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Learning Gaps in Science Education through AI: Scale Development among Junior High School Students in a Laboratory High School

Mary-an A. Mangubat, Kenth R. Manait, Lovely Joy M. Marianito, Steve I. Embang*
College of Education, Northwestern Mindanao State College of Science and Technology, Tangub City, Philippines

*Corresponding Author Email: steve.embang@nmsc.edu.ph

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Abstract. The integration of Artificial Intelligence (AI) into education offers promising opportunities to address persistent learning gaps in science, particularly in under-resourced secondary schools; however, few validated instruments assess the impact of AI tools on students' learning challenges. This study aimed to develop and validate the Artificial Intelligence Learning Gap (AILG) Scale, which measures disparities in science education related to AI use by capturing students' experiences and identifying key dimensions of learning gaps. Employing an exploratory sequential mixed-methods design, the research began with interviews and focus groups involving 20 junior high school students, alongside a literature review that informed the creation of a 4-point Likert scale. The instrument was then administered to 120 students for validation through Exploratory Factor Analysis (EFA) and reliability analysis. The final AILG Scale comprises 29 items spanning four dimensions: Engagement with AI Tools, Cognitive Challenges, Motivation and Personalization, and Teaching Practices. These dimensions collectively explain 41.36% of the variance, with Cronbach's Alpha values ranging from 0.670 to 0.843, indicating acceptable to high reliability. This scale offers a practical, evidence-based tool for diagnosing science learning gaps in AI-enhanced classrooms, supporting targeted interventions, teacher training, and further research, particularly in contexts where educational technology is becoming increasingly integral.

Keywords: Artificial intelligence; Artificial intelligence learning gaps scale; Exploratory factor analysis; Learning gaps; Science education.

1.0 Introduction

Science education, encompassing the teaching and learning of scientific concepts across all age groups, is a multifaceted field that integrates content knowledge, scientific processes, social science perspectives, and pedagogical strategies (Jia et al., 2023). The overarching aim of science education is to cultivate scientific literacy, equipping students with the capacity for critical thinking, creativity, and informed decision-making (Hunter, 2020). This is achieved through standards that guide the development of understanding from early education through to adulthood, spanning disciplines such as physical, life, earth, space, and human sciences (Bartell & Vespia, 2023). Despite its foundational importance, science education is widely regarded as one of the most challenging academic domains, owing to its high cognitive demands, abstract nature, and the necessity for a robust base of prerequisite knowledge (Smith et al., 2022). These challenges often manifest as low student engagement and elevated dropout rates, underscoring the need for innovative approaches to teaching and learning (Reyna et al., 2025).

In the contemporary era, science education is undergoing a significant transformation, driven by the imperatives of technological advancement and the demands of a rapidly evolving workforce (Verawati & Purwoko, 2024). Inquiry-based learning and the integration of digital technologies have emerged as central trends, aiming to enhance student engagement and foster a deeper understanding of science (Getenet & Tualaulelei, 2023). However, persistent obstacles—including inadequate infrastructure, resistance to technology adoption, and misalignment between curriculum and instructional practices—continue to impede progress (Singun, 2025). The integration of 21st-century skills and interdisciplinary approaches, connecting science with technology, society, and the environment, is increasingly recognized as essential for preparing students to navigate complex global challenges (Adames et al., 2023).

The Philippine context exemplifies these global trends and challenges. The adoption of a spiral progression approach within the K-12 curriculum, the shift toward flexible and blended learning models, and the introduction of innovative programs such as "Lab-in-a-Box" reflect ongoing efforts to enhance science education (Pavlou & Castro-Varela, 2024). Nevertheless, significant disparities in digital access, a shortage of qualified science teachers, and declining student performance in science and mathematics remain pressing concerns (Reynolds et al., 2022). The COVID-19 pandemic has further exacerbated these issues, resulting in substantial learning losses and heightened inequities, particularly among marginalized populations (Alejo et al., 2023).

Central to these challenges is the concept of learning gaps—discrepancies between the expected and actual understanding or competency of students in science (Sphero, 2021). These gaps may arise from insufficient instructional resources, varying levels of teacher preparedness, socio-economic disparities, and curricular structures that prioritize breadth over depth (Pitcher, 2024). The pandemic has intensified these gaps, with students falling significantly behind in core subjects (Lewis & Kuhfeld, 2023).

In response, the integration of Artificial Intelligence (AI) in education has emerged as a promising avenue for addressing learning gaps (Roshanaei et al., 2023). AI technologies offer the potential to personalize learning experiences, automate administrative tasks, and provide adaptive instructional resources tailored to individual student needs (Yılmaz, 2024). In science education, AI-driven platforms can deliver interactive simulations, virtual laboratories, and real-time feedback, thereby enhancing engagement and conceptual understanding (Vorsah & Oppong, 2024). Despite these advances, there remains a paucity of measurement tools specifically designed to assess the impact of AI on learning gaps in science education, particularly within the Philippine context (Funa, 2025). This study seeks to identify the specific learning gaps prevalent in science education, examine the influence of AI integration on addressing these gaps, and develop a novel measurement scale—the AILG scale—to evaluate the effectiveness of AI interventions. Addressing these research questions, the study aims to contribute to the ongoing discourse on educational innovation and equity, providing empirical insights that are both contextually relevant and globally significant.

2.0 Methodology

2.1 Research Design

This study employed an exploratory sequential design, a mixed-methods research approach characterized by an initial phase of qualitative data collection and analysis, followed by a quantitative phase that built upon the qualitative findings (Creswell & Clark, 2017). This design proved helpful when researchers sought to explore a topic in depth before developing quantitative instruments or testing hypotheses (Saharan et al., 2024). By starting with qualitative data, researchers gained insights into participants' experiences and perspectives, which informed the development of quantitative measures, ensuring that these instruments were relevant and contextually appropriate (Lim, 2024). In practice, exploratory sequential design allowed researchers to create a more nuanced understanding of complex phenomena by integrating qualitative and quantitative data (Toyon, 2021). For example, a study might have begun with interviews to identify key themes related to a specific issue, and then used those themes to develop a survey that quantitatively assessed the prevalence of those themes across a larger population. This approach not only enhanced the validity of the research findings but also provided a comprehensive view of the research question by allowing for the triangulation of data sources (Jalaluddin et al., 2025). Exploratory sequential design is a valuable methodology in mixed methods research, as it facilitates the exploration of complex issues while ensuring that subsequent quantitative measures are grounded in the lived experiences of participants (Munce et al., 2020).

In the context of identifying learning gaps in science education, this study employed an exploratory sequential design, implementing two distinct phases: qualitative and quantitative. The qualitative phase focused on gathering in-depth information to understand the underlying issues related to learning gaps. This phase involved interviews, focus groups, or observations to capture detailed insights from participants. Based on the findings from this phase, a scale instrument was developed and tested in the subsequent quantitative phase. This approach aligned with Creswell and Plano Clark's (2024) QUAL-quan strategy, where qualitative results were prioritized to inform the design and focus of the quantitative phase. The quantitative phase involved using the developed scale to assess the prevalence and extent of the identified learning gaps across a larger sample. This phase aimed to test the generalizability of the qualitative findings and validate the theoretical constructs developed during the qualitative phase. Creswell and Plano Clark (2024) described this process as crucial for ensuring that the research findings were not only contextually rich but also broadly applicable. The integration of these qualitative and quantitative methods enhanced the study's validity and reliability through triangulation, which helped confirm the findings through multiple data sources and methods (Flick, 2018).

2.2 Research Locale

The study was conducted appropriately at a Laboratory High School, involving Junior High School students from Misamis Occidental, in Grades 7 to 10, with a focus exclusively on science-related subjects.

2.3 Research Participants

The participants of this study were Junior High School students at a Laboratory High School during the 2024-2025 school year. A purposive sampling technique was used to ensure that only students directly involved in science education were included. For the qualitative phase, a total of 20 participants participated in Focus Group Discussions (FGDs), allowing them to share their experiences with science learning (Lai, 2023). with five students selected from each grade level (Grades 7-10). For the quantitative phase, 120 students were selected as respondents to gather more comprehensive data for the study.

2.4 Research Instrument

In the initial qualitative phase, the researchers prioritized collecting rich, in-depth data through semi-structured interviews and focus group discussions (Tkyildizümün AKYILDIZ & Ahmed, 2021). This method enabled a nuanced exploration of participants' experiences, fostering an open sharing of insights (Tamminen et al., 2021). Semi-structured interviews provided a balance between structured questions and the flexibility to explore emerging themes (Adeoye-Olatunde & Olenik, 2021). This phase aimed to capture complexities that might be missed in quantitative methods alone, thereby informing the design of the next phase.

Based on the qualitative findings, the researchers developed a questionnaire integrating both closed- and open-ended questions. This instrument reflected identified themes and enabled validation through broader quantitative analysis. The combination ensured the data collected was both rich and statistically meaningful, enhancing the study's rigor and depth (Scribbr, 2021). The qualitative analysis revealed recurring patterns that deepened understanding of student attitudes. These insights guided the development of targeted survey questions grounded in participants' lived experiences, thereby improving the relevance of the quantitative phase. The questionnaire included Likert scale items, a widely used tool for measuring opinions by asking respondents to rate their agreement with various statements (Kusmaryono et al., 2022). This approach allowed the researchers to quantify subjective attitudes and identify patterns in responses (Tempelaar et al., 2020). The Likert scale also simplified analysis and improved respondent engagement through clear, intuitive response options.

During the quantitative phase, the researchers administered the refined questionnaire to a larger, representative sample. Sampling procedures were based on the target population and available resources, ensuring statistical validity (Jayaweera et al., 2024). Researchers provided clear instructions to reduce errors and maximize response quality. After data collection, the team employed descriptive and inferential statistics, including regression, ANOVA, and factor analysis, to examine patterns and test hypotheses derived from the qualitative phase. The integration of both data sets enabled the researchers to draw robust conclusions and make informed recommendations, ensuring comprehensive and actionable insights (Creswell, 2024).

2.5 Data Gathering Procedure

In this study, the researcher sought to understand the challenges in science education and how Artificial Intelligence (AI) addressed these issues by analyzing qualitative data through content analysis. This method, known for its effectiveness in examining textual data, was aligned with the naturalistic paradigm and included three specific approaches: conventional, directed, and summative content analysis. Through conventional content analysis, coding categories were derived directly from the raw data. In the directed approach, existing theories and previous research findings informed the initial codes. Meanwhile, the summative method involved counting and comparing keywords to interpret deeper meanings within the data (McGowan et al., 2020).

The analysis began by coding relevant sections of the data using both deductive and inductive strategies. Deductive codes stemmed from initial assumptions about students' learning challenges in science, while inductive codes naturally emerged during the coding process. These codes were then organized into broader, abstract themes using a codes-to-text technique. The development of a measurement scale was guided by key domains: people ("who"), setting ("where"), time ("when"), and contextual elements such as communication and emotions ("what"). Each participant's response was carefully examined, and similar ideas were grouped and coded to uncover recurring patterns. To strengthen the analysis, the researcher applied Ahmed et al.'s (2025) six-phase thematic approach. This began with familiarization—transcribing interviews and organizing notes to recognize initial insights. Initial coding was followed, generating potential themes that were then identified, sorted, and validated against the data narratives. These themes were refined further, and a thematic book was created, detailing categories and supporting quotations. Finally, the results were presented using compelling participant quotes to address the research questions clearly.

Quantitative Data Analysis

Quantitative data were collected using the AILG scale from a broader population sample. To analyze this data, the researcher employed Exploratory Factor Analysis (EFA), a statistical method suitable for large sample sizes, with a minimum of 50 participants, as suggested by Sürücü et al. (2022). The main objective of the analysis was to reduce the dataset, making it easier to interpret relationships and patterns among variables. The EFA process involved clustering variables that shared common variance in order to isolate latent constructs and concepts, following the assumption that observed variables could be traced back to a smaller number of unobservable, shared factors (Widaman & Helm, 2023). The researcher applied both orthogonal rotation (such as Varimax) and oblique rotation (such as Direct Oblimin) to analyze factor loadings and interpret eigenvalues effectively. As described by DeCoster (1998), EFA was also used to determine the number of factors influencing the observed variables and to identify which variables naturally grouped. This process helped the researcher understand the underlying structures within the data and assess the significance of each item in classifying constructs within the scale. Before conducting the analysis, a data-cleaning procedure was carried out to eliminate errors and inconsistencies. The online survey format ensured that all questions were answered, thus preventing missing data. Textual responses and demographic information were numerically coded to facilitate analysis, and negative items on the scale were reverse-coded to maintain consistency across all measurements.

2.6 Ethical Considerations

In line with Lincoln and Guba's (1985) principles of trustworthiness and ethical practice, the researchers strictly followed proper procedures in conducting the study. A formal request letter was submitted to the school principal to obtain approval and permission to implement the research within the institution. Since the participants were minors, parental consent forms were distributed along with student assent forms to ensure that participation was voluntary. The purpose of the study, as well as their rights as participants, were clearly explained, emphasizing that they could withdraw at any time without penalty. For the qualitative phase, an interview protocol was carefully prepared and applied to maintain consistency, fairness, and respect during the Focus Group Discussions. To protect participants' confidentiality, no personal identifiers were used in reporting results, and all responses were treated with strict anonymity. Collected data were stored securely and used solely for academic purposes related to this research.

3.0 Results and Discussion

The following table presents key insights derived from the Interview Focus Group Discussion (IOTEM) regarding students' learning challenges and preferences in science education. The statements reflect students' experiences with various aspects of the learning process, particularly focusing on difficulties related to the pace of lessons, understanding complex topics, and the need for additional support through AI tools. Students also shared their preferences for structured and interactive teaching methods. The table below translates these student perspectives into clear statements, providing valuable information for understanding the factors that influence their learning outcomes and highlighting areas where educational strategies can be improved.

Table 1. *Items from Interview Focus Group Discussion*

Translation	Statement
I struggle when lessons are fast-paced and lack time for questions.	I find it difficult to keep up when the teacher speaks quickly or doesn't allow time for questions.
I have trouble understanding complex science topics and memorizing formulas.	I struggle with complex terms, formulas, and memorizing the Periodic Table.
I prefer lessons with clear examples and interactive teaching methods.	I learn better with more examples, interactive lessons, and hands-on activities.
I feel shy to ask questions during fast-paced lectures.	I find it hard to ask questions in class when the teacher speaks quickly.
I rely on AI tools for extra help and clarification on topics.	I use AI for explanations and homework help, but I double-check for accuracy.
I prefer organized lessons with detailed notes or copies for easier understanding.	I like when the teacher provides organized materials and notes to help me understand better.

In developing the items from the literature, the researcher conducted a thorough review of published articles from 2014 to 2024. The articles focused on how AI addressed learning gaps in science education. Various journal repositories were utilized, including the Scopus database, Google Scholar, ScienceDirect, and ERIC (eric.ed.gov). The researcher identified the specific learning gaps that AI addressed.

Table 2. *Items from Literature Review*

Author(s) and Year	How AI Addresses Learning Gaps	Sample Statement
Heeg & Avraamidou (2023)	Reduces teacher workload and increases engagement	AI lightens my workload and helps engage students.
Lai et al. (2023)	Identifies learning needs and personalizes support	AI helps me spot students who need support and adjust lessons for them.
Mpu (2024)	Supports special needs learners	AI reduces barriers for learners with special needs.
Yim & Su (2024)	Enables game-based and project-based learning	I enjoy learning through AI-powered games and projects.
Gligorea et al. (2023)	Adapts to individual learning levels	I learn better when AI adjusts content to my level.
Bayly-Castaneda et al. (2024)	Acts as a personal tutor	AI feels like a personal tutor that guides my learning.
Eden et al. (2024)	Promotes equity in science education	AI helps ensure all students get equal learning opportunities.
Mohebi (2024)	Enhances problem-solving and language skills	AI tools support my problem-solving and learning in science.
Rieber (2005)	Provides interactive visual learning	I understand better using interactive simulations.
Southworth et al. (2023)	Prepares students for real-world challenges	Learning AI prepares me for real-world science problems.

For the development of items based on theories, the researcher extensively searched for theories related to AI that address learning gaps in science education. The researcher read these theories to identify various learning gaps that AI addresses. These gaps were listed, and question items were generated from them.

Table 3. *Items from Theories (THEOREM)*

Theory & Author	Key Factor	Simplified Statement
Cognitive Load (Sweller, 1988)	Managing mental effort	I learn best when lessons aren't too overwhelming.
Differentiated Instruction (Allen, 2007)	Tailored activities	I feel included when lessons match my interests and level.
Experiential Learning (Kolb, 2014)	Hands-on learning	I understand through real-life tasks and feedback.
Inquiry-Based Learning (Furtak, 2012)	Student exploration	I learn better when I can explore and ask questions.
Universal Design (Hall, 2012)	Flexible learning methods	I like choosing how to show what I've learned.
Problem-Based Learning (Tan, 2003)	Teamwork and reflection	I gain confidence through group work and solving problems.
Connectivism (Kropf, 2013)	Learning through networks	I learn when I connect with others online or in class.
Human Constructivism (Bretz, 2001)	Connecting ideas	I engage when I can link new info to what I know.
Multimedia Learning (Mayer, 2005)	Smart use of visuals and text	I learn best with clear, well-designed videos or slides.
Social Cognitive (Zimmerman, 1989)	Goal setting and self-tracking	I'm motivated when I track my own progress.
Social Learning (Bandura, 1973)	Learning by observing	I learn best when I watch and work with others.
Behaviorism (Fontana, 1984)	Feedback and rewards	I improve when I get instant feedback.
Bloom's Taxonomy (Bloom, 1994)	Levels of thinking	I feel proud when I go from recalling facts to creating something new.
Cognitivism (Piaget)	Mental development stages	I learn best when lessons fit my learning stage.
Constructivism (Steffe, 1995)	Active learning	I stay focused when I solve problems with classmates.
Humanism (Dewey, 1938)	Personal growth	I feel inspired when learning helps me grow as a person.
Information Processing (Slate, 1989)	Focus and memory	I learn best when lessons support focus and memory.
Multimodal Learning (Lu, 2023)	Using multiple senses	I learn best with text, visuals, and sounds combined.

Multiple Intelligences (Gardner, 1983)	Learning based on strengths	I'm more engaged when lessons fit my abilities.
Moral Development (Crain, 1985)	Thinking about right and wrong	I reflect deeply when we discuss real-life ethical issues.
Gestalt Theory (Smith, 1988)	Organized presentation	I understand better when content is clear and well-structured.
Self-Determination (Martin, 2017)	Motivation through autonomy	I'm driven when I can make choices and feel capable.

Table 4. *Final Rotated Component Matrix*

Factor	Item No.	Statement	Loading
Factor 1: Engagement with AI Tools	16	I find using tools like ChatGPT, Google, and YouTube helpful for understanding topics.	0.809
	49	I use AI for quick answers and extra explanations.	0.739
	50	I rely on AI to better understand my teacher's lessons.	0.702
	51	I use Canva and AI tools for creating reports and presentations efficiently.	0.687
	52	I verify AI results, especially for calculations, to ensure correctness.	0.675
	60	I feel AI simplifies finding answers for assignments.	0.630
	94	I think AI-driven strategies help promote equity in science education.	0.600
	95	I feel that AI enhances teaching and learning effectiveness.	0.533
Factor 2: Cognitive Challenges	1	I struggle when the teacher discusses topics quickly with no time for questions.	0.816
	2	I find it difficult to understand Earth Science because of complex terminologies.	0.806
	7	I struggle with science topics that involve mathematical problem-solving.	0.758
	9	I find visualizing concepts like plate tectonics challenging due to unclear drawings.	0.773
	12	I have trouble understanding space studies that are only discussed without visuals.	0.751
	5	I struggle to memorize Physics formulas for problem-solving.	0.738
	42	I feel that lessons should be slower with periodic understanding checks.	0.554
	29	I wish the teacher provided more examples to help understand Astronomy.	0.517
Factor 3: Motivation and Personalization	65	I feel included when my learning activities are tailored to my interests and skill level.	0.756
	66	I understand concepts better with hands-on experimentation and feedback.	0.771
	67	I feel motivated when the classroom supports inquiry and provides resources.	0.752
	80	I learn best when lessons match my cognitive abilities.	0.746
	73	I am more motivated when I set learning goals and track progress.	0.725
	70	I feel more confident with teamwork-based problem-solving.	0.649
	92	I personalise my learning by adjusting content to my needs.	0.620
	98	I feel motivated when AI provides tailored learning support.	0.611
Factor 4: Teaching Practices	21	I feel the teacher should be more interactive and passionate in discussions.	0.620
	23	Teaching strategies should be adapted for better student understanding.	0.611
	24	Questions should be answered thoroughly after discussions.	0.648
	25	Teachers should ask if we understood before moving on.	0.571
	27	Lessons should focus on key details only.	0.501

3.1 The final four-factor structure

The final four-factor structure represents the refined and interpretable dimensions extracted through Exploratory Factor Analysis (EFA). This structure was determined after evaluating eigenvalues, applying oblimin rotation, and carefully interpreting factor loadings to ensure clarity and alignment with theoretical constructs. Each factor was defined by a set of variables with strong loadings (≥ 0.4) and minimal cross-loadings, indicating a clear relationship between the items and their respective factors. The following factors explain the challenges that students face and how AI can help bridge the learning gaps in science education to meet the standards expected of students: engagement with AI tools, cognitive challenges, motivation, personalization, and effective teaching practices.

Factor 1: Engagement with AI tools

Overview of the Factor. Engagement with AI Tools highlights the transformative role of technology in fostering active participation, sustained interest, and meaningful interaction in learning. This factor, which explained 13.90% of the total variance, emerged as the most influential among the four, underscoring that student engagement—when supported by AI tools—is foundational in addressing learning gaps in science education.
Role of AI in Enhancing Student Engagement

Enhancing Student Engagement through AI. AI technologies, including chatbots, multimedia platforms, and virtual simulations, fundamentally reshape how students interact with learning materials. By offering real-time feedback, they help students identify and correct errors immediately, accelerating comprehension and reducing misconceptions (Rajaram, 2024). For instance, AI-driven chatbots respond instantly to questions, fostering both autonomy and confidence in learning.

Interactive and Accessible Learning Experiences. Interactive and gamified AI platforms further sustain engagement by allowing students to explore abstract scientific concepts in immersive ways, such as through virtual labs and AR models (Renacido, 2025). Beyond engagement, AI tools extend accessibility: their 24/7 availability provides continuous support outside classroom hours (Zawacki-Richter et al., 2019). This accessibility empowers learners to manage their learning journeys, which is particularly valuable in science education, where complex concepts often demand repeated exposure and varied modes of explanation.

Simplifying Complex Scientific Concepts. AI's strength also lies in making complex concepts more tangible. Visualizations of molecular structures or body systems transform abstract processes into concrete representations, offering alternative pathways for students who struggle with traditional text-based approaches (Zhai et al., 2022). By bridging cognitive barriers, these tools not only sustain engagement but also enhance comprehension and understanding.

Connections with Other Factors. Although engagement is distinct, it closely interacts with other dimensions of learning. Its moderate correlation with Factor 3 (Motivation and Personalization) shows that AI tools are most effective when tailored to individual learning needs through adaptive pathways and personalized recommendations (Mishra et al., 2024). Similarly, its link to Factor 4 (Teaching Practices) suggests that AI can extend and enrich traditional methods, enabling students to revisit lessons at their own pace (Córdova-Esparza, 2025). Thus, AI engagement should be viewed not in isolation but as part of an integrated learning ecosystem.

Challenges and Recommendations. Despite these advantages, inequitable access to AI technologies remains a pressing concern, especially in under-resourced schools (Jia et al., 2023). Furthermore, teacher readiness to integrate AI effectively is limited, highlighting the need for professional development aligned with pedagogical goals. To maximize impact, schools should (1) integrate AI into curricula with clear learning objectives, (2) implement training for teachers, (3) encourage AI developers to design culturally responsive, student-centered tools, and (4) foster partnerships among institutions, policymakers, and technology providers to ensure equitable access.

Factor 2: Cognitive Challenges

Understanding Cognitive Barriers in Science Education. Cognitive Challenges highlight the significant mental effort required by students to navigate the complexities of science education, explaining 11.03% of the total variance in the exploratory factor analysis. The findings suggest that this factor is a significant barrier that many students encounter in mastering complex scientific concepts, where abstract reasoning, multi-step problem-solving, and information overload converge to create substantial cognitive demands (Chew & Cerbin, 2021). These challenges are particularly acute in science education, where abstract concepts—such as energy conservation, molecular bonding, or photosynthesis—often require students to move beyond rote memorization to deep understanding and application. For instance, balancing chemical equations or calculating gravitational forces demands both mathematical precision and conceptual clarity, which can overwhelm students, especially those with weaker foundational skills or prior knowledge gaps (Caduceus International Publishing, 2022).

Impact of Cognitive Overload on Student Learning. One key insight from this factor is the extent to which cognitive overload hinders student progress. Science curricula are often dense with technical vocabulary, detailed explanations, and interconnected concepts, making it difficult for students to process and retain information (Lee & Wan, 2022). The hierarchical nature of science topics further compounds this issue; gaps in understanding foundational principles can cascade, leaving students ill-prepared to tackle more advanced material. For example, a lack of clarity in understanding basic Newtonian mechanics may prevent a student from grasping more complex topics, such as momentum or energy transfer. These struggles are not just academic; they can also lead to frustration, reduced confidence, and disengagement, creating a cycle that further widens the learning gap (National Academies of Sciences, Engineering, and Medicine, 2020).

AI as a Tool for Cognitive Scaffolding. AI tools offer promising solutions to these cognitive challenges by providing scaffolding and support tailored to students' individual needs. Adaptive learning systems, for instance, can diagnose specific areas where students struggle and adjust content accordingly. If a student fails to understand the periodic table, the system might revert to simpler exercises or interactive simulations that break the concept into digestible chunks (Paul, 2024). The potential of AI in offering step-by-step guidance is particularly compelling. Tools like intelligent tutoring systems can walk students through complex processes, such as solving a physics problem or analyzing a chemical reaction, while providing instant feedback and corrective explanations (Di Eugenio et al., 2021). This iterative approach not only helps students master complex tasks but also reduces the cognitive load by focusing their attention on manageable steps rather than overwhelming them with the entire problem at once.

Enhancing Conceptual Understanding Through AI-Driven Visualizations. Moreover, AI-driven visualizations can transform abstract scientific principles into tangible, relatable experiences. Concepts that students often find difficult to imagine, such as the structure of DNA or the dynamics of a solar system, can be vividly represented using 3D models, animations, or augmented reality (AR) (Sandiego.edu, 2024). These tools bridge the gap between theory and practice, making learning more intuitive and less intimidating. For example, an AI-powered simulation of a chemical reaction allows students to manipulate variables and observe real-time outcomes, enabling them to understand causality and build connections between theoretical and practical knowledge.

Interconnectedness with Other Factors. However, addressing cognitive challenges is not solely about simplifying content; it also involves tailoring content to meet individual needs. This factor's moderate correlation with Factor 1 (Engagement with AI Tools) and Factor 3 (Motivation and Personalization) underscores the importance of creating an engaging, personalized learning environment that sustains students' interest and aligns with their cognitive needs. A personalized AI tool might detect that a student learns better through visual aids and adjust its teaching approach accordingly, presenting more diagrams and fewer text-heavy explanations. Such adaptations not only support cognitive processes but also help maintain motivation by reducing frustration and increasing the perceived relevance of the content.

Despite these benefits, this research also revealed significant barriers that must be addressed to fully realize AI's potential in alleviating cognitive challenges. One major limitation is the lack of customization in many AI tools, which often adopt a one-size-fits-all model. This approach overlooks the diverse cognitive profiles of students, particularly those with learning disabilities or varying levels of prior knowledge (Zawacki-Richter et al., 2019). Additionally, while AI tools provide immediate support, their long-term impact on cognitive skills—such as critical thinking and problem-solving—remains unclear. There is a risk that over-reliance on AI could lead to surface-level learning, where students achieve short-term success without developing the deeper, transferable skills necessary for future challenges, according to Beale (2025).

Strategies for Addressing Cognitive Challenges. To address these issues, we propose several targeted strategies. First, AI tools should incorporate more robust diagnostic capabilities to identify and address individual cognitive challenges more effectively. This includes designing systems that adapt not only to performance but also to learning styles and cognitive preferences (Halkiopoulos & Gkintoni, 2024). Second, AI tools must strike a balance between guided support and opportunities for independent problem-solving, ensuring that students develop critical thinking skills alongside content mastery (Chew & Cerbin, 2021). Third, educators should be equipped with professional development resources that help them integrate AI tools effectively into their teaching practices. Teachers play a crucial role in contextualizing AI support, ensuring it complements rather than replaces traditional pedagogical methods (American Progress, 2024). Ultimately, partnerships among AI developers, educators, and policymakers are crucial for creating scalable, inclusive solutions that address the cognitive challenges faced by all learners, regardless of their socioeconomic or geographic context (Jia et al., 2023).

So, Factor 2 Cognitive Challenges underscores the significant barriers students face in navigating the complexities of science education and highlights the critical role AI tools can play in mitigating these difficulties. By simplifying abstract concepts, providing step-by-step guidance, and offering personalized support, AI has the potential to reduce cognitive overload and enhance learning outcomes. However, realizing this potential requires addressing limitations in customization, ensuring long-term skill development, and fostering collaboration between stakeholders. Research highlights that this factor is a key area for further study, particularly in exploring how AI interventions can be refined to meet the diverse cognitive needs of students while promoting more profound, more meaningful learning experiences.

Factor 3: Motivation and Personalization

Fostering Student Motivation through Personalization. This factor, which explained 10.80% of the total variance, emphasizes the importance of tailoring educational experiences to sustain motivation and improve learning outcomes. Traditional, one-size-fits-all methods often fail to address the diverse needs of students in science education, where abstract concepts and rigorous problem-solving can lead to disengagement. Personalization counters this by aligning content, pace, and strategies with individual abilities and interests. For example, students who struggle with abstract reasoning may benefit from visual simulations, while those with stronger foundations may require more advanced challenges to stay motivated (Falloon, 2020). By ensuring that students feel both supported and challenged, personalization fosters a stronger sense of ownership over learning.

AI as a Driver of Personalized Motivation. AI systems enhance motivation by dynamically adjusting lessons based on real-time performance. When a student demonstrates mastery, the system can introduce more advanced material; if difficulties arise, remedial exercises or alternative explanations are provided (Altinay, 2024). This adaptability not only prevents frustration but also sustains momentum by keeping students within their optimal learning zone. Furthermore, AI tools accommodate diverse learning preferences—visual, textual, or problem-solving—ensuring that students engage with science in ways that resonate with them (Huang et al., 2023).

Gamification as a Motivational Tool. Gamified elements within AI platforms add an extra layer of motivation. Features such as badges, progress tracking, and interactive challenges create a sense of achievement and encourage persistence through complex topics (Wang & Lehman, 2021). For instance, virtual lab simulations that reward problem-solving foster a positive association with learning, transforming science from a source of anxiety into an enjoyable, motivating experience.

Interconnectedness with Other Factors. While distinct, motivation and personalization are closely linked with Factor 1 (Engagement with AI Tools). Engagement is heightened when students view AI tools as personally relevant, while motivation grows when content is accessible and adaptive (Zawacki-Richter et al., 2019). This reciprocal relationship indicates that personalization sustains motivation, which in turn strengthens overall engagement.

Challenges and Recommendations. Despite these benefits, two key challenges limit the full potential of personalization. First, over-reliance on AI risks reducing opportunities for collaborative learning and teacher interaction, which remain essential in science education (Zawacki-Richter et al., 2019). Second, personalization depends heavily on the quality of AI design; poorly designed systems that oversimplify or misdiagnose learner needs can reduce motivation instead of enhancing it (Yiu, 2025). To address these issues, we recommend: (1) embedding culturally relevant examples into AI systems (Lopez, 2025), (2) improving diagnostic capabilities to identify nuanced learning needs (Chew & Cerbin, 2021), and (3) equipping teachers with training to integrate AI effectively as a complement to traditional instruction.

So, factor 3 illustrates that motivation thrives when learning experiences are both adaptive and meaningful. AI-driven personalization holds immense potential for sustaining students' interest and addressing diverse challenges in science education. However, its success depends on thoughtful tool design, balanced integration with human-led teaching, and equitable access. This makes motivation and personalization a crucial dimension for future research on long-term academic success in science.

Factor 4: Teaching Practices

The Role of Pedagogical Strategies in Enhancing Science Education. Teaching Practices are a crucial component in understanding how pedagogical strategies contribute to the effectiveness of science education. This factor, which explained 5.63% of the total variance in the exploratory factor analysis, underscores the role of teaching methods in creating a positive and effective learning environment. It is recognized that this factor is central to the success of any educational framework, particularly in the context of science education, where the complexity of the subject matter requires thoughtful and strategic instructional design to engage students and foster deep learning.

Interactive Learning and Active Student Participation. The variables associated with Factor 4: Teaching Practices highlight the significant impact of pedagogical approaches, including interactive learning, the use of visual aids, and active student participation. These teaching practices are grounded in the idea that science is not merely about the transmission of knowledge but about creating an environment where students actively engage with the material and develop the skills to apply their knowledge in real-world contexts (Shivolo & Mokiwa, 2024). Science, with its abstract theories and complex concepts, often necessitates teaching strategies that transcend passive learning. Traditional lectures, while helpful in introducing concepts, are often insufficient for deep understanding and retention. Active learning strategies, such as inquiry-based learning, problem-based learning, and hands-on experiments, are crucial for engaging students and helping them develop the critical thinking skills necessary to navigate scientific challenges (Golhar, 2025).

Use of Visual Aids and Representations. One key insight from this factor is the importance of visual aids and interactive methods in science education. Concepts such as cellular processes or chemical reactions are inherently difficult to grasp through text-based explanations alone. Visual representations—such as diagrams, animations, and interactive simulations—play a pivotal role in bridging the gap between abstract knowledge and student comprehension (Teplá et al., 2022). For instance, using 3D models of molecular structures or virtual lab simulations can provide students with a tangible representation of complex processes, making them more accessible and easier to understand. It has been observed that these teaching practices are particularly effective for students who struggle with abstract thinking or are visual learners. By utilizing these tools, teachers can foster a more inclusive learning environment that accommodates the diverse cognitive needs of students.

Moreover, interactive teaching methods—such as group discussions, collaborative projects, and problem-solving activities—are essential for fostering student engagement. These methods encourage students to take an active role in their learning process, facilitating more profound understanding and retention. In science education, where concepts often build on one another, interactive methods allow students to engage in active problem-solving, applying what they have learned to new situations (Yannier et al., 2020). For example, during a lesson on ecosystems, students might work in groups to simulate the effects of different environmental factors on a local habitat, applying their knowledge of ecological principles in a hands-on, collaborative environment.

Interconnectedness with Other Factors. The relationship between Factor 4: Teaching Practices and the other factors—Factor 1 (Engagement with AI Tools) and Factor 2 (Cognitive Challenges)—suggests that effective teaching practices are not standalone but rather are closely intertwined with the use of technology and the addressing of cognitive challenges. For example, teachers who integrate AI tools into their teaching practices can provide students with personalized learning experiences that help them overcome cognitive barriers. Adaptive learning systems can identify areas where students are struggling and provide targeted interventions, while interactive simulations can complement traditional teaching methods by offering dynamic visualizations of complex scientific concepts (Zawacki-Richter et al., 2019). Thus, the effective integration of AI tools into teaching practices enhances the overall learning experience by personalizing the content and making it more accessible to diverse learners. Thus, the findings underscore the need for comprehensive strategies to facilitate inclusive classrooms that cater to the needs of both students and educators (Pasumala et al., 2024).

Challenges in Implementing Teaching Practices. However, despite the clear advantages of interactive and visually based teaching practices, there are notable challenges that must be addressed to realize their potential fully. One of the main barriers is the insufficient training of teachers in utilizing these methods effectively. While many educators recognize the importance of active learning and visual aids, they often lack the necessary skills or resources to incorporate these strategies into their classrooms effectively (Singh, 2024). Additionally, the availability of technology is a key challenge. Not all schools have access to the necessary tools and resources to implement AI-driven simulations or interactive learning platforms, particularly in underfunded or rural areas. This creates an equity issue, where students in more affluent schools may benefit from cutting-edge teaching practices, while those in disadvantaged schools may be left behind (Jia et al., 2023).

As researchers, we recommend several strategies to enhance the effectiveness of science education teaching practices. First, professional development programs for teachers should focus on integrating active learning strategies, visual aids, and technology into science instruction. Teachers should be equipped not only with the knowledge of these strategies but also with the practical skills to implement them effectively in their classrooms (Mishra, 2024). Second, the development and implementation of AI tools should be designed with teachers in mind, providing them with user-friendly platforms that enhance, rather than replace, traditional pedagogical methods. This ensures that technology is used as a complement to effective teaching practices, rather than a substitute (Zawacki-Richter et al., 2019). Third, policymakers should prioritize increasing the accessibility of educational technology to all schools, ensuring that students from all socioeconomic backgrounds have access to the necessary tools to succeed (Jia et al., 2023).

We conclude that Factor 4: Teaching Practices underscores the essential role that pedagogical strategies play in enhancing science education. Effective teaching practices—such as interactive methods, visual aids, and encouraging active student participation—are crucial for fostering deep understanding and engagement, particularly in subjects as complex as science (Yannier et al., 2020). The integration of AI tools into these practices can further enhance their effectiveness, providing personalized learning experiences that address individual cognitive challenges. However, to fully realize the potential of these teaching methods, educators must receive adequate training, and schools must have access to the necessary resources and technology. Research highlights that this factor is a cornerstone of effective science education, with the potential to improve learning outcomes when properly implemented and supported significantly.

4.0 Conclusion

In summary, this study highlights the critical role that artificial intelligence (AI) can play in addressing learning gaps in science education, with a particular emphasis on integrating AI-driven tools into instructional practices. The findings underscore that engagement with AI tools, cognitive challenges, motivation, personalization, and teaching practices are pivotal factors that influence students' learning experiences and outcomes. AI tools such as chatbots, simulations, and other interactive technologies were found to be instrumental in enhancing students' comprehension of complex scientific concepts, providing personalized and interactive learning opportunities that address individual learning needs. The implications of these findings are multifaceted.

First, it is recommended that teachers at this Laboratory High School adopt the AILG scale to assess students' learning gaps before and after instruction. This diagnostic tool will enable teachers to identify specific areas of difficulty, allowing for more targeted teaching strategies and interventions. Second, the integration of AI tools into regular lessons should be prioritized, particularly to assist students with complex science topics. Professional development opportunities for teachers are essential to ensure effective use of AI technologies in the classroom. By equipping teachers with the necessary skills and resources, AI tools can be effectively integrated into the learning process, enhancing student engagement and understanding.

Nonetheless, this study has certain limitations. Since it was conducted in a single institution with purposive sampling, the findings may not be fully generalizable to other schools with different contexts and populations. Moreover, the focus on short-term outcomes leaves the long-term impact of AI integration on student performance and motivation still uncertain. The AILG scale also requires further validation through confirmatory factor analysis (CFA) and replication in diverse educational settings to ensure its reliability and broader applicability.

Finally, future research should explore the broader application and effectiveness of the AILG scale as a diagnostic tool for identifying and addressing learning gaps in science education. Confirmatory factor analysis (CFA) should be employed to validate the scale's reliability further and refine its application in diverse educational contexts. Furthermore, future studies could investigate the long-term effects of AI integration on student performance and motivation, particularly in the science domain. This research contributes to the growing body of literature on AI in education, providing both a theoretical framework and a practical tool for educators. The AILG scale represents a significant step forward in understanding and addressing learning gaps in science education, with the potential to inform teaching practices, curriculum design, and educational policy.

5.0 Contribution of Authors

The author conceptualized and designed the study, collected and analyzed the data, and wrote the manuscript. Authors B and C contributed to data analysis, interpretation, and manuscript revisions. Author D provided critical feedback on the study design, supervised the research process, and approved the final manuscript. All authors read and approved the final version of the manuscript and agree to be accountable for its contents.

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7.0 Conflict of Interest

The authors declare no conflict of interest related to this study.

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