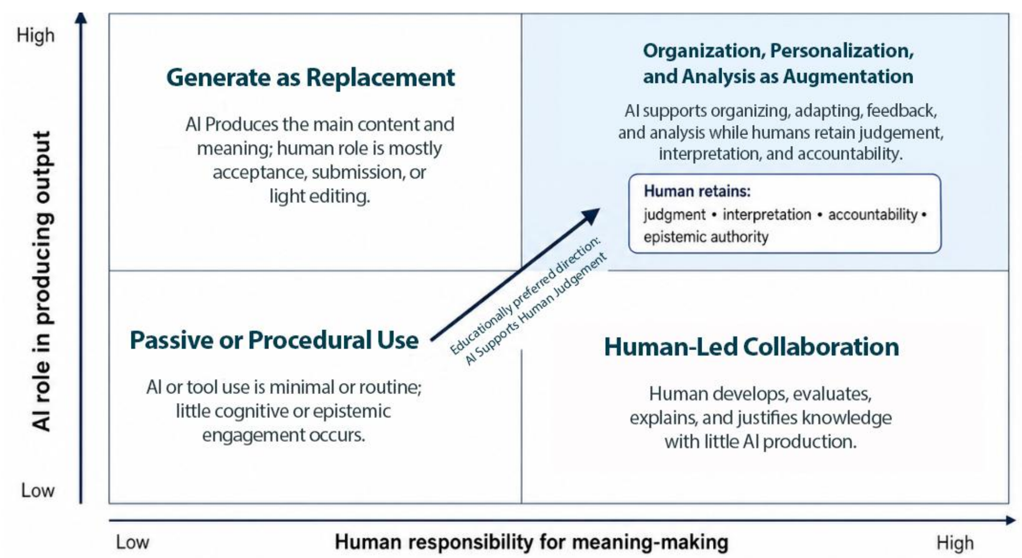

Figure 1: The GOPA framework: Human responsibility in AI-supported educational work

Foundational Assumptions

The GOPA Framework rests on four assumptions. First, learning emerges through cognitive engagement rather than passive information acquisition, so educational technologies should be evaluated not only by output quality but also by their influence on learning processes (Chi, 2009; Greene, Sandoval, & Braten, 2016). Second, human agency remains essential because meaningful AI use depends on preserving human participation in learning, interpretation, and decision making (Gomez, Cho, Ke, Huang, & Unberath, 2024; Shneiderman, 2020). Third, epistemic authority should remain human-centered: although AI can generate information, identify patterns, and provide recommendations, humans must remain responsible for determining meaning, evaluating evidence, and making judgments (Greene, Sandoval, & Braten, 2016; Wu, Lee, Chai, & Tsai, 2025). Fourth, AI is most educationally meaningful when it augments human thinking rather than replacing it (Kakon, Kamoun, Fenniri, & Lisimachio, 2025; Schonewille, 2026).

Generation: AI-Centered Production

Generation refers to the use of AI systems to produce content, responses, or artifacts with limited human intellectual engagement beyond prompting. In generation-oriented interactions, AI assumes primary responsibility for creating, structuring, framing, and expressing ideas, while the human user primarily accepts, lightly modifies, or evaluates the resulting output. Examples include requesting an essay, lesson plan, assessment, summary, or response and adopting the output with minimal revision or critical engagement. Within the GOPA Framework, Generation is the form of human–AI interaction most closely associated with cognitive replacement and epistemic offloading. Although Generation can increase efficiency and reduce workload, it may also reduce opportunities for evaluation, interpretation, justification, and knowledge construction when users engage mainly with completed outputs rather than with the intellectual processes through which those outputs are created. The educational concern is not Generation itself; in some contexts, AI-generated output may be useful, appropriate, or necessary. The concern arises when users accept generated outputs without sufficient interpretation, evaluation, or revision, thereby transferring responsibility for meaning making from the human participant to the AI system. For this reason, Generation represents AI-Centered Production where AI serves as the primary producer of content and meaning.

Organization: Human-Centered Synthesis

Organization refers to the use of AI systems to structure, synthesize, clarify, and refine ideas that originate from human knowledge, research, experience, or intent. In organization-oriented interactions, AI helps manage complexity and improve coherence, but the human participant directs the intellectual purpose of the work and evaluation throughout the process. Organization may include using AI to group ideas, identify relationships, refine arguments, organize evidence, clarify structure, or improve communication. In these cases, AI supports the human participant in making existing thinking more coherent, connected, and usable. The intellectual foundation remains human because the quality and direction of the work depend on the knowledge, intentions, and judgments contributed by the learner or educator. Organization preserves productive cognitive friction through the process of evaluating, accepting, rejecting, revising, and contextualizing AI-supported suggestions. It therefore represents Human-Centered Augmentation because AI supports synthesis while humans retain agency, authorship, accountability, and epistemic authority.

Personalization: Human-Centered Adaptation

Personalization refers to the use of AI systems to adapt content, learning experiences, resources, or outputs in response to the needs, goals, contexts, or perspectives of specific learners or groups. In personalization-oriented interactions, AI assists with adaptation, but humans remain responsible for determining what is relevant, appropriate, and educationally meaningful. Personalization may include adapting reading levels, generating alternative explanations, suggesting accommodations, creating practice opportunities, modifying examples, or adjusting complexity. These adaptations can reduce unnecessary barriers and make learning more accessible. However, personalization does not mean eliminating challenge. Its purpose is to align productive cognitive friction with learner needs, developmental readiness, and instructional goals. Personalization represents Human-Centered Augmentation when AI helps educators and learners make more informed adaptive decisions without replacing educational judgment. Its value lies not in making learning easier, but in making the right forms of intellectual engagement more accessible.

Analysis: Human-Centered Interpretation

Analysis refers to the use of AI systems to identify patterns, relationships, possibilities, or insights within information while preserving human responsibility for interpretation, evaluation, and decision making. In analysis-oriented interactions, AI may surface possibilities, but humans determine their significance. Examples include using AI to examine learner performance data, assessment results, instructional outcomes, research findings, feedback patterns, or complex information sets. AI may summarize trends, generate visualizations, identify anomalies, or propose interpretations. However, Analysis within the GOPA Framework differs from automated decision making. AI may help reveal what might matter, but humans remain responsible for deciding what does matter, why it matters, and what should be done in response. Analysis often involves productive cognitive friction because individuals must evaluate competing explanations, interpret evidence, challenge assumptions, and make judgments under uncertainty. These activities contribute to learning, expertise development, and epistemic growth. Analysis therefore represents Human-Centered Augmentation because AI supports interpretation without replacing it.

Distinguishing AI-Centered Production from Human-Centered Augmentation

The central distinction within the GOPA Framework is not technological but epistemic. Generation positions AI as the primary producer of content and interpretive direction. Organization, Personalization, and Analysis position AI as a cognitive support that helps humans construct, adapt, refine, and interpret meaning. This distinction matters because it influences whether learners and educators remain engaged in the productive cognitive activities associated with learning. Whereas Generation may increase the risk of cognitive replacement and epistemic offloading, Organization, Personalization, and Analysis preserve opportunities for evaluation, interpretation, reflection, justification, and decision making. Consequently, educational AI should be evaluated not only according to what it produces, but according to how it distributes responsibility for cognitive and epistemic work.

Figure 2 clarifies the distinction between AI-Centered Production and Human-Centered Augmentation. AI-Centered Production occurs when AI functions as the primary producer of content and interpretive direction, leaving humans mainly to accept, select, or lightly edit outputs. In these cases, opportunities for evaluation, interpretation, reflection, justification, and decision making may be reduced. Human-Centered Augmentation occurs when AI supports organization, personalization, and analysis while humans retain responsibility for interpretation, judgment, and meaning making.

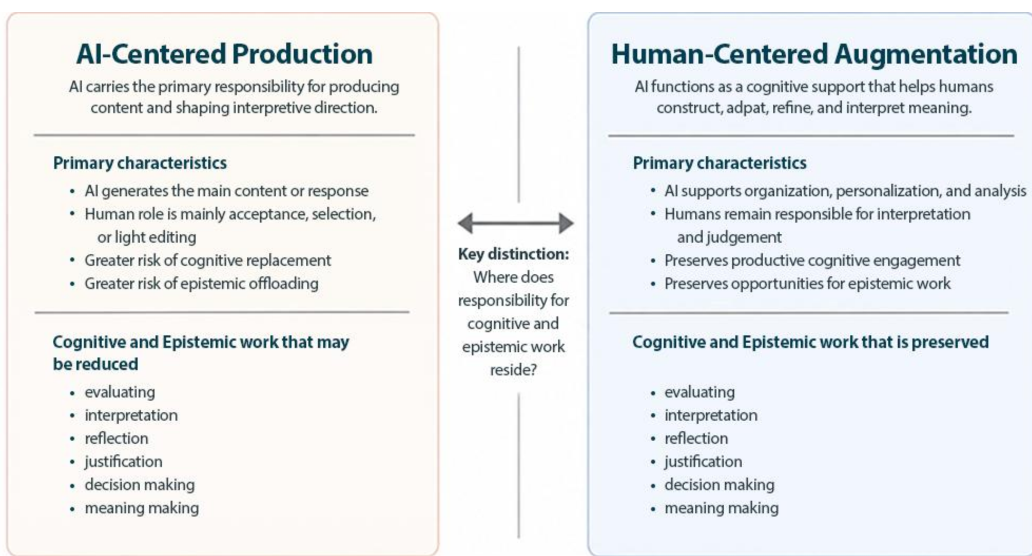

Figure 2: Distinguishing AI-centered production from human-centered augmentation

Applications of the GOPA Framework

The GOPA Framework provides educators with a shared vocabulary for examining how cognitive and epistemic responsibilities are distributed within human–AI interactions. Rather than evaluating AI use only by technological capability or output quality, GOPA asks where agency, authorship, accountability, and epistemic authority reside throughout the learning process. The following examples illustrate how the framework distinguishes AI-Centered Production from Human-Centered Augmentation across common educational contexts.

Instructional Design and Lesson Planning

Instructional design is one of the most common educational applications of generative AI, with educators using AI systems to generate lesson plans, learning activities, assessments, instructional materials, and curricular resources (Dogan, 2025; Sabzalieva & Valentini, 2023). A generation-oriented approach may involve requesting a complete lesson plan from AI and implementing the output with minimal modification. While efficient, this approach shifts substantial responsibility for content selection, sequencing, instructional design, and pedagogical framing toward the AI system.

In contrast, an organization-oriented approach positions AI as a collaborative tool. Educators contribute curricular goals, pedagogical intentions, contextual knowledge, disciplinary expertise, and learner considerations, while AI assists in organizing resources, synthesizing information, identifying connections, and refining instructional ideas. The key distinction is not whether AI contributes to the lesson plan, but whether educators remain responsible for the decisions that shape learning.

Personalized Learning

Personalized learning provides a clear example of Human-Centered Augmentation when adaptation remains guided by educational judgment. Within GOPA, personalization is not defined as reducing difficulty or eliminating challenge; rather, it involves adapting learning experiences while preserving meaningful cognitive engagement.

AI can support personalization by adapting reading levels, generating alternative explanations, recommending resources, providing scaffolds, or identifying areas where support may be beneficial (Holmes & Tuomi, 2022; Kakon, Kamoun, Fenniri, & Lisimachio, 2025). These uses can reduce unnecessary barriers to participation, including in language-rich tasks such as reading, writing, and academic communication. However, learners and educators remain responsible for determining relevance, evaluating usefulness, and selecting appropriate learning pathways. The purpose of personalization is not to eliminate productive cognitive friction, but to align cognitive challenge with learner needs, goals, and developmental readiness.

Learning Analytics and Educational Decision Making

Learning analytics provides a strong example of Analysis within GOPA. Historically, educational data analysis has required specialized expertise in statistics, visualization, and interpretation. AI has long been used in higher education for profiling, prediction, assessment, evaluation, adaptive systems, and learner support (Holmes & Tuomi, 2022; Zawacki-Richter, Marin, Bond, & Gouverneur, 2019). More recently, generative AI has shown potential to reduce technical barriers in learning analytics by enabling educators and other non-experts to interact with data through more accessible, conversational interfaces (Ochoa, Huang, & Shao, 2025).

AI can summarize trends, identify patterns, generate visualizations, and propose possible interpretations. These capabilities reduce unproductive friction and make educational data more accessible; however, AI does not determine meaning. Teachers remain responsible for evaluating evidence, considering context, identifying limitations, interpreting findings, and determining appropriate instructional responses. The educational value of analytics emerges not from pattern detection alone, but from the interpretation and decision making that follow.

Using GOPA as a Reflective Tool

GOPA is not intended to determine automatically whether a particular use of AI is appropriate. Rather, it provides educators with language for examining how AI participates in cognitive and epistemic work. A central reflective question emerges from the framework: Who is responsible for meaning making? When AI is positioned as the primary producer of content and interpretive direction, interactions align more closely with Generation and AI-Centered Production. When humans remain responsible for interpreting information, evaluating ideas, adapting content, making judgments, and determining significance, interactions align more closely with Human-Centered Augmentation. Viewed in this way, GOPA functions as a reflective tool for evaluating where agency, authorship, accountability, and epistemic authority reside within human–AI interactions. The central challenge of educational AI is not technological adoption alone, but instructional design: how can human–AI interactions preserve the forms of human participation through which meaningful learning occurs?

Discussion

Reframing Educational AI Through Shared Vocabulary

The rapid adoption of generative artificial intelligence has encouraged educational conversations to focus heavily on what AI can produce, including lesson plans, assessments, instructional materials, essays, feedback, summaries, and other educational artifacts (Dogan, 2025; Sabzalieva & Valentini, 2023). At the same time, broader discussions of AI in higher education remain shaped by vague definitions and shifting assumptions about authority and accountability (Bearman, Ryan, & Ajjawi, 2023). GOPA offers a different point of entry by asking where responsibility for meaning making resides. When AI functions primarily as the producer of content and interpretive direction, the interaction aligns more closely with AI-Centered Production. When humans remain responsible for interpreting, evaluating, adapting, and judging AI-supported work, the interaction aligns more closely with Human-Centered Augmentation. The same AI tool may therefore support or weaken learning depending on how the interaction is designed.

Rethinking AI Literacy

The framework also contributes to emerging discussions of AI literacy. Much of the current AI literacy discourse emphasizes technical proficiency, prompt design, tool selection, responsible use, and awareness of AI limitations (Holmes & Tuomi, 2022; Sabzalieva & Valentini, 2023). These competencies remain important, but they are not sufficient. Educators and learners also need language for evaluating the role AI plays in cognitive and epistemic work.

From this perspective, AI literacy involves more than knowing how to use AI effectively. It also involves recognizing when AI is functioning as a producer of meaning and when it is functioning as a support for human meaning making. Learners and educators should be able to ask whether AI is replacing or supporting interpretation, evaluation, adaptation, and decision making. This shifts AI literacy from a primarily technical competence toward a more educationally grounded capacity: the ability to judge how AI participation affects agency, authorship, accountability, epistemic authority, and learning.

This expanded view of AI literacy is important because many educational risks associated with AI are not visible at the level of output quality. An AI-generated response may be accurate and coherent while still reducing opportunities for learners to engage in reasoning, justification, or reflection. Conversely, an imperfect AI output may become educationally valuable if it prompts critique, revision, comparison, and deeper inquiry. GOPA helps educators and learners attend to these differences by focusing on the human work that remains active within AI-supported activity.

Cognitive Friction as a Design Principle

The GOPA Framework also positions cognitive friction as a design principle for human–AI interaction. Educational technologies are often judged by their ability to reduce effort, yet research on desirable difficulties, cognitive load, productive failure, and active knowledge construction suggests that not all effort is educationally equivalent (Bjork &

Bjork, 2011; Chi, 2009; de Bruin, 2023; Kapur, 2008; Sweller, 1988). GOPA suggests that educators should instead examine which forms of effort are being reduced.

When AI reduces effort associated with information management, organization, formatting, translation, accessibility, or administrative work, it may reduce unproductive friction and create more space for learning. However, when AI removes opportunities for evaluation, interpretation, reflection, critique, justification, and decision making, it may also reduce the productive cognitive friction through which learning occurs. Cognitive friction should therefore not be understood as resistance to innovation, but as a way to identify the forms of intellectual engagement that should remain present within AI-supported learning environments.

Implications for Educational Practice

The GOPA Framework offers several implications for educators, instructional designers, and educational leaders. First, AI integration efforts should focus less on whether AI can perform educational tasks and more on how AI can support meaningful human participation within those tasks. The goal is not to eliminate cognitive work, but to direct effort toward activities that contribute to learning and expertise.

Second, decisions about AI adoption should include questions about the distribution of cognitive and epistemic responsibility. Educators should ask who is determining meaning, evaluating evidence, adapting content, making judgments, and taking responsibility for outcomes. These questions should accompany discussions of efficiency, productivity, and access.

Third, teacher education and professional learning initiatives should prepare educators to evaluate human–AI interactions, not simply to use AI tools. This is consistent with calls for more educationally grounded, critically reflective, and human-centered approaches to AI integration (Bearman, Ryan, & Ajjawi, 2023; Dogan, 2025; Holmes & Tuomi, 2022; Wu, Lee, Chai, & Tsai, 2025). Building on the GOPA Framework, effective AI literacy requires educators to recognize whether AI is functioning as a collaborator, scaffold, shortcut, or substitute, and whether that use preserves or displaces human responsibility for interpretation, judgment, and meaning making.

Finally, institutions should approach AI integration as instructional design rather than technological adoption alone. Assessment, curriculum design, instructional planning, professional learning, and learning analytics can benefit from Human-Centered Augmentation when AI reduces unnecessary barriers while preserving productive cognitive friction.

Limitations and Future Research

As a conceptual framework, GOPA provides a theoretical lens and shared vocabulary rather than an empirically validated model. Further research should examine how educators and learners apply the framework across contexts such as instructional design, assessment, personalized learning, learning analytics, academic writing, and professional learning. Empirical studies need to test whether GOPA helps users distinguish AI-Centered Production from Human-Centered Augmentation and make more intentional decisions about agency, authorship, accountability, epistemic authority, and cognitive friction. Future research should also examine how different forms of human–AI interaction influence learning outcomes, professional judgment, metacognition, epistemic cognition, and perceptions of agency.

Conclusion

Generative artificial intelligence has introduced significant opportunities and challenges for education, but its educational value cannot be judged by productivity, efficiency, or output quality alone. What matters is not simply what AI can produce, but how human–AI interactions shape the cognitive and epistemic processes through which learning occurs.

This paper argued that broad labels such as “AI-generated” and “AI-assisted” are insufficient for describing the range of ways AI participates in educational work. To address this limitation, the paper introduced the GOPA Framework: Generation, Organization, Personalization, and Analysis. GOPA distinguishes AI-Centered Production from Human-Centered Augmentation by examining how responsibility for meaning making is distributed between humans and AI systems. Generation positions AI as the primary producer of content and meaning, while Organization, Personalization, and Analysis describe forms of AI use that support human thinking while preserving human responsibility for interpretation, adaptation, evaluation, and judgment.

The framework is grounded in the principle that educationally meaningful AI use should reduce unproductive friction while preserving productive cognitive friction. GOPA therefore contributes not as a classification of AI capabilities, but as a language for examining responsibility within human–AI interactions. As AI continues to evolve, the future of educational AI should not be defined by how effectively technology replaces human thinking, but by how thoughtfully human–AI interactions are designed to support it.

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