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Artificial Intelligence as a Science Teacher Assistant: An Analysis of Machine Learning Utilization in Diagnosing Student Misconceptions: A Review

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Abstract: Diagnosing these misconceptions in a crowded classroom context is very difficult, time-consuming, and subjective when using conventional methods, which often leads to ineffective teaching interventions. To address the urgent need for accurate and objective diagnosis, this article proposes and analyzes the role of Artificial Intelligence (AI), specifically Machine Learning (ML) technologies such as natural language processing (NLP). ML models can analyze student response data (essays) quickly and consistently, acting as science teacher assistants to strengthen diagnostic capabilities. This study uses a systematic literature review method to analyze and synthesize existing research findings regarding Artificial Intelligence as a Science Teacher's Assistant: An Analysis of the Utilization of Machine Learning in Diagnosing Student Misconceptions. This research aims to analyze and explain Artificial Intelligence as a Science Teacher's Assistant: An Analysis of the Utilization of Machine Learning in Diagnosing Student Misconceptions. The brief objectives of this study are as follows: to analyze the utilization of Machine Learning (ML) models in objectively diagnosing, categorizing, and predicting students' misconceptions in science. The findings of this review study indicate that student misconceptions are a persistent barrier to learning, and conventional (manual, paper-based) diagnostic methods have proven inefficient and subjective for crowded classrooms. This validates the urgent need for technological solutions.

Keywords: Artificial intelligence; Machine learning; Misconception

Introduction

Modern science education faces the complex challenge of ensuring that each student not only memorizes facts but also attains a deep conceptual understanding of natural phenomena. A primary goal of science teaching is to build a cognitive framework aligned with accepted scientific perspectives (Vaesen & Houkes, 2021; Morris, 2025). However, this process is often significantly hampered by the presence of student misconceptions. These misconceptions are not simply random errors; rather, they are deeply ingrained views, intuitions, or distorted interpretations derived from students' everyday experiences or their own rudimentary prior understanding. For example, the belief that "force always requires contact" or that "the Earth is hotter when it is closer to the Sun" are common examples that are highly resistant to traditional teaching. In the context of a crowded classroom, where a single teacher must manage dozens of students with diverse backgrounds and learning styles, diagnosing misconceptions becomes a particularly difficult and

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burdensome task (Dawes et al., 2024; Darling-Hammond et al., 2024). Time-Consuming Manual Process: Teachers typically rely on written tests, observations, or oral interviews.

Manually analyzing each student's essay or long-form responses to identify underlying and specific error patterns (rather than simply arithmetic errors) is a very time-consuming process (Adytia Putri et al., 2023); The Vulnerability of Subjectivity: This diagnosis is prone to bias and subjectivity, and relies entirely on the teacher's experience and attention span at the time (Upu et al., 2022). As a result, misconceptions are often missed or misdiagnosed. Accurate and timely diagnosis is a prerequisite for successful intervention (El-Bouzaidi & Abdoun, 2023; Sorsa et al., 2020). When misconceptions are not addressed effectively, they become permanent barriers that prevent students from assimilating new concepts (Zhou et al., 2025; Olde Bekkink et al., 2016). Therefore, there is an urgent need for tools that can automate, accelerate, and increase objectivity in this diagnostic process (Madanchian & Taherdoost, 2025; Affengruber et al., 2024; Zachariadis & Leligou, 2024). As the digital revolution advances, Artificial Intelligence (AI) has emerged as a catalyst, offering innovative and scalable solutions to address diagnostic challenges in science education . AI, with its ability to process massive volumes of data and identify hidden patterns, is well-suited for tasks that require high objectivity and complex analysis (Kumar et al., 2024; Hamilton et al., 2023; Tu et al., 2024). Specifically, this article focuses its analysis on Machine Learning (ML) technology (Tamascelli et al., 2024; Yang et al., 2025).

ML models, such as classification algorithms and natural language processing (NLP), have the potential to interpret and analyze student response data (whether multiple-choice, short-answer, or long-form essays) with speed and consistency that surpass human manual analysis capabilities. Thus, ML acts as an effective science teacher's assistant, a computational entity that does not aim to replace teachers but rather enhances their diagnostic capabilities (Schmidt et al., 2025; Lameras & Arnab, 2021). By analyzing case studies, relevant algorithms (such as natural language processing), and implementation frameworks, this study explores how AI can provide personalized diagnostic feedback to teachers, enabling more targeted and adaptive instructional interventions (Bashir et al., 2025). Ultimately, this article seeks to highlight the transformative role of AI in improving science teaching efficiency and student learning outcomes in the digital age.

Based on the background described, a review of research was carried out that aims to examine Artificial Intelligence as a Science Teacher's Assistant: An Analysis of the Utilization of Machine Learning in Diagnosing Student Misconceptions.

Method

The research method used is a literature review, or systematic review, which aims to comprehensively understand a topic by synthesizing, analyzing, and evaluating existing research. The goal is to identify current knowledge, identify research gaps, and provide a basis for future studies.

Main Steps of a Literature Review

Formulating Research Questions

Determining specific, relevant, and answerable questions based on the literature. This is the foundation of all research.

Determining Inclusion and Exclusion Criteria

Establishing clear boundaries regarding which studies to include (e.g., peer-reviewed journals, year range, topic focus) and which to exclude (e.g., unpublished conference papers, opinion articles) to ensure relevance.

Systematic Literature Search

Conducting structured and documented data collection: Selecting databases (e.g., Scopus, Web of Science); Using keywords combined with Boolean operators (AND, OR, NOT); Documenting all search processes for transparency.

Article Screening and Selection

Conducted a two-stage selection process: Title and Abstract Screening to identify potential relevance; Full Text Reading to ensure articles fully met the inclusion criteria.

Data Extraction

Extracting relevant key information from each selected article (e.g., study objectives, methodology, main findings, and conclusions) into a structured datasheet.

Data Synthesis and Analysis

The core stage in which findings are summarized, integrated, and evaluated: Identifying Themes: Grouping findings based on emerging themes; Comparing and Contrasting: Highlighting similarities and differences between studies; Identifying Gaps: Identifying areas of under-research or conflicting results; Evaluating Quality: Critically assessing the methodology and reliability of the reviewed studies. Artificial Intelligence as a Science Teacher's Assistant: An Analysis of the Utilization of Machine Learning in

Diagnosing Students' Misconceptions", here are three main areas of study that will be discussed in your research or literature review: Theoretical and Practical Analysis of Students' Misconceptions in Science; Utilization of Machine Learning (ML) for Diagnosis; Pedagogical Implications of Artificial Intelligence as a Teacher's Assistant.

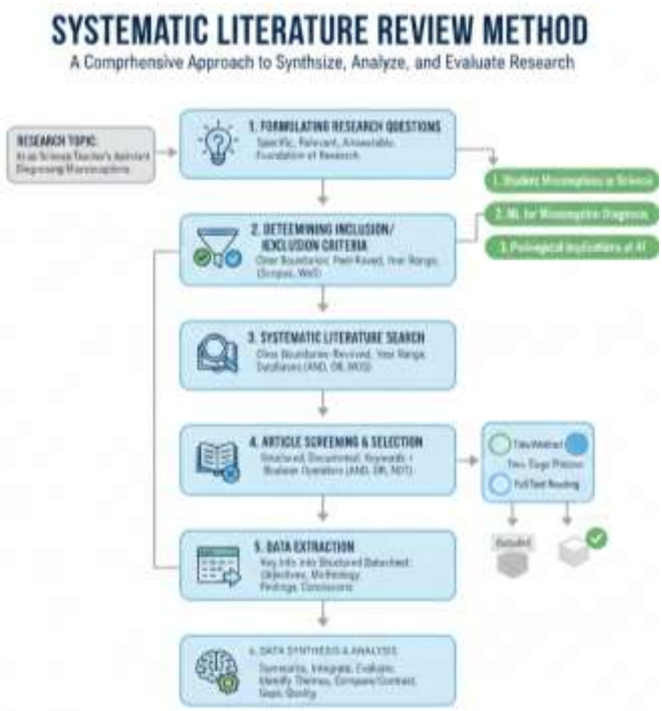

Figure 1. Method scheme

Results and Discussion

The discussion on the theoretical and practical analysis of student misconceptions in science is divided into several focused and structured paragraphs.

Theoretical and Practical Analysis of Student Misconceptions in Science

The Nature and Persistence of Conceptual Misconceptions

The discussion begins by defining student misconceptions as views or mental constructs that deviate from accepted scientific concepts, not simply miscalculations or ignorance (Nunez-Oviedo & Clement, 2019; Rost & Knuuttila, 2022). Theoretically, these misconceptions are often rooted in everyday intuitions formed from non-scientific experiences or erroneous conceptual simplifications early in learning. Their persistent and persistent nature makes them a major epistemological barrier to the acquisition of new knowledge. If not identified and addressed, these misconceptions can hinder deeper conceptual understanding, with students tending to use their own faulty frameworks instead of adopting correct scientific models (Chittleborough & Treagust, 2009; Wiese et al., 2024).

Limitations of Conventional Diagnostic Methods in the Classroom

Practically, the greatest challenge for science teachers is accurate diagnosis in a crowded classroom environment. Conventional diagnostic methods, such as standardized multiple-choice tests or closed-ended questionnaires, often only measure the results without revealing the underlying reasons behind the errors. While clinical interviews or open-ended essay analysis provide rich qualitative data, these processes are time-consuming and resource-intensive, making them unrealistic to routinely implement for every student (Towler et al., 2023; Hadi Mogavi et al., 2024). These limitations result in delayed or partial diagnoses, making instructional interventions less targeted. Manual diagnosis is also prone to subjectivity, relying on individual teacher interpretation and experience (Musullulu, 2025; Franz et al., 2023).

The Importance of Detailed Diagnosis for Intervention

This study confirms that misconception diagnosis must be conducted in detail and in real time for instructional interventions to be effective. Successful intervention requires teachers to understand not only what is wrong, but also why students think that way and the underlying type of misconception (e.g., structural, analogical, or teleological misconceptions). Therefore, there is a critical need for tools that can automate the complex and high-volume process of analyzing student responses. This need provides a logical bridge to the subsequent discussion on the role of Artificial Intelligence and Machine Learning as solutions to provide objective, rapid, and granular diagnostic capabilities (Manorat et al., 2025; Mariani et al., 2023). Utilizing Machine Learning (ML) for Diagnosing Student Misconceptions, divided into several focus paragraphs:

Utilizing Machine Learning (ML) for Diagnosing Misconceptions

The Key Role of Machine Learning in Automated Diagnosis

Machine Learning (ML) is at the heart of AI-based diagnostic solutions. Its ability to analyze large datasets and identify non-linear patterns in the data makes it an ideal tool for addressing the complexity of student misconceptions (Oise et al., 2025). ML models can be trained using thousands of examples of student responses (correct, incorrect, or containing specific misconceptions) to learn to distinguish between trivial errors (such as typos or miscalculations) and deep-seated conceptual misconceptions. By automating this pattern identification process, ML drastically reduces the teacher's cognitive load, enabling fast, consistent, and objective diagnoses (Sozio et al., 2024; Chen et al., 2021; Wang et al., 2024).

Specific Models and Algorithms: NLP and Classification

The implementation of ML in misconception diagnosis relies heavily on specific algorithms, particularly Natural Language Processing (NLP). NLP is crucial for analyzing open-ended answers and student essays. Through techniques such as tokenization, sentiment analysis, and topic modeling, NLP can extract the essence of students' arguments and compare them to correct representations of scientific concepts (Kampatzis et al., 2024; El Azzouzy et al., 2025). In addition to NLP, classification algorithms (such as Artificial Neural Networks or Support Vector Machines (SVMs) are used to perform the following tasks: classify student responses into predefined misconception categories (e.g., kinematic misconceptions or thermal misconceptions); and predict the likelihood that a student will develop a particular misconception in a subsequent topic based on their performance history (Romero et al., 2024; Albalawi et al., 2020).

Input Data and Model Accuracy Challenges

The success of ML models is largely determined by the quality and quantity of input data. The data used includes not only the final answers but also student performance metadata, such as response times and problem-solving order. However, ML implementations face significant challenges related to validity and accuracy (Tufail et al., 2023; Pennisi et al., 2025; Surur et al., 2025). Models must be trained on highly diverse and rich datasets to avoid bias and ensure they can generalize misconceptions beyond the training examples. The data annotation process—where subject matter experts label each response as a specific misconception type—is time-intensive but crucial for achieving high sensitivity in diagnosis. A good model not only tells the teacher that the student is wrong, but also explains why the student thinks that way, offering actionable insights (Gross et al., 2025; Meletiou-Mavrotheris et al., 2025). The Pedagogical Implications of Artificial Intelligence (AI) as a Teacher Assistant are divided into several focus paragraphs:

Pedagogical Implications of Artificial Intelligence as a Teacher Assistant

Shifting the Teacher's Role: From Deliverer to Intervention Designer

The use of Artificial Intelligence, particularly in diagnosing misconceptions, fundamentally shifts the traditional role of the science teacher. AI does not aim to replace educators, but rather acts as a sophisticated diagnostic assistant. AI provides detailed, real-time diagnostic reports, a capability that teachers would be unable to achieve within a limited timeframe. With tools like visual dashboards that show a conceptual "map" of the classroom—for example, 35% of students have a misconception about Newton's Third Law, and 20% have difficulty distinguishing between heat and temperature—teachers can free up their time from administrative work and focus on higher-level pedagogical decisions. The teacher's role transforms from that of a conveyor of information to that of an informed and effective intervention designer (Brown et al., 2020; Van Der Steen et al., 2022).

Promoting Adaptive and Personalized Teaching

The most significant pedagogical implication of AI is its ability to facilitate adaptive teaching and personalized learning. Once a machine learning model precisely identifies and categorizes student misconceptions, teachers can implement highly specific remediation strategies (Vieriu & Petrea, 2025; Strielkowski et al., 2025). For example, students with similar misconceptions can be grouped and given assignments or learning resources specifically designed to address their underlying issues, a process known as targeted instruction. This is far more effective than repeating the same lesson to the entire class. AI provides teachers with the data they need to dynamically adjust the pace, complexity, and teaching methods, ensuring that each student receives the support they need to overcome their conceptual barriers (Katona & Gyonyoru, 2025; Yaseen et al., 2025).

Ethical Challenges and Teacher Training Needs

Despite its significant pedagogical potential, implementing AI as a teaching assistant poses ethical and practical challenges that must be addressed. Ethically, there are fundamental issues related to the privacy and security of student data, as well as the potential for algorithmic bias that might replicate or reinforce educational inequities if the model is trained on biased datasets. Practically, the success of these systems depends on adequate professional training for teachers. Teachers not only need to learn how to operate AI software, but more importantly, they must develop data literacy to interpret the diagnostic insights generated by AI and translate them into meaningful pedagogical actions. Without adequate training, AI-generated data risk becoming unused insights, reducing the technology's effectiveness in improving student learning outcomes (Filiz et al., 2025; Mulyani et al., 2025).

Conclusion

This study concludes that student misconceptions are a persistent barrier to learning and are difficult to diagnose effectively using conventional, subjective, and time-consuming methods. These limitations underscore the urgent need for real-time, detailed diagnostics. The analysis suggests that Machine Learning (ML) offers a transformative solution. Models such as NLP have proven effective in automatically diagnosing and categorizing misconceptions from students' qualitative responses. Pedagogically, AI serves as a diagnostic assistant, empowering teachers with detailed data to design adaptive and personalized teaching interventions. However, successful implementation depends heavily on addressing challenges such as ensuring model validity and accuracy, addressing data ethics issues, and providing adequate teacher training.

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Conceptualization; methodology; I. P.; validation; formal analysis; investigation; R. F. W.; resources; data curation; A. H.; writing—original draft preparation; writing—review and editing; visualization F. E. All authors have read and approved the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest

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