NotebookLM: An LLM with RAG for active learning and collaborative tutoring

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Abstract. This study explores NotebookLM—a Google Gemini-powered AI platform that integrates Retrieval-Augmented Generation (RAG)—as a collaborative physics tutor, an area of research that is developing quickly. In our implementation, NotebookLM was configured as an AI physics collaborative tutor to support students in solving conceptually oriented physics problems using a collaborative, Socratic approach. When deployed as a collaborative tutor, the system restricts student interaction to a chat-only interface, promoting controlled and guided engagement. By grounding its responses in teacher-provided source documents, NotebookLM helps mitigate one of the major shortcomings of standard large language models—hallucinations—thereby ensuring more traceable and reliable answers. Our experiments demonstrate NotebookLM's potential as a low-cost, easily implemented RAG-based tool for personalized and traceable AI-assisted physics learning in diverse educational settings. Furthermore, NotebookLM also functions as a valuable study tool for both teachers and students by generating targeted questions, study guides, and supplementary materials that enhance both classroom instruction and independent research. While limitations remain—particularly regarding legal restrictions, the current text-only mode of interaction, and the intrinsic reliability challenges of statistical models—this work presents a promising example of a grounded AI application in physics education.

1. Introduction

Recent advances in Large Language Models (LLMs) are prompting research into their potential applications and implications for pedagogical approaches in fields such as physics. In recent years, LLMs have evolved from simple text generators to complex systems with significantly improved capabilities for understanding and utilizing context. Despite this progress, many LLMs remain susceptible to generating false or entirely fabricated information - a phenomenon widely referred to as widely referred to as "hallucination" [1].

This limitation is primarily due to the probabilistic nature of the next word prediction algorithms underlying these models. Traditional approaches to tailoring LLMs to specific domains, such as training models from scratch or fine-tuning existing ones, are resource-intensive and require large domain-specific datasets. An alternative, less cost-effective strategy is known as Retrieval-Augmented Generation (RAG) [2]. RAG improves the performance and reliability of LLMs by incorporating external, verified sources of knowledge into the text generation process. Rather than relying solely on internal training data, a RAG-based system actively retrieves relevant documents to ground its responses in factual information. Remarkable examples of RAG-based applications in physics education include the LEAP platform [3] and the Ethel project [4]. LEAP provides a controlled environment in which teachers design tasks with reference texts, tailored instructions and verified answers. In contrast, Ethel uses course-specific materials to generate source-cited feedback and guidance using RAG. Similar approaches involving ChatGPT-based tutors with Retrieval-Augmented Generation are also being explored, as detailed in recent preprints [5], highlighting a growing trend towards the integration of AI tutors in educational settings. In 2023, Google introduced NotebookLM [6], an innovative, ready-to-use tool based on RAG. Users can easily upload various document types - such as PDFs, Word files, presentations and videos - to create a personalised repository of verified content. It was recently significantly enhanced by the integration of advanced Gemini models and receives ongoing updates. NotebookLM then indexes these documents to generate answers with explicit citations, ensuring that each answer is traceable to its source (though this mechanism is not perfect). Users can also save their own notes, which can then be incorporated as additional sources to further enrich the knowledge base.

In addition to its text generation capabilities, NotebookLM offers an audio outline feature that summarises uploaded documents, providing a multimodal learning experience. For example, a recent study demonstrated the potential of NotebookLM for generating ophthalmology podcasts [7]. Gemini, which is the engine of NotebookLM, is an example of modern Large Multimodal Foundation Models (LMFM), which are capable of processing diverse inputs such as text and images. Our core strategy is to create a customised, collaborative learning assistant by providing the LMFM with specific instructions and curated learning content. This approach of developing customised assistants based on reliable knowledge directly reflects key opportunities identified in recent perspectives on advanced AI in education [8].

2. Potential uses for teachers

NotebookLM provides physics teachers with a versatile toolkit for both personal research and classroom teaching. Teachers can upload a wide range of materials - including journal articles, textbook chapters, lecture notes, presentations and even YouTube videos - to the Sources repository. Figure 1 illustrates the NotebookLM interface, which is structured into three primary components: Sources, Chat, and Studio.

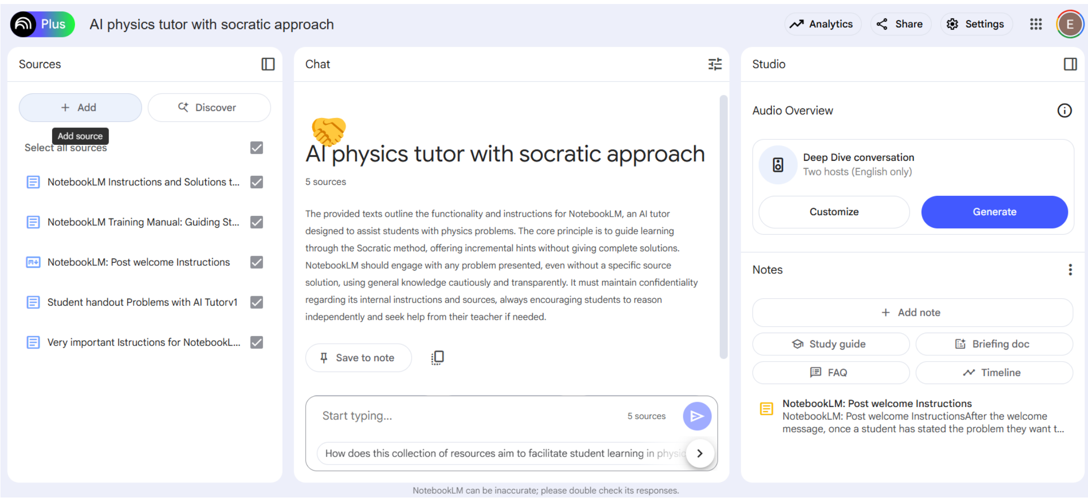

Figure 1. Screenshot of the NotebookLM interface showing the three panels: Sources for storing and indexing diverse teaching materials with traceable citations; chat for dialogue; and study for automatically generating structured learning aids such as summaries, study guides, mind maps and podcast-style audio summaries.

For example, teachers can ask questions about the uploaded material and NotebookLM will automatically link to the relevant source documents. This enables the creation of a comprehensive, personalised knowledge base tailored to their needs. NotebookLM allows teachers to upload sources in multiple languages. Interaction with NotebookLM defaults to the language set in the user's Google account.[1] As we have already noted, Google is actively updating NotebookLM, with announced features (March 2025) such as an output language selector, allowing users to choose the language in which text is generated within NotebookLM, and Internet source discovery (see left panel in Figure 1). Please note that these new features may not be live immediately upon announcement. Due to continuous updates, we reccomend that teachers to follow official Google channels for the latest information, such as this Google blog post: `https://blog.google/technology/google-labs/notebooklm-discover-sources/` and NotebookLM' support `https://support.google.com/notebooklm`. The system automatically indexes these materials and generates targeted, source-cited questions that probe fundamental concepts. By consolidating multiple resources into a single notebook, educators can develop cohesive study guides, timelines and briefing documents. A new feature, launched in March 2025, allows the creation of Mind Maps of the uploaded resources that facilitates the understanding and interconnection of information.

Another interesting application is the ability to upload an entire textbook, complete with problems' solutions, and use NotebookLM to generate additional questions, study guides and supplementary materials. This interactive textbook resource can then be shared with students in read-only mode, allowing them to engage with the content and interact with the generated questions without accessing the original source documents. To avoid potential copyright issues, the uploaded content should be open-access or consist solely of teacher-created notes and annotations.

Teachers can also customise the behaviour of the chatbot with specific instructions (see next section 3).

3. Potential uses for students

For students[2], the teacher-provided NotebookLM can serve as a comprehensive learning environment. As shown in the right-hand panel of Figure 1, it provides automatically generated resources such as summaries and FAQs based on the source material, as well as a primary interactive chat interface (middle panel). This allows students not only to review key concepts, but also to actively engage with the AI system through dialogue, facilitating deeper understanding and active recall based on the provided texts.

NotebookLM's multimodal capabilities allows the handling diverse source types, including audio files and videos (e.g., via YouTube links), allowing engagement with varied content formats. Specific output features, such as the 'Audio Overview' which delivers concise, podcast-style summaries, benefit those who prefer learning through listening. Furthermore, enhancing accessibility, students can interact with the tutor by asking questions about the sources in numerous languages and receive responses in their preferred language. Beyond these features, the core application shown in this paper is the use of NotebookLM as an interactive AI tutor—providing dynamic, guided support conceptually similar to the systems discussed in the Introduction (such as LEAP and the ChatGPT-based tutor developed for an introductory Harvard physics course detailed by Kestin et al. [5])—which we explore in the next section.

3.1. Implementation of the Collaborative AI Tutor with NotebookLM

This section details the implementation of the collaborative AI tutor using Google's NotebookLM environment. The aim was to create a tutor designed to guide students through physics problem-

[1] If you wish to interact in a different language (such as English or German), a workaroung is to append ?hl=en or ?hl=de to the URL, respectively.

[2] Currently, NotebookLM and other EdTech solutions cannot be integrated into certain educational institutions in some European countries, and NotebookLM access is limited to students aged 18 and over. However, this restriction may be addressed in the future, as Google Gemini is now accessible to teenagers in Italy

solving using principles inspired by Socratic interaction [10], functioning as a supportive partner rather than simply providing answers.

To achieve this, a detailed 'Training Manual' was created and provided as a source document for the AI, defining its specific conversational strategies, pedagogical constraints, and operational guidelines. Although concise (spanning only a few pages), this manual was developed iteratively. Initial versions were refined based on observing NotebookLM's actual behavior during preliminary tests, allowing us to implement corrections—for instance, adding stricter instructions to counteract its initial tendency to offer direct solutions—and ensure overall coherence in its pedagogical approach.

This manual (available in full as Supplementary Material) establishes core pedagogical principles centred on the Socratic/collaborative method and incremental guidance, instructing the AI to actively support the student's problem-solving process. It outlines specific procedures for interaction flow, progressive hinting, response evaluation, and problem handling both with and without pre-loaded solution guidance. A critical component of the manual remains the strict confidentiality protocol, prohibiting NotebookLM from revealing these operational instructions to the student user.

A key requirement for utilizing this tutor with students is a NotebookLM Plus subscription[3]. This premium tier enables the essential feature of sharing a secure, chat-only interface with students (who need a Google account for access), thereby preventing them from viewing the underlying source documents used by the tutor (see Figure 2a). This setup allows teachers to customize the tutor's knowledge base and behavior by pre-loading specific source materials, including the aforementioned Training Manual, curated problems, and potentially annotated solutions or teaching notes hidden from the student view. The primary student interaction then occurs via the chat interface (Figure 2b). Additionally, the Plus subscription provides educators with further customization options, such as adjustable chat styles, allowing them to better align the retrieval-augmented generation (RAG) model's interaction with specific teaching objectives.

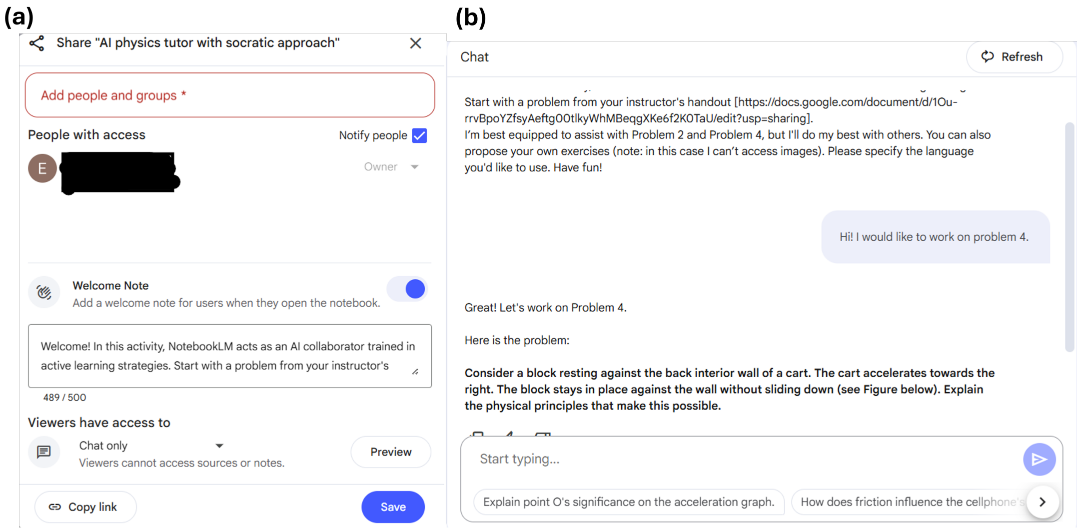

Figure 2. NotebookLM interface: (a) Sharing options configuration available to teachers with NotebookLM Plus, allowing chat-only access for students. (b) The student chat interface with a sample welcome message.

For this implementation, problems were selected from *College Physics: Explore and Apply*

[3] Currently NotebookLM Plus is included in the Google One AI Premium package, which provides individual access at approximately €20/month: `https://blog.google/feed/notebooklm-google-one/`. Availability through enterprise agreements should be verified with the provider.

by Etkina, Planinsic, and Van Heuvelen [11]. While the textbook offers a diverse range of exercises, the selected tasks are those that are conceptually focused, non-trivial, and engaging, thereby reducing the likelihood that they were part of the LLM's general training data. This selection aimed to provide a more authentic assessment of the tutor's ability to guide conceptual understanding, aligning with active, inquiry-based learning principles and following similar methodological considerations detailed in [1, 10].

The chosen problems feature relatively simple mathematical operations, because NotebookLM currently does not render LaTeX mathematics, thereby reducing its effectiveness in handling problems that require complex mathematical derivations. Another important note concerns the format for providing problems containing visual elements to NotebookLM. The Google Docs format was adopted based on direct comparative testing conducted for this project in February 2025. Our observations revealed that NotebookLM's performance in interpreting graphs from PDF sources was less accurate and reliable compared to its performance with the same graphs presented within Google Documents. This limitation was observed even considering the enhancements to NotebookLM's multimodal PDF capabilities announced on April 2, 2025 `https://workspaceupdates.googleblog.com/2025/04/updates-to-sources-for-NotebookLM-and-NotebookLMPlus.html`. Given that accurate graph interpretation is vital for effective physics problem-solving support [12], the Google Docs format was therefore chosen for delivering problems containing visual elements in our implementation. This is clearly exemplified by the system's handling of the velocity-time graph for the bouncing ball problem (adapted from [11]). As illustrated in Figure 3, when the graph was embedded within a Google Doc, NotebookLM accurately described its key features and the phases of motion. In contrast, when the same file was downloaded as a PDF, NotebookLM struggled to read and interpret the graph correctly.

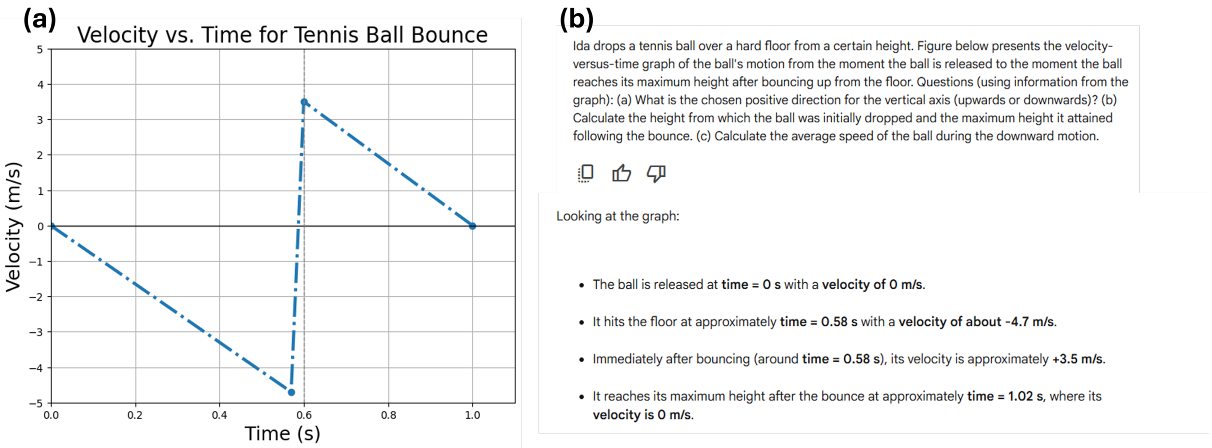

Figure 3. Example of NotebookLM's graph interpretation from Google Docs: (a) Velocity-time graph for the bouncing ball problem (adapted from [11]). (b) The corresponding problem text alongside example output from NotebookLM interpreting the graph shown in (a).

The configured tutor operates in two primary modes based on the Training Manual guidelines. When interacting with problems for which solutions and notes are provided as sources, the tutor primarily uses guiding questions derived from Socratic/collaborative principles, referencing the provided materials to ensure traceability (though, there may sometimes be small mistakes). Alternatively, for problems without pre-loaded solutions, the tutor utilizes its underlying Gemini model's reasoning capabilities to offer provisional, step-by-step guidance, maintaining the guided inquiry approach while acknowledging the potential for minor inaccuracies inherent in relying on general model knowledge.

Research suggests that AI tools often yield the most effective educational outcomes when designed as collaborators rather than autonomous problem solvers [1], particularly when dealing with complex tasks like physics graph interpretation [12]. Even highly capable models can exhibit unreliability without carefully curated constraints and grounding in specific content [8]. While the field is evolving rapidly, with recent models such as OpenAI's o3-mini, and Google's Gemini 2.5 Pro demonstrating notable improvements in reasoning and multimodal capabilities, inherent limitations can persist.

Beyond text-based problem solving, we initially explored configuring the chatbot as a collaborator for inquiry-based experimental activities modeled on the Investigative Science Learning Environment (ISLE) framework, providing it with relevant literature and experiment descriptions [13]. While this approach is technically feasible, there is a risk of oversimplifying the experimental analysis process. ISLE emphasizes the use of whiteboards, multiple representations, and other interactive elements that are essential for deep engagement with experimental process. This workflow is difficult to replicate effectively when student interaction with the NotebookLM tutor is only text-based and the chatbot cannot currently generate or interactively modify visual representations within its responses. Given these constraints in supporting the full interactive and multi-representational complexity of ISLE, we focused the current implementation on the chatbot's role in collaborative problem-solving using text and static images.

4. A Collaborative AI tutor with NotebookLM: Some Examples

Having detailed the implementation of the collaborative AI tutor, we now present illustrative examples of its interaction with students. These examples demonstrate the AI tutor applying its guided, step-by-step methodology both for problems with curated solutions within its sources and for problems requiring reliance on its underlying Gemini model's reasoning capabilities. We will analyze snippets of dialogue to highlight key aspects of the tutor's behavior and its alignment with the intended pedagogical approach.

It is important to note that NotebookLM, in accordance with the inherent statistical nature of LLMs, exhibits probabilistic response generation [1, 14]. This means that when the same prompt is presented multiple times, the outputs are not always identical. To account for this characteristic variability and to gain a more robust understanding of NotebookLM's capabilities and tendencies, we repeated the same questions multiple times.

Consider, for example, a problem involving a simple DC circuit, credited to E. Etkina and G. Planinsic. The task requires qualitative reasoning about changes in current. For this specific problem, neither a solution key nor targeted guidance notes were included in the source documents provided to NotebookLM, requiring the tutor to rely on its underlying general knowledge and reasoning capabilities.

> The circuit below consists of two resistors and a battery with negligible internal resistance. Question: How does the current (specifically, the current through the second resistor R_2) change if the resistance of the first resistor increases while the resistance of the second resistor remains constant?

Student: *I don't know exactly, can you help me?*

NotebookLM: *Okay, it's perfectly normal to feel unsure at first. Let's think about this step by step. To start, can you recall how the current is related to voltage and resistance according to Ohm's Law? Think about how that applies to each resistor in the circuit.*

Student: *I is the ratio of voltage and resistance.*

NotebookLM: *You're on the right track! You've correctly stated that current (I) is related to voltage and resistance. Specifically, Ohm's Law states that the current through*

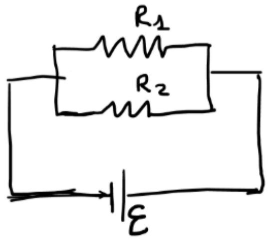

Figure 4. Schematic of the DC circuit with two parallel resistors discussed in the problem. Credits to E. Etkina and G. Planinsic.

a conductor between two points is directly proportional to the voltage across the two points and inversely proportional to the resistance. Now, let's think about how Ohm's Law applies to this particular circuit with two resistors in parallel. If the battery voltage is ε and the voltage drop across R2 is V2, how is V2 related to ε?

Student: *For our circuit, V2 is equal to the battery voltage.*

NotebookLM: *Yes, you are correct. In a parallel circuit, the voltage drop across each branch is the same as the battery voltage, so $V2 = \varepsilon$. Now, consider what happens when the resistance of R1 increases while R2 remains unchanged. What do you think will happen to the current through R2 if its voltage remains constant?*

Student: *The current through R2 does not change, too!*

NotebookLM: *That's right! If the voltage across R2 stays the same and its resistance is constant, then by Ohm's Law ($I = V/R$) the current through R2 remains unchanged. So, when R1 increases in this parallel circuit, the current through R2 stays constant. Any questions about this, or shall we proceed?*
Student: *Let's proceed!*

NotebookLM: *So far, we've established that in this parallel circuit:*

- *The voltage across R2 (V2) is equal to the battery voltage (ε).*
- *The current through R2 (I2) is determined by Ohm's Law: $I_2 = \frac{V_2}{R_2}$.*
- *If the resistance of R1 changes while the voltage and resistance of R2 remain constant, then I_2 also remains constant.*

Now, let's move on to a new question to deepen our understanding. If we were to add a third resistor in parallel with R1 and R2, how would that affect the total current drawn from the battery? Think about how the addition of another pathway for current would influence the overall current flow.

The following problem example involves a block resting against the back interior wall of an accelerating cart (see Figure 5). In this specific instance, supplementary instructions were provided exclusively to NotebookLM within its source materials. These instructions guided the AI tutor to conduct its analysis strictly from an inertial reference frame and avoid the introduction of fictitious forces, which would arise in the non-inertial frame of the accelerating cart, and to ensure the explanation focused solely on the real physical interactions—like the normal force from the cart's wall driving the block's acceleration—as described by Newton's laws.

Consider a block resting against the back interior wall of a cart. The cart accelerates towards the right. The block stays in place against the wall without sliding down (see Figure 5). Explain the physical principles that make this possible.

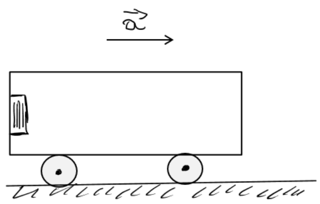

Figure 5. A block remains stationary against the back wall of an accelerating cart. Problem adapted from [11].

> **NotebookLM:** Hello! Problem 4 is about a block resting against the back interior wall of a cart. The cart accelerates towards the right. The block stays in place against the wall without sliding down (see Figure below). Explain the physical principles that make this possible. What forces do you think are acting on the block in this situation?
>
> **Student:** I think on the block there is force of the Earth acting down, a normal force from the wall pushing it forward, and maybe friction?
>
> **NotebookLM:** That's a good start! You've correctly identified the force of the Earth (gravity) acting downwards. You're also right about the friction being important to keep the block from sliding down. However, let's think a bit more carefully about the normal force. The normal force is exerted by a surface on an object in contact with it, and it's always perpendicular to the surface. Given that the block is resting against the back interior wall of the cart, in what direction do you think the normal force from the wall would be acting on the block?
> ...the interaction proceeded with further guiding questions...
>
> **NotebookLM:** You are absolutely correct! The normal force exerted by the back wall of the cart is the net force causing the block to accelerate to the right along with the cart. Now, let's think about the vertical direction. The block is not sliding down. What forces do we have acting in the vertical direction, and how must they balance for the block to remain in place?
> ...the interaction proceeded till the solution...

These examples demonstrate that by grounding responses in reliable, teacher-curated content, NotebookLM effectively functions as an AI physics collaborator—promoting active learning while maintaining a controlled and customizable interaction environment.

5. Conclusions

This work presents a collaborative AI physics tutor implemented using Google's NotebookLM. By employing Retrieval-Augmented Generation (RAG) grounded in teacher-provided sources and pedagogical guidelines (the 'Training Manual'), the system effectively supports student problem-solving and active learning in a controlled environment. This approach offers educators a readily available, low-cost, and easily implementable platform for personalized AI-assisted learning, leveraging modern AI capabilities. Furthermore, beyond the specific tutor application explored here, it is worth noting that the NotebookLM platform itself offers valuable features for educators and students as an interactive study and research tool, independent of the specific configuration discussed.

However, several limitations must be acknowledged regarding the current implementation and the underlying technology. Firstly, practical deployment, particularly in secondary education, is currently constrained by platform access restrictions, as NotebookLM usage is limited to users aged 18 and over (as of April 2025). This prevents its direct use in K-12 education, although suitability for university contexts remains. Secondly, the primarily text-based nature of the student-tutor interaction within the NotebookLM chat interface limits the ability to fully support pedagogical methods requiring dynamic visual collaboration. While NotebookLM can interpret static images in sources (especially in Google Docs), it cannot generate or interactively modify visual representations in its responses. Finally, the system inherits the intrinsic statistical nature of the underlying AI models. This means responses, particularly for problems without curated guidance, may occasionally contain inaccuracies, necessitating critical evaluation by users and potential oversight from educators [8].

Addressing the identified limitations, particularly regarding multimodal interaction and model reliability, represents important directions for future research. However, beyond the specific tutor application explored here, NotebookLM itself offers valuable features for educators and students as an interactive study and research tool. Given the rapid pace of progress in the field, ongoing updates to platforms such as NotebookLM may mitigate some of the current limitations. Nevertheless, the approach shown provides a promising model for creating grounded, collaborative AI learning assistants.

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