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Article

# Interactive AI-Assisted Multimodal Learning: A Qualitative Study of Student Experiences Using the NotebookLM Platform

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**Abstract:** This study explores undergraduate students' learning experiences in an AI-driven multimodal learning environment, focusing on Google's NotebookLM platform. Grounded in a qualitative inquiry, the research analyzes the experiences of 123 students in Israel—predominantly female (93.5%)—who engaged in inquiry-based tasks utilizing Retrieval-Augmented Generation (RAG), source-based questioning, mind mapping, structured study guides, and podcast-generated summaries. Data analysis was based exclusively on students' reflective self-reports, without systematic artifact analysis due to limited access to student-generated products. A rigorous thematic analysis was conducted independently by both researchers using a reflexive interpretive approach. The researchers then compared their coding, discussed emerging themes, and reached consensus through iterative dialogue to enhance the credibility and trustworthiness of the findings. This collaborative analytical process resulted in the identification of four primary themes: active multisensory engagement, enhanced conceptual depth through dual-coding pathways, learner autonomy through prompt-based interaction, and persistent challenges related to cognitive overload and content credibility. The findings support a novel Interactive AI-Assisted Constructivism model, which extends traditional constructivist perspectives by positioning artificial intelligence as a co-constructive mediator in knowledge building. Importantly, the study proposes practical pedagogical strategies for reducing hallucination risks and improving the reliability of AI-generated content, including systematic cross-checking of AI responses against uploaded primary sources, citation tracing and source alignment verification, comparison between AI-generated summaries and original texts to identify omissions or distortions, the use of contradiction prompts to test consistency across sources, and instructor-guided peer review of AI outputs. These strategies contribute to the development of critical AI literacy, epistemic responsibility, and evidence-based learning practices. Overall, the study positions NotebookLM as a distinctive educational tool that fosters personalized, reflective, deep, and accountable learning within contemporary higher education.

**Keywords:** AI-driven learning, Multimodal learning, NotebookLM, AI literacy, Learner autonomy, Interactive AI-Assisted Constructivism

## 1. Introduction

In an era where generative artificial intelligence (GenAI) is fundamentally restructuring the educational landscape, the shift from static digital tools to dynamic pedagogical partners is accelerating. While traditional AI applications often function as simple information retrieval systems, newer platforms like Google's NotebookLM represent a shift toward Retrieval-Augmented Generation (RAG) frameworks, offering a highly personalized, interactive, and multimodal learning environment.

Unlike broad-spectrum LLMs (e.g., ChatGPT or Claude), NotebookLM's unique contribution lies in its "source-grounded" architecture, which allows students to anchor AI synthesis within specific, curated datasets. This positioning is critical as education moves toward more secure, accurate, and context-aware digital ecosystems, including emerging paradigms like digital twins and edge computing, where personalized data processing meets real-time educational simulation.

This study introduces and explores the "Interactive AI-Assisted Constructivism" model. This framework extends traditional constructivist theories—which emphasize the learner's active role in building knowledge—by integrating AI as a co-constructor that facilitates synthesis, dual-coding, and recursive inquiry. While classical constructivism relies on human-to-human or human-to-content interaction, our proposed model examines how AI-driven tools mediate the gap between raw information and deep conceptual understanding through features such as interactive podcasts, automated mind mapping, and cross-source synthesis.

Despite the rapid adoption of these tools, there is a pressing need to understand the human-machine interface within specialized academic contexts. This research employs an exploratory, interpretive approach to investigate how undergraduate students utilize NotebookLM as a primary research tool. We specifically focus on how the platform's multimodal capabilities trigger cognitive pathways and support information integration. Furthermore, this study addresses the pedagogical implications and ethical challenges of AI integration, such as content credibility and the necessity of "human-in-the-loop" verification strategies. By evaluating the intersection of high interactivity and personalized experience, this work provides a roadmap for the future of AI-mediated higher education.

## 2. Literature Review

### 2.1 Smart Technology for Personalized Learning: The Case of NotebookLM

The integration of artificial intelligence (AI) into personalized learning environments has evolved rapidly in recent years, with platforms such as NotebookLM emerging as important tools for self-directed academic inquiry. More broadly, AI in higher education has increasingly been associated with adaptive support, intelligent feedback, and personalized learning opportunities, while also raising pedagogical and ethical questions regarding reliability, transparency, and the role of educators [1–3]. Within this broader landscape, NotebookLM represents a distinctive development because it combines large language model capabilities with a Retrieval-Augmented Generation (RAG) architecture, enabling learners to work directly with their own uploaded materials.

Unlike general-purpose generative AI systems, NotebookLM is designed to generate responses on the basis of user-provided sources. In RAG-based systems, relevant documents are first retrieved and then used to condition the generated output, thereby improving contextual relevance, factual alignment, and source traceability [4,5]. This architecture is particularly significant in academic settings because it provides a stronger degree of grounding in the learner's own corpus of texts, notes, and documents. As studies on hallucinations in language generation have shown, large language models may produce fluent but inaccurate or fabricated content when their outputs are not sufficiently anchored to reliable sources [6,7]. By contrast, NotebookLM's source-grounded design helps reduce hallucinations and strengthens academic reliability, especially in tasks such as literature review, synthesis, concept clarification, and source comparison.

This distinction is especially important when comparing NotebookLM with tools such as ChatGPT or Claude. While ChatGPT and Claude are powerful general-purpose conversational systems that can support brainstorming, drafting, and explanation, their outputs often depend primarily on pretrained knowledge and prompt formulation unless external retrieval or browsing functions are explicitly activated. NotebookLM, by contrast, is built around the learner's own uploaded sources and therefore offers a more explicitly grounded and transparent environment for academic work. In this sense, NotebookLM is not merely another generative AI assistant; it is a source-based academic partner that supports evidence-oriented inquiry, reduces the likelihood of unsupported claims, and promotes greater trust in AI-assisted learning processes [5, 6, 8].

NotebookLM's pedagogical strength lies in its adaptive and learner-centered design. It allows students to upload various materials—articles, lecture notes, websites, transcripts, and audio files—and synthesize them into thematic insights. By enabling context-specific querying across one or multiple documents, it supports knowledge construction through user-defined interests and preferred pathways of engagement. Over time, the system can function as a personalized study companion that helps organize concepts, identify patterns across sources, and present information in alternative forms, including summaries and podcast-like outputs. This positions NotebookLM as more than a productivity tool; it becomes an intelligent scaffold for academic development and reflective inquiry.

Research in AI-enhanced education supports this broader pedagogical potential. Reviews of AI in higher education suggest that such tools can enhance feedback, personalization, and instructional flexibility, while recent work on generative AI highlights both its transformative possibilities and the need for careful pedagogical integration [1, 8, 9]. In this sense, NotebookLM exemplifies the potential of smart technologies to transform learning from passive content consumption into interactive, personalized, and dynamically grounded knowledge construction.

### 2.2 Active Learning Theory in the Age of AI: From Student Engagement to Personalized Inquiry

Active learning is a dynamic pedagogical approach that shifts educational practice from teacher-centered transmission toward student-centered engagement, emphasizing participation, inquiry, and knowledge construction. Commonly associated with learners' involvement in meaningful tasks accompanied by reflection on their actions, active learning has consistently been linked to higher academic achievement, stronger motivation, deeper cognitive engagement, and improved learning outcomes across diverse educational contexts. In contemporary AI-mediated environments, however, active learning extends beyond traditional classroom participation to include iterative, dialogic, and personalized interaction with intelligent systems, where students actively question, refine, evaluate, and co-construct understanding through continuous engagement with digital tools [10–14].

Recent developments in educational technology, particularly AI-driven platforms, have expanded the ways in which active learning can be enacted. NotebookLM exemplifies this shift by enabling students to upload their own materials, ask targeted questions, generate personalized explanations, create summaries, and transform source materials into alternative formats. Such interaction fosters deeper engagement because learners are not merely receiving information; they are actively shaping the direction, pace, and structure of their inquiry. As recent scholarship suggests, generative AI can support personalized learning experiences, but its educational value depends on whether learners remain cognitively active, reflective, and critical in their engagement with the system [8, 9].

This study proposes the concept of Interactive AI-Assisted Constructivism (A2) to describe this emerging pedagogical configuration. Traditional constructivism emphasizes that learners build knowledge actively, either individually or through social interaction, often with the support of a More Knowledgeable Other (MKO). In the proposed A2 model, AI functions as an asynchronous dialogic MKO. Rather than replacing the teacher or the learner, the AI serves as a responsive cognitive partner that supports questioning, reformulation, reflection, and immediate engagement with learning materials. Through repeated interaction, students can test interpretations, refine ideas, revisit concepts, and receive on-demand scaffolding that is grounded in their own source materials. In this way, AI becomes part of an extended constructivist learning process in which knowledge is co-developed through dialogic interaction with an intelligent system.

The A2 model therefore extends conventional constructivist learning theory into the age of source-grounded AI. It preserves the constructivist emphasis on learner agency and meaning making, while adding a new layer of immediate, iterative, and personalized epistemic support. This is especially relevant in environments where students work independently outside class time and require timely scaffolding for comprehension, synthesis, and reflection. In such contexts, NotebookLM can support active learning not only by providing answers, but by sustaining a process of inquiry in which learners continuously interact with content, reorganize meaning, and deepen conceptual understanding.

Moreover, recent work in AI and education has stressed the importance of human-centered design, ethical responsibility, and pedagogically meaningful integration of AI systems [2, 3, 8]. From this perspective, the educational value of NotebookLM lies not merely in efficiency but in its capacity to support an active, reflective, and learner-driven process of knowledge construction. Thus, active learning in the AI era can be reconceptualized as a form of structured, dialogic inquiry in which learners engage not only with content and peers, but also with grounded AI systems that scaffold understanding in real time.

### 2.3 Learner Agency in the Age of AI: Revisiting Engagement Theory with NotebookLM

Astin’s theory of student involvement [15] emphasizes that cognitive, emotional, and behavioral engagement is central to academic success. Subsequent scholarship has broadened this perspective by highlighting the role of self-regulation, intrinsic motivation, and socio-cognitive participation in meaningful learning [16]. In AI-supported environments, learner engagement increasingly includes the ability to direct one’s own interactions with intelligent systems, manage inquiry paths, and critically evaluate AI-generated support.

NotebookLM aligns closely with this expanded view of learner agency. Rather than positioning students as passive recipients of information, it allows them to become active participants who select sources, formulate questions, compare interpretations, and generate outputs that reflect their own academic needs and intentions. This degree of control over both content and process can strengthen ownership of learning, especially when the system responds directly to the learner’s uploaded materials. In this respect, AI-supported environments may foster a form of co-regulated learning in which the student remains the central agent while the AI provides contingent scaffolding.

Recent literature on generative AI in higher education supports the view that these tools can enhance autonomy, self-directed exploration, and metacognitive engagement, provided they are used critically and with appropriate guidance [8, 9]. At the same time, the literature also warns that overreliance on AI may weaken independent reasoning if the technology is used merely as a shortcut rather than as a scaffold. This tension makes grounded systems such as NotebookLM especially significant. Because responses are tied to user-provided materials, learners are more likely to remain connected to the underlying sources, compare claims against texts, and engage in reflective verification. In other words, grounded interaction may support agency more effectively than decontextualized conversational generation.

This point also connects to the A2 model proposed in the present study. If AI is understood as an asynchronous MKO, learner agency does not disappear; rather, it is reconfigured. The learner remains the one who initiates inquiry, selects materials, evaluates outputs, and determines whether the AI's support is meaningful or valid. Agency, therefore, lies not only in participation but also in the learner's capacity to orchestrate a productive dialogue with the system. NotebookLM's structure may be particularly effective in this regard because it embeds student inquiry within a source-aware environment, thereby supporting both autonomy and epistemic responsibility.

In sum, NotebookLM can be understood as a platform that enhances learner agency by supporting personalized, question-driven, and source-grounded academic engagement. Its pedagogical contribution lies in enabling students to move from passive reception toward active orchestration of their own learning processes, while maintaining closer alignment between AI-generated output and the academic materials on which learning is based.

### 2.4 Enhancing Learning through Multimodal Media: Integrating Text, Audio, and Visual Tools with NotebookLM

Multimodal learning enables learners to engage with information through multiple representational channels, such as reading, listening, viewing, and mapping. Research on multimodal learning has long suggested that combining formats can support comprehension, retention, and deeper processing when such combinations are pedagogically coherent [17–19]. In AI-supported learning environments, multimodality becomes especially significant because learners increasingly expect to move flexibly across formats rather than rely on a single medium.

NotebookLM supports this kind of multimodal engagement by allowing users to work with textual documents, web-based materials, transcripts, audio, and generated summaries within one integrated environment. It can also help transform source-based content into alternative representations, such as concise textual syntheses or podcast-style explanations. This capacity aligns with long-standing theories such as dual coding and multimedia learning, which suggest that learning is strengthened when verbal and nonverbal channels are meaningfully coordinated [18,20]. In this way, NotebookLM may help learners build richer conceptual networks by revisiting the same content across multiple forms.

The educational value of this multimodal flexibility is reinforced by recent AI-in-education scholarship, which highlights the role of personalized and adaptive systems in supporting diverse learners and learning preferences [1,2,9]. When students can move from reading to listening, from summarizing to questioning, and from source analysis to thematic synthesis, they may be better positioned to sustain attention, deepen understanding, and engage in reflective meaning making. This is particularly relevant in higher education contexts where students often work with dense, fragmented, or conceptually demanding materials.

At the same time, multimodality does not automatically guarantee effective learning. As cognitive load theory suggests, excessive or poorly structured information can overwhelm learners and reduce comprehension [13]. The challenge, therefore, is not simply to provide multiple modes, but to organize them in ways that support incremental processing and conceptual clarity. NotebookLM's ability to segment, summarize, and reorganize content may help address this challenge by enabling students to engage with complex information in smaller and more manageable units. In this sense, multimodal AI-supported learning is most effective when it remains pedagogically scaffolded, source-aware, and responsive to learners' cognitive needs.

Overall, NotebookLM's multimodal affordances strengthen its value as a learning environment that integrates textual, auditory, and conceptual forms of engagement. Combined with its source-grounded architecture and dialogic potential, this multimodal flexibility supports a richer model of academic learning—one in which students do not merely consume information, but interact with it across forms, revisit it through different representations, and use AI as a scaffold for deeper understanding.

## 3. Methods

### 3.1 Research Design

This study adopts a qualitative, exploratory–interpretive research design aimed at understanding how undergraduate students experience learning with the NotebookLM platform within teacher education contexts. A qualitative approach was selected to capture the depth and complexity of participants' subjective experiences, reflective processes, and meaning-making practices while engaging with generative artificial intelligence.

The study is grounded in an interpretive paradigm that seeks to understand how learners construct meaning through interaction with AI-based systems, aligning with contemporary qualitative approaches that emphasize context, reflexivity, and co-construction of knowledge [21, 22]. The use of semi-structured reflective accounts further allows for capturing both structured responses and emergent insights, consistent with recent developments in qualitative interviewing research [23].

### 3.2 Participants and Sampling

The study included 123 undergraduate students enrolled in teacher education programs at academic institutions in Israel. Participants were recruited from courses related to pedagogy, digital learning, and educational technology, using a convenience-based sampling strategy within intact course groups. This approach enabled access to a naturalistic learning setting in which students were already engaged in AI-supported academic tasks.

The sample is characterized by a strong predominance of female participants, reflecting the demographic profile of teacher education programs in Israel. While this composition enhances ecological validity within the studied context, it also introduces a limitation regarding the generalizability of findings to more gender-balanced populations.

### 3.3 Participant Characteristics

The participant group represents a range of academic stages within teacher education, from early coursework to advanced stages of training. This diversity enables the study to capture a broad spectrum of learning experiences, levels of digital familiarity, and pedagogical perspectives. The overrepresentation of female participants reflects the structural gender distribution in teacher education programs such as those at Kaye and Achva Colleges. Additionally, the inclusion of students with varying levels of prior AI experience strengthened the analytical depth, enabling comparison between novice users and those accustomed to working with intelligent digital systems.

### 3.4 Research Procedure

Participants were asked to engage with a selected academic topic by producing three complementary learning artifacts: a mind map, a structured study guide, and a podcast aimed at explaining the topic to peers. These tasks were designed to promote multimodal learning, synthesis of information, and reflective engagement with content. The topics addressed contemporary issues in education, including AI in education, digital pedagogy, and data-informed teaching practices.

The learning process was conducted via NotebookLM, allowing participants to upload sources, query content, and generate outputs. As part of this process, students engaged in prompt-based interactions that guided their learning. Typical prompts included requests such as summarizing academic texts with emphasis on methodology, comparing multiple sources, and generating explanatory podcasts based on selected materials. Upon completing the tasks, participants responded to an open-ended, in-depth online questionnaire.

### 3.5 Data Analysis

The qualitative data were analyzed collaboratively by the two researchers using reflexive thematic analysis. following the approach outlined by Lochmiller [24]. The analysis involved a recursive process of familiarization with the data, generation of initial codes, identification of patterns, development of themes, and iterative refinement.

### 3.6 Reflexivity and Trustworthiness

The analysis was conducted collaboratively by the two researchers, who adopted a reflexive approach throughout the analytical process. Reflexivity is recognized as a central component of qualitative rigor [25]. Continuous reflection, iterative revisiting of the data, and conscious efforts to remain grounded in participants' voices were employed. Methodological transparency and systematic documentation of analytic decisions were maintained to enhance credibility and dependability.

### 3.7 Triangulation and Data Sources

The primary data source consisted of participants' reflective responses. While additional data sources such as student-generated artifacts (e.g., mind maps) could further strengthen triangulation, access was limited within the scope of the current study. Future research may benefit from incorporating multiple data sources, including direct analysis of interaction logs.

### 3.8 Ethical Considerations

Participation was voluntary and anonymous. Informed consent was obtained from all participants prior to data collection. No personally identifiable information was collected, and all data were handled confidentially and stored securely. As this study involved adult participants, posed no more than minimal risk, and did not collect sensitive or identifiable personal information, formal ethical approval was not required according to the institutional guidelines governing this type of research.

## 4. Findings

### 4.1 Organizing Information from Multiple Sources

Participants described NotebookLM as a tool that enabled them to organize and centralize information from different sources within a single environment. Students referred to the ability to collect materials such as texts, videos, and notes in one place, which facilitated structured learning and reduced fragmentation of information. One participant noted:

"It was very convenient having everything centralized in one place."

Several students highlighted that working with multiple sources simultaneously allowed them to identify connections between ideas and better structure their understanding. Another participant explained:

"I could connect different materials and see how everything fits together."

Participants also emphasized the role of combining different formats, including reading materials, videos, and generated summaries, in supporting their learning process. A student described this experience as follows:

"I used texts, videos, and summaries together, and it helped me understand the topic more clearly."

In addition, students reported that the ability to visually organize information, particularly through tools such as mind maps, supported their comprehension. One participant stated:

"The mind map helped me organize the information and remember the main ideas."

Overall, participants described the platform as enabling structured organization of information from diverse sources, which supported their ability to manage and navigate learning materials.

### 4.2 Interactive Learning Experiences

Participants reported that the interactive features of NotebookLM played a central role in their learning experience. The ability to ask questions and receive immediate responses was described as particularly helpful for clarifying concepts and addressing gaps in understanding. One student noted:

"The option to ask questions in real time helped me understand things I didn’t get at first."

Students also described how interaction with the system supported continuous engagement with the material. Another participant shared:

"I kept asking questions until I fully understood the topic."

Several participants referred specifically to their experience with audio and podcast-based learning. They described the ability to interact with content while listening as a useful feature that supported focus and comprehension. One student explained:

"I could listen to the podcast and ask questions about parts I didn’t understand."

In addition, some participants mentioned using generated quizzes and follow-up questions as part of their learning process. These features were described as helping them review content and check their understanding. A participant stated:

"The questions helped me see what I understood and what I needed to review."

Overall, participants described the learning process as interactive and dynamic, with continuous opportunities to engage with the content through questioning and response.

### 4.3 Autonomy and Control over Learning

Participants consistently reported a sense of autonomy when using NotebookLM. They described having control over the pace, structure, and depth of their learning. One participant expressed this experience by stating:

"I could stop whenever I wanted and go back to things I didn't understand."

Students also highlighted the flexibility to adjust content according to their needs. For example, one participant noted:

"I could ask for shorter explanations or more detailed ones depending on what I needed."

Another participant emphasized the ability to revisit content multiple times:

"I went over the same material more than once until I felt confident."

Some students described this flexibility as reducing pressure during the learning process. A participant shared:

"I didn't feel stressed because I could learn at my own pace."

In addition, participants reported that having control over how they accessed information—whether through reading, listening, or summaries—allowed them to adapt the learning process to their preferences. One student noted:

"I chose how to learn the material in a way that worked best for me."

Overall, participants described the platform as supporting self-directed learning by enabling them to manage their own learning pace and strategies.

### 4.4 Challenges in Multimodal Learning

Alongside the reported benefits, participants also described several challenges when using NotebookLM. One of the most frequently mentioned difficulties was the amount of information available, which sometimes led to confusion. One participant noted:

"There was a lot of information, and sometimes it was hard to focus on what was important."

Some students expressed the need to verify the information they received. A participant stated:

"I felt like I needed to check the information with other sources to be sure it was correct."

Participants also reported challenges related to podcast-based learning. In particular, the speed and clarity of the audio were mentioned as barriers. One student explained:

"Sometimes the podcast was too fast, and I had to listen again to understand."

Another participant noted difficulties maintaining concentration during longer audio segments:

"It was hard to stay focused when the podcast was long."

Despite these challenges, participants indicated that they attempted to manage these difficulties by revisiting content, replaying audio, or focusing on specific parts of the material.

Overall, participants described both opportunities and challenges in working with multimodal content, particularly in relation to managing information load and processing audio materials.

## 5. Discussion

### 5.1 Reframing Learning through Interactive AI-Assisted Constructivism

The findings extend beyond a descriptive account of students' experiences and can be interpreted through the lens of Interactive AI-Assisted Constructivism (A2). This framework conceptualizes AI not as a content delivery system but as an asynchronous, source-grounded dialogic mediator of knowledge construction. Learning is therefore understood as an iterative process in which learners continuously negotiate, refine, and reorganize knowledge through interaction with both human-curated sources and AI-mediated responses.

From this perspective, the educational value of NotebookLM does not primarily stem from its ability to aggregate information. Rather, its significance lies in its capacity to externalize cognitive dialogue and support reflective meaning-making. The system facilitates distributed constructivist scaffolding by partially offloading epistemic activities—such as questioning, validating, and reorganizing knowledge—to an AI environment that remains grounded in learner-selected sources. This interpretation aligns with contemporary views that AI systems should function as cognitive partners embedded within knowledge construction rather than as autonomous authorities of knowledge [14,18,25].

### 5.2 Multimodality as Cognitive Reorganization Rather than Representation Variety

Within the A2 framework, multimodality is more than an instructional enhancement. It functions as a mechanism for reorganizing cognitive representations of knowledge. Instead of treating textual, audio, and visual formats as parallel channels for delivering information, the findings suggest that learners actively translate between these representational systems to stabilize meaning.

This interpretation extends Dual Coding Theory and multimedia learning research by shifting attention from processing efficiency to representational negotiation. The educational benefit therefore lies not simply in exposure to multiple modalities but in learners' ability to coordinate and reconstruct meaning across them [8,26,27]. In this process, AI serves as a mediating infrastructure that supports flexible movement between representations and promotes epistemic mobility across modalities.

### 5.3 Dialogicity and AI as an Asynchronous Constructivist Partner

An important theoretical implication concerns the meaning of interaction in AI-supported learning. Rather than defining interaction as a simple exchange between user and system, the A2 model conceptualizes it as dialogic epistemic engagement in which learners' questions shape the ongoing development of understanding.

From this perspective, AI functions as an asynchronous constructivist partner that approximates—but does not replace—the role of a More Knowledgeable Other. Unlike traditional scaffolding, however, this mediation is neither socially embodied nor temporally synchronized. Instead, it is embedded in retrieval-based responses grounded in learner-selected sources. Knowledge construction therefore emerges through iterative cycles of inquiry and AI-generated reinterpretation [23,27]. This perspective moves beyond describing student engagement and instead explains how AI reshapes the conditions under which dialogic learning occurs.

### 5.4 Learner Agency as Epistemic Governance

Within the A2 model, learner autonomy extends beyond procedural control over learning pace. It represents a deeper form of epistemic governance in which learners regulate knowledge validation and determine whether AI-generated responses are meaningful, accurate, or incomplete.

This interpretation shifts the concept of agency from self-directed learning toward distributed epistemic responsibility. Cognitive work is shared between learner judgment and AI mediation. Previous research on AI-supported personalization similarly suggests that adaptive technologies enhance metacognitive regulation only when learners maintain responsibility for interpretive decisions [4,14,28]. Accordingly, A2 reframes autonomy as the ability to critically orchestrate AI assistance rather than simply learn independently.

### 5.5 Cognitive Load as a Function of Representational Excess

The A2 framework also offers a different interpretation of cognitive overload. Instead of viewing overload as a peripheral limitation, it conceptualizes it as an inherent tension within multimodal constructivist systems. The central challenge is not merely the amount of information available but the density of representations presented without sufficient epistemic filtering.

Under these conditions, cognitive overload emerges when representational possibilities expand more rapidly than learners' ability to stabilize meaning across them. This interpretation is consistent with Cognitive Load Theory while extending it into dynamic AI-mediated learning environments rather than static instructional settings [29]. Effective AI-assisted constructivism therefore requires not only multimodal richness but also adaptive mechanisms that structure learners' epistemic pathways.

### 5.6 Grounding, Hallucination, and the Epistemology of Retrieval-Based AI

Another important theoretical contribution concerns the epistemological role of retrieval-based AI systems. Unlike open generative models, NotebookLM generates responses that are grounded in user-provided sources. This design reduces the likelihood of hallucinations and positions AI output as derivative interpretation rather than autonomous knowledge production [11,20,30].

Nevertheless, the A2 framework argues that grounding does not eliminate epistemic uncertainty. Instead, it shifts the location of uncertainty from factual existence to interpretive fidelity between the original source and the AI-generated synthesis. Learners therefore face a second-order epistemic task: evaluating whether meaning has been accurately preserved throughout the transformation process. AI literacy should consequently be understood not only as the ability to detect misinformation but also as the ability to critically evaluate AI-mediated interpretations.

### 5.7 Toward Contextualized and Distributed AI Learning Architectures

Finally, the findings support a future extension of the A2 framework toward distributed and adaptive AI learning architectures, including edge-based and personalized educational systems. Such developments could provide increasingly context-sensitive representations of learner cognition and support more individualized forms of constructivist scaffolding over time [5,22,31].

Within this emerging trajectory, the concept of a digital learning twin should not be interpreted as a literal replication of the learner. Instead, it may be understood as a continuously updated computational representation of epistemic behavior that enables progressively more precise and personalized support for knowledge construction.

## 6. Conclusion

Reinterpreted through Interactive AI-Assisted Constructivism, the study suggests that AI-supported learning environments should be understood as dialogic epistemic systems rather than instructional tools. Their educational value lies in enabling iterative meaning construction through grounded interaction, multimodal translation, and distributed cognitive regulation. Accordingly, NotebookLM is not best conceptualized as a knowledge provider, but as a constructivist mediation layer that reorganizes how learners access, validate, and reconstruct academic meaning.

## 7. Theoretical and Practical Contribution of the Study

The theoretical contribution of this study lies in extending existing constructivist and learner-centered perspectives into the context of source-grounded generative AI. By proposing the model of Interactive AI-Assisted Constructivism, the study offers a framework for understanding how AI can support knowledge construction not merely by delivering answers, but by participating in an iterative process of questioning, reflection, and reformulation. This contribution builds on constructivist, active learning, and multimodal learning traditions while adapting them to the affordances of retrieval-based AI systems [23,29,32].

The practical contribution lies in demonstrating how a grounded AI platform can be integrated into higher education in ways that support student agency, multimodal engagement, and source-based academic work. The findings suggest that tools such as NotebookLM may be particularly useful in tasks involving synthesis, explanation, reorganization of content, and reflective study. In this sense, the study contributes to emerging work on AI-supported higher education by showing that educational value increases when the system is not merely generative, but pedagogically structured and anchored in the learner's own academic materials [1,2,5,18,33].

## 8. Practical Recommendations

Based on the findings, several practical recommendations emerge for the educational use of NotebookLM and similar AI-supported platforms:

- Segmenting Content: Instructors should guide students in working with multimodal materials in smaller, manageable segments in order to reduce overload and support focused processing.
- Adaptive Control: Platforms should allow flexible control over audio playback, repetition, and content length so that students can adapt learning materials to their pace and comprehension needs.
- Critical AI Literacy: Educators should explicitly develop students' AI literacy. Learners should be trained to engage in cross-referencing: checking original sources, verifying interpretive accuracy, and identifying possible simplifications or distortions.
- Analytical Prompting: Instructors should model effective prompting strategies that promote analysis (comparing sources, identifying methodological differences) rather than passive dependence.

## 9. Limitations of the Study

This study has several limitations. First, the participants were drawn from a specific teacher education context in Israel, which limits transferability to other settings. Second, the sample was overwhelmingly female, reflecting the demographic profile of teacher education but limiting gender-based generalization. Third, the study relied primarily on reflective accounts rather than interaction logs or longitudinal follow-up. Fourth, the findings reflect the affordances of evidence-bounded (source-grounded) AI environments, which may differ substantially from open-ended generative systems. Future research should examine these environments across broader disciplines and longer instructional periods.

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