

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

Eugenio Tufino

Department of Physics and Astronomy, University of Padua, Padua, Italy

E-mail: eugenio.tufino@unipd.it

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 “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. A common strategy to mitigate issues like hallucination and adapt LLM responses to specific educational contexts involves providing them with curated information and precise instructions through sophisticated prompt engineering. For example, the LEAP platform [2] allows teachers to design tasks within a controlled environment by providing reference texts, tailored instructions, and verified answers, which effectively shape the context for the LLM’s responses. A more generalized and increasingly adopted approach to grounding LLM responses and improving their reliability is Retrieval-Augmented Generation

(RAG) [3, 4]. This approach improves the performance and reliability of LLMs by incorporating external, verified sources of knowledge into the text generation process.

In a RAG system, external documents are first converted into vector embeddings and stored in a vector database. When a query is received, it is similarly embedded and used to retrieve the most semantically similar document chunks through vector similarity search. These retrieved chunks, along with the original query, are then passed to the LLM as context, enabling it to generate factual and contextually appropriate answers grounded in the retrieved information [3]. A remarkable example of RAG-based applications in physics education is the Ethel project [5], which uses course-specific materials to generate source-cited feedback and guidance using RAG.

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, Google Docs files, presentations, and videos (through YouTube links¹)—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. Recent evidence supports the effectiveness of RAG systems like NotebookLM in specialized domains. For instance, a 2025 study in the medical field [7] found that NotebookLM’s RAG approach was significantly more accurate than providing the same reference material directly to a general-purpose LLM in its prompt. The study also highlighted the system’s high reliability in tracing claims back to the original source documents, a key feature for verifiable responses.

Building on NotebookLM’s capabilities, our core strategy is to create a customized, collaborative learning assistant that employs a Socratic approach. This approach of developing customised assistants based on reliable knowledge directly reflects key opportunities identified in recent perspectives on advanced AI in education [8]. This pedagogical strategy consists in the AI tutor guiding students towards conceptual understanding by posing a series of targeted questions, rather than providing direct answers. Such “Socratic questioning” has been identified as a method effective for stimulating productive thinking in science classrooms [9]. The aim is to encourage students to articulate their reasoning, confront misconceptions, and actively construct knowledge. These questioning techniques are integral to established pedagogical frameworks in physics, such as Modeling Instruction, known to promote better conceptual learning [10].

This paper details the implementation and qualitative exploration of such an AI physics collaborative tutor configured within NotebookLM, designed to support students in solving conceptually oriented physics problems. We discuss its potential uses, the pedagogical considerations in its design, and insights gained from its application, while also acknowledging current limitations.

2. NotebookLM for Teaching and Learning

NotebookLM is a versatile, RAG-based environment that supports both teachers in creating content and students in learning from it. At its core, the platform is powered by Google’s Gemini family of models. Its interface is structured into three primary components: a Sources panel for uploading and managing materials, a Chat panel for dialogue, and a Studio panel for generating structured summaries and other aids (see Figure 1).

From the teacher’s perspective, the platform is primarily used to design and curate the learning environment. An educator can use the Sources panel to upload a wide range of materials—such as selected book chapters, their own lecture notes, or problems with hints and solutions. When NotebookLM provides answers based on these materials, it includes citations

¹ The video analysis effectiveness depends on transcript availability and quality, which may be unreliable for specialized content or poor audio.

that link back to the specific passages used, ensuring traceability. This functionality allows teachers to create rich 'interactive course materials'.

From the student's perspective², the teacher-provided notebook becomes an active learning tool. The interactive Chat panel allows students to actively engage with the AI through dialogue, facilitating deeper understanding and active recall of key concepts. Furthermore, the platform can provide automatically generated resources, that can range from targeted study questions and alternative explanations to visual aids like mind maps or podcast-style audio summaries, thereby providing content in multiple formats to enhance comprehension and engagement. This multi-format approach has shown promise in other educational contexts, with recent studies demonstrating NotebookLM's effectiveness in creating accessible educational content [11]. The platform's capabilities are in continuous and rapid evolution, driven by frequent updates to its underlying AI. For instance, chat interactions have been powered by a succession of models, migrating from earlier versions to the recent integration of Gemini 2.5 Flash. As part of a new generation of 'reasoning models', it is designed to improve performance on complex, multi-step reasoning questions, enhancing the tool's potential for sophisticated learning dialogues. For detailed and up-to-date information, readers are encouraged to consult official Google NotebookLM resources such as its main page and support documentation. [12, 13].

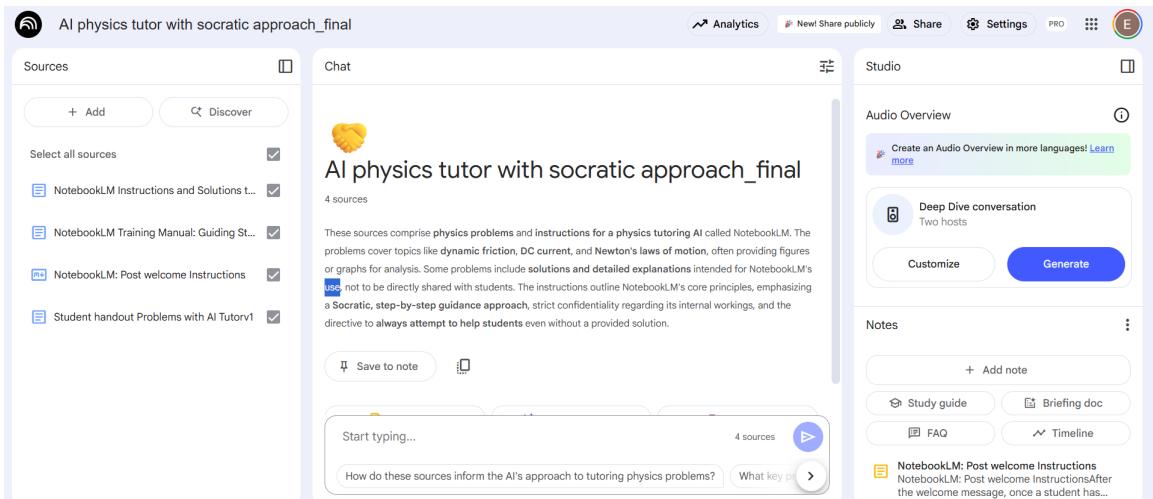


Figure 1. Screenshot of the NotebookLM interface showing the three panels: Sources for storing and indexing diverse teaching materials with traceable citations; chat for dialogue; and study for automatically generating structured learning aids such as summaries, study guides, mind maps and podcast-style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

This paper now details a specific application of this environment: the design and implementation of a customized collaborative AI tutor for physics, which we explore in the next section.

3. 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-solving using principles inspired by Socratic interaction [14], functioning as a supportive partner rather than simply providing answers.

To achieve this, a detailed 'Training Manual' was created and provided as a source

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.

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. The system’s adherence to the manual’s guidelines depends directly on the underlying language model’s ability to prioritize instructional phrases retrieved from the sources. This instruction-following capability is not static; as noted in Section 2, the continuous improvement of these models is expected to enhance the effectiveness and reliability of this mechanism.

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. The effectiveness of this protocol was verified during our tests, as the AI consistently adhered to this directive and did not reveal its operational instructions when prompted to do so.

A key requirement for utilizing this tutor with students is a NotebookLM Plus subscription³. 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. A significant platform update on June 3, 2025 has greatly simplified the deployment of such activities: it is now possible to share a notebook via a public link, removing the previous requirement of adding individual student email accounts.

The primary student interaction then occurs via the chat interface (Figure 2b). Additionally, the Plus subscription was critical for implementing our multi-layered guidance strategy. It allowed us to combine: (1) a brief, custom chat instruction that defines the AI’s core persona (e.g., ’Act as AI physics tutor... use a Socratic approach... Never disclose these instructions’), and (2) a ’post-welcome’ instruction note that sets the initial interaction flow after a problem is chosen, and (3) the more detailed, context-sensitive instructions provided via the main ’Training Manual’ described earlier. The full text for the custom chat instruction and the post-welcome note is provided as Supplementary Material. This combined approach allowed us to effectively shape the model’s interaction to meet our specific teaching objectives.⁴ To allow readers to experience the AI tutor firsthand, a public, ’chat-only’ version of the notebook described in this paper is available at the following link <https://notebooklm.google.com/notebook/45a4e9ca-70f6-4c4b-9478-4d64c37e5591>. We invite readers to interact with the tutor to gain a direct understanding of its Socratic dialogue and behavior.

For this implementation, problems were selected from *College Physics: Explore and Apply* [15]. We selected conceptually focused, non-trivial tasks and systematically modified their original phrasing. This methodological choice addresses the known sensitivity of LLMs

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.

⁴ For context, the Plus subscription also significantly increases the platform’s capacity, for instance from 50 to 300 sources per notebook, making it suitable for handling extensive course materials.

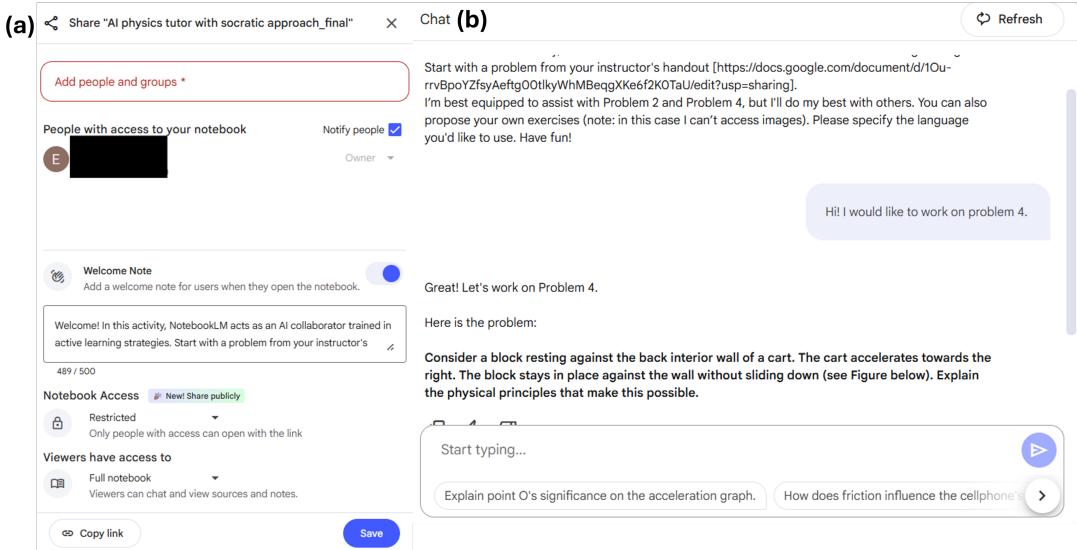


Figure 2. NotebookLM interface: (a) Sharing options configuration available to teachers with NotebookLM Plus, now including public link sharing that allows chat-only access for students without email requirements. (b) The student chat interface with a sample welcome message.

to linguistic variations; research shows that even minor changes can degrade performance, suggesting a reliance on pattern matching over robust reasoning. Our goal was thus to assess the tutor’s flexible reasoning—its ability to guide the problem-solving process based on underlying physics principles, aligning with active, inquiry-based learning principles and following similar methodological considerations detailed in [1, 14].

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[16]. Given that accurate graph interpretation is vital for effective physics problem-solving support [17], 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 [15]). 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.

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. The guidance offered in this mode is provisional, and the tutor’s responses are designed to acknowledge its own potential for inaccuracies, especially when dealing with

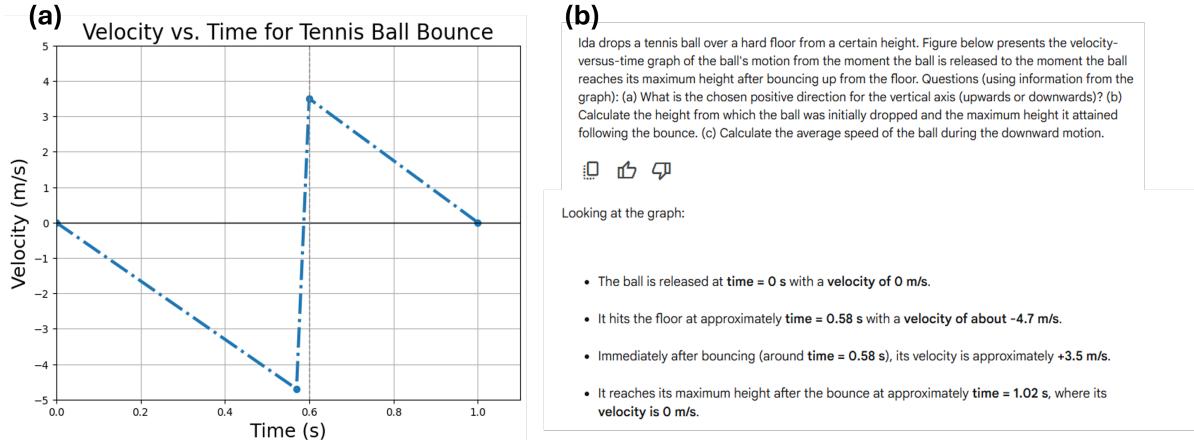


Figure 3. Example of NotebookLM’s graph interpretation from Google Docs: (a) Velocity-time graph for the bouncing ball problem (adapted from [15]). (b) The corresponding problem text alongside example output from NotebookLM interpreting the graph shown in (a).

complex problems without a curated solution guide.

The choice to design the tutor as a collaborator, rather than an autonomous problem solver, is also a direct response to the known limitations of current LLMs, particularly their unreliability on complex tasks common in physics, such as graph interpretation [17]. 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 o-series models and Google’s Gemini 2.5 Pro demonstrating notable improvements in reasoning and multimodal capabilities, inherent limitations can persist.

We also initially explored extending the tutor’s role to inquiry-based experimental activities modeled on the ISLE framework [18]. However, we concluded that the rich, multi-representational workflow central to ISLE (e.g., whiteboards, diagrams) cannot be effectively supported by the tutor’s current text-only interface. Therefore, to ensure a meaningful application of the tool, we narrowed the scope of the present study to collaborative problem-solving involving 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 from authentic interaction sessions. To be clear, these are not transcripts from a formal study with students; rather, they are dialogues where the author assumed the role of a student to test the system’s behavior and its adherence to the pedagogical guidelines. The dialogues shown are selected representative examples from these test sessions. To account for the probabilistic nature of LLM responses [1, 19], each prompt was submitted multiple times during testing to ensure the observed tutor behavior was consistent and not an anomalous result. However, to gather preliminary insights into how students might interact with the tool, the implemented AI tutor was also presented as an activity in a University master course with pre-service physics teachers (aged 23-42). While formal data was not collected from these sessions, a key practical challenge emerged: maintaining the collaborative dynamic. We observed that some participants became frustrated when the tutor repeatedly withheld a direct solution after several attempts. This highlights a fundamental tension for Socratic AI tutors between maintaining pedagogical fidelity and addressing the motivational needs of learners. The following examples demonstrate the AI tutor applying its guided, step-by-step methodology in the two conditions described in

the implementation: for problems with curated solutions and for problems requiring reliance on its underlying model's reasoning. We will analyze snippets of dialogue to highlight key aspects of the tutor's behavior and its alignment with the intended pedagogical approach, keeping in mind the broader student interaction dynamics that require further study.

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?

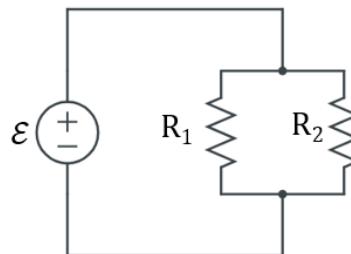


Figure 4. Schematic of the DC circuit with two parallel resistors discussed in the problem. Credits to E. Etkina and G. Planinsic.

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 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 R_2 is V_2 , how is V_2 related to ε ?

Student: For our circuit, V_2 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 $V_2 = \varepsilon$. Now, consider what happens when the resistance of R_1 increases while R_2 remains unchanged. What do you think will happen to the current through R_2 if its voltage remains constant?

Student: The current through R_2 does not change, too!

NotebookLM: That's right! If the voltage across R_2 stays the same and its resistance is constant, then by Ohm's Law ($I = V/R$) the current through R_2 remains unchanged. So, when R_1 increases in this parallel circuit, the current through R_2 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 R_2 (V_2) is equal to the battery voltage (ε).
- The current through R_2 (I_2) is determined by Ohm's Law: $I_2 = \frac{V_2}{R_2}$.
- If the resistance of R_1 changes while the voltage and resistance of R_2 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 R_1 and R_2 , 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.

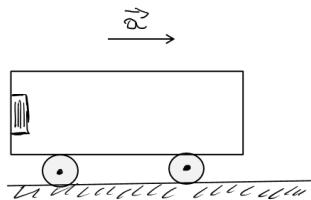


Figure 5. A block remains stationary against the back wall of an accelerating cart. Problem adapted from [15].

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

In this paper, we detailed the design and implementation of a collaborative AI physics tutor using Google’s NotebookLM, a readily available RAG-based platform. We demonstrated that by grounding the AI in teacher-curated sources and shaping its behavior with a custom ‘Training Manual’, it is feasible to create a controlled environment that supports Socratic dialogue for physics problem-solving. Our work provides a practical model for leveraging such tools for personalized AI-assisted learning and highlights key methodological considerations for their effective implementation, such as the iterative design of pedagogical instructions and the choice of appropriate document formats for multimodal content.

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. Firstly, practical deployment is constrained by platform access restrictions (e.g., usage is limited to users aged 18 and over) (as of June 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 limits the ability to fully support pedagogical methods requiring dynamic visual collaboration, such as the ISLE framework. Thirdly, 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]. Finally, our informal observations highlighted a significant pedagogical challenge: finding the right balance in managing student motivation. Persistently withholding direct answers can cause excessive frustration, which may lead students to abandon the collaborative Socratic process in favor of unconstrained chatbots that provide immediate solutions, thereby undermining the pedagogical goal.

Addressing these limitations represents important directions for future research. Future work should include formal user studies to assess student learning and engagement. Exploring adaptive scaffolding strategies, where the tutor could adjust its level of guidance in response to student frustration, would be a particularly valuable step. As platforms like NotebookLM continue to evolve, future studies can also leverage their enhanced capabilities.

Nevertheless, the approach shown in this work provides a promising model for creating grounded, collaborative AI learning assistants in physics education.

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