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# Developing an AI Educator Readiness Matrix for AI-Enabled Science Laboratory: Bridging Generations in Science Education

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***ABSTRACT***

*The increasing integration of artificial intelligence (AI) in science education has created new opportunities for enhancing laboratory instruction while simultaneously requiring educators to possess the competencies necessary for effective AI adoption. This study assessed educators' readiness to implement AI in science laboratory instruction and developed an AI Educator Readiness Matrix (AERM) to support institutional decision-making and professional development. Employing a descriptive quantitative research design, data were collected from 23 science educators via a validated survey. Descriptive statistics, including frequencies, percentages, weighted means, and rankings, were used to analyze the respondents' profiles and levels of readiness across five dimensions: knowledge of AI concepts, technical skills, instructional confidence, institutional support, and attitude toward AI use in science education. The findings revealed that the respondents were predominantly Millennial educators with six to ten years of teaching experience who had primarily acquired AI knowledge through webinars and online seminars. Overall, educators were found to be ready to implement AI in science laboratory instruction (M = 3.59). Among the readiness dimensions, attitude toward AI (M = 3.89), knowledge of AI concepts (M = 3.83), and institutional support (M = 3.47) were rated as ready, whereas technical skills (M = 3.36) and instructional confidence (M = 3.39) were only moderately ready, indicating the need for targeted capacity-building initiatives. Based on these findings, the study developed the AI Educator Readiness Matrix (AERM), a practical assessment and decision-support tool that enables educational institutions to evaluate educator readiness, identify competency gaps, and design evidence-based professional development interventions prior to implementing AI-enabled science laboratory instruction. The matrix provides a systematic framework for strengthening AI integration while promoting sustainable, ethical, and pedagogically sound science laboratory practices.*

***Keywords:*** *- artificial intelligence, science laboratory instruction, educator readiness, AI Educator Readiness Matrix, AI integration, science education, professional development.*

## INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most transformative technologies shaping contemporary education, particularly in science teaching where data analysis, virtual experimentation, intelligent tutoring, predictive modeling, and adaptive learning environments are becoming increasingly prevalent. The transition toward AI-enhanced education aligns with the broader movement from Industry 4.0 to Industry 5.0, where intelligent technologies are expected not only to automate processes but also to augment human decision-making, creativity, and personalized learning (Adel, 2024). In science education, AI has expanded opportunities for improving laboratory instruction through virtual laboratories, AI-powered simulations, automated feedback systems, image recognition technologies, and intelligent learning platforms that enhance students' conceptual understanding and scientific inquiry (Cooper, 2023; Lee et al., 2023). Consequently, the successful implementation of AI-enabled science laboratories depends not only on technological infrastructure but also on the readiness of educators who will design, facilitate, and evaluate AI-supported learning experiences.

Recent studies demonstrate the growing interest in AI integration within science education. Bibliometric analyses reveal a substantial increase in research focusing on AI applications in science teaching, laboratory innovation, and educational technologies over the past decade (Akhmadieva et al., 2023; Jia et al., 2024). Existing literature has explored various applications of AI, including intelligent tutoring systems, virtual laboratory environments, generative AI, machine learning, and automated assessment tools that support inquiry-based science instruction (Cooper & Tang, 2024; Lee et al., 2023). These developments highlight the significant potential of AI to improve laboratory efficiency, learner engagement, and scientific problem-solving. However, technological advancement alone does not ensure successful classroom implementation, as educators remain the primary agents responsible for translating these innovations into meaningful instructional practice.

Educator readiness has therefore become a critical determinant of effective AI integration. Readiness extends beyond technological awareness and encompasses conceptual understanding, technical competence, instructional confidence, institutional support, and positive attitudes toward innovation. Previous studies have shown that teachers generally recognize the educational value of AI but often demonstrate varying levels of preparedness to apply AI in authentic teaching contexts (AlKanaan, 2022; Sysoyev, 2023). Likewise, Kim and Kwon (2023) emphasized that AI competencies among educators involve not only technical proficiency but also pedagogical decision-making, ethical awareness, and continuous professional learning. Tondeur et al. (2019) similarly argued that teacher educators serve as gatekeepers of technology integration, making their readiness essential to the successful adoption of emerging educational technologies.

Despite the growing body of research on AI in education, several important gaps remain. First, much of the existing literature has focused on AI applications, technological innovations, or students' learning outcomes, while comparatively fewer studies have examined the multidimensional readiness of science educators responsible for implementing AI-enabled laboratory instruction (Akhmadieva et al., 2023; Jia et al., 2024). Second, previous investigations have often explored isolated aspects of readiness, such as digital competence,

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technological acceptance, or AI awareness, without integrating knowledge, technical skills, instructional confidence, institutional support, and attitudes into a comprehensive readiness assessment (de Obesso et al., 2023; Zhang & Villanueva, 2023). Third, although organizational readiness instruments have been developed for technology-enhanced learning environments (Edralin & Pastrana, 2021), there remains a lack of practical assessment tools specifically designed to evaluate educator readiness for AI-enabled science laboratory instruction. Existing frameworks largely conceptualize readiness but offer limited guidance on identifying readiness levels, diagnosing competency gaps, and informing institutional interventions.

Furthermore, limited attention has been given to the influence of educators' demographic characteristics, including generational affiliation, teaching experience, AI-related training, and familiarity with AI tools, on their readiness to adopt AI in science laboratories. As educational institutions increasingly pursue AI integration, understanding how these contextual factors shape readiness becomes essential for designing responsive professional development programs and institutional support systems. Bridging generational differences is particularly important, as educators from different cohorts possess varying technological experiences, instructional practices, and professional learning needs that collectively influence AI adoption (Kim & Kwon, 2023).

Addressing these gaps, this study assessed the profile of science educators and examined their readiness to implement AI in science laboratory instruction across five dimensions: knowledge of AI concepts, technical skills in operating AI-based educational tools, instructional confidence, access to institutional support, and attitudes toward AI use in science education. Building upon these empirical findings, the study developed the AI Educator Readiness Matrix (AERM), a practical assessment and decision-support tool designed to assist educational institutions in evaluating educator readiness, identifying competency gaps, and planning evidence-based professional development initiatives prior to implementing AI-enabled science laboratory instruction. By transforming descriptive readiness data into a structured institutional assessment tool, the study contributes a practical resource that supports sustainable, ethical, and pedagogically sound AI integration in science education.

**Statement of the Problem**

This study assessed science educators' readiness to implement artificial intelligence (AI) in science laboratory instruction to inform the development of an AI Educator Readiness Matrix (AERM).

Specifically, it sought to answer the following questions:

1. What is the profile of the respondents in terms of:
    a. age group;
    b. years of teaching experience;
    c. science course(s) taught;
    d. AI-related trainings attended; and
    e. familiarity with AI tools and platforms?
2. What is the level of educator readiness to implement AI in science laboratory instruction in terms of:

   a. knowledge of AI concepts relevant to science teaching;
   b. skills in operating AI-based educational tools in laboratory settings;
   c. confidence in integrating AI in classroom and laboratory instruction;
   d. access to institutional support (infrastructure, policies, and training); and
   e. attitude toward AI use in science education?
3. Based on the findings of the study, what AI Educator Readiness Matrix (AERM) can be developed to support the implementation of AI-enabled science laboratory instruction?

## Scope and Delimitations

This study assessed the readiness of science educators to implement artificial intelligence (AI) in science laboratory instruction as the basis for developing the AI Educator Readiness Matrix (AERM). Specifically, it examined the respondents' profile in terms of age group, years of teaching experience, science course(s) taught, AI-related trainings attended, and familiarity with AI tools and platforms. It also assessed educator readiness across five dimensions: knowledge of AI concepts relevant to science teaching, skills in operating AI-based educational tools in laboratory settings, confidence in integrating AI into classroom and laboratory instruction, access to institutional support, and attitudes toward AI use in science education. The findings from these dimensions served as the empirical basis for developing the proposed AI Educator Readiness Matrix, a practical assessment and decision-support tool intended to guide educational institutions in evaluating faculty readiness and planning professional development initiatives for AI-enabled science laboratory instruction.

The study was delimited to selected science educators teaching General Science, Biology, Chemistry, Physics, and Environmental Science who met the established inclusion criteria and voluntarily participated in the research. A descriptive quantitative research design was employed, with a researcher-developed survey questionnaire as the primary data-collection instrument. Data analysis was limited to descriptive statistics, including frequency counts, percentages, weighted means, and rankings, to describe the respondents' profiles and assess their readiness levels. While the study developed the AI Educator Readiness Matrix (AERM) based on empirical findings, it did not implement, pilot test, or evaluate the matrix's effectiveness in actual educational settings. Furthermore, the study did not investigate students' learning outcomes, institutional AI implementation practices, or the long-term impact of AI integration in science laboratory instruction. Consequently, the findings and the proposed matrix should be interpreted within the context of the participating educators and may serve as a foundation for future validation and implementation studies

## Review of Related Literature

### *Artificial Intelligence in Science Education*

Artificial intelligence (AI) has rapidly transformed educational systems by introducing intelligent technologies that enhance teaching, learning, assessment, and classroom management. In science education, AI has become increasingly significant for its ability to support complex scientific inquiry, laboratory experimentation, personalized learning, and data-driven instruction. Intelligent tutoring systems, machine learning applications,

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virtual laboratories, predictive analytics, and generative AI platforms have expanded the ways educators facilitate scientific investigations while improving students' engagement and conceptual understanding. As education transitions toward Industry 5.0, AI is increasingly viewed as a collaborative technology that complements human expertise rather than replacing teachers (Adel, 2024).

The growing prominence of AI in science education is reflected in recent scholarly literature. Akhmadieva et al. (2023) conducted a bibliometric review and reported a substantial increase in AI-related research focusing on science education, highlighting applications in laboratory instruction, adaptive learning systems, intelligent tutoring, and scientific visualization. Similarly, Jia et al. (2024) found that research trends over the past decade have increasingly emphasized AI-supported inquiry, laboratory simulations, and personalized science instruction. These developments indicate that AI is becoming an essential component of contemporary science education, requiring educators to possess the competencies necessary to integrate these technologies effectively into laboratory teaching.

Recent innovations further illustrate AI's expanding role within science laboratories. Lee et al. (2023) developed a hands-free AI speaker system designed specifically for laboratory instruction, demonstrating how AI can facilitate experimental procedures, improve learner engagement, and reduce instructional interruptions. Likewise, Cooper (2023) explored the capabilities of generative AI in science education and concluded that AI can effectively support content generation, laboratory preparation, and scientific explanation when used responsibly under the supervision of educators. Together, these studies demonstrate that AI is reshaping laboratory instruction by expanding instructional possibilities while simultaneously requiring educators to develop new competencies.

*Educator Readiness for Artificial Intelligence Integration*

The successful implementation of AI in education depends not only on the availability of technology but also on educators' readiness to adopt, use, and sustain AI-supported instructional practices. Educator readiness is recognized as a multidimensional construct encompassing knowledge, technical competence, instructional confidence, institutional support, and positive attitudes toward technology integration.

AlKanaan (2022) investigated science teachers' awareness regarding AI integration and found that although educators generally recognized AI's educational value, many demonstrated only moderate understanding of its practical applications in science teaching. The study concluded that strengthening educators' conceptual understanding of AI is essential before meaningful classroom integration can occur. Similarly, Sysoyev (2023) reported that university faculty generally possessed positive perceptions of AI but differed considerably in their actual readiness and frequency of AI use, suggesting that awareness alone does not necessarily translate into classroom implementation.

Teacher competency has likewise emerged as a central factor influencing AI adoption. Kim and Kwon (2023) developed an AI competency framework for elementary school teachers and emphasized that effective AI integration requires a combination of technological knowledge, pedagogical competence, ethical awareness, and continuous professional learning. Likewise, Zhang and Villanueva (2023) argued that educators' technological competence significantly predicts their preparedness to implement AI in instructional settings, highlighting the importance of continuous competency development as educational technologies continue to evolve.

*Knowledge and Skills for AI Integration*

Effective AI integration requires educators to possess both conceptual understanding and operational competence. Knowledge enables teachers to understand AI principles, ethical implications, and instructional applications, while technical skills enable them to utilize AI tools effectively within authentic learning environments.

de Obesso et al. (2023) found that students' perceptions of educators' digital competence were strongly associated with teachers' ability to utilize emerging technologies confidently and effectively. Their findings suggest that digital competence extends beyond technical operation and includes instructional decision-making and responsible technology use. Likewise, Nkundabakura et al. (2023) reported that although educators increasingly employ innovative digital tools in mathematics and science education, significant variations remain in their ability to integrate these technologies into meaningful classroom activities.

Within laboratory contexts, AI technologies increasingly require specialized competencies. Bannigan et al. (2021) demonstrated how machine learning applications support scientific experimentation through predictive modeling and data analysis, while Mudunuru et al. (2023) emphasized AI's growing contribution to scientific simulation, computational modeling, and environmental prediction. These innovations highlight the importance of equipping science educators with the technical skills necessary to operate AI-enabled laboratory tools and interpret AI-generated outputs effectively.

*Instructional Confidence in AI-Enabled Teaching*

Instructional confidence influences educators' willingness to experiment with emerging technologies and integrate them into teaching practice. Teachers with greater confidence are more likely to adopt innovative instructional strategies and sustain technology integration despite implementation challenges.

Hartono et al. (2023) reported that teachers' experiences with AI are strongly influenced by their confidence in applying technological tools within instructional contexts. Although educators generally acknowledged AI's usefulness, confidence varied depending on prior experience, institutional support, and access to professional development opportunities. Similarly, Cooper (2023) noted that while science educators increasingly appreciate the capabilities of generative AI, many remain cautious regarding lesson planning, laboratory assessment, and responsible AI implementation due to limited instructional experience.

Confidence also develops through authentic practice and repeated exposure. Maria Josephine Arokia Marie (2021) emphasized that blended learning environments strengthen educators' pedagogical confidence by providing opportunities for continuous technology integration. These findings suggest that instructional confidence is not solely an individual characteristic but develops progressively through professional learning experiences and

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institutional encouragement.

*Institutional Support for AI Integration*

Institutional readiness plays a significant role in sustaining educators' adoption of AI technologies. Successful implementation requires supportive leadership, adequate infrastructure, professional development, technical assistance, and organizational policies that encourage instructional innovation.

Edralin and Pastrana (2021) emphasized that organizational readiness entails aligning leadership, infrastructure, technological resources, and professional development to ensure sustainable educational innovation. Likewise, Romero-Rodríguez et al. (2020) found that educators' perceptions of the usefulness of technology are strongly influenced by institutional policies, administrative commitment, and access to technological resources. These findings indicate that institutional support extends beyond infrastructure to include the creation of an organizational culture that encourages experimentation and continuous improvement.

Tondeur et al. (2019) further argued that teacher educators serve as gatekeepers of technology integration, as they influence how future teachers perceive and use emerging technologies. Consequently, higher education institutions have a critical responsibility to establish supportive environments that enable educators to develop AI competencies and to model effective technology integration for future science teachers.

*Attitudes Toward Artificial Intelligence in Education*

Positive attitudes toward AI significantly influence educators' willingness to adopt technological innovations. Teachers who perceive AI as beneficial are generally more receptive to experimenting with new instructional approaches and participating in professional development initiatives.

Akhmadieva et al. (2023) concluded that favorable perceptions of AI contribute substantially to successful technology adoption within educational settings. Similarly, Cooper (2023) found that educators increasingly view generative AI as a valuable instructional partner that can enhance science teaching when used responsibly and ethically. Nevertheless, the literature also recognizes concerns regarding academic integrity, overreliance on automation, and ethical decision-making, highlighting the importance of preparing educators to use AI critically rather than unconditionally.

Khlaif et al. (2023) further noted that technological acceptance may be influenced by technostress and educators' confidence in managing emerging technologies. Consequently, fostering positive attitudes toward AI requires not only demonstrating technological benefits but also providing adequate support systems that reduce anxiety and promote sustained engagement.

*AI Readiness Assessment and Professional Development*

The growing integration of AI has increased the need for systematic assessment of educator readiness. Readiness assessments provide educational institutions with evidence regarding faculty competencies, identify professional development priorities, and guide institutional planning before implementing AI initiatives.

Goh et al. (2022) emphasized that competency frameworks provide structured guidance for identifying essential educator competencies while supporting curriculum improvement and faculty development. Likewise, Tondeur et al. (2019) advocated competency-based professional development that combines technological knowledge, pedagogical expertise, and institutional support to strengthen technology integration among educators. These perspectives suggest that readiness assessment should extend beyond measuring technological competence to include organizational conditions, instructional confidence, and professional attitudes.

*Synthesis of the Literature*

The reviewed literature demonstrates that AI has become an increasingly important component of science education, particularly in laboratory instruction where intelligent technologies support experimentation, scientific inquiry, and personalized learning. Existing studies consistently identify educator readiness as a multidimensional construct involving knowledge, technical skills, instructional confidence, institutional support, and positive attitudes toward AI. However, previous investigations have largely examined these dimensions independently or focused primarily on technology adoption, digital competence, or AI awareness. Comparatively few studies have integrated these readiness dimensions into a comprehensive assessment framework specifically designed for science laboratory instruction.

Furthermore, although several studies have proposed competency models and readiness frameworks, there remains limited evidence of practical assessment tools that educational institutions can use to evaluate science educators’ preparedness before implementing AI-enabled laboratory instruction. This gap highlights the need for an evidence-based instrument that translates empirical readiness indicators into an actionable institutional resource. Addressing this need, the present study assesses educators’ readiness across multiple dimensions and develops the AI Educator Readiness Matrix (AERM) as a practical assessment and decision-support tool to guide faculty development and support the implementation of AI-enabled science laboratory instruction.

## Theoretical Framework

This study is anchored in the Technology Acceptance Model (TAM) developed by Davis (1989), the Technological Pedagogical Content Knowledge (TPACK) Framework proposed by Mishra and Koehler (2006), and Diffusion of Innovations Theory by Rogers (2003). These complementary theories provide a comprehensive explanation of educators’ readiness to integrate artificial intelligence (AI) into science laboratory instruction and serve as the theoretical foundation for the development of the AI Educator Readiness Matrix (AERM).

The Technology Acceptance Model (TAM) explains that an individual’s intention to adopt a new technology is primarily influenced by two factors: perceived usefulness and perceived ease of use (Davis, 1989). When educators perceive AI technologies as

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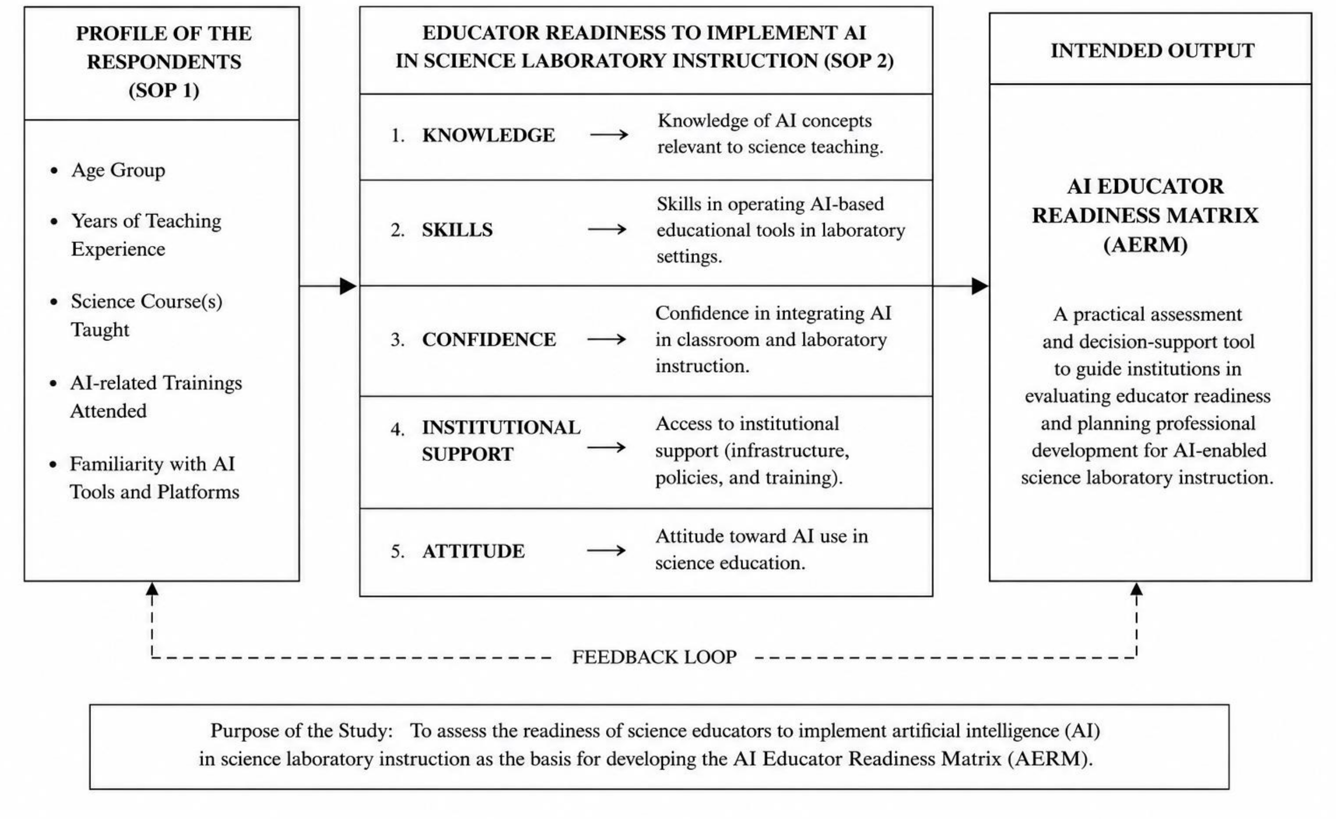
beneficial for improving science laboratory instruction and believe that these technologies are manageable and easy to use, they are more likely to develop positive attitudes and demonstrate greater willingness to integrate AI into their teaching practices. Within this study, TAM provides the theoretical basis for examining educators' attitudes toward AI, their confidence in using AI-supported instructional tools, and their readiness to adopt AI-enabled laboratory instruction. The model supports the premise that positive perceptions and acceptance are essential precursors to successful AI implementation in educational settings.

The study is likewise grounded in the Technological Pedagogical Content Knowledge (TPACK) Framework developed by Mishra and Koehler (2006). The framework emphasizes that effective technology integration requires teachers to possess an interconnected understanding of content, pedagogical, and technological knowledge. Rather than mastering technology alone, educators must understand how AI tools complement science concepts and instructional strategies to facilitate meaningful learning experiences. Within the context of AI-enabled science laboratories, TPACK explains the importance of educators' knowledge of AI concepts, technical skills in operating AI-based educational tools, and confidence in designing and implementing AI-supported laboratory instruction. The framework therefore supports the multidimensional assessment of educator readiness undertaken in this study.

The third theoretical foundation is Diffusion of Innovations Theory proposed by Rogers (2003), which explains how innovations are introduced, adopted, and sustained within organizations and social systems. According to the theory, successful adoption of an innovation depends on factors such as individual readiness, organizational support, communication, and the perceived advantages of the innovation. In educational settings, AI represents an instructional innovation that requires educators to acquire new competencies while institutions establish policies, infrastructure, leadership support, and professional development opportunities. This perspective aligns closely with the institutional support dimension of the study, recognizing that educator readiness is influenced not only by individual competence but also by the organizational environment in which AI implementation occurs.

Collectively, these theoretical perspectives provide a comprehensive explanation of educator readiness for AI integration. The Technology Acceptance Model explains educators' acceptance and attitudes toward AI technologies; the TPACK Framework emphasizes the integration of technological, pedagogical, and content knowledge required for effective AI-enabled science laboratory instruction; and Diffusion of Innovations Theory highlights the critical role of institutional support and organizational readiness in facilitating technology adoption. Together, these theories underpin the investigation of science educators' readiness across knowledge, technical skills, instructional confidence, institutional support, and attitudes toward AI use. They likewise provide the theoretical basis for the development of the AI Educator Readiness Matrix (AERM) as a practical assessment and decision-support tool for educational institutions seeking to implement AI-enabled science laboratory instruction.

## Conceptual Framework




The first component presents the profile of the respondents in terms of age group, years of teaching experience, science courses taught, AI-related trainings attended, and familiarity with AI tools and platforms. These characteristics provide important context for understanding differences in educators' exposure to technology, professional experience, and preparedness for AI integration. Variations in age, teaching experience, training background, and familiarity with AI may influence how educators perceive, adopt, and apply emerging technologies in laboratory instruction. Although the study primarily uses these variables to describe the participants, they also help institutions interpret readiness results in relation to educators' professional and technological backgrounds.

The second component focuses on educator readiness to implement AI in science laboratory instruction across five dimensions: knowledge, skills, confidence, institutional support, and attitude. Knowledge refers to educators' understanding of AI concepts and their relevance to science teaching. Skills pertain to the ability to operate AI-based educational tools in laboratory settings, while confidence concerns educators' perceived capability to integrate AI into classroom and laboratory instruction. Institutional support encompasses access to infrastructure, policies, technical assistance, and training, whereas attitude reflects educators' openness to, acceptance of, and perceived value of AI in science education. Together, these dimensions provide a comprehensive assessment of readiness by recognizing that successful AI integration depends not only on technical competence but also on pedagogical assurance, institutional conditions, and willingness to adopt innovation.

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The framework's intended output is the AI Educator Readiness Matrix. The AERM is designed as a practical assessment and decision-support tool that educational institutions may use to evaluate educator readiness, identify strengths and competency gaps, and determine appropriate professional development interventions. By translating the five readiness dimensions into measurable indicators and corresponding readiness classifications, the matrix offers a structured basis for planning AI-related training, mentoring, technical support, and institutional initiatives. In this way, the AERM moves beyond merely describing readiness and provides an actionable mechanism for supporting the implementation of AI-enabled science laboratory instruction.

The framework also includes a feedback loop, emphasizing that educator readiness is developmental and should be reassessed over time. As educators gain additional training, experience, and institutional support, their readiness profiles may change, requiring corresponding revisions in professional development strategies and implementation plans. Continuous assessment and feedback therefore allow institutions to monitor progress, refine interventions, and ensure that AI integration remains responsive to educators' needs and evolving technological conditions. Overall, the framework positions educator readiness as a multidimensional and continuously developing condition that must be systematically assessed and supported before AI can be integrated effectively, ethically, and sustainably into science laboratory instruction.

## METHODOLOGY

This chapter presents the research methodology employed in conducting the study. It describes the research design, participants and sampling procedures, research instrument, validation process, data collection procedures, and data analysis techniques utilized to assess the readiness of science educators to implement artificial intelligence (AI) in science laboratory instruction. The chapter also discusses the ethical considerations and study limitations observed throughout the research process. These methodological procedures provided a systematic and rigorous approach to data collection and analysis, serving as the empirical basis for developing the AI Educator Readiness Matrix (AERM) as a practical assessment and decision-support tool for AI-enabled science laboratory instruction.

### Research Design

This study employed a descriptive quantitative research design to assess the readiness of science educators to implement artificial intelligence (AI) in science laboratory instruction and to develop the AI Educator Readiness Matrix (AERM). The descriptive design was deemed appropriate because it systematically described the respondents' profile and determined their level of readiness across five dimensions: knowledge of AI concepts, skills in operating AI-based educational tools, confidence in AI integration, access to institutional support, and attitudes toward AI use in science education. No variables were manipulated, as the study aimed to provide an accurate description of the existing readiness of science educators. The quantitative findings served as the empirical basis for developing the AERM, a practical assessment and decision-support tool intended to guide educational institutions in evaluating faculty preparedness and planning targeted professional development initiatives for AI-enabled science laboratory instruction.

## Research Steps

The study followed a systematic sequence of procedures to ensure the validity and reliability of the findings. Initially, the researcher conducted an extensive review of related literature and previous studies on artificial intelligence, science laboratory instruction, educator readiness, and technology integration. The review established the study's theoretical foundation, identified research gaps, and guided the formulation of research objectives and the development of the conceptual framework.

Following the conceptualization of the study, the researcher developed the survey questionnaire based on the identified readiness dimensions: knowledge of AI concepts, technical skills, instructional confidence, institutional support, and attitudes toward AI use in science education. The instrument likewise included items describing the respondents' demographic profile. The questionnaire was subsequently submitted to experts in science education, educational technology, and research methodology for content validation. The validators' recommendations were incorporated to improve the instrument's clarity, relevance, and alignment with the study's objectives.

After securing the necessary permissions from the relevant authorities, the validated questionnaire was administered to the selected science educators who met the study's inclusion criteria. Participants were informed of the purpose of the research, and informed consent was obtained prior to data collection. Responses were collected via an online survey platform, allowing participants to complete the questionnaire at their convenience and ensuring confidentiality and voluntary participation.

Upon completion of data collection, the responses were coded, organized, and analyzed using descriptive statistics, including frequency counts, percentages, weighted means, and rankings. These analyses were used to describe the respondents' profile and determine their level of readiness across the five identified dimensions.

Finally, the results of the statistical analyses were synthesized to identify educators' strengths and areas requiring improvement. The empirical findings served as the basis for developing the AI Educator Readiness Matrix (AERM), a practical assessment and decision-support tool for evaluating educator readiness and guiding professional development initiatives to support the implementation of AI-enabled science laboratory instruction.

## Data Collection and Sample Selection

The study employed purposive sampling in selecting the respondents. Participants were selected based on predetermined inclusion criteria to ensure they possessed the necessary qualifications and experience relevant to the study's objectives. Eligible respondents were science educators currently teaching one or more science disciplines, including General Science, Biology, Chemistry, Physics, or Environmental Science, and were actively involved in classroom and laboratory instruction. They were likewise expected to have varying levels of exposure to artificial intelligence (AI) technologies, enabling the study to capture a broad range of readiness levels regarding AI-enabled science laboratory instruction.

Prior to data collection, the researcher secured the necessary permissions from the

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appropriate institutional authorities to conduct the study. After obtaining approval, prospective participants were informed of the purpose of the research, the procedures involved, the voluntary nature of their participation, and the confidentiality of the information they would provide. Those who agreed to participate were asked to complete an informed consent form before completing the survey questionnaire.

Data were collected using a researcher-developed questionnaire that underwent expert validation to ensure content validity and alignment with the study's objectives. The questionnaire was administered via an online survey platform, allowing respondents to complete it at their convenience and ensuring wider accessibility and efficient data collection. The instrument gathered information regarding the respondents' demographic profile and assessed their readiness to implement AI in science laboratory instruction across the five identified dimensions: knowledge of AI concepts, skills in operating AI-based educational tools, confidence in AI integration, access to institutional support, and attitudes toward AI use in science education.

Upon completion of the data collection period, all responses were reviewed to determine completeness and consistency. Incomplete or duplicate submissions were excluded from the final dataset. The validated responses were subsequently encoded, organized, and prepared for statistical analysis. These data served as the empirical basis for describing educator readiness and for developing the AI Educator Readiness Matrix (AERM), the study's primary output.

### Data Analysis Methods

The data gathered from the completed questionnaires were organized, coded, and analyzed using appropriate descriptive statistics to address the study's objectives. The respondents' profile, including age group, years of teaching experience, science course(s) taught, AI-related trainings attended, and familiarity with AI tools and platforms, was summarized using frequency counts and percentages to describe the distribution of the participants across the identified demographic variables.

To determine the level of educator readiness to implement artificial intelligence in science laboratory instruction, weighted mean was employed for each indicator and for the five readiness dimensions: (1) knowledge of AI concepts relevant to science teaching, (2) skills in operating AI-based educational tools in laboratory settings, (3) confidence in integrating AI in classroom and laboratory instruction, (4) access to institutional support, and (5) attitude toward AI use in science education. The overall weighted mean was likewise computed to determine the respondents' general level of readiness.

Finally, the results of the descriptive statistical analyses served as the empirical basis for developing the AI Educator Readiness Matrix (AERM). The readiness levels obtained from each of the five dimensions were synthesized to identify educators' strengths, competency gaps, and corresponding professional development priorities. These findings informed the development of the matrix as a practical assessment and decision-support tool that educational institutions may use to evaluate faculty readiness and plan capacity-building initiatives for implementing AI-enabled science laboratory instruction.

### Research Hypothesis and Validation

The present study employed a descriptive quantitative research design to determine the profile and level of readiness of science educators in implementing artificial intelligence (AI) in science laboratory instruction and to develop the AI Educator Readiness Matrix (AERM). Since the study was descriptive in nature and did not examine relationships, differences, or predictive effects among variables, no inferential statistical analyses were conducted. Consequently, the study did not formulate or test any research hypotheses. Instead, it focused on describing the existing readiness of science educators and utilizing the empirical findings as the basis for developing the proposed AI Educator Readiness Matrix.

To ensure the validity of the data collection instrument, the researcher-developed questionnaire underwent a comprehensive content validation process prior to its administration. The instrument was evaluated by a panel of experts in science education, artificial intelligence in education, educational technology, measurement and evaluation, and research methodology. The validators assessed the questionnaire for content relevance, language clarity, indicator appropriateness, logical organization, and alignment with the study's objectives. Particular attention was given to determining whether the instrument adequately measured the five dimensions of educator readiness, namely knowledge of AI concepts, skills in operating AI-based educational tools, confidence in AI integration, access to institutional support, and attitudes toward AI use in science education.

Based on the recommendations of the experts, revisions were made to improve the wording of selected items, simplify technical terminology, eliminate ambiguous statements, and enhance the logical flow of the questionnaire. These modifications strengthened the instrument's content validity and ensured that each indicator appropriately represented the construct it was intended to measure. The validated questionnaire subsequently served as the primary data-collection instrument, providing reliable and relevant information to assess educator readiness and to develop the AI Educator Readiness Matrix (AERM) as the principal output of the study.

## Study Limitations and Ethical Considerations

The researcher ensured that the study was conducted in accordance with established ethical principles governing educational research. Prior to conducting the study, permission to administer the survey was obtained from the appropriate institutional authorities. All prospective participants were informed of the purpose of the study, the research procedures, the expected duration of their participation, and the intended use of the data. Participation was entirely voluntary, and informed consent was obtained from each respondent before the questionnaire was administered. Participants were likewise informed that they could decline to participate or withdraw from the study at any stage without penalty or disadvantage.

The researcher maintained the confidentiality, anonymity, and privacy of all respondents throughout the research process. No personally identifiable information was disclosed in the presentation, analysis, or interpretation of the findings. The responses were treated with strict confidentiality and were used solely for academic and research purposes. All completed questionnaires and electronic data were securely stored and were accessible only to the

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researcher. The researcher likewise ensured that the data were analyzed objectively and reported honestly without fabrication, falsification, or misrepresentation of the findings, thereby upholding the principles of research integrity, beneficence, respect for persons, and justice.

Despite these ethical safeguards, certain limitations should be considered when interpreting the study's findings. The investigation was limited to selected science educators teaching General Science, Biology, Chemistry, Physics, and Environmental Science, and the results therefore reflect only the readiness of the participating respondents within the context of the institutions included in the study. The use of a descriptive quantitative research design provided a snapshot of educator readiness at the time of data collection and did not examine causal relationships or changes in readiness over time. In addition, the data were based on self-reported responses, which may be influenced by respondents' personal perceptions and experiences despite efforts to ensure honest and objective responses.

Furthermore, the study focused exclusively on assessing educator readiness in terms of knowledge, skills, confidence, institutional support, and attitudes toward AI implementation in science laboratory instruction. It did not investigate the actual classroom implementation of AI technologies, students' learning outcomes, institutional effectiveness, or the long-term impact of AI integration on science education. Although the AI Educator Readiness Matrix (AERM) was developed based on the study's empirical findings, it was not pilot-tested or implemented in educational institutions. Consequently, future studies are encouraged to validate, implement, and refine the matrix across different educational contexts to further establish its effectiveness as an institutional assessment and decision-support tool for AI-enabled science laboratory instruction.

## RESULTS AND DISCUSSION

***SOP 1. What is the profile of the respondents in terms of age group, years of teaching experience, science courses taught, AI-related trainings attended, and familiarity with AI tools and platforms?***

This section presents the demographic profile of the respondents, which provides context for interpreting their readiness and perspectives toward an AI-enabled science laboratory. The variables such as age group, years of teaching experience, science course(s) taught and exposure to technology are described to show the diversity of backgrounds that may influence their level of familiarity and adaptability in integrating artificial intelligence into science education.

**Table1a Profile of the Respondents**
***(n=23)***

| Profile Variable | Category | f | % |
|---|---|---|---|
| | Generation X (born 1965–1980) | 5 | 21.7 |

| | | | |
|---|---|---|---|
| Age Group | Millennial (born 1981–1996) | 14 | 60.9 |
| | Generation Z (born 1997–2012) | 4 | 17.4 |
| Years of Teaching Experience | 1–5 years | 5 | 21.7 |
| | 6–10 years | 12 | 52.2 |
| | 11–15 years | 2 | 8.7 |
| | 16–20 years | 1 | 4.3 |
| | More than 20 years | 3 | 13.0 |

Table 1a shows the distribution of respondents according to age group and years of teaching experience. Out of 23 participants, the majority belong to the Millennial generation (1981–1996) with 14 respondents, accounting for 60.9 percent of the sample. This is followed by Generation X (1965–1980) with 5 respondents or 21.7 percent, and Generation Z (1997–2012) with 4 respondents or 17.4 percent. In terms of teaching experience, the highest concentration is in the 6–10 years category with 12 respondents or 52.2 percent, followed by 1–5 years with 5 respondents or 21.7 percent. Fewer respondents reported longer experience, with 2 (8.7 percent) having 11–15 years, 1 (4.3 percent) in the 16–20 years category, and 3 (13 percent) with more than 20 years of teaching.

The results indicate that the profile of the respondents is predominantly shaped by Millennial educators who have been in the teaching profession for less than a decade. This suggests that the majority of participants are at an early to mid-career stage, a period often characterized by openness to technological adoption and professional development opportunities. The smaller representation of Generation X and Generation Z shows that while intergenerational perspectives are present, the bulk of insights come from those in the middle cohort. From a teaching experience standpoint, more than half of the respondents fall within 6–10 years, aligning with the developmental stage in which teachers are consolidating their pedagogical practices and beginning to integrate advanced technologies into instruction.

The presence of Millennials as the dominant group highlights their crucial role in bridging generations in science education. Millennials are positioned between Generation X, who may have more traditional instructional orientations, and Generation Z, who are considered digital natives with high familiarity with emerging technologies (Kim & Kwon, 2023). This middle-ground positioning may allow Millennials to act as mediators in adapting artificial intelligence into laboratory practices while supporting intergenerational knowledge transfer. The teaching experience data also emphasizes that a majority of respondents are not yet veteran educators, making readiness for AI integration likely tied to their flexibility and ongoing pursuit of innovative practices.

These findings resonate with the assertions of AlKanaan (2022), who noted that awareness and adaptability of pre-service and in-service teachers toward AI integration depend on both generational affiliation and professional exposure. Similarly, de Obesso et al. (2023) emphasized that educators' digital competence is strongly influenced by their career stage and experience in implementing technology in classroom contexts. Therefore, the generational and experiential profiles observed in this study suggest a readiness environment where Millennials, supported by their relative teaching experience, could spearhead the development and adoption of a practical framework for AI-enabled science laboratories.

**Table 1b Science Course(s) Taught**
***(n=23)***

| | Responses | | Percent of |
|---|---|---|---|
| | N | Percent | Cases |

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| | | | | |
|---|---|---|---|---|
| Science Course(s) Taught[a] | General Science | 11 | 25.6% | 47.8% |
| | Biology | 4 | 9.3% | 17.4% |
| | Chemistry | 11 | 25.6% | 47.8% |
| | Physics | 6 | 14.0% | 26.1% |
| | Environmental Science | 11 | 25.6% | 47.8% |
| Total | | 39 | 100.0% | 187.0% |

*a. Dichotomy group tabulated at value 1.*

Table 1b presents the distribution of science courses taught by the respondents. Out of the 23 respondents, a total of 39 course mentions were recorded since some educators handle more than one subject. General Science, Chemistry, and Environmental Science were each taught by 11 respondents, representing 25.6 percent of total responses and 47.8 percent of cases. Physics was taught by 6 respondents, accounting for 14 percent of responses and 26.1 percent of cases, while Biology was taught by 4 respondents, comprising 9.3 percent of responses and 17.4 percent of cases. This shows a balanced distribution of teaching responsibilities, with General Science, Chemistry, and Environmental Science emerging as the most common specializations.

The data suggests that the respondents' teaching assignments are spread across major branches of science, but a larger concentration is observed in areas considered foundational and interdisciplinary such as General Science and Environmental Science. The prominence of Chemistry also highlights its importance as a core science subject in secondary and tertiary education. The relatively fewer cases in Biology and Physics may reflect either the limited specialization of respondents in these areas or institutional scheduling practices that concentrate teaching loads on broader or integrative science courses.

The prevalence of teachers handling General Science, Chemistry, and Environmental Science indicates a strong alignment between their teaching exposure and the potential integration of artificial intelligence in laboratory instruction. These subjects often involve complex data analysis, simulations, and modeling—domains where AI applications have been increasingly recognized as beneficial (Bannigan et al., 2021; Mudunuru et al., 2023). For example, AI-enabled laboratory tools can support data visualization in Chemistry, environmental modeling in Environmental Science, and interdisciplinary applications in General Science. The limited number of Biology and Physics teachers in this sample, while smaller, still represents important domains where AI-driven experimentation and simulations are becoming significant (Lee et al., 2023).

The results also suggest that most respondents already engage with courses that lend themselves to digital and AI-supported enhancements. According to Jia, Sun, and Looi (2024), science education trends over the past decade show a shift toward the integration of intelligent technologies to improve laboratory efficiency, learner engagement, and analytical skills. Similarly, Nkundabakura et al. (2023) emphasized that innovative methods, including modernized tools, have been widely used in teaching science to enhance comprehension and application. Thus, the representation of respondents teaching multiple science courses underscores their potential to adopt and implement AI-driven laboratory practices across diverse subject areas.

**Table 1c AI-Related Trainings Attended**
***(n=23)***

| | Responses | | Percent of Cases |
|---|---|---|---|
| | N | Percent | |
| Workshop (in-person) | 8 | 21.1% | 38.1% |

| | | | | |
|---|---|---|---|---|
| AI Related Trainings Attended[a] | Webinar or Online Seminar | 18 | 47.4% | 85.7% |
| | Formal Course (credit-based or university/college course) | 1 | 2.6% | 4.8% |
| | Self-paced Online Course (e.g., Coursera, Udemy, etc.) | 3 | 7.9% | 14.3% |
| | In-house School or Institution Training | 6 | 15.8% | 28.6% |
| | Peer-led Training / Mentorship | 2 | 5.3% | 9.5% |
| Total | | 39 | 100.0% | 181.0% |

*a. Dichotomy group tabulated at value 1.*

Table 1c summarizes the types of AI-related trainings attended by the respondents. Out of the 23 participants, there were 39 reported training instances, as some individuals engaged in more than one type of training. The most common mode was webinars or online seminars, reported 18 times, which accounts for 47.4 percent of responses and 85.7 percent of cases. This is followed by in-person workshops with 8 responses (21.1 percent; 38.1 percent of cases), in-house school or institutional training with 6 responses (15.8 percent; 28.6 percent of cases), and self-paced online courses with 3 responses (7.9 percent; 14.3 percent of cases). Peer-led training or mentorship was reported 2 times (5.3 percent; 9.5 percent of cases), while only 1 respondent (2.6 percent; 4.8 percent of cases) attended a formal, credit-bearing university or college course.

The results reveal that online platforms, particularly webinars, are the dominant channel through which educators gain exposure to AI-related knowledge. This prevalence may reflect both the accessibility of virtual training and the lingering influence of post-pandemic educational practices where online professional development became normalized. The relatively strong presence of in-person workshops and institutional training indicates that schools and professional organizations also provide structured opportunities for AI upskilling. However, the very limited engagement in formal credit-bearing courses highlights that AI training remains largely non-formal and supplementary rather than systematically embedded in higher education curricula.

This pattern suggests that educators' readiness for AI integration in science laboratories is being developed primarily through short-term, flexible training formats rather than formalized professional or academic programs. Such reliance on webinars and workshops may provide rapid access to emerging AI knowledge but may not always ensure depth of mastery, which is better supported in structured university-based courses (Edralin & Pastrana, 2021). Furthermore, the limited peer-led and mentorship-based training reflects a missed opportunity for sustainable capacity-building, since peer collaboration has been identified as a key driver of technology integration in educational institutions (Tondeur et al., 2019).

The findings align with the observations of Jia, Sun, and Looi (2024), who documented that AI-related professional development in education over the past decade has been dominated by non-formal, short-term engagements such as workshops and online webinars. Similarly, Sysoyev (2023) noted that while many faculty express awareness of AI tools, institutionalized pathways for advanced training are often lacking, leading to fragmented knowledge and uneven competence. For this study, the reliance on short-term training formats demonstrates both opportunities and limitations: educators are willing to pursue learning about AI, but the depth and sustainability of their readiness may depend on how institutions institutionalize AI-related professional development programs.

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**Table 1d Familiarity with AI Tools and Platforms**
***(n = 23)***

| Types of AI Tool/Application | Not Familiar | Slightly Familiar | Somewhat Familiar | Moderately Familiar | Extremely Familiar |
|---|---|---|---|---|---|
| 1. Labster (Virtual lab simulation) | 0 (0.0%) | 0 (0.0%) | 11 (47.8%) | 9 (39.1%) | 3 (13.0%) |
| 2. Teachable Machine (AI model training) | 0 (0.0%) | 2 (8.7%) | 8 (34.8%) | 12 (52.2%) | 1 (4.3%) |
| 3. Cognii / AI tutors | 0 (0.0%) | 4 (17.4%) | 9 (39.1%) | 8 (34.8%) | 2 (8.7%) |
| 4. Google Science Journal | 1 (4.3%) | 2 (8.7%) | 10 (43.5%) | 7 (30.4%) | 3 (13.0%) |
| 5. Wolfram Alpha / Symbolab | 1 (4.3%) | 3 (13.0%) | 8 (34.8%) | 10 (43.5%) | 1 (4.3%) |
| 6. PhET Simulations (with AI feedback) | 1 (4.3%) | 1 (4.3%) | 10 (43.5%) | 8 (34.8%) | 3 (13.0%) |
| 7. AI Chatbots (e.g., ChatGPT, Bing AI) for lesson/lab planning | 0 (0.0%) | 2 (8.7%) | 7 (30.4%) | 12 (52.2%) | 2 (8.7%) |
| 8. Image recognition tools (for lab use, e.g., species ID) | 1 (4.3%) | 1 (4.3%) | 8 ( 34.8%) | 12 (52.2%) | 1 (4.3%) |
| 9. LabXchange | 1 (4.3%) | 1 (4.3%) | 9 ( 39.1%) | 9 (39.1%) | 3 (13.0%) |
| 10. BioDigital Human | 1 (4.3%) | 3 (13.0%) | 10 (43.5%) | 5 (21.7%) | 4 (17.4%) |
| *Sub-mean* | ***3.47– Moderately Familiar*** | | | | |

Legend: 4.21 – 5.00 (Extremely Familiar); 3.41 – 4.20 (Moderately Familiar); 2.61 – 3.40 (Somewhat Familiar); 1.81 – 2.60 (Slightly Familiar); 1.00 – 1.80 (Not Familiar)

The results in Table 1d reveal that science educators are generally moderately familiar with AI tools and platforms used in laboratory instruction, with a sub-mean of 3.47. This suggests that while they have some degree of awareness and usage of these tools, their familiarity is not yet at an advanced or highly confident level.

Looking at specific tools, Teachable Machine (AI model training) stands out, with more than half of the respondents (52.2%) rating themselves as moderately familiar and 34.8% as somewhat familiar. This indicates that many educators have been exposed to introductory AI training platforms but may not have fully explored their advanced features. Similarly, AI chatbots (e.g., ChatGPT, Bing AI) show strong familiarity, as 52.2% reported being moderately familiar and 30.4% somewhat familiar, showing that conversational AI has quickly become a go-to support tool for lesson and lab planning.

For simulation-based platforms, Labster and PhET Simulations also show promising results, with nearly half of the educators reporting being somewhat familiar (47.8% and 43.5%, respectively) and more than a third being moderately familiar. These findings reflect growing exposure to virtual laboratory simulations, although the degree of integration into teaching practice may still be limited. Google Science Journal and LabXchange follow a similar pattern, with responses evenly split between somewhat and moderately familiar, suggesting occasional but not consistent use.

On the other hand, tools like Cognii/AI tutors and Wolfram Alpha/Symbolab are less familiar. While about 39.1% and 34.8% of educators reported being somewhat familiar with these platforms, a notable proportion remained only slightly familiar (17.4% and 13.0%, respectively). This implies that AI tutors and computational AI engines are less commonly used than simulation tools and chatbots. Similarly, BioDigital Human shows greater variance, with 43.5% somewhat familiar but higher percentages of slightly and extremely familiar responses than other tools, indicating inconsistent exposure.

Finally, image recognition tools for laboratory use show relatively positive engagement: 52.2% are moderately familiar and 34.8% somewhat familiar, while only a small minority are at the extremes (not familiar or extremely familiar). This suggests these tools are practical and accessible but not yet mainstream in all science classes.

Overall, the findings highlight that educators' familiarity with AI tools is strongest with accessible, widely promoted platforms (chatbots, Teachable Machine, simulations) but weaker with specialized AI tutors and visualization systems. This moderate familiarity indicates a foundation that can be strengthened through targeted training, institutional support, and hands-on practice to move educators from "moderately familiar" toward "extremely familiar."

***SOP 2. What is the level of educator readiness to implement AI in science laboratory instruction in terms of knowledge of AI concepts relevant to science teaching, skills in operating AI-based educational tools in laboratory settings, confidence in integrating AI in classroom and laboratory instruction, access to institutional support, and attitude toward AI use in science education?***

This section presents the respondents' overall readiness to integrate artificial intelligence in science laboratory instruction. The results capture their knowledge, skills, confidence in AI integration, institutional support, and attitude toward AI use, providing a comprehensive view of the extent to which educators are prepared to adopt AI-driven approaches. These findings serve as the foundation for identifying strengths and gaps that inform the development of a practical framework for AI-enabled science laboratories.

**Table 2a Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Knowledge of AI Concepts Relevant to Science Teaching *(n = 23)***

| Knowledge of AI Concepts Relevant to Science Teaching | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 1. Demonstrates understanding of fundamental AI concepts applicable to education. | 0 (0.0%) | 2 (8.7%) | 7 (30.4%) | 11 (47.8%) | 3 (13.0%) |
| 2. Recognizes the relevance of AI in science teaching and learning. | 0 (0.0%) | 1 (4.3%) | 7 (30.4%) | 7 (30.4%) | 8 (34.8%) |

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**Table 2a Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Knowledge of AI Concepts Relevant to Science Teaching *(n = 23)***

| Knowledge of AI Concepts Relevant to Science Teaching | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 3. Explains the general principles of machine learning and how it applies to education. | 0 (0.0%) | 1 (4.3%) | 4 (17.4%) | 13 (56.5%) | 5 (21.7%) |
| 4. Identifies examples of AI tools used in laboratory instruction. | 0 (0.0%) | 2 (8.7%) | 4 (17.4%) | 15 (65.2%) | 2 (8.7%) |
| 5. Understands ethical considerations involved in applying AI in the classroom. | 0 (0.0%) | 0 (0.0%) | 8 (34.8%) | 9 (39.1%) | 6 (26.1%) |
| 6. Describes the role of AI in supporting virtual science laboratory environments. | 0 (0.0%) | 0 (0.0%) | 7 (30.4%) | 9 (39.1%) | 7 (30.4%) |
| 7. Differentiates AI technologies from other forms of educational technology. | 0 (0.0%) | 0 (0.0%) | 8 (34.8%) | 10 (43.5%) | 5 (21.7%) |
| 8. Remains informed about current trends in AI integration in education. | 0 (0.0%) | 0 (0.0%) | 6 (26.1%) | 13 (56.5%) | 4 (17.4%) |
| 9. Understands the role of AI in analyzing student-generated scientific data. | 0 (0.0%) | 1 (4.3%) | 7 (30.4%) | 13 (56.5%) | 2 (8.7%) |
| 10. Describes how AI supports differentiated and adaptive science instruction. | 0 (0.0%) | 2 (8.7%) | 6 (26.1%) | 13 (56.5%) | 2 (8.7%) |
| *Sub-mean* | | | ***3.83– Ready*** | | |

Legend: 4.21 – 5.00 (Very Ready); 3.41 – 4.20 (Ready); 2.61 – 3.40 (Moderately Ready);
1.81 – 2.60 (Slightly Ready); 1.00 – 1.80 (Not Ready)

Table 2a presents the level of educator readiness to implement AI in science laboratory instruction in terms of their knowledge of AI concepts. The sub-mean score of 3.83 indicates that, overall, respondents are in the "Ready" category. Among the ten indicators, the highest levels of readiness are observed in the ability to explain the principles of machine learning (56.5% ready, 21.7% very ready), staying informed about current trends in AI integration (56.5% ready, 17.4% very ready), and identifying AI tools for laboratory instruction (65.2% ready). Ethical understanding also emerges as a relatively strong area, with 39.1 percent ready and 26.1 percent very ready. On the other hand, the lowest readiness appears in the statement on demonstrating understanding of fundamental AI concepts, where 8.7 percent are still slightly ready and only 13 percent very ready, as well as in describing how AI supports differentiated instruction (8.7 percent slightly ready, 8.7 percent very ready).

The analysis suggests that respondents possess sufficient baseline knowledge of AI concepts, particularly in relation to practical applications such as identifying AI tools, analyzing student data, and applying machine learning in education. This finding indicates that educators are not merely aware of AI in general terms but are beginning to align their knowledge with classroom and laboratory practices. The prominence of readiness in areas such as ethical considerations and adaptive instruction shows that teachers are aware of both the opportunities and responsibilities associated with AI integration. However, the presence of slight readiness ratings in fundamental concepts and differentiated instruction highlights areas where conceptual grounding and pedagogical application still require strengthening.

The interpretation points to an important distinction: educators appear to be more comfortable with applied knowledge and observable trends than with deeper theoretical foundations. This aligns with Akhmadieva et al. (2023), who found that much of the engagement with AI in education has been practice-oriented, with less emphasis on theoretical and conceptual grounding. Similarly, AlKanaan (2022) stressed that while pre-service and in-service teachers recognize the relevance of AI in science education, consistent gaps remain in their ability to articulate and explain its fundamental underpinnings. Addressing this gap is essential since a robust framework for AI-enabled laboratories requires educators to balance conceptual clarity with application.

The results also reflect intergenerational dynamics. Millennials and Gen Z teachers, who are more digitally immersed, may be driving the higher levels of readiness in applied and trend-based indicators, while Generation X teachers may contribute strength in ethical awareness and critical evaluation, consistent with findings by Kim and Kwon (2023). This balance illustrates the potential of bridging generations in AI integration, where different cohorts bring complementary strengths. Building on these, institutions can cultivate a more comprehensive readiness by ensuring that foundational AI knowledge is embedded in professional development, while sustaining the applied focus that resonates with laboratory instruction.

**Table 2b Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Skills in Operating AI-Based Educational Tools in Lab Settings**
***(n = 23)***

| Skills in Operating AI-Based Educational Tools in Lab Settings | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 1. Operates AI-powered simulations for science laboratory activities. | 1 (4.3%) | 2 (8.7%) | 11 (47.8%) | 8 (34.8%) | 1 (4.3%) |
| 2. Utilizes AI tools to analyze and monitor student performance in lab work. | 1 (4.3%) | 3 (13.0%) | 10 (43.5%) | 7 (30.4%) | 2 (8.7%) |
| 3. Sets up and manages virtual laboratories with AI functionalities. | 1 (4.3%) | 2 (8.7%) | 11 (47.8%) | 7 (30.4%) | 2 (8.7%) |

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**Table 2b Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Skills in Operating AI-Based Educational Tools in Lab Settings**
***(n = 23)***

| Skills in Operating AI-Based Educational Tools in Lab Settings | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 4. Applies AI-driven tutoring systems during lab instruction | 1 (4.3%) | 2 (8.7%) | 12 (52.2%) | 4 (17.4%) | 4 (17.4%) |
| 5. Integrates AI tools within digital platforms used for science education. | 1 (4.3%) | 3 (13.0%) | 8 (34.8%) | 9 (39.1%) | 2 (8.7%) |
| 6. Resolves common technical issues related to AI instructional tools. | 1 (4.3%) | 3 (13.0%) | 8 (34.8%) | 9 (39.1%) | 2 (8.7%) |
| 7. Assists students in navigating and using AI tools during laboratory tasks. | 2 (8.7%) | 2 (8.7%) | 8 (34.8%) | 9 (39.1%) | 2 (8.7%) |
| 8. Incorporates AI tools in the planning and design of experiments. | 2 (8.7%) | 1 (4.3%) | 7 (30.4%) | 10 (43.5%) | 3 (13.0%) |
| 9. Navigates AI-enabled educational platforms independently. | 2 (8.7%) | 1 (4.3%) | 7 (30.4%) | 11 (47.8%) | 2 (8.7%) |
| 10. Develops lab tasks and learning modules that incorporate AI tools. | 2 (8.7%) | 1 (4.3%) | 8 (34.8%) | 8 (34.8%) | 4 (17.4%) |
| *Sub-mean* | | ***3.36– Moderately Ready*** | | | |

Legend: 4.21 – 5.00 (Very Ready); 3.41 – 4.20 (Ready); 2.61 – 3.40 (Moderately Ready);
1.81 – 2.60 (Slightly Ready); 1.00 – 1.80 (Not Ready)

Table 2b presents the level of educator readiness in terms of their skills in operating AI-based educational tools in science laboratory settings. The overall sub-mean of 3.36 places respondents in the "Moderately Ready" category, showing that while they have some degree of competence, there are clear gaps that prevent full readiness. The strongest performance is noted in navigating AI-enabled educational platforms, where 47.8 percent reported being ready and 8.7 percent very ready. Similarly, incorporating AI tools in experiment planning (43.5% ready; 13% very ready) and applying AI-driven tutoring systems (17.4% ready; 17.4% very ready) show relatively high ratings. Conversely, the lowest skills readiness appears in developing laboratory tasks and modules that incorporate AI (8.7% not ready; 4.3% slightly ready), and assisting students in navigating AI tools (8.7% not ready; 8.7% slightly ready).

The analysis reveals that educators are more confident in using AI tools that are already embedded in structured systems or pre-designed platforms, but less adept when it comes to creating or customizing AI-integrated learning modules. This suggests a reliance on ready-made applications rather than the capacity to independently design AI-driven instruction. The lower ratings in student assistance and module development underscore a skills gap in transferring AI knowledge directly into pedagogical practices, which is critical for laboratory settings where hands-on facilitation is essential.

These findings align with the work of Nkundabakura et al. (2023), who highlighted that teachers often use modernized tools but struggle with integrating them into classroom design and student-centered tasks. Similarly, Hartono et al. (2023) noted that while educators recognize the usefulness of AI tools, their ability to independently navigate, troubleshoot, and apply them in practical contexts varies widely, often due to differences in training depth and institutional support. The disparity between competence in navigating platforms and challenges in module development reflects what Edralin and Pastrana (2021) described as a skills gap between technological awareness and application.

The intergenerational context also provides insight into this readiness profile. Millennial and Gen Z educators, being more familiar with digital platforms, are likely driving the higher ratings in navigating and applying AI-enabled tools, while Generation X educators may require additional technical training to close the skills gap (Kim & Kwon, 2023). The weaker ratings in student assistance and lab task development highlight a need for collaborative, cross-generational professional development where more digitally fluent teachers can share strategies with their peers, while senior educators can bring pedagogical experience to guide instructional integration.

Overall, the results indicate that educators are moderately skilled in operating AI tools for science laboratories but remain at a transitional stage where competence in using pre-set systems does not always translate into designing, developing, and facilitating AI-driven laboratory activities. Addressing this imbalance through targeted technical training, mentorship, and opportunities for collaborative practice is essential for strengthening overall readiness and ensuring sustainable AI integration in science education.

**Table 2c Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Confidence in Integrating AI in Classroom and Laboratory Instruction**
***(n = 23)***

| Confidence in Integrating AI in Classroom and Laboratory Instruction | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 1. Displays confidence in using AI tools during laboratory instruction. | 2 (8.7%) | 3 (13.0%) | 4 (17.4%) | 11 (47.8%) | 3 (13.0%) |
| 2. Adapts instructional strategies to accommodate AI integration. | 2 (8.7%) | 3 (13.0%) | 5 (21.7%) | 11 (47.8%) | 2 (8.7%) |
| 3. Manages AI-supported instruction with minimal assistance. | 2 (8.7%) | 2 (8.7%) | 8 (34.8%) | 8 (34.8%) | 3 (13.0%) |
| 4. Facilitates collaborative laboratory activities using AI tools. | 2 (8.7%) | 3 (13.0%) | 8 (34.8%) | 7 (30.4%) | 3 (13.0%) |
| 5. Communicates clearly about the functions and | 2 (8.7%) | 1 (4.3%) | 5 (21.7%) | 12 (52.2%) | 3 (13.0%) |

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**Table 2c Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Confidence in Integrating AI in Classroom and Laboratory Instruction**
***(n = 23)***

| Confidence in Integrating AI in Classroom and Laboratory Instruction | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| benefits of AI in science education. | | | | | |
| 6. Manages classroom dynamics while incorporating AI tools effectively. | 2 (8.7%) | 2 (8.7%) | 7 (30.4%) | 11 (47.8%) | 1 (4.3%) |
| 7. Conducts AI-supported instruction in both face-to-face and online settings. | 2 (8.7%) | 2 (8.7%) | 5 (21.7%) | 11 (47.8%) | 3 (13.0%) |
| 8. Designs lesson plans that include the use of AI in laboratory instruction. | 3 (13.0%) | 2 (8.7%) | 5 (21.7%) | 11 (47.8%) | 2 (8.7%) |
| 9. Responds confidently to challenges related to AI use in teaching. | 2 (8.7%) | 2 (8.7%) | 5 (21.7%) | 11 (47.8%) | 3 (13.0%) |
| 10. Integrates AI tools in student assessment within laboratory environments. | 3 (13.0%) | 2 (8.7%) | 5 (21.7%) | 9 (39.1%) | 4 (17.4%) |
| *Sub-mean* | | ***3.39– Moderately Ready*** | | | |

Legend: 4.21 – 5.00 (Very Ready); 3.41 – 4.20 (Ready); 2.61 – 3.40 (Moderately Ready);
1.81 – 2.60 (Slightly Ready); 1.00 – 1.80 (Not Ready)

Table 2c shows the respondents' confidence in integrating AI into classroom and laboratory instruction. The sub-mean score of 3.39 places them in the "Moderately Ready" category, suggesting that while educators are beginning to build confidence in using AI, there are still noticeable gaps. The strongest ratings appear in communicating the functions and benefits of AI in science education, where 52.2 percent were ready and 13 percent very ready, as well as in managing classroom dynamics (47.8% ready) and adapting instructional strategies (47.8% ready). Likewise, conducting AI-supported instruction across modalities (face-to-face and online) also received higher readiness ratings. Conversely, the lowest confidence levels are evident in designing lesson plans (13% not ready; 8.7% slightly ready) and integrating AI tools in student assessment (13% not ready; 8.7% slightly ready), indicating that deeper instructional planning and evaluative application of AI remain challenging areas.

The analysis shows that teachers are most confident in visible, communicative, and facilitative aspects of AI use, such as explaining its benefits, managing student engagement, and applying tools within ongoing classroom practices. These results suggest that educators are gradually overcoming initial hesitations toward AI integration, aligning with findings by Romero-Rodríguez et al. (2020), who highlighted that confidence tends to emerge once teachers see AI's relevance to instructional communication and classroom management.

However, the lower confidence in lesson planning and assessment points to areas requiring targeted professional development. These tasks demand not only tool operation but also deeper pedagogical adjustments, which can be intimidating for teachers unfamiliar with AI-driven evaluative systems (Zhang & Villanueva, 2023).

The findings also mirror broader trends in AI adoption in education, where teachers tend to integrate AI into supportive and supplementary roles before embedding it into core planning and assessment functions (Jia et al., 2024). This reflects a transitional stage of readiness: teachers can facilitate AI-supported activities when tools are readily available but face greater difficulty in creating structured lessons or assessments that depend on AI functionality. The variation in confidence levels across indicators further shows that readiness is uneven and context-specific, with higher comfort in practical execution but weaker assurance in technical and evaluative aspects.

Generational differences also provide context for these outcomes. Millennials and Generation Z, being more exposed to digital technologies, may be driving the higher confidence in adapting strategies and using AI in blended or online settings, while Generation X teachers may be more cautious, especially in planning and assessment design (Kim & Kwon, 2023). This reinforces the need for generational collaboration, where younger educators can demonstrate technological applications and older educators can provide expertise in pedagogy and assessment design, bridging confidence gaps across cohorts.

Overall, the results indicate that educators are moderately confident in integrating AI, with strengths in communication and classroom facilitation but weaknesses in designing lessons and assessments. Institutional initiatives should therefore focus on professional development that strengthens pedagogical integration of AI into planning and evaluation, ensuring that confidence in classroom-level application extends into deeper instructional design.

**Table 2d Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Access to Institutional Support (Infrastructure, Policies, and Training)**
***(n = 23)***

| Access to Institutional Support | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 1. Participates in institution-led training programs related to AI in education. | 0 (0.0%) | 0 (0.0%) | 11 (47.8%) | 9 (39.1%) | 3 (13.0%) |
| 2. Has access to functioning AI tools and platforms for teaching. | 0 (0.0%) | 2 (8.7%) | 8 (34.8%) | 12 (52.2%) | 1 (4.3%) |
| 3. Receives administrative support in implementing AI-enabled teaching strategies. | 0 (0.0%) | 4 (17.4%) | 9 (39.1%) | 8 (34.8%) | 2 (8.7%) |
| 4. Operates within an institution that has clear guidelines on AI integration. | 1 (4.3%) | 2 (8.7%) | 10 (43.5%) | 7 (30.4%) | 3 (13.0%) |
| 5. Receives technical assistance for using AI tools in science instruction. | 1 (4.3%) | 3 (13.0%) | 8 (34.8%) | 10 (43.5%) | 1 (4.3%) |

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**Table 2d Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Access to Institutional Support (Infrastructure, Policies, and Training)**
***(n = 23)***

| Access to Institutional Support | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 6. Benefits from leadership initiatives promoting AI use in classrooms. | 1 (4.3%) | 1 (4.3%) | 10 (43.5%) | 8 (34.8%) | 3 (13.0%) |
| 7. Works in an institution that considers AI in its academic and technology plans. | 0 (0.0%) | 2 (8.7%) | 7 (30.4%) | 12 (52.2%) | 2 (8.7%) |
| 8. Attends professional development sessions focused on AI in education. | 1 (4.3%) | 1 (4.3%) | 8 (34.8%) | 12 (52.2%) | 1 (4.3%) |
| 9. Accesses teaching resources aligned with AI-supported instruction. | 1 (4.3%) | 1 (4.3%) | 9 (39.1%) | 9 (39.1%) | 3 (13.0%) |
| 10. Receives institutional recognition or encouragement for adopting AI in teaching. | 1 (4.3%) | 3 (13.0%) | 10 (43.5%) | 5 (21.7%) | 4 (17.4%) |
| *Sub-mean* | | | ***3.47– Ready*** | | |

Legend: 4.21 – 5.00 (Very Ready); 3.41 – 4.20 (Ready); 2.61 – 3.40 (Moderately Ready);
1.81 – 2.60 (Slightly Ready); 1.00 – 1.80 (Not Ready)

Table 2d presents educators' readiness in terms of access to institutional support such as infrastructure, policies, and training. With a sub-mean of 3.47, the overall level falls within the "Ready" category, indicating that institutions are beginning to provide sufficient structures to support AI integration in science laboratory instruction. The highest rating was seen in participation in institution-led training programs (47.8% moderately ready, 39.1% ready, 13% very ready) and access to AI-inclusive academic and technology plans (52.2% ready, 8.7% very ready). Similarly, attending professional development sessions focused on AI also scored high (52.2% ready). On the other hand, the lowest ratings were observed in areas such as administrative support (17.4% slightly ready), technical assistance (13% slightly ready), and institutional recognition (13% slightly ready, 4.3% not ready), revealing uneven support across different aspects of institutional provision.

The analysis suggests that while institutions are providing visible opportunities for training and inclusion of AI in planning, they may not yet have fully institutionalized AI through consistent policies, recognition systems, and technical support structures. Teachers appear to benefit more from policy-level initiatives, such as technology plans and professional development, than from day-to-day assistance or incentives. This imbalance reflects the broader trend in educational technology adoption where policies often outpace practical support systems (Romero-Rodríguez et al., 2020). For example, while institutions may declare AI readiness in strategic documents, teachers still face challenges accessing technical support or receiving recognition for adopting AI tools.

The interpretation also indicates that professional development remains the strongest institutional channel for readiness. With most respondents reporting readiness in training and development programs, institutions are succeeding in exposing educators to AI-related knowledge. However, without corresponding recognition and consistent technical support, the sustainability of this readiness may be undermined. This observation aligns with Tondeur et al. (2019), who emphasized that teacher educators serve as gatekeepers of technology adoption, and institutional reinforcement must extend beyond one-time training events. Moreover, de Obesso, Núñez-Canal, and Pérez-Rivero (2023) highlighted that educators' digital competence is influenced as much by organizational culture and recognition as by infrastructure and resources.

The generational dimension further contextualizes the findings. Millennials and Gen Z educators, who reported stronger participation in training and use of AI-inclusive plans, are likely maximizing institutional opportunities for exposure, while Generation X educators may depend more heavily on direct administrative support and recognition to encourage sustained adoption (Kim & Kwon, 2023). The uneven ratings of recognition and assistance indicate that institutional support is not uniformly experienced across generations, which could widen confidence gaps if left unaddressed.

Overall, while institutions are laying the groundwork through policy direction and training programs, the results point to a need for more consistent, hands-on, and rewarding support mechanisms. Strengthening technical assistance, creating formal recognition systems, and ensuring equitable access to resources will enable institutions to move beyond "ready" status toward the sustained, systemic integration of AI into science laboratory instruction.

**Table 2e Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Attitude Toward AI use in Science Education**
***(n = 23)***

| Attitude Toward AI use in Science Education | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 1. Believes that AI enhances the quality of science laboratory instruction. | 0 (0.0%) | 2 (8.7%) | 2 (8.7%) | 15 (65.2%) | 4 (17.4%) |
| 2. Maintains openness toward the use of AI in classroom practices. | 0 (0.0%) | 2 (8.7%) | 1 (4.3%) | 15 (65.2%) | 5 (21.7%) |
| 3. Acknowledges the instructional value of AI in science education. | 0 (0.0%) | 2 (8.7%) | 1 (4.3%) | 17 (73.9%) | 3 (13.0%) |
| 4. Views AI as a tool for improving students' understanding of science concepts. | 1 (4.3%) | 1 (4.3%) | 1 (4.3%) | 17 (73.9%) | 3 (13.0%) |
| 5. Welcomes the use of AI-based platforms in planning lab instruction. | 1 (4.3%) | 1 (4.3%) | 2 (8.7%) | 13 (56.5%) | 6 (26.1%) |
| 6. Accepts AI as a complement to traditional laboratory teaching methods. | 1 (4.3%) | 1 (4.3%) | 5 (21.7%) | 14 (60.9%) | 2 (8.7%) |
| 7. Supports the inclusion of AI in the science curriculum. | 0 (0.0%) | 2 (8.7%) | 1 (4.3%) | 14 (60.9%) | 6 (26.1%) |

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**Table 2e Level of Educator Readiness to Implement AI in Science Laboratory Instruction in terms of Attitude Toward AI use in Science Education**
***(n = 23)***

| Attitude Toward AI use in Science Education | Not Ready | Slightly Ready | Moderately Ready | Ready | Very Ready |
|---|---|---|---|---|---|
| 8. Trusts AI tools to support instruction and feedback mechanisms. | 0 (0.0%) | 2 (8.7%) | 5 (21.7%) | 14 (60.9%) | 2 (8.7%) |
| 9. Recognizes AI as relevant to 21st-century science teaching. | 0 (0.0%) | 2 (8.7%) | 3 (13.0%) | 12 (52.2%) | 6 (26.1%) |
| 10. Values AI integration as part of professional instructional development. | 0 (0.0%) | 2 (8.7%) | 2 (8.7%) | 16 (69.6%) | 3 (13.0%) |
| *Sub-mean* | | | ***3.89– Ready*** | | |

Legend: 4.21 – 5.00 (Very Ready); 3.41 – 4.20 (Ready); 2.61 – 3.40 (Moderately Ready);
1.81 – 2.60 (Slightly Ready); 1.00 – 1.80 (Not Ready)

Table 2e presents the respondents' level of readiness in terms of their attitudes toward AI use in science education. The overall sub-mean score of 3.89 places them in the "Ready" category, indicating a generally positive disposition toward AI integration. The strongest ratings were observed in acknowledging the instructional value of AI (73.9% ready, 13% very ready) and in believing that AI enhances the quality of laboratory instruction (65.2% ready, 17.4% very ready). Similarly, openness to classroom use (65.2% ready, 21.7% very ready) and welcoming AI-based platforms in planning instruction (56.5% ready, 26.1% very ready) show high acceptance. On the other hand, the lowest ratings appeared in accepting AI as a complement to traditional laboratory methods (21.7% moderately ready; 8.7% very ready but with 4.3% not ready), and in trusting AI tools for feedback (21.7% moderately ready, 8.7% very ready, but with 8.7% slightly ready), highlighting areas where skepticism or caution still exists.

The analysis suggests that respondents generally embrace AI as an instructional innovation, recognizing its relevance to improving students' conceptual understanding and aligning with 21st-century science education. Their willingness to incorporate AI in curriculum planning and professional development indicates strong attitudinal support for systematizing AI within science instruction. However, the mixed ratings regarding the complementary use of traditional methods and the trust in AI tools for feedback reflect underlying concerns about over-reliance on technology and the reliability of AI-driven assessments. This reveals that while educators value AI as an enhancement, they still prioritize balancing it with conventional teaching approaches, which is consistent with current debates on AI complementarity in education (Cooper, 2023; Hartono et al., 2023).

The interpretation points to a readiness that is anchored more in openness and belief in AI's instructional benefits than in uncritical acceptance. According to Akhmadieva et al. (2023), educators' attitudes toward AI often determine the success of its adoption, with positive perceptions leading to more effective experimentation and eventual integration. Similarly, Sysoyev (2023) highlighted that readiness is not only about skills and infrastructure but also about fostering a mindset that is receptive to innovation. The relatively high ratings across most items in this table show that the attitudinal foundation for AI integration is already in place among respondents.

Generational perspectives further contextualize these findings. Millennials and Gen Z, with stronger exposure to emerging technologies, likely contribute to the high ratings in openness and belief in AI's instructional value. Generation X teachers, while slightly more cautious, may explain the lower confidence in trusting AI-based feedback and balancing traditional methods, as they are more attuned to conventional pedagogical frameworks (Kim & Kwon, 2023). This variation across generations underscores the importance of bridging perspectives: younger cohorts bring technological enthusiasm, while older cohorts ensure a critical lens on pedagogical balance.

Overall, the results suggest that educators are attitudinally ready for AI integration, with a strong belief in its value for science teaching. However, sustaining this readiness requires addressing concerns about reliability, complementarity, and balance with traditional instruction. Institutions can build on these positive attitudes by fostering collaborative dialogue, highlighting successful AI use cases, and reinforcing AI's role as a supportive rather than substitutive tool in science laboratory instruction.

**Table 2f Summary of the Level of Educator Readiness to Implement AI in Science Laboratory Instruction**

| Indicator | Sub-mean | Verbal Interpretation |
|---|---|---|
| Knowledge of AI Concepts Relevant to Science Teaching | 3.83 | Ready |
| Skills in Operating AI-Based Educational Tools | 3.36 | Moderately Ready |
| Confidence in Integrating AI in Instruction | 3.39 | Moderately Ready |
| Access to Institutional Support | 3.47 | Ready |
| Attitude Toward AI Use in Science Education | 3.89 | Ready |
| **Overall Average Weighted Mean** | **3.59** | **Ready** |

Table 2f summarizes respondents' readiness to implement AI in science laboratory instruction across five key indicators. The overall weighted mean of 3.59 indicates that educators are generally "Ready" for AI integration. Among the indicators, the highest readiness is reflected in attitudes toward AI (3.89, Ready) and knowledge of AI concepts (3.83, Ready), suggesting that teachers both value AI's role in science education and possess foundational understanding of its application. Access to institutional support also ranked within the "Ready" category (3.47), showing that schools are providing basic infrastructure, training, and policy-level support. In contrast, the lowest ratings were in skills in operating AI tools (3.36, Moderately Ready) and confidence in integration (3.39, Moderately Ready), highlighting practical and affective gaps in application despite positive attitudes and knowledge.

The analysis demonstrates that readiness is uneven across dimensions: while teachers are mentally and conceptually prepared, they are less secure in the practical operation and confident application of AI tools in science instruction. This reflects a readiness profile that is

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stronger in perception and belief, yet weaker in execution. It suggests that professional development and institutional interventions should prioritize skills training and confidence-building exercises to complement existing knowledge and positive attitudes. This pattern mirrors the findings of Jia, Sun, and Looi (2024), who noted that AI adoption in education often begins with favorable attitudes and awareness but falters without sustained capacity-building in technical competence. Similarly, Zhang and Villanueva (2023) emphasized that technological competence is a critical mediating factor between willingness and actual classroom implementation.

The results also show the critical role of institutional structures. Although access to support scored within the "Ready" range, the slight gap between institutional readiness and teacher skills indicates that support mechanisms must extend beyond policy and training into more practical assistance, recognition, and peer-led mentorship. This aligns with Tondeur et al. (2019), who stressed that institutional reinforcement plays a decisive role in bridging the gap between knowledge and practice in technology integration.

Generational dynamics further enrich this interpretation. Millennials and Gen Z respondents, who dominate the sample, appear to drive the higher ratings in knowledge, attitudes, and openness to AI. Meanwhile, the lower scores in skills and confidence may reflect not only training gaps but also variations in generational learning styles, where younger teachers may feel comfortable conceptually but still need structured experiences to build confidence, while Generation X educators may rely more heavily on institutional reinforcement (Kim & Kwon, 2023). Bridging these generational strengths through collaborative learning communities could raise overall readiness.

In sum, the summary highlights a readiness profile that is promising but incomplete: educators are ready in mindset, supported by institutional structures, yet still moderately prepared in terms of skills and confidence. This imbalance points to the need for a practical framework that not only sustains knowledge and attitudes but also enhances technical proficiency and confidence, ensuring that AI readiness translates into effective laboratory practice.

***SOP 3. ased on the findings of the study, what AI Educator Readiness Matrix (AERM) can be developed to support the implementation of AI-enabled science laboratory instruction?***

The AI Educator Readiness Matrix (AERM) is a practical assessment tool designed to evaluate educators' readiness to implement artificial intelligence in science laboratory instruction. It guides school administrators, department heads, teacher educators, and faculty development offices in identifying readiness levels, determining professional development needs, and planning institutional interventions before implementing AI-enabled science laboratories.

| Readiness Domain | Key Indicators | Evidence for Validation | Readiness Level | Recommended Institutional Action |
|---|---|---|---|---|
| 1. AI Knowledge | Demonstrates understanding of AI concepts, machine learning, ethics, adaptive | Knowledge assessment, certification, interview, professional | ☐ Not Ready ☐ Slightly Ready ☐ Moderately Ready ☐ | Strengthen conceptual AI training, ethics seminars, and |

| | | | | |
|---|---|---|---|---|
| | learning, and AI applications in science laboratories. | development records | Ready ☐ Very Ready | AI literacy programs. |
| 2. Technical Skills | Operates AI-powered laboratory tools, virtual laboratories, simulations, AI tutors, data analytics platforms, and troubleshooting procedures. | Classroom observation, laboratory demonstration, performance tasks, portfolio | ☐ Not Ready ☐ Slightly Ready ☐ Moderately Ready ☐ Ready ☐ Very Ready | Conduct intensive hands-on laboratory workshops and competency-based technical training. |
| 3. Instructional Confidence | Designs AI-supported laboratory activities, facilitates AI-integrated instruction, develops AI-based assessments, and manages AI-supported learning environments. | Lesson plans, instructional materials, teaching demonstration, peer evaluation | ☐ Not Ready ☐ Slightly Ready ☐ Moderately Ready ☐ Ready ☐ Very Ready | Implement mentoring, coaching, collaborative lesson planning, and demonstration teaching. |
| 4. Institutional Support | Has access to AI infrastructure, institutional policies, technical assistance, administrative support, professional development, and AI resources. | Institutional documents, infrastructure inventory, faculty interviews, policy review | ☐ Not Ready ☐ Slightly Ready ☐ Moderately Ready ☐ Ready ☐ Very Ready | Enhance AI infrastructure, formulate institutional AI policies, strengthen technical support, and establish faculty incentive systems. |
| 5. Attitude toward AI | Demonstrates openness, acceptance, | Attitude survey, reflective | ☐ Not Ready ☐ Slightly Ready ☐ | Promote AI awareness campaigns, |

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|---|---|---|---|---|
| | ethical responsibility, willingness to innovate, and positive perceptions toward AI-supported science instruction. | journals, interviews, faculty evaluation | Moderately Ready ☐ Ready ☐ Very Ready | ethical AI discussions, communities of practice, and innovation recognition programs. |

The AI Educator Readiness Matrix (AERM) was developed from the empirical findings of the study to provide a practical and systematic tool for assessing educators' readiness to implement artificial intelligence in science laboratory instruction. The matrix synthesizes the respondents' demographic characteristics and readiness levels into five interrelated domains: AI knowledge, technical skills, instructional confidence, institutional support, and attitude toward AI use. Rather than functioning solely as a descriptive summary of the findings, the AERM translates the quantitative results into a decision-support framework that educational institutions may utilize to evaluate faculty readiness, identify competency gaps, and formulate targeted professional development interventions before implementing AI-enabled science laboratories.

The first domain, AI knowledge, represents the conceptual foundation of educator readiness. The findings revealed that respondents were generally ready in their knowledge of AI concepts, indicating adequate understanding of AI applications, ethical considerations, machine learning principles, and the role of AI in science teaching. This suggests that educators possess the cognitive readiness necessary to appreciate the educational value of AI. However, conceptual understanding alone does not ensure effective classroom implementation. AlKanaan (2022) emphasized that awareness of AI must be accompanied by deeper pedagogical understanding to enable meaningful instructional integration, while Jia et al. (2024) argued that AI literacy has become an essential competency for science educators as intelligent technologies become increasingly embedded in laboratory instruction. Consequently, the matrix identifies conceptual knowledge as the entry point for AI readiness while recognizing the need for continuous learning as AI technologies evolve.

The second and third domains, technical skills and instructional confidence, emerged as the principal developmental needs among the respondents. Although educators demonstrated positive readiness in knowledge and attitudes, their ratings in operating AI-enabled laboratory tools and confidently integrating AI into instructional planning remained only moderately ready. These findings indicate the presence of a knowledge-to-practice gap, where educators understand AI conceptually but experience uncertainty when applying it within authentic laboratory environments. Similar observations were reported by Zhang and Villanueva (2023), who found that technological competence significantly influences educators' preparedness to integrate AI into teaching. Likewise, Sysoyev (2023) observed that many faculty members possess favorable perceptions of AI but require sustained practical experiences to build confidence in designing AI-supported learning activities. For this reason, the AERM positions technical competence and instructional confidence as priority domains for institutional capacity-building through competency-based training, mentoring, and classroom application.

The fourth domain, institutional support, recognizes that educator readiness extends beyond individual competencies and is strongly influenced by organizational conditions. The respondents generally perceived their institutions as ready in providing AI-related training, infrastructure, and policy support; however, the findings also identified areas requiring improvement, particularly in technical assistance, administrative reinforcement, and recognition mechanisms. These results reinforce the argument of Tondeur et al. (2019) that technology integration depends not only on teacher competence but also on institutional commitment to creating supportive learning environments. Similarly, Edralin and Pastrana (2021) emphasized that organizational readiness encompasses leadership, infrastructure, policies, and continuous professional development. Accordingly, the AERM incorporates institutional support as an essential domain because sustainable AI integration requires coordinated efforts among administrators, technology units, and faculty development offices rather than relying solely on individual educators.

The fifth domain, attitude toward AI, reflects educators' openness to innovation and their willingness to incorporate AI into science laboratory instruction. Among all readiness dimensions, attitude obtained the highest readiness rating, indicating that respondents generally recognize AI as a valuable complement to traditional science teaching. Positive attitudes are particularly important because they influence educators' willingness to participate in professional development, experiment with emerging technologies, and sustain long-term instructional innovation. Akhmadieva et al. (2023) highlighted that favorable perceptions toward AI significantly facilitate technology adoption in educational settings, while Cooper (2023) demonstrated that science educators increasingly acknowledge the potential of generative AI to enrich teaching and laboratory learning when implemented responsibly. The AERM therefore identifies attitude as the motivational foundation that encourages educators to transform knowledge and skills into effective classroom practice.

Collectively, the five domains form a comprehensive assessment framework that recognizes educator readiness as a multidimensional construct rather than a single measure of technological competence. The matrix allows educational institutions to classify educators according to their readiness levels, determine evidence-based interventions, and monitor progress over time. Unlike existing readiness frameworks that primarily describe technological competence or institutional preparedness, the AERM integrates educator characteristics, AI competencies, organizational support, and professional attitudes into a single practical assessment instrument specifically designed for AI-enabled science laboratory instruction. As such, the matrix contributes both theoretically and practically by providing higher education institutions with a structured mechanism for guiding faculty development, strengthening institutional readiness, and supporting the responsible integration of artificial intelligence into science laboratory education.

## SUMMARY

This study assessed the readiness of science educators to implement artificial intelligence (AI) in science laboratory instruction and utilized the findings as the basis for developing the AI Educator Readiness Matrix (AERM). The results revealed that the respondents were

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predominantly Millennial educators with early to mid-career teaching experience who handled various science disciplines and had primarily acquired AI-related knowledge through webinars and online professional development activities. They also demonstrated a moderate level of familiarity with commonly used AI tools and platforms, particularly AI chatbots, virtual laboratory simulations, and introductory machine learning applications. In terms of educator readiness, the respondents were generally ready to implement AI in science laboratory instruction, exhibiting strengths in their knowledge of AI concepts, access to institutional support, and positive attitudes toward AI use. However, they were only moderately ready with respect to their technical skills in operating AI-based educational tools and their confidence in integrating AI into laboratory instruction, indicating areas that require further professional development. Guided by these findings, the study developed the AI Educator Readiness Matrix (AERM) as a practical assessment and decision-support tool that enables educational institutions to evaluate faculty readiness, identify competency gaps, and formulate targeted interventions that will strengthen educators' capacity to implement AI-enabled science laboratory instruction effectively, responsibly, and sustainably.

## CONCLUSIONS

The findings of the study indicate that science educators possess a generally favorable level of readiness to implement artificial intelligence (AI) in science laboratory instruction. Educators demonstrated adequate knowledge of AI concepts, positive attitudes toward AI integration, and sufficient institutional support, suggesting that the foundational conditions necessary for AI adoption are already present within the participating institutions. These findings imply that science educators recognize the educational value of AI and are receptive to incorporating emerging technologies into laboratory teaching and learning.

Despite this overall readiness, the study revealed that educators remain only moderately prepared in terms of their technical skills and confidence in operating and integrating AI-based educational tools within science laboratory instruction. This suggests that while educators are conceptually prepared and motivated to adopt AI, practical competencies required for effective classroom implementation still require further development. The disparity between knowledge and practical application underscores the importance of continuous professional development, hands-on training, mentoring, and sustained institutional support to strengthen educators' operational capabilities.

The study further concludes that educator readiness for AI integration is multidimensional, encompassing not only technological knowledge and skills but also confidence, institutional support, and positive professional attitudes. Successful implementation of AI-enabled science laboratories therefore requires a balanced approach that simultaneously addresses individual competencies and organizational readiness. Institutions must recognize that investments in infrastructure alone are insufficient without corresponding initiatives that enhance faculty capability and instructional confidence.

Finally, the development of the AI Educator Readiness Matrix (AERM) constitutes the principal contribution of the study. The matrix provides a structured, evidence-based assessment framework that educational institutions may utilize to evaluate educator readiness, identify competency gaps, prioritize professional development initiatives, and guide institutional planning for AI-enabled science laboratory instruction. As a practical decision-support tool, the AERM offers a systematic approach to strengthening faculty preparedness and promoting the effective, ethical, and sustainable integration of artificial intelligence into science education.

## RECOMMENDATIONS

Based on the findings of the study, it is recommended that educational institutions strengthen professional development initiatives that focus on enhancing science educators' technical skills and instructional confidence in integrating artificial intelligence (AI) into science laboratory instruction. Training programs should move beyond introductory awareness seminars and provide sustained, hands-on learning experiences that allow educators to operate AI-based laboratory tools, design AI-supported laboratory activities, develop AI-enhanced instructional materials, and implement AI-assisted assessment strategies. Such capacity-building initiatives may help bridge the gap between educators' conceptual understanding of AI and its effective classroom application.

Higher education institutions are likewise encouraged to establish stronger institutional support mechanisms by developing clear policies, improving technological infrastructure, expanding access to AI-powered educational resources, and providing continuous technical assistance. Creating mentoring programs, faculty learning communities, and collaborative professional development opportunities may further strengthen educators' readiness while promoting the sharing of best practices in AI-enabled science laboratory instruction. Institutional recognition and incentives for innovative AI integration may also encourage sustained faculty engagement and continuous professional growth.

The AI Educator Readiness Matrix (AERM) developed in this study may be adopted as a practical assessment and decision-support tool for evaluating faculty readiness, identifying competency gaps, and designing evidence-based professional development programs. Educational leaders and policymakers may utilize the matrix as part of faculty development planning, curriculum enhancement, institutional technology planning, and quality assurance initiatives to ensure that AI implementation is systematic, responsive, and aligned with institutional goals. Periodic administration of the matrix may also assist institutions in monitoring educators' progress and evaluating the effectiveness of AI-related interventions over time.

Finally, future researchers are encouraged to validate and implement the AI Educator Readiness Matrix across diverse educational settings and disciplines to further establish its applicability, reliability, and effectiveness. Subsequent studies may also examine the relationships between educator readiness and actual AI implementation practices, investigate the impact of AI readiness on student learning outcomes and laboratory performance, or explore additional institutional and technological factors that influence the successful integration of artificial intelligence in science education.

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**AI DECLARATION STATEMENT**

AI-supported tools helped with grammar and structure in creating this article. No AI tools were used to collect, analyze, or interpret data; all authors are credited for their academic contributions.

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