
This is the **accepted version** of the journal article:

Kahaleh, Rabih; López Simó, Víctor. «Evaluating Large Language Models in High School Physics Education : Addressing Misconceptions and Fostering Conceptual Understanding». *Physics education*, Vol. 60, Num. 2 (2025), art. 025013 DOI 10.1088/1361-6552/adb235

This version is available at <https://ddd.uab.cat/record/328107>

under the terms of the  license.

Instructor Evaluation of Meta Smart Glasses: Assessing AI Accuracy, Explanation Quality, and Misconception Detection in Physics

Rabih Kahaleh¹

¹ Faculty of Engineering, University of Balamand, Koura, Lebanon

E-mail: rabih.kahaleh@balamand.edu.lb

Abstract

This study investigates how effectively the Llama2-based AI embedded in Ray-Ban Meta Smart Glasses solves upper-level high school physics problems, classifies problem types, and addresses common misconceptions. Fifteen experienced physics instructors tested the AI's performance behind the Meta smart glasses on three representative problems—projectile motion, Newtonian equilibrium, and energy conservation. We evaluated the AI on (1) accuracy, (2) explanation quality, (3) misconception handling, and (4) usability in a hands-free format. While the system demonstrated proficiency in recognizing problem types and generating fundamental quizzes, it showed inconsistencies in multi-step calculations and occasional misinterpretation of prompts. This study does not assess students' conceptual learning outcomes; rather, it focuses on instructors' assessments of AI-generated solutions. Findings indicate that wearable AI effectively classifies physics problems and supports basic conceptual tasks, yet exhibits limitations in multi-step problem-solving and formula application. The variability in instructor evaluations highlights the need for improved speech recognition, refined error-detection algorithms, and clearer multi-step reasoning processes. Future research should include larger-scale studies directly measuring student conceptual change.

Keywords: Meta Smart Glasses, Llama2 AI model, Physics education, AI-based learning tools, assessment tools, problem-solving, motion, forces, conservative energy.

1. Introduction

Technology is transforming educational processes through the integration of digital tools, with smartphones and tablets reshaping how teachers deliver content, and students process information (Attallah et al., 2018; Al-Taweel et al., 2020). This digital transformation has made knowledge more accessible, engaging, and interactive, fundamentally changing how students learn and interact with educational content. In physics education, students continue to struggle with complex concepts, commonly misunderstanding principles like projectile motion as requiring constant horizontal force or viewing energy as being "used up" rather than conserved within a system (Thornton et al., 1998). While traditional teaching methods often fall short in addressing these challenges, emerging AI-powered technologies present promising solutions for providing real-time feedback and adaptive explanations to bridge these persistent learning gaps (Wink et al., 2023).

The recent collaboration between Meta and Ray-Ban has produced sophisticated AI-powered smart glasses that could transform this educational landscape (Meta, 2023). These glasses represent a significant advancement in educational technology, offering hands-free interaction with digital content through various sensors that enable immersive learning experiences (Strzys et al., 2019; Fesol et al., 2022). Powered by the Llama2 AI model, they facilitate real-time, human-like interactions in an everyday wearable form. While traditional AI systems excel at solving well-defined problems, they often create barriers in dynamic learning environments through their reliance on text input, file uploads, or structured screen-based interactions (Kortemeyer, 2024). The Ray-Ban Meta Smart Glasses overcome these limitations by enabling hands-free, natural interaction with AI assistance.

To leverage these capabilities, our study implements an approach where instructors display physics problems on desktop screens for consistency, while utilizing the smart glasses for hands-free, real-time AI interaction. Unlike conventional AI tools that interrupt learning flow through manual device manipulation, these glasses enable seamless engagement with AI-driven support. This integration makes them particularly valuable in laboratory environments, and work involving paper-based exercises or physical setups, where context-aware, hands-free

assistance naturally complements active learning strategies (Schreiber et al., 2024). Given these advantages, it becomes essential to investigate the following research questions:

- How well does the AI model behind the smart glasses solve and explain physics problems related to motion, forces, and energy in terms of accuracy, problem-solving ability, explanation quality, and user interaction?
- What are instructors' perceptions of interaction quality and their overall experience using these smart glasses for physics problem-solving, particularly regarding support for user experience and instructional effectiveness?

2. Theoretical Framework

2.1. Challenges in Physics Education

Physics education faces persistent challenges, particularly in conveying abstract concepts such as motion, forces, and energy conservation. Many students struggle to relate these principles to real-world experiences, leading to fragmented understanding and reliance on rote memorization. A common misconception in projectile motion is the belief that a constant force is required to sustain horizontal movement, disregarding the independence of horizontal and vertical motions (Trowbridge et al., 1981; Thornton et al., 1998). Similarly, students often assume that a projectile's speed remains unchanged after launch, failing to account for gravity's continuous influence on vertical motion (Dilber et al., 2009).

Misconceptions about forces are equally prevalent among physics learners. Many students perceive forces as inherent properties of objects rather than interactions between them, complicating their understanding of fundamental concepts such as Newton's Third Law, which states that every action has an equal and opposite reaction (Hestenes et al., 1992). For instance, students frequently misunderstand tension, equilibrium, and force decomposition, particularly when dealing with angled forces, often believing that an object at rest does not experience forces or that stationary objects cannot have balanced forces acting on them (Wells et al., 2020). These misconceptions persist partly due to traditional instructional methods, which tend to emphasize procedural problem-solving at the expense of deeper conceptual comprehension. Consequently, physics education researchers are actively exploring technology-enhanced learning approaches, including artificial intelligence (AI), to address these conceptual difficulties. AI, particularly when integrated into real-time interactive tools, can dynamically detect and respond to student misconceptions, providing targeted, personalized interventions that promote deeper understanding rather than superficial memorization (Williamson et al., 2024). Such AI-driven approaches offer the promise of bridging persistent learning gaps by enabling adaptive, context-sensitive instruction tailored to students' specific misconceptions.

2.2. AI in Physics Education

Artificial intelligence (AI) has emerged as a transformative tool in physics education, offering innovative solutions to address conceptual difficulties. AI-driven applications, including intelligent tutoring systems, adaptive learning platforms, and natural language processing (NLP) tools, provide personalized instruction and real-time feedback, enhancing students' engagement and understanding (Verawati et al., 2024). AI-powered simulations enable learners to visualize complex physics phenomena, bridging the gap between theoretical concepts and tangible real-world applications (Yeadon et al., 2023).

Large language models (LLMs) such as ChatGPT have demonstrated potential in assisting students by diagnosing misconceptions, guiding problem-solving, and prompting reflective thinking (West, 2023). These AI-driven platforms analyze students' responses, detect error patterns, and offer personalized interventions to support conceptual development (Verawati et al., 2024). AI-assisted learning environments also promote active engagement through interactive dialogue, automated feedback, and Socratic questioning, which encourages students to think critically rather than passively absorb information (Yeadon et al., 2023). Among the various AI-driven tools, wearable AI technology—such as Meta Smart Glasses—has the potential to provide a hands-free, interactive learning experience, making physics concepts more accessible and engaging (Kuhn et al., 2016). The following section explores how Meta Smart Glasses serve as AI-powered learning assistants in physics education.

2.3. Meta Smart Glasses as AI-Powered Learning Assistants in Physics Education

2.3.1. Features and Capabilities

As AI continues to evolve in educational settings, wearable AI devices such as Ray-Ban Meta Smart Glasses, powered by the Llama 2 AI model, introduce a novel AI-assisted learning approach in physics education. Unlike Augmented Reality (AR) glasses, which overlay digital content onto the real world, these smart glasses serve as an AI-powered voice-interactive tool that allows users to capture images, engage in hands-free AI interaction, and receive audio-based feedback on various tasks (Meta, 2023), including physics problem-solving and explanations. Equipped with built-in cameras, microphones, and AI processing, these glasses enable voice commands, real-time data retrieval, and multimodal AI interaction, enhancing both accessibility and engagement in learning.

2.3.2. Meta View Application and Educational Benefits

These glasses enable users to document physics problems via image capture and engage in AI-assisted dialogue for explanations and problem-solving strategies. The AI model behind the smart glasses leverages speech recognition and natural language processing (NLP) to interpret spoken inquiries, extract relevant physics concepts, and generate explanations. NLP allows the system to process and understand human language in real-time, enabling seamless voice-based interactions that enhance learning experiences (Chowdhary et al., 2020).

A key feature that enhances the educational potential of Meta Smart Glasses is the Meta View application (Meta, 2023), which automatically records all AI-generated responses and user interactions. By enabling learners to revisit AI-generated explanations and problem-solving steps, this feature supports reflective learning and long-term retention. Research has shown that reflection-based learning strengthens conceptual understanding by helping learners identify knowledge gaps and reinforce key physics principles (Naik et al., 2024). Additionally, Meta View supports scaffolded learning by offering structured AI interaction reviews, gradually guiding students toward independent problem-solving (Zhu et al., 2024).

2.3.3. AI Capabilities and Pedagogical Implications

Meta Smart Glasses leverage Llama 2's AI capabilities to deliver real-time, personalized feedback grounded in constructivist learning theory, operating within the Zone of Proximal Development (ZPD) (Chaiklin, 2003; Ferguson et al., 2023). By adjusting hints, cues, and follow-up questions, the system can help learners identify gaps in their understanding, thus supporting “productive struggle” rather than rote memorization (Shamshin et al., 2024). This support adjusts to student competence levels, fostering gradual development of independent problem-solving skills.

Research suggests that AI-based tutoring tools can act as dynamic scaffolds within ZPD by adapting difficulty levels and prompting learners to refine their reasoning through interactive questioning. This active learning approach encourages learners to engage deeply with physics concepts rather than passively receive answers (Cai et al., 2024).

The AI system functions as an intelligent scaffolding tool within the ZPD framework, offering structured guidance through physics concepts (Ferguson et al., 2023). For example, when addressing Newton's Third Law misconceptions, the AI provides conceptual prompts, real-world analogies, and systematic solution approaches, maintaining active student engagement throughout the learning process.

However, caution is warranted: if prompts or answers are incorrect or incomplete, the AI might inadvertently reinforce misconceptions. Reliance on speech or image recognition also poses reliability issues (Kotsis, 2024), requiring careful instructor oversight to ensure accurate interpretation of domain-specific terms (e.g., tension vs. friction).

The AI behind the smart glasses relies on three key recognition capabilities: text recognition via Optical Character Recognition (OCR), speech-to-text processing for verbal inputs, and image-based problem identification (Meta, 2023). While OCR facilitates text conversion, its accuracy depends on lighting conditions and font clarity, which can introduce errors in problem interpretation. Similarly, the AI's speech recognition may struggle with domain-specific physics terminology, leading to inconsistencies in response accuracy (Bulathwela et al., 2024).

The glasses facilitate active learning through image capture and AI-assisted dialogue, using speech recognition and NLP to process inquiries and generate real-time explanations. This voice-interactive approach enhances conceptual

understanding by enabling students to articulate their reasoning and engage in guided problem-solving discussions (Alsaadi et al., 2025). Research demonstrates that such voice-based AI tutoring improves learning outcomes by promoting verbal reasoning and reflective thinking, ultimately supporting deeper engagement in physics education. Nevertheless, direct measurement of improved conceptual gains would require extended classroom trials with robust pre-post assessment designs—beyond the scope of this study. Despite these challenges, the interactive nature of AI-assisted learning environments continues to evolve, offering promising solutions to bridge conceptual gaps in physics education.

2.3.4. Technological Advancement

Meta Smart Glasses represent a significant advancement in technology-enhanced learning (TEL). Unlike earlier wearable devices, such as Google Glass, which primarily focused on AR visualization rather than AI-driven tutoring, Meta Smart Glasses integrate speech recognition, multimodal AI processing, and conversational feedback, offering a more interactive and accessible educational experience (Waisberg et al., 2023).

This combination of hands-free AI interaction, adaptive feedback, and recorded AI-student interactions through Meta View establishes Meta Smart Glasses as a promising AI-driven tool in physics education. While they do not provide AR-based visualization, their real-time, conversational AI assistant offers a practical solution for addressing physics misconceptions, reinforcing problem-solving strategies, and fostering deeper cognitive engagement in STEM learning.

2.4. Challenges and Limitations of Meta Smart Glasses

The integration of smart glasses in education faces challenges such as limited battery life, processing speed, and reliance on stable internet connectivity, which restrict their usability in extended or offline scenarios (Iqbal et al., 2022). The high cost of smart glasses remains a significant barrier to adoption, particularly in resource-limited settings (Waisberg et al., 2023). Additionally, effective deployment requires sufficient training for both students and educators, as the need for onboarding and adaptation to new technologies is critical (Iqbal et al., 2022).

Despite these concerns, wearable AI devices still present unique educational opportunities. By offering dynamic, context-aware feedback and supporting domain-specific datasets, they can enrich student inquiry in real-world environments. While further empirical research is necessary to evaluate long-term educational impacts, the potential of AI-powered wearable devices like Meta Smart Glasses to transform physics education remains an exciting avenue for future exploration and pedagogical innovation. Given these educational challenges and theoretical foundations, we designed a structured methodological approach specifically to evaluate the Meta Smart Glasses' capability in solving physics problems and detecting misconceptions in real-time.

3. Methods

We conducted a three-month study explicitly designed to evaluate the problem-solving accuracy, explanatory clarity, and misconception-handling abilities of the AI integrated into Meta Ray-Ban Smart Glasses. Specifically, we assessed the AI's capability to recognize, analyze, solve, and clearly explain physics problems commonly encountered in upper-level high school curricula. Rather than directly evaluating student interactions, the study leveraged the expertise of physics educators to objectively assess the technological and instructional value of these glasses. Fifteen experienced high school physics instructors participated independently in this evaluation. Each instructor selected one of three carefully chosen physics problems—projectile motion, equilibrium involving forces at angles, or energy conservation—based on their individual expertise and instructional preferences. These specific topics were intentionally chosen due to their known association with persistent student misconceptions (Hestenes et al., 1992; Thornton & Sokoloff, 1998). Allowing instructors to select problems based on preference aimed at maximizing evaluation depth, accuracy, and relevance, thereby enhancing the reliability and validity of the findings.

The evaluation process consisted of four distinct yet interconnected phases, explicitly addressing our primary research objectives:

- **Phase 1 (Brainstorming & Survey Design):**
Ten instructors collaboratively participated in structured brainstorming sessions to develop a comprehensive evaluation framework, specific assessment criteria, and a structured survey explicitly aligned with our research objectives regarding AI accuracy, explanatory depth, and user experience.

- **Phase 2 (Testing AI Performance on Physics Exercises):**
Each instructor independently evaluated their preferred physics problem using smart glasses, specifically assessing the AI's real-time problem-solving abilities, accuracy, and explanatory quality.
- **Phase 3 (Data Extraction & Annotation):**
AI-generated responses from each instructor's selected problem were systematically documented, reviewed, and annotated, enabling structured evaluations based on criteria developed in Phase 1.
- **Phase 4 (Evaluation & Survey):**
Instructors completed detailed assessments through the structured survey developed in Phase 1, rating the AI's accuracy, explanatory capabilities, misconception handling, and overall usability based on their individually selected problem.

3.1. Participant demographics

Fifteen experienced high school physics instructors participated in this study. Their demographic and professional backgrounds are as follows:

- Mean Age: 38.7 years (SD = 4.2)
- Gender Distribution: 9 male, 6 female
- Teaching Experience: 12.3 years on average (SD = 3.5)
- Teaching Level: All instructors teach high school (grades 10–12)

These instructors were selected for their expertise in physics instruction, ensuring an informed evaluation of the AI's ability to solve problems, detect misconceptions, and provide meaningful explanations.

3.2. Phase 1: Brainstorming and survey design

In the initial phase, 10 of the 15 instructors participated in three structured brainstorming sessions (2.5 hours each) to develop an evaluation framework. These sessions shaped a survey instrument assessing four key domains of the glasses' AI performance:

1. **Content Accuracy:** Correct classification of problems, identification of relevant variables, and resolution of misconceptions.
2. **Problem-Solving Ability:** Effectiveness of AI in guiding logical steps toward solutions.
3. **Explanation Quality:** Depth and clarity of AI-generated explanations, including additional learning prompts (e.g., quizzes).
4. **User Interaction and Experience:** Intuitiveness, accessibility, and overall usability of AI-based assistance.

These domains were used to structure a standardized survey for evaluating the AI's responses. The image below, "**Figure 1: Survey Design with Criteria for Evaluation**" illustrates the survey design questions and criteria for the 3 exercises.

Question	Motion	Forces	Energy conservation
Problem Classification Accuracy: Did the glasses correctly classify the type of physics problem (e.g., motion, forces, energy conservation)?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Key Variable Identification: Did the glasses identify all relevant variables (e.g., initial speed, angle, tension) necessary for solving the problem and ability to interpret the diagram?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Formula Application: Were the appropriate physics formulas applied correctly?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Misconception Detection: Did the glasses identify and address any potential misconceptions related to the problem?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Error-Detection Capability: Were incorrect answers or missteps flagged for review?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Step-by-Step Guidance: Did the glasses provide logical, step-by-step guidance throughout the problem?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Problem-Solving Strategies: Did the glasses use appropriate strategies (e.g., kinematics, energy conservation) for solving different types of problems?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Clarity of Explanation: Were explanations clear and easy to follow?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Relevance to the Problem: Was the explanation directly related to the problem being solved?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Depth of Explanation: Did the glasses provide in-depth explanations (including underlying physics concepts) when necessary?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Real-Time Feedback: Did the glasses provide feedback in real-time, enhancing engagement and learning, particularly in situations requiring clarification?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾
Satisfaction with Hands-Free Interaction: Did the hands-free functionality enhance the learning experience?	--Select One-- ▾	--Select One-- ▾	--Select One-- ▾

Figure 1: Survey Design with Criteria for Evaluation

3.3. Phase 2: Testing the glasses with Physics Exercises

3.3.1. Exercises and Approaches

In the second phase, 15 instructors (including five who had participated in Phase 1) were divided into three distinct groups of five members each, with each group evaluating AI performance on one of three upper-level high school physics problems. The following Table “*Table 1: Approaches and strategies used*” summarizes the core problem for each exercise along with the primary strategies instructors would typically employ by instructors.

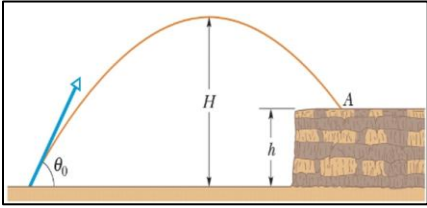
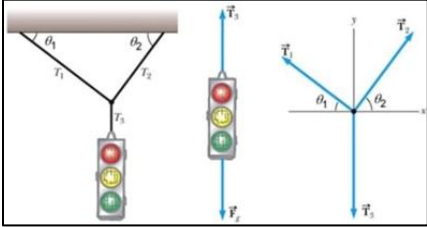
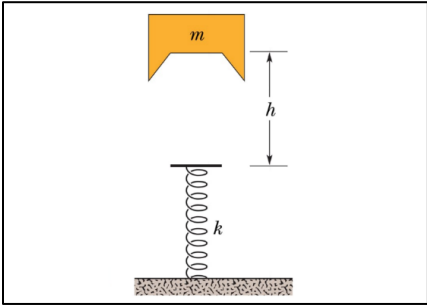
Exercise	Statement	Strategies
Cliff Projectile Motion  <i>(See Annex A for the full exercise)</i>	The problem involves a stone launched at 42.0 m/s at an angle of 60° above the horizontal, striking a cliff 5.50 seconds later. Determine the height of the cliff, the stone's impact speed, its maximum height, and whether its speed remains constant during flight.	kinematic equations to find height, final speed, and maximum height, while analyzing speed variations during flight.
Traffic Light Tension  <i>(See Annex B for the full exercise)</i>	The problem involves a 122 N traffic light suspended by three cables, with the upper cables forming angles of 39° and 51° with the horizontal. Determine whether the tensions in the upper cables exceed their 130 N limit, potentially causing them to break.	trigonometric functions and equilibrium equations to calculate the tensions in the cables and determine if any exceed the 130N limit.
Spring Compression by Dropped Mass  <i>(See Annex C for the full exercise)</i>	The problem involves a 2.0 kg block falling from a height of 40 cm onto a spring with a spring constant of 1960 N/m. Determine the maximum compression of the spring when the block comes to rest.	conservation of mechanical energy to relate gravitational potential energy to determining the maximum compression of the spring.

Table 1: Approaches and strategies used

These specific physics exercises are Cliff Projectile Motion, Traffic Light Tension, and Spring Compression by Dropped Mass were intentionally selected due to their documented prevalence as sources of persistent student misconceptions (Trowbridge et al., 1980; Hestenes et al., 1992).

3.3.2. Standardized Interaction and dual role of Meta Ray-Ban Smart Glasses

To start the interaction, instructors wore Meta Ray-Ban Smart Glasses and displayed the assigned physics exercise on a computer, tablet, or any screen that the glasses could capture. They initiated the conversation by saying “Hi Meta” or “Hey Meta,” followed by the command “take a look,” which prompted the glasses to capture and interpret the problem through its image recognition system. After processing the image, instructors used additional commands - such as “analyze,” “explain,” or “solve,”—to request further AI feedback (*see Figure 2 for the standardized prompt sequence*).

The use of smart glasses was chosen to assess hands-free, real-time AI assistance, simulating real-world physics applications where instructors or students might analyze lab setups or handwritten problems without needing manual input.

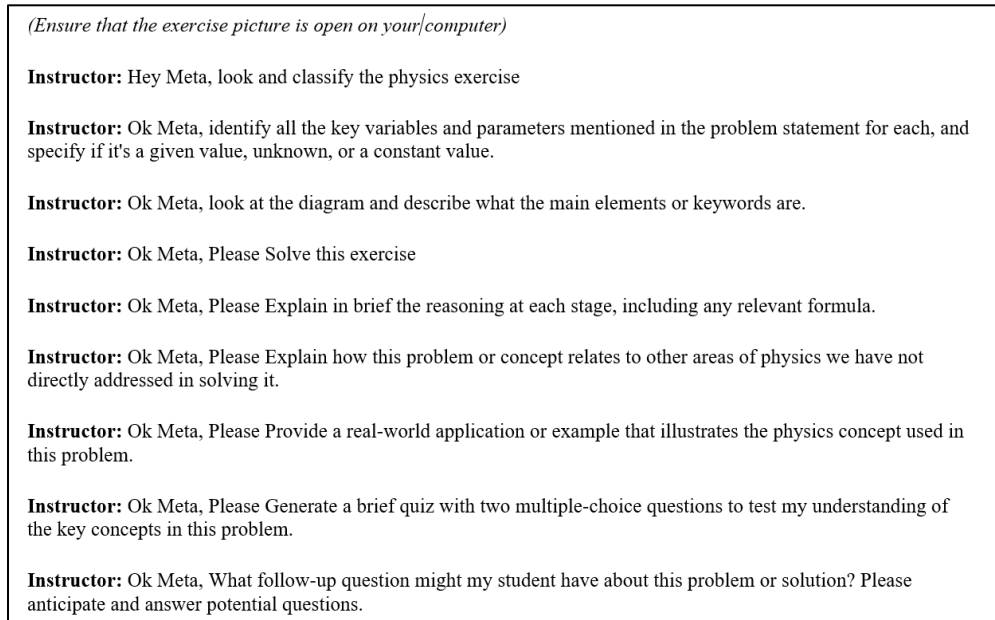


Figure 2: Common Prompt instructed to Meta Smart Glasses

During interactions, the glasses fulfilled two distinct roles:

- **Student Role** → "AI Learner" - When the AI acts as a student, solving physics problems and providing step-by-step solutions.
- **Instructor Role** → "AI Tutor" - When the AI takes on a teaching role, posing questions, testing understanding, and guiding deeper reflection.

This distinction aligns with the AI functioning as both a problem solver (as a "student") and an explainer guide (as an "instructor").

3.4. Phase 3: Data Extraction and Annotation

To ensure proper documentation, instructors manually captured screenshots of the conversations, as the system does not have a direct export feature for text-based interactions. Each captured image was processed using Optical Character Recognition (OCR) to extract text. For each trial, instructors compiled a document containing AI-generated responses and annotated them based on predefined evaluation criteria. These annotations provided a structured basis for assessing AI performance using the survey developed in Phase 1. A compiled Word document includes detailed annotations and corresponding images of each exercise, all of which are accessible through the GitHub repository.

https://github.com/rabihkahaleh/Dialogue_Instructor_Meta_With_Annotation/

3.5. Phase 4: Survey Evaluation

After each session, once instructors had completed their assigned exercise with the Meta Smart Glasses, extracted data, and performed annotations, they filled out a one-time web-based evaluation survey to assess the glasses' performance. The survey focused on four main criteria:

- Content Accuracy
- Problem-Solving Ability
- Explanation Quality and Teaching
- User Interaction and Experience

Instructors rated each criterion on a 5-point scale from 0 (Very Poor) to 4 (Excellent). For clarity, this scale was further segmented and color-coded:

- 0–1 (red): Low performance
- 1–2 (orange): Moderately low
- 2–3 (yellow): Moderate/neutral
- 3–4 (green): Good to excellent

The middle point (2) represented a neutral evaluation, whereas 0 and 4 marked the extremes of performance.

4. Results

This section presents the performance of the Meta Smart Glasses on three physics exercises - Projectile Motion, Traffic Light Tension, and Conservation of Energy - as evaluated by five instructors per exercise. In line with the methods described in Section 3.5, each instructor used the 0–4 scale (0 = Very Poor, 4 = Excellent) to quantify the glasses' performance across four criteria.

- Content Accuracy
- Problem-Solving Ability
- Explanation Quality
- User Interaction

The following subsections provide numerical ratings, highlighting overall strengths and areas for improvement.

4.1. Summary of Results

The evaluation results are summarized in Figure 6, categorizing the AI's performance using a color-coded rating system for clarity:

- Red (0–1): Low performance
- Orange (1–2): Moderately low performance
- Yellow (2–3): Neutral to moderate performance
- Green (3–4): Good to excellent performance

Findings indicate strong performance (green) in classifying problems and providing real-time feedback, moderate performance (yellow) in identifying key variables and structuring problem-solving strategies, and lower effectiveness (orange to red) in formula application and handling complex scenarios, particularly in the Traffic Light Tension problem.

Among the three exercises:

- Conservation of Energy received the highest instructor ratings, especially in concept classification (2.8 ± 0.45) and explanations of energy transformations (2.6 ± 0.55), indicating robust AI performance in clearly articulating fundamental energy concepts.

- Projectile Motion demonstrated moderate AI performance, scoring notably well in equation application (2.6 ± 0.55) but showing inconsistencies in reasoning clarity and depth of explanations (1.8 ± 0.84). These results suggest strengths in computational accuracy but challenges with consistently clear conceptual reasoning.
- Traffic Light Tension exhibited significant weaknesses, especially in formula application (0.4 ± 0.55) and explanatory depth (1.2 ± 0.45), reflecting substantial difficulties in handling multi-step equilibrium problems involving simultaneous vector forces.

It is important to note that each set of five instructors evaluated only one of the three tasks, which means the results for the tasks are not directly comparable. Different instructors bring varied assessment styles, which can produce large rating differences. Additionally, no single task received uniformly high ratings from all five instructors, indicating that the AI's performance remains inconsistent across multiple users.

		Projectile Motion Problem (n=5)	Traffic Light Problem (n=5)	Conservative Energy Problem (n=5)
Content Accuracy	Problem Classification Accuracy	3.4 ± 0.55	2.0 ± 0.71	3.6 ± 0.55
	Key Variable Identification	3.4 ± 0.55	2.4 ± 0.55	3.4 ± 0.55
	Formula Application	1.6 ± 0.55	0.4 ± 0.55	2.6 ± 0.55
	Misconception Detection	2.2 ± 0.84	1.2 ± 0.84	2.8 ± 0.45
	Error-Detection Capability	2.6 ± 0.55	1.4 ± 0.55	2.2 ± 0.45
Problem Solving	Step-by-Step Guidance	2.4 ± 0.55	1.4 ± 0.55	2.8 ± 0.45
	Problem-Solving Strategies	2.4 ± 0.55	1.4 ± 0.55	2.8 ± 0.45
Explanation	Clarity of Explanation	2.6 ± 0.55	1.6 ± 0.55	2.8 ± 0.45
	Relevance to the Problem	3.0 ± 0.00	2.0 ± 0.00	3.4 ± 0.55
	Depth of Explanation	2.6 ± 0.55	1.4 ± 0.55	2.4 ± 0.55
	Handling of Complex Scenarios	1.4 ± 0.55	0.4 ± 0.55	2.0 ± 0.00
User Interaction	Real-Time Feedback	3.4 ± 0.55	2.4 ± 0.55	3.8 ± 0.45
	Satisfaction with Hands-Free Interaction	2.6 ± 0.55	1.6 ± 0.55	3.2 ± 0.45

Figure 6: A Summary for the Results across the Three Exercises with Mean and Standard Deviation

As illustrated in Table X, overall performance varies considerably across the three exercises and evaluation criteria. The Traffic Light problem exhibits the lowest scores for formula application (0.4 ± 0.55) and problem-solving strategies (1.4 ± 0.55), reflecting the AI's difficulty with multi-step tension analysis. Meanwhile, the Conservation of Energy task reports higher averages, such as 3.6 ± 0.55 for content accuracy and 3.8 ± 0.45 for real-time feedback, indicating that the AI can perform competently under certain conditions. Projectile Motion falls in a mid-range but still shows moderate shortcomings in formula application (1.6 ± 0.55). Notably, the standard deviations suggest inconsistent reliability across different instructors—some encountered significant errors, while others saw relatively strong performance. Given these mixed outcomes, it is premature to deploy the system widely in classrooms. However, continued improvements in the AI model, such as enhanced error detection and refined multi-step reasoning, could unlock the glasses' potential as a promising hands-free learning tool once the underlying issues are resolved or mitigated through future updates.

4.2. Detailed Analysis of Meta's Performance and Rating

The following sections outline the criteria for each exercise, highlighting responses rated as low (0 to 1) and high (3 to 4). Each section includes instructional annotations and justifications provided by instructors, organized into three groups of five: Instructor 1 through Instructor 5, Instructor 6 through Instructor 10, and Instructor 11 through instructor 15. These groupings reduced each individual's workload but further restricted cross-exercise comparability. However, they offer valuable insights into how the AI performed across different instructor expectations.

4.2.1. Exercise 1 - Projectile Motion

“Table 2” presents selected annotations from instructors across various files, reflecting Meta’s performance in solving a Projectile Motion exercise. The table highlights gaps in low-rated responses—such as misapplied formulas and misunderstood queries—while showcasing high-rated strengths, such as accurate classification of the problem type, proper equation selection, and concise explanations.

Criteria	Context	Low-Rated Response (~0-1)	High-Rated Response (~3-4)
Content Accuracy	Calculating cliff height	Instructor (2) Annotation: Even though the formula for range is correct, it has nothing to do with finding the vertical height of the cliff. Vertical distance is never equal to the horizontal distance. Instructor (2) Justification: Incorrectly uses the range equation $R = \frac{v_0^2 \sin(2\theta)}{g}$ to calculate the height of the cliff, leading to a fundamental misunderstanding of the vertical motion aspect.	Instructor (5) Annotation: Meta correctly identified the problem and mentioned the key equations for solving it. Instructor (5) Justification: The response correctly classifies the projectile motion scenario, identifies all parameters (including time of flight), and relates height calculation to vertical motion using correct kinematic equations.
Problem-Solving Abilities	Time to reach the cliff	Instructor (1) Annotation: Solution should not be divided into two parts (up and down). It should be solved in one step using $\Delta h = -\frac{1}{2}gt^2 + v_0 \sin \theta \cdot t$ Instructor (1) Justification: Breaks the problem into irrelevant parts, such as dividing up and down motion unnecessarily. Incorrectly calculates height by neglecting given time data.	Instructor (3) Annotation: Correct use of equations; a thoughtful application of concepts. Instructor (3) Justification: Uses vertical motion equations with time and initial velocity to find height and calculates speed just before impact using appropriate methods.
Explanation Quality	User asked for a relevant formula	Instructor (4) Annotation: The question was understood wrong; user likely asked for 'a relevant formula,' but Meta interpreted it as 'irrelevant formula'. Instructor (4) Justification: Provides incorrect reasoning and uses irrelevant formulas (e.g., volume of a sphere) due to misinterpreting the user’s request for a “relevant formula.”	Instructor (5) Annotation: Meta provided clear and concise reasoning for solving the problem. Instructor (5) Justification: Accurately explains each step with relevant formulas and reasoning for calculating height and final speed.
User Interaction	Response to a quiz question about vertical velocity	Instructor (2) Annotation: Meta incorrectly stated the vertical velocity	Instructor (5) Annotation: Meta anticipated useful follow-up questions and gave thoughtful answers relevant to

		'remains constant' at maximum height, which is false. Instructor (2) Justification: Fails to correctly address the user's answers to a quiz and provides inaccurate validation.	advanced discussions of projectile motion. Instructor (5) Justification: Anticipates student questions, providing thoughtful answers and meaningful insights into related real-world applications.
--	--	---	--

Table 2: Evaluation Criteria and Performance for Projectile Motion

4.2.2. Exercise 2 - Traffic Light Problem

“Table 3” presents selected annotations from instructors across various files, reflecting Meta’s performance on the Traffic Light problem. It highlights low-rated responses—such as incorrect tension assumptions and incomplete equilibrium reasoning—and high-rated responses demonstrating accurate classification, methodical force analysis, and real-world connections that enhance relevance.

Criteria	Context	Low-Rated Response (~0-1)	High-Rated Response (~3-4)
Content Accuracy	Classifying forces in a static system	Instructor (6) Annotation: The instructor's feedback indicates that while the AI correctly interpreted the scenario as a real-life situation, it failed to explicitly connect the problem to Newton’s First Law, which explains that the traffic light remains stationary due to the balance of forces. Instructor (6) Justification: Misclassified the physics context, failing to associate the scenario with Newton's first law.	Instructor (9) Annotation: Meta correctly identified this as a problem involving forces, tension, and equilibrium. Instructor (9) Justification: Accurately categorized the exercise and linked it to Newton's laws of motion.
Problem-Solving Abilities	Calculating cable tensions	Instructor (7) Annotation: It failed to solve it. Not all information is identified, only weight. Instructor (7) Justification: Meta identified key forces but failed to address critical constraints, such as summation of forces along the x-axis.	Instructor (10) Annotation: Excellent explanation but no execution so no result. Instructor (10) Justification: Provided a clear and structured method for solving cable tensions, including detailed force balance equations, but did not complete the calculations.
Explanation Quality	Reasoning for solving tensions	Instructor (7) Annotation: It didn’t solve and didn’t mention anything about Newton's first law. Instructor (7) Justification: Offered incomplete reasoning and ignored fundamental concepts like Newton’s first law.	Instructor (10) Annotation: Correct but no execution so no result. Instructor (10) Justification: Provided a concise and accurate explanation of solving tensions, using Newton's laws and trigonometry.
User Interaction	Real-world application quiz	Instructor (6) Annotation: Previously, Meta answered weight as the primary force. The term ' <i>primary force</i> ' is not logical. Instructor (6) Justification: Failed to define ' <i>primary force</i> ' in the quiz, leading to vague and potentially misleading user feedback.	Instructor (9) Annotation: Meta provided thoughtful follow-up questions and answered potential queries effectively. Instructor (9) Justification: Anticipated meaningful student questions and clarified the relationship between tension and stability in suspended systems.

Table 3: Evaluation Criteria and Performance for Traffic Light

4.2.3. Exercise 3 - Conservative Energy Problem

“Table 4” presents selected annotations from instructors across various evaluations, reflecting Meta's performance in solving a Spring Compression problem. The table highlights gaps in low-rated responses, such as vague explanations of energy transitions and incomplete connections to broader physics concepts. High-rated responses demonstrate strengths in accurate problem categorization, clear explanation of conservation principles, and meaningful real-world applications that enhance understanding.

Criteria	Context	Low-Rated Response (~0-1)	High-Rated Response (~3-4)
Content Accuracy	Classifying spring compression problem	Instructor (12) Annotation: Meta's response identifies the scenario but lacks a deeper connection to energy conservation principles. Instructor (12) Justification: The response classifies the problem but misses emphasizing the underlying physics concept of energy conservation.	Instructor (13) Annotation: Meta correctly classified the problem and noted how gravitational potential energy converts to elastic potential energy. Instructor (13) Justification: Links problem classification to the core physics concepts for better clarity.
Problem-Solving Abilities	Explaining energy transitions	Instructor (11) Annotation: Meta's explanation is concise but lacks clarity on energy transition between gravitational and elastic potential energy. Instructor (11) Justification: Offered basic reasoning but failed to provide deeper insights into the energy transformation process.	Instructor (14) Annotation: Meta provides a detailed breakdown using conservation of energy and Hooke's Law. Instructor (11) Justification: Accurately applies formulas and explains how energies transition step by step.
Explanation Quality	Connecting concepts to SHM	Instructor (12) Annotation: Meta connects to Simple Harmonic Motion but lacks an example of oscillatory energy transition. Instructor (11) Justification: Fails to elaborate on how the problem relates to oscillations and energy dynamics.	Instructor (15) Annotation: Meta provides a strong link to SHM and energy oscillations with clear examples. Instructor (11) Justification: Effectively relates spring compression to oscillatory behavior and energy principles.
User Interaction	Quiz and follow-up questions	Instructor (11) Annotation / Instructor (3) annotation: Meta's quiz questions are relevant but lack depth, focusing only on formula-based understanding, and sometimes deliver incorrect answers. Instructor (11) / Instructor (3) Justification: The questions assess understanding but miss exploring deeper conceptual aspects like energy transformations.	Instructor (14) Annotation: Meta anticipates follow-up questions about varying parameters like mass or spring constant. Instructor (14) Justification: Encourages critical thinking and connects theoretical concepts to real-world scenarios effectively.

Table 4: Evaluation Criteria and Performance for Conservative Energy

5. Discussion

5.1. Summary of Key Findings

The integration of wearable AI technology, specifically the Ray-Ban Meta Smart Glasses, shows promising potential for enhancing physics education. This study demonstrated that the glasses excel in simpler tasks such as problem classification and key variable identification corresponding (3.4) for Projectile Motion and (3.6) for Conservation of Energy. However, the glasses struggled with context-dependent or multi-variable scenarios, particularly the Traffic Light Tension problem, where classification accuracy dropped to (2.0) and formula application sank to (0.4) (Table 3). These findings underscore the need to enhance the AI model's ability to manage complex relationships among multiple variables and to provide clearer, and step-by-step reasoning.

Overall, the results confirm that while the glasses can operate in both “solver” and “instructor” modes, their true educational value depends on thoughtful integration into teaching. Students might otherwise bypass deeper cognitive engagement if the AI simply delivers final answers, which is contrary to constructivist learning principles (Guo et al., 2024).

5.2. Pedagogical Integration

Based on these performance patterns, a major theme that emerged concerns the effective integration of AI into the instructional process. Over-reliance on automatically provided solutions risks diminished mental effort, which contradicts the principles of active, constructivist learning (Guo et al., 2024). According to Vygotsky's zone of proximal development (ZPD) framework, scaffolding should be "just enough" to help learners advance while preserving their productive struggle.

To optimize learning outcomes, instructors can incorporate Socratic questioning techniques when using AI. For instance, instead of allowing students to receive direct numerical solutions, instructors could prompt them with guiding questions such as "What forces act on this object?" or "How does the velocity change over time?" Such interactions encourage students to articulate their reasoning and apply fundamental physics concepts, reinforcing conceptual understanding.

The results of our study provide further guidance on how to practically integrate these AI-powered smart glasses. Given the AI's strong performance in concept classification (2.8 ± 0.45) and explanations of energy transformations (2.6 ± 0.55) within Conservation of Energy problems, instructors could confidently employ the glasses to reinforce fundamental concepts and support initial conceptual understanding. Similarly, the AI's moderate but notable strength in equation application for Projectile Motion (2.6 ± 0.55) suggests their use as an effective support tool for computational tasks.

However, the identified inconsistencies, especially concerning reasoning clarity (1.8 ± 0.84 for Projectile Motion) and significant weaknesses in multi-step equilibrium problem-solving (formula application rating of 0.4 ± 0.55 for Traffic Light Tension), highlight critical areas requiring instructor oversight. Instructors are encouraged to cautiously supplement AI-generated explanations with additional guided questions and targeted scaffolding when addressing these more complex topics. For example, instructors can explicitly guide students through multi-step reasoning processes, prompting reflection on each step to maintain active engagement and deeper cognitive processing.

Research on adaptive tutoring systems reinforces this balanced approach, indicating AI is most effective when complemented by teacher oversight, thus ensuring students meaningfully engage in problem-solving rather than passively receiving answers (Williamson et al., 2024). Ultimately, using AI as a support tool rather than a replacement for critical thinking ensures its effective and responsible application within physics education contexts.

5.3. Technical & Explanatory Improvements

Although the AI performed well in certain areas, its limitations in error detection and multi-step reasoning remain evident. The Traffic Light Tension problem, for instance, revealed weaknesses in managing simultaneous force calculations and equilibrium conditions. Several changes could address these shortcomings:

- **Confidence-Based Feedback:** The AI model could display a confidence score (e.g., “80% certainty”) and prompt students to review specific steps when confidence levels are low.
- **Multi-Step Verification:** The AI model could implement symbolic vs. numerical validation to cross-check responses for internal consistency.
- **Real-Time Formula Library:** Integrating an automated physics formula database could help verify calculations and prevent incorrect assumptions.

Explanation quality also varied significantly across exercises. While Projectile Motion and Conservation of Energy received moderate to high clarity ratings (2.6–2.8), the Traffic Light Tension explanations lagged at 1.6. Future research should investigate how varied instructional prompts influence the AI’s ability to provide deeper and more conceptually rich explanations.

From a cognitive load perspective, wearable AI reduces the mental effort required to switch between a problem-solving task and an external computational device. Desktop-based AI, though effective in structured learning environments, requires users to manually input text or navigate interfaces, introducing cognitive overhead. Wearable AI, by contrast, allows for seamless, voice-driven interactions, ensuring students remain immersed in conceptual understanding rather than procedural distractions (Romine et al, 2020).

5.4. Broader AI Challenges & Ethical Considerations

Beyond the technical and pedagogical aspects, broader concerns about reliability and equitable access emerged in this study.

- **Reliability and Interpretation Variability:** Instructor ratings indicated variability in the AI’s interpretation of prompts, emphasizing a well-documented challenge in natural language processing that necessitates model enhancements tailored for domain-specific applications such as physics.
- **Digital Divide:** The cost of wearable AI tools may restrict access for many instructors and students, widening the gap in technology-enhanced learning opportunities.
- **AI Bias and Misconception Reinforcement:** If the AI fails to detect specific misconceptions or consistently validates incorrect reasoning, it could reinforce flawed mental models of physics.

To mitigate these risks, AI should be integrated with instructor oversight to ensure it supports student learning without replacing critical thinking. A hybrid approach, where instructors guide AI interactions and intervene, when necessary, can help balance these challenges while leveraging AI as an effective educational tool (Kim, 2024).

5.5. Study Limitations

This study acknowledges several limitations that impact the interpretation and generalizability of the findings. For clarity and transparency, these limitations are structured into four key categories:

Personal Limitations:

The evaluation involved 15 instructors divided into three groups, each assessing only one physics exercise. This design minimized individual workload but introduced variability due to differing assessment styles, perceptions, and expectations. Additionally, individual interpretations of AI responses may have influenced ratings, reflecting subjective biases inherent in qualitative evaluations. Instructors’ varying familiarity with AI and wearable technology may also have influenced the quality and depth of their evaluations, especially in how they interacted with and interpreted the device’s outputs.

Hardware Limitations:

The Meta Smart Glasses are dependent on hardware constraints, including limited battery life, processing power, and reliance on stable internet connectivity. These factors could have affected AI responsiveness and performance consistency during testing sessions. Furthermore, environmental conditions such as lighting impacted the accuracy of Optical Character Recognition (OCR), potentially leading to misinterpretation of problem statements.

Technical Limitations:

The AI exhibited challenges in handling multi-step reasoning, accurate speech recognition, and error detection. Speech recognition errors, particularly in noisy or variable acoustic environments, may have led to occasional misinterpretations of user prompts. Variability in AI responses also highlighted limitations in natural language processing, particularly with domain-specific terminology in physics. Additionally, the AI model employed was a general-purpose language model not specifically fine-tuned for physics education contexts. This lack of domain-specific optimization may have contributed to inconsistency in conceptual explanations and problem-solving accuracy. Given the rapid evolution of AI technologies, the evaluated model represents a snapshot in time. More advanced versions may already exist, potentially addressing some of the limitations identified in this study.

Environmental Limitations:

The study was conducted in a controlled setting, which does not fully replicate dynamic classroom environments or real-time instructional scenarios. Given the controlled context, it is unclear whether participants experienced AI functionality exactly as intended, especially considering individual variability in interaction styles, perceptions, and technological expectations. The absence of real-world classroom variability limits the applicability of findings to typical educational contexts. Future studies should replicate these conditions in authentic classroom settings to improve ecological validity and assess the effectiveness of wearable AI under more complex, distraction-rich environments.

By clearly outlining these limitations, this study aims to provide a transparent foundation for future research. Addressing these challenges—through larger, more diverse participant groups, real-time classroom implementations, and enhancements to both hardware and AI systems—will be critical in refining the role of wearable AI in physics education.

5.6. Future Classroom Implementation

While this study focused on expert instructor evaluations, the approach is to assess the impact of wearable AI on student learning. Future research should be investigated:

- **Student Conceptual Development:** Assessing learning progression and conceptual understanding through pre- and post-assessments, as well as validated conceptual inventory.
- **Learner Engagement Metrics:** Analyzing real-time student interactions to evaluate the impact of AI integration on motivation, cognitive engagement, and participatory learning behaviors.
- **Pedagogical Implementation in Classroom Settings:** Investigating the effectiveness of AI-powered smart glasses in laboratory environments and collaborative learning contexts, comparing their pedagogical affordances with traditional, screen-based AI tools.

Such studies will help clarify whether hands-free AI interaction offers distinct advantages in physics education, particularly in experimental and inquiry-based learning environments.

6. Conclusion

This study addressed two core research questions: firstly, assessing how effectively the AI embedded in Meta Smart Glasses solves and explains high-school physics problems related to motion, forces, and energy; and secondly, understanding instructor perceptions of interaction quality and instructional effectiveness of these glasses. The findings demonstrate strong capabilities in problem classification and conceptual feedback but highlight significant weaknesses in multi-step calculations and handling complex scenarios. Instructor evaluations revealed varied perceptions of usability, emphasizing the need for technical improvements and thoughtful pedagogical integration.

Several methodological limitations must be acknowledged. The small sample size ($n = 15$) and the division of instructors into three groups, each evaluating only one physics exercise, limit the generalizability of our findings. Additionally, substantial variability in instructor ratings suggests that the AI system's performance is inconsistent across different evaluators. While some instructors rated explanations as clear and relevant, others found them inadequate, particularly in complex scenarios. For instance, ratings for "Handling of Complex Scenarios" ranged from a low 0.4 (Traffic Light Problem) to 2.0 (Conservation of Energy), highlighting the AI's struggle with advanced problem structures. Furthermore, this study was conducted in a controlled setting where instructors, not students, tested the AI—meaning the direct impact on student learning remains unmeasured. Future studies should incorporate student interactions to assess conceptual understanding gains and validate real-world applications.

In terms of technological performance, the AI exhibited varying levels of accuracy across different physics problems. It performed well in classifying physics problems such as Projectile Motion (3.4 ± 0.55) and Conservation of Energy (3.6 ± 0.55). However, it struggled with more complex topics like the Traffic Light Tension problem, where classification accuracy dropped to 2.0 ± 0.71 , and formula application fell to 0.4 ± 0.55 . The AI also demonstrated inconsistent ability to detect errors, with ratings as low as 1.4 ± 0.55 in the Traffic Light Problem compared to 2.6 ± 0.55 in Projectile Motion. These findings suggest that while AI can effectively support basic conceptual instruction, its ability to handle multi-step problem-solving remains a challenge, requiring additional algorithmic refinement.

Instructor evaluations highlighted key pedagogical considerations. While the glasses provided real-time feedback and interactive engagement (scoring 3.4 ± 0.55 for Projectile Motion and 3.8 ± 0.45 for Conservation of Energy), instructors emphasized that over-reliance on AI-generated solutions could reduce student engagement in critical thinking. The AI performed moderately well in providing step-by-step guidance (2.4 ± 0.55 in Projectile Motion, 2.8 ± 0.45 in Conservation of Energy), but its ability to detect and address misconceptions was inconsistent, with ratings as low as 1.2 ± 0.84 in the Traffic Light Problem. This highlights the need for AI to function as a scaffolding tool rather than a direct problem solver, reinforcing Socratic questioning and instructor moderation.

Technical improvements are necessary to enhance the AI's reliability and explanatory power. Our findings suggest three priority areas for development: (1) confidence-based feedback systems to indicate when AI-generated responses are uncertain, (2) multi-step verification protocols to improve symbolic vs. numerical validation, and (3) integration of physics-specific formula databases to enhance formula selection accuracy. For example, the AI's depth of explanation was inconsistent, ranging from 1.4 ± 0.55 in the Traffic Light Problem to 2.6 ± 0.55 in Projectile Motion, indicating a need for improved structured reasoning. Implementing these enhancements could significantly improve the system's reliability and performance in advanced problem-solving tasks.

A key consideration in this study was the choice of wearable AI over traditional desktop-based AI. While a desktop interface could have produced similar results in this controlled setting, the smart glasses provided a unique hands-free advantage, particularly beneficial for real-time physics applications such as laboratory experiments or fieldwork. However, instructor ratings for satisfaction with hands-free interaction varied, with lower scores in the Traffic Light Problem (1.6 ± 0.55) compared to the Conservation of Energy exercise (3.2 ± 0.45), suggesting that ease of use may depend on problem type and interface design. This study serves as an initial step in evaluating the feasibility of wearable AI in education, with future research needed to explore its role in dynamic learning environments.

Future research should explore large-scale trials involving diverse educational settings, direct assessment of student conceptual understanding through pre- and post-tests, and enhancements to the AI model addressing the noted limitations in multi-step reasoning and error detection. Ensuring equitable access and addressing AI bias remain critical for ethical and effective AI integration in education.

This research was conducted within the framework of the Doctoral Program in Education at the Universitat Autònoma de Barcelona, with a specific focus on AI integration in science education.

In this paper, we used AI tools to assist in rephrasing and refining text.

Annexes

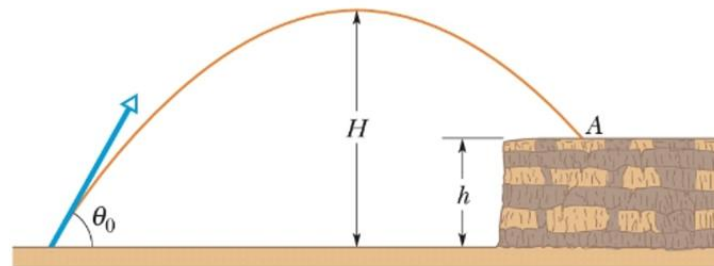
Exercise

In Fig 4-34. A stone is projected at a cliff of height (h) with an initial speed of 42.0 m/s directed at angle $\theta_0 = 60.0^\circ$ above the horizontal. The stone strikes at A , 5.50 s after launching.

Question1:

- Find the height (h) of the cliff
- Find the speed of the stone just before impact at A
- Find the maximum height (H) reached above the ground.

Question2: When a stone is projected upward at an angle of 60.0° with an initial speed of 42.0 m/s, does the stone's speed remain constant throughout its flight because the initial speed was high?



Annex A: Exercise 1 - Cliff Projectile Motion

Exercise 2 - A Traffic Light at Rest

Problem:

A traffic light weighing 122 N hangs from a cable tied to two other cables fastened to a support, as shown in Figure below. The upper cables make angles of 39° and 51° with the horizontal. These upper cables are not as strong as the vertical cable and will break if the tension in them exceeds 130 N

Question:

- Do the traffic lights remain in this situation, or will one of the cables breaks?

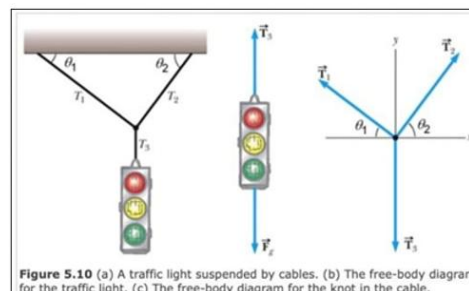


Figure 5.10 (a) A traffic light suspended by cables. (b) The free-body diagram for the traffic light. (c) The free-body diagram for the knot in the cable.

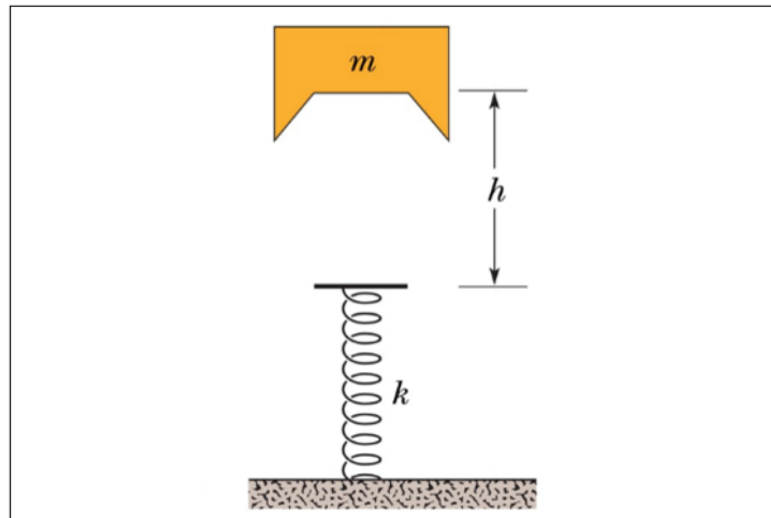
Annex B: Exercise 2 - Traffic Light Tension

Exercise

A block of mass $m=2.0$ kg is dropped from height $h=40$ cm onto a spring of spring constant $k=1960$ N/m. Find the maximum distance the spring is compressed.

Question:

- Find the maximum distance the spring is compressed.



Annex C: Exercise 3 - Spring Compression by Dropped Mass

References

- Al-Taweel, F. B., Abdulkareem, A. A., Gul, S. S., & Alshami, M. L. (2021). Evaluation of technology-based learning by dental students during the pandemic outbreak of coronavirus disease 2019. *European Journal of Dental Education*, 25(1), 183–190. <https://doi.org/10.1111/eje.12589>
- Alsaadi, M., Keshta, I., Ramesh, J. V., Nimma, D., Shabaz, M., Pathak, N., Singh, P. P., Kiyosov, S., & Soni, M. (2025). Logical reasoning for human activity recognition based on multisource data from wearable device. *Scientific Reports*, 15(1), 1-16. <https://doi.org/10.1038/s41598-024-84532-8>
- Attallah, B., & Ilagure, Z. (2018). Wearable technology: Facilitating or complexing education. *International Journal of Information and Education Technology*, 8(6), 433–436. <https://doi.org/10.18178/ijiet.2018.8.6.1077>
- Bulathwela, S., Pérez-Ortiz, M., Holloway, C., Cukurova, M., & Shawe-Taylor, J. (2024). Artificial intelligence alone will not democratise education: On educational inequality, techno-solutionism and inclusive tools. *Sustainability*, 16(2), 781.
- Cai, L., Msafiri, M. M., & Kangwa, D. (2024). Exploring the impact of integrating AI tools in higher education using the Zone of Proximal Development. *Education and Information Technologies*, 1-74.
- Chaiklin, S. (2003). The zone of proximal development in Vygotsky's analysis of learning and instruction. *Vygotsky's educational theory in cultural context*, 1(2), 39-64.
- Chowdhary, K., & Chowdhary, K. R. (2020). Natural language processing. *Fundamentals of artificial intelligence*, 603-649.
- Dede, C. (2009). Immersive interfaces for engagement and learning. *Science*, 323(5910), 66–69. <https://doi.org/10.1126/science.1167311>
- Dilber, R., Karaman, I., & Duzgun, B. (2009). High school students' understanding of projectile motion concepts. *Educational Research and Evaluation*, 15(3), 203–222. <https://doi.org/10.1080/13803610902899101>
- Ferguson, C., van den Broek, E. L., & van Oostendorp, H. (2022). AI-induced guidance: Preserving the optimal zone of proximal development. *Computers and Education: Artificial Intelligence*, 3, 100089.
- Fesol, S. F. A., Arshad, M. M., Salam, S., & Samah, K. A. F. A. (2022). Youth perception of the usage of wearable technology in technical MOOC education. *International Journal of Information and Education Technology*, 10(2), 89–94. <http://dx.doi.org/10.6007/IJARBS/v12-i13/14161>
- Guo, H., Yi, W., & Liu, K. (2024). Enhancing constructivist learning: The role of generative AI in personalised learning experiences. In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024)* (Vol. 1, pp. 767-770).
- Hestenes, D., Wells, M., & Swackhamer, G. (1992). Force concept inventory. *The Physics Teacher*, 30(3), 141–158.
- Iqbal, M. Z., & Campbell, A. G. (2023). Adopting smart glasses responsibly: Potential benefits, ethical, and privacy concerns with Ray-Ban stories. *AI Ethics*, 3, 325–327. <https://doi.org/10.1007/s43681-022-00155-7>
- Kim, J. (2024). Leading teachers' perspective on teacher-AI collaboration in education. *Education and Information Technologies*, 29(7), 8693-8724.

Kortemeyer, G. (2023). Toward AI grading of student problem solutions in introductory physics: A feasibility study. *Physical Review Physics Education Research*, 19(2), 020163.

Kotsis, K. T. (2024). ChatGPT in teaching physics hands-on experiments in primary school. *European Journal of Education Studies*, 11(10).

Kuhn, J., Lukowicz, P., Hirth, M., Poxrucker, A., Weppner, J., & Younas, J. (2016). gPhysics—Using smart glasses for head-centered, context-aware learning in physics experiments. *IEEE Transactions on Learning Technologies*, 9(4), 304-317.

Liu, G., & Fang, N. (2017). Student misconceptions of work and energy in engineering dynamics. In *Proceedings of the 2017 ASEE Gulf-Southwest Section Annual Conference*. ASEE.

Meta. (2021). Introducing Ray-Ban Stories: First-generation smart glasses. *Meta Newsroom*. Retrieved from <https://about.fb.com/news/2021/09/introducing-ray-ban-stories-smart-glasses/>

Meta. (2023, September). New Ray-Ban Meta smart glasses. *Meta Newsroom*. Retrieved from <https://about.fb.com/news/2023/09/new-ray-ban-meta-smart-glasses/>

Naik, A., Yin, J. R., Kamath, A., Ma, Q., Wu, S. T., Murray, C., Bogart, C., Sakr, M., & Rose, C. P. (2024). Generating situated reflection triggers about alternative solution paths: A case study of generative AI for computer-supported collaborative learning. *arXiv*. <https://arxiv.org/abs/2404.18262>

Romine, W., Schroeder, N., Graft, J., Yang, F., Sadeghi, R., Zabihimayvan, M., Kadariya, D., & Banerjee, T. (2020). Using Machine Learning to Train a Wearable Device for Measuring Students' Cognitive Load during Problem-Solving Activities Based on Electrodermal Activity, Body Temperature, and Heart Rate: Development of a Cognitive Load Tracker for Both Personal and Classroom Use. *Sensors*, 20, 4833. <https://doi.org/10.3390/s20174833>

Schreiber, D., & Hyatt, L. (2018). Smart glasses as digital strategy for learning in higher education. In *Transnational Perspectives on Innovation in Teaching and Learning Technologies* (pp. 242-261). Brill.

Shamshin, A. (2024). Implementation of Artificial Intelligence in an Online Platform for Solving and Checking the Solutions of Physical Problems. In E. Faure, et al. (Eds.), *Information Technology for Education, Science, and Technics. ITEST 2024. Lecture Notes on Data Engineering and Communications Technologies* (Vol. 222). Springer, Cham. https://doi.org/10.1007/978-3-031-71804-5_27

Strzys, M. P., Thees, M., Kapp, S., Knierim, P., Schmidt, A., Lukowicz, P., & Kuhn, J. (2019). Smart glasses as assistive tools for undergraduate and introductory STEM laboratory courses. In M. Krannich & M. Lewalter (Eds.), *Perspectives on Wearable Enhanced Learning (WELL): Current Trends, Research, and Practice* (pp. 35–58). Springer. https://doi.org/10.1007/978-3-319-64301-4_2

Thornton, R. K., & Sokoloff, D. R. (1998). Assessing student learning of Newton's laws: The force and motion conceptual evaluation and the evaluation of active learning laboratory and lecture curricula. *American Journal of Physics*, 66(4), 338–352. <https://doi.org/10.1119/1.18863>

Trowbridge, D. E., & McDermott, L. C. (1980). Investigation of student understanding of the concept of velocity in one dimension. *American Journal of Physics*, 48(12), 1020–1028. <https://doi.org/10.1119/1.12298>

Verawati, N. N. S. P., & Nisrina, N. (2024). The role of artificial intelligence (AI) in transforming physics education: A narrative review. *Lensa: Jurnal Kependidikan Fisika*, 12(2), 212–228. <https://doi.org/10.33394/j-lkf.v12i2.13523>

Waisberg, E., Ong, J., Masalkhi, M., ... (2024). Meta smart glasses—Large language models and the future for assistive glasses for individuals with vision impairments. *Eye*, 38, 1036–1038. <https://doi.org/10.1038/s41433-023-02842-z>

Wells, J., Henderson, R., Traxler, A., Miller, P., & Stewart, J. (2020). Exploring the structure of misconceptions in the force and motion conceptual evaluation with modified module analysis. *Physical Review Physics Education Research*, 16(1), 010121.

West, C. G. (2023). AI and the FCI: Can ChatGPT project an understanding of introductory physics? *arXiv*. <https://doi.org/10.48550/arXiv.2303.01067>

Williamson, B., Molnar, A., & Boninger, F. (2024). Time for a Pause: Without Effective Public Oversight, AI in Schools Will Do More Harm Than Good. *Commercialism in Education Research Unit*.

Wink, R., & Bonivento, W. M. (2023). Artificial intelligence: New challenges and opportunities in physics education. In M. Streit-Bianchi, M. Michelini, W. Bonivento, & M. Tuveri (Eds.), *New challenges and opportunities in physics education* (pp. 197–213). Springer. https://doi.org/10.1007/978-3-031-37387-9_27

Wu, J., You, H., & Du, J. (2025). AI Generations: From AI 1.0 to AI 4.0. *ArXiv*. <https://arxiv.org/abs/2502.11312>

Yeadon, W., & Hardy, T. (2023). The impact of AI in physics education: A comprehensive review from GCSE to university levels. *arXiv*. <https://doi.org/10.48550/arXiv.2309.05163>

Zhu, G., Sudarshan, V., Kow, J. F., & Ong, Y. S. (2024). Human-generative AI collaborative problem solving who leads and how students perceive the interactions. *arXiv*. <https://arxiv.org/abs/2405.13048>