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The State of AI Readiness: Age, Education, and Perceived Competence Among Science Teachers in Davao de Oro.

Clyde Evan Gines

Graduate Student, Davao Del Norte State College

Abstract

This study addresses the critical challenge of AI integration in non-urban Philippine settings by assessing the readiness of Science teachers in the Division of Davao de Oro. Global literature indicates high teacher optimism regarding AI but notes significant implementation failure due to structural and training deficits. This research quantitatively mapped the influence of teacher profile characteristics on their perceived AI readiness, bridging a critical gap in localized empirical data needed for evidence-based policy formulation. The study determined the profile of the Science teachers, assessed their level of AI readiness across five critical dimensions (Competence, Resources, Training, Attitudes, and Barriers), and tested the significant relationship and difference between demographic variables and overall readiness. Methods: A descriptive-correlational design was employed using a standardized 35-item Likert Scale survey. Data analysis utilized descriptive statistics (Mean, SD), Pearson's r for continuous variables (Age, Years in Service), and One-Way ANOVA for categorical variables (Highest Educational Attainment). Results: Teachers showed Overall High Readiness (Mean=3.57), driven by high Attitudes (Mean=4.04). However, this was critically hampered by Moderate Readiness in Resources (Mean=3.17) and Professional Development (Mean=3.10). A statistically significant, weak negative correlation was found between Age and readiness ($r=-0.178$, $p<0.05$), but no significant difference was found across educational attainment groups ($p=0.282$). AI readiness is high in disposition but low in structural support. The Division must pivot strategy from attitude reinforcement to targeted investment in infrastructure and subject-specific AI literacy training, as general experience and academic degrees are not predictors of technological preparedness.

Keywords: AI Literacy, AI Readiness, Correlational Study, Davao de Oro, Digital Divide, Professional Development, Science Teachers

1 Introduction

The global educational landscape in the twenty-first century has changed significantly due to the rapid growth and integration of Artificial Intelligence (AI). This rapid change, called Education 5.0, requires a reevaluation of teaching and learning methods, especially in science disciplines where technological skills are essential (Fudalan, 2025; Pandya, 2024). Effective transformation relies less on the technology itself and more on the teachers' readiness, skills, and mindset who will implement it. This study aims to explore this important human factor in a specific location in the Philippines, in the division of Davao de Oro.

Current trends show that while teachers are positive and hopeful about AI's potential for tasks such as lesson planning and assessment, they often lack the formal training and institutional support needed to use it effectively and ethically. This is where the notable gap is (Malazzab, 2024; Uygun, 2024).

The rise of AI in education is not just a vision for the future; it has become a global priority (Walter, 2024). Organizations like the United Nations Educational, Scientific and Cultural Organization (UNESCO) have highlighted the need for clear strategies to equip teachers for an AI-focused future. They argue that AI literacy is now an integral and essential professional skill (UNESCO, 2023). This preparation goes beyond basic technical know-how; it includes understanding AI's ethical issues and challenges, leveraging its ability to tailor learning, and applying it to effective administrative tasks (Marr, 2023).

The Transformative Potential of AI in Science Education

Science teaching, with its inherent reliance on data analysis, complex modeling, and laboratory safety protocols, stands to benefit greatly from AI integration. AI tools can effectively manage differentiated instruction by analyzing individual student performance data, pinpointing conceptual obstacles, and automatically providing remedial materials (Farahani & Ghasmi, 2024; Ruslim & Khalid, 2024). For example, AI-driven virtual labs offer immersive, risk-free environments for complex or costly experiments, thereby improving access and quality of instruction, especially in resource-constrained areas (Zhao et al., 2022). Furthermore, generative AI tools assist teachers in quickly creating diverse assessments and feedback mechanisms, allowing them to focus from mechanical grading to higher-order pedagogical tasks rather than mechanical grading (Fitria, 2021; Uygun, 2024).

However, the efficacy of these tools is directly influenced by the teacher's Perceived Competence—their confidence in their ability to use AI effectively. Studies on global teacher readiness consistently shows that while teachers are generally optimistic about AI's potential, this positive outlook often contrasts sharply with low self-efficacy in using AI tools in the classroom (Iddrisu & Iddrisu, 2025; Alshorman, 2024; Malazzab, 2024). Barriers such as data privacy issues, the risk of AI to widen the digital divide, and fears of job displacement further complicate the situation (UNESCO, 2021). The real challenge, therefore, is not technological but pedagogical and systemic, focusing on closing the gap between perceived value and practical skills.

Demographics as Predictors of Technology Readiness

A significant body of literature correlates demographic variables with technology adoption. Age and Years in Service are often found to be negative predictors of technology integration. Older and more experienced teachers may display higher levels of anxiety (computer anxiety) and skepticism towards new technology, often due to inertia created by established teaching practices and a perceived higher cost of switching methods (Pew Research Center, 2022; An et al, 2024; Shin et al., 2018). Conversely, while younger teachers may possess greater digital nativity, they may lack the Pedagogical Content Knowledge (PCK) to integrate AI into complex instructional scenarios seamlessly (Ning et al., 2024; Szymkowiak et al., 2021).

Highest Educational Attainment (e.g., Master's or Doctoral degrees) is generally considered a positive predictor, as advanced studies typically expose educators to research, technology integration frameworks, and higher-level critical thinking, which enhances their capacity to evaluate and adopt innovative tools responsibly (Zhao et al., 2022). Understanding these relationships is vital because it moves policy beyond generalized training toward differentiated professional development that respects the varied learning needs of the teaching workforce (Takona, 2024).

While global and regional studies offer broad insights, the specific realities of technology adoption in the Philippine educational context, particularly in non-urban divisions, highlight a critical research gap.
The Philippine Context and the Digital Divide
The Philippines has officially integrated AI into its strategy with the adoption of the National AI Roadmap (DTI, 2021). DepEd recognizes the urgency of embedding technology within the K-12 curriculum, requiring swift action from the country's large teaching workforce. Nonetheless, the country's geographical and infrastructural challenges, especially the urban-rural digital divide, pose significant obstacles. Philippine-specific studies confirm that, despite generally positive attitudes toward technology among Filipino teachers, actual implementation faces major barriers such as limited physical resources, unreliable internet, and a lack of localized professional development suited to their teaching contexts (Alfeche & Abarquez, 2024; Co, 2025; Rodrigo & Talandron-Felipe, 2024).

The Local Focus: Davao de Oro

Davao de Oro, a province in the Davao Region, highlights the challenges faced by non-metro divisions. Its administrative and geographical setup includes many schools situated in remote or developing communities where access to reliable power, high-speed internet, and maintenance support for advanced AI hardware is often inconsistent (Rodrigo & Talandron-Felipe, 2024). Decision-makers within the Division of Davao de Oro need precise local data to justify capital spending on AI-related infrastructure and to create effective training programs. Currently, the data required to establish this baseline—such as quantifying the relationship between a teacher's background and their readiness across key areas like Perceived Competence, Resources, Training, Attitudes, and Barriers—is not available.

This study directly addresses this empirical and contextual void. By specifically surveying the Science teachers, the research focuses on the subject area most impacted by technological advancement, providing targeted evidence to transform policy into effective practice in the Division of Davao de Oro. The lack of current, quantitative, demographic-specific data for this province represents the central research niche that this paper seeks to occupy.

Theoretical and Conceptual Framework

This study is theoretically anchored on a blended framework that integrates the Technology Readiness Index (TRI) (Parasuraman, 2000) and Bandura's Theory of Self-Efficacy (1997).

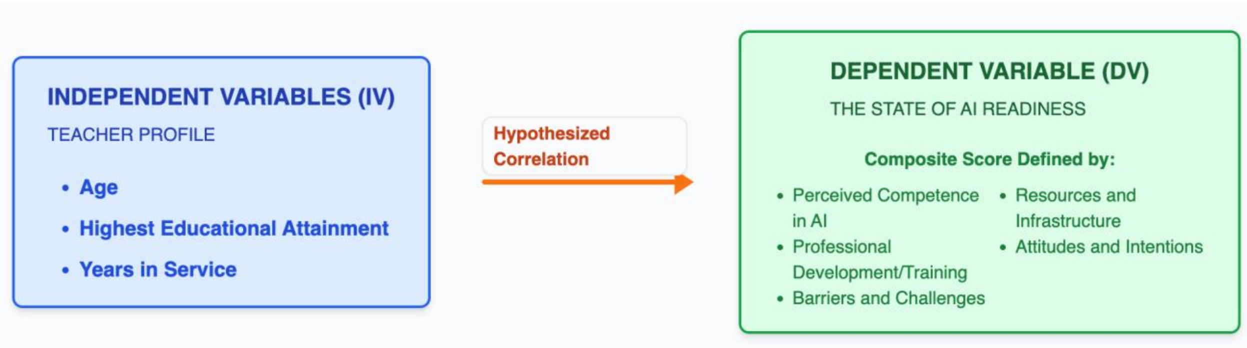
Technology Readiness Index (TRI): TRI posits that an individual's readiness to adopt new technologies is a composite of four dimensions:

- Enthusiasm and Optimism (Positive drivers, related to the Attitudes and Intentions dimension in the survey).
- Innovativeness (Positive drivers, reflecting a willingness to experiment).
- Insecurity (Negative inhibitors, related to Barriers and Challenges).
- Discomfort (Negative inhibitors, related to Perceived Competence).

Bandura's Self-Efficacy Theory states that a person's belief in their ability to perform specific tasks affects their motivation, actions, and perseverance (Bandura, 1997). When applied to AI, a teacher's Perceived Competence in AI—our main dependent variable—is a reflection of their task-specific self-efficacy with AI tools, shaped heavily by previous experiences and professional support such as training and resources.

This conceptual framework, as shown in Figure 1, illustrates a Correlational Model where the Independent Variables (IVs), specifically the measurable characteristics of the science teachers' profiles (Age, Highest Educational Attainment, and Years in Service), are hypothesized to relate to the Dependent Variable (DV), which is the State of AI Readiness. The central hypothesis, represented by a single, bold arrow labeled "Hypothesized Correlation," suggests that changes in the teachers' demographics will statistically correlate with their level of readiness. The DV, The State of AI Readiness, is not viewed as a single concept but is defined by the composite score combined from five distinct components: Perceived Competence, Resources and Infrastructure, Professional Development/Training, Attitudes and Intentions, and Barriers and Challenges. This structure is critical for the statistical analysis, as the study aims to identify which specific profile factors (IVs) are significant predictors of the overall AI Readiness score (DV), providing targeted, evidence-based guidance for policy interventions in the Division of Davao de Oro.

Figure 1. Conceptual Framework: Correlational Model



Objectives of the Study

The primary objective of this study is to determine and analyze the state of Artificial Intelligence (AI) readiness among Science teachers in the Division of Davao de Oro. Specifically, this research aims:

1. To describe the profile of the teacher-respondents in terms of their age, highest educational attainment, and years of service.

2. To assess the level of AI readiness among the teacher-respondents across the five dimensions: Perceived Competence in AI, Resources, and Infrastructure, Professional. Development and Training, Attitudes and Intentions, and Barriers and Challenges.
3. To determine if a significant relationship exists between the teacher-respondents' profile variables (Age and Years in Service) and their overall level of AI readiness.
4. To determine if a significant difference exists in the overall level of AI readiness when the teacher-respondents are grouped according to their Highest Educational Attainment.

Significance of the Study

The findings of this study are anticipated to have far-reaching practical and theoretical implications for various stakeholders:

Division of Davao de Oro/DepEd: The quantitative data will provide a precise, evidence-based roadmap for policy formulation, resource allocation, and budget prioritization related to AI integration. Instead of general workshops, the Division can design differentiated professional development programs that specifically address the competence gaps of specific age groups or those with lower educational attainment.

Science Teachers: The study will serve as a needs assessment, ensuring that subsequent training modules and resource provisions are relevant, timely, and responsive to their self-reported barriers (e.g., lack of time, fear of ethics, resource scarcity).

Curriculum Planners: The results will inform the integration of AI literacy into pre-service and in-service training materials, ensuring that training content aligns with teachers' actual needs and competence levels in the field.

Future Researchers: This study establishes a crucial empirical baseline for AI readiness in a non-metro Philippine province, providing a foundation for future comparative, longitudinal, and interventional research.

2 METHODOLOGY

Study Design

This study employs a Quantitative Descriptive-Correlational Research Design. The research is Descriptive because its primary function is to systematically characterize and summarize the current condition of the teacher-respondents' AI readiness across five specific dimensions (Perceived Competence, Resources, Training, Attitudes, and Barriers) using descriptive statistics such as means and standard deviations. The study is also Correlational because it seeks to determine the strength, direction, and significance of the relationships between the independent variables (Age and Years in Service) and the dependent variable (AI Readiness), and to test for significant differences in the dependent variable when grouped by the other independent variable (Highest Educational Attainment). This design is appropriate as it allows the researcher to quantify the link between demographic background and perceived technological preparedness without manipulating any variables.

Sample and Population of the Study

The target population for this quantitative inventory study is the entire population of Science teachers—including both elementary and secondary levels—under the jurisdiction of the Division of Davao de Oro. Based on recent divisional data, the total population of these teachers is approximately 154 individuals. Since the population size is manageable and well-defined, the researcher used a Complete Enumeration Technique to survey every Science Teacher. This thorough approach, supported by established methodological literature (Besekar et al., 2024; Creswell & Creswell, 2018), maximizes statistical power and ensures that the results are fully representative and broadly generalizable across the division, eliminating sampling error. The study functions as an inventory of AI readiness, in line with recent descriptive studies in educational technology (Alshorman, 2024; Uygun, 2024). Strict inclusion criteria limited participants to full-time Science teachers currently employed in public schools within the Division of Davao de Oro during data collection.

Data Gathering Tools

The primary instrument for data collection is a Standardized Survey Questionnaire (Adapted). The instrument is a 35-item, 5-point Likert-scale survey, carefully adapted from the instrument used by Alshorman (2024) in the study titled "The Readiness to Use AI in Teaching Science: Science Teachers' Perspective."

The questionnaire is composed of two main parts:

Part I: Demographic Profile: Collects essential independent variable data: Age (specific number), Highest Educational Attainment (Categorical), and Years in Service (Categorical: 0–5, 6–10, 11–15, 16+ Years).

Part II: AI Readiness Assessment: Consists of 35 statements rated on a 5-point Likert scale (5=Strongly Agree to 1=Strongly Disagree). This part is organized into five key dimensions, which serve as sub-variables of the overall AI Readiness dependent variable:

A) Perceived Competence in AI
B) Resources and Infrastructure
C) Professional Development and Training
D) Attitudes and Intentions
E) Barriers and Challenges

Data Gathering Procedures

The data gathering process will follow a rigorous, sequential, and ethical procedure, meticulously tracking institutional approvals to ensure compliance with both academic and divisional policies:

Institutional Endorsement: The researcher first secured initial written approval and academic endorsement from the Master of Science in Teaching (MST) Program Head and the Subject Professor at the Graduate

School. This formal endorsement served as the validation of the study's academic necessity and ethical review by the university.

Division Approval: The researcher then submitted the endorsed research proposal and the formal letter of request to the Science Education Program Specialist within the Division of Davao de Oro. This step ensured the study aligned with the division's research priorities and granted official authorization to proceed with data collection in the schools.

School Coordination: Following official approval, the researcher will coordinate with the respective Science District Coordinator to obtain site consent and collaboratively schedule the data collection. This ensures that the survey administration causes zero disruption to class instruction time.

Respondent Recruitment and Consent: The researcher will send the survey link with the Science teachers collectively or individually. Each potential respondent will receive a detailed Informed Consent Form explaining the study's purpose, the voluntary nature of participation, confidentiality guarantees, and data use. Participation will only commence after signed consent is received.

Survey Administration: The survey will be administered in a format (online via Microsoft Forms) that ensures maximum response rate and convenience.

Data Retrieval and Consolidation: The researcher will personally oversee the collection or monitor the electronic submission portal. Once all data is gathered, it will be securely encoded, cleaned, and verified for accuracy and completeness before proceeding to the statistical analysis phase.

Treatment of Data

All data collected will be analyzed using Jeffrey's Amazing Statistics Program (JASP) software. The following statistical tools will be applied to address the research objectives:

Research Objective	Statistical Tool	Purpose
Objective 1 (Profile)	Frequency Distribution and Percentage	To summarize the demographic data (Age, Highest Educational Attainment, Years in Service).
Objective 2 (Readiness Level)	Mean and Standard Deviation	To determine the central tendency and dispersion of AI Readiness across all five dimensions. The Weighted Mean score will be interpreted using a pre-determined scale (e.g., 4.21–5.00=Very High Readiness, 3.41–4.20=High Readiness, 2.61–3.40=Moderate Readiness, 1.81–2.60=Low Readiness, 1.00–1.80=Very Low Readiness).
Objective 3 (Relationship:	Pearson Product-Moment	To determine the presence, strength, and direction of the linear relationship between the

Age/Service vs. Readiness)	Correlation Coefficient (r)	continuous independent variables (Age and Years in Service) and the dependent variable (Overall AI Readiness).
Objective 4 (Difference: Education vs. Readiness)	One-Way Analysis of Variance (ANOVA)	To test for significant differences in the Overall AI Readiness scores when respondents are grouped according to the categories of Highest Educational Attainment.

The study will strictly adhere to the ethical guidelines for research involving human participants. Informed Consent will be secured from all respondents, ensuring they understand their rights to voluntary participation, withdrawal at any time, and the purpose of the study. Confidentiality and Anonymity will be maintained by coding the data and ensuring that no names or identifying school information are reported in the final paper. The raw data will be stored securely and will be destroyed upon completion of the master's program, as per institutional policy. The researcher guarantees that the findings will be reported truthfully and objectively, reflecting the data collected without bias or manipulation.

3 RESULTS

Profile of the Teacher-Respondents

Table 1. Profile of the Teacher-Respondents

Category	Group	Frequency	Percentage (%)
Age	26 – 33	36	23.4
	34 – 41	45	29.2
	42 – 49	42	27.3
	50 – 57	26	16.9
	58 – 65	5	3.2
Highest Educational Attainment	Bachelor’s	77	50.0
	Master’s (earned units)	5	3.2
	Master’s	68	44.2
	Doctorate	4	2.6
Years in Service	0-5 years	26	16.9
	6-10 years	41	26.6
	11-15 years	27	17.5
	16 years and up	60	39.0

Table 1 presents the demographic profile of the 154 Science teachers. The largest age group falls within 34–41 years (29.2%), followed closely by the 42–49 years (27.3%) group, indicating a teaching population dominated by mid-career educators. Regarding Highest Educational Attainment, exactly half of the respondents (50.0%) possess a Bachelor’s Degree, while a significant portion (44.2%) have Master’s Degrees, suggesting a high level of academic qualification in the division. Finally, in terms of Years in Service, the majority (39.0%) fall under the "16 years and up" category, highlighting a large base of veteran teachers in the sample. This distribution implies that AI implementation efforts must cater to both the digital fluency of younger teachers and the professional experience of the senior workforce (Ng et al., 2023; Kitcharoen et al., 2024).

Level of AI Readiness Across Dimensions

Table 2. Level of AI Readiness Across Dimensions

Dimension	Mean	SD	Interpretation
Perceived Competence	3.84	0.60	High Readiness
Access to Resource	3.17	0.71	Moderate Readiness
Professional Development	3.10	0.73	Moderate Readiness
Attitudes Towards AI in Education	4.04	0.57	High Readiness
Barriers and Challenges	3.72	0.52	High Readiness
OVERALL	3.57	0.47	High Readiness

Table 2 presents the summary of the AI readiness levels across all five dimensions. The Overall AI Readiness for Science teachers in Davao de Oro is rated as High Readiness (Mean = 3.57, SD = 0.47). This indicates that, on average, teachers are prepared and generally agree on their ability and disposition towards AI integration.

However, a closer look at the dimensions reveals critical variances:

Attitudes and Intentions (Mean = 4.04) received the highest rating, also interpreted as High Readiness. This is consistent with national findings showing Filipino teachers' positive disposition toward technology (Rodrigo & Talandron-Felipe, 2024), indicating strong behavioral intent to use AI, a key construct in the Technology Acceptance Model (Schorr, 2023).

Perceived Competence (Mean = 3.84) and Barriers and Challenges (Mean = 3.72) also rated as High Readiness. The high mean in Barriers and Challenges (which is an agreement scale) suggests that teachers strongly agree that barriers (such as data privacy and keeping up with change) exist, highlighting the substantial concerns that temper their optimism.

The lowest ratings, interpreted as Moderate Readiness, were recorded in Resources and Infrastructure (Mean = 3.17) and Professional Development and Training (Mean = 3.10). This is the study's most critical finding. While teachers want to use AI (Attitudes) and feel somewhat capable (Competence), the lack of formal, tailored training and insufficient school resources/technical support acts as a substantial bottleneck to effective implementation. This mirrors the findings of Alshorman (2024), who also identified insufficient professional development as a significant challenge to AI integration among Science teachers, often linked to the need for a stronger Technological Pedagogical Content Knowledge (TPACK) framework (Celik, 2022; Koehler et al., 2007).

Relationship Between Profile and AI Readiness

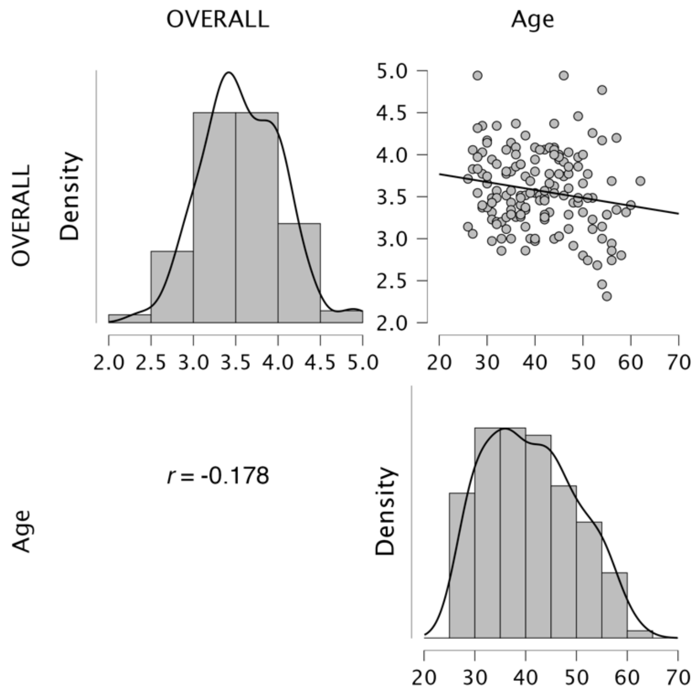
Table 3. Correlation between Age, Years in Service and Overall AI Readiness

Independent Variable	Dependent Variable (Overall AI Readiness)	
	Pearson's r	p-value
Age	-0.178	0.028*
Years in Service	-0.129	0.111

*significant at 0.05 level

Table 3 presents the results of the Pearson Product-Moment Correlation analysis. Age and Overall AI Readiness showed a small, negative, and statistically significant relationship (r = -0.178, p = 0.028). This suggests that as the age of the teacher increases, their overall AI readiness score tends to slightly decrease. This supports the general literature on the impact of age on technology acceptance, where younger teachers often show higher levels of digital familiarity (Asirit & Hua, 2023).

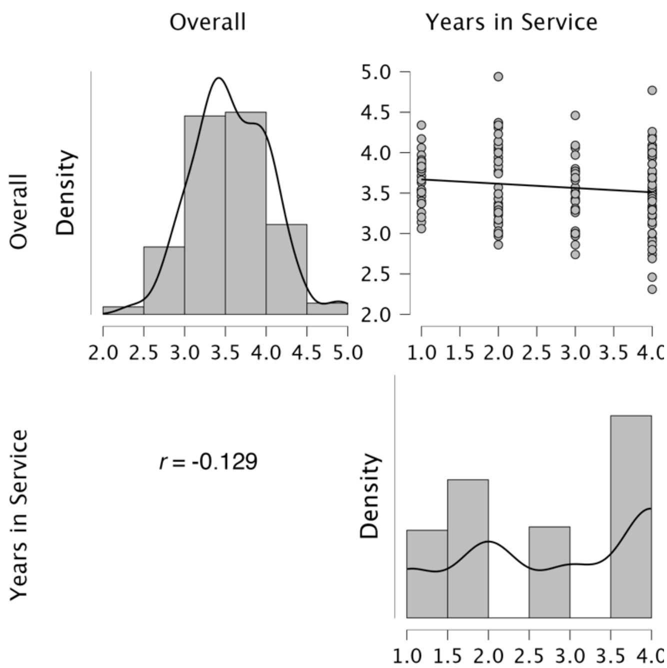
Figure 2. Density and Correlation Plots of Age and Overall AI Readiness



Years in Service and Overall AI Readiness showed a negative correlation (r = -0.129) but was not statistically significant (p = 0.111). This indicates that a teacher's total length of service, regardless of age, might not reliably predict their readiness to adopt AI. A veteran teacher who actively seeks training may

have higher readiness than a younger teacher who does not, highlighting that ongoing professional development (not just years on the job) is essential.
As shown by figure 2 the correlation plot visually confirms a weak, negative relationship between teacher age and overall AI readiness, as evidenced by the Pearson coefficient (r) of -0.178. The scatter plot in the top right shows that as age increases (moving right along the X-axis), the average AI readiness score slightly decreases (the line of best fit slopes gently downward). This finding, combined with the histograms showing that the majority of readiness scores cluster in the mid-range (3.0 to 4.0), suggests that while younger teachers may have a minor advantage, age is a weak predictor of AI readiness, emphasizing that the majority of teachers, regardless of age, fall into the "High Readiness" category.

Figure 3. Density and Correlation Plots of Years in Service and Overall AI Readiness



The correlation plot from figure 3 visually represents the relationship between a teacher's years of service and their overall AI readiness score, showing a weak, non-significant negative correlation (r = -0.129). The scatter plot confirms a wide dispersion of data points along the horizontal axis, indicating that readiness scores are highly varied regardless of experience level. While the line of best fit trends slightly downward, the weak correlation value and the scattered data underscore the finding that teaching experience is not a predictive factor of AI readiness; instead, a teacher's technological preparedness is likely influenced by factors other than tenure, such as specific training or access to resources.

Difference in AI Readiness by Educational Attainment

Table 4. ANOVA Results for Overall AI Readiness by Highest Educational Attainment

	Sum of Squares	df	Mean Square	F	p-value
Group	0.298	3	0.099	0.449	0.718
Residuals	33.162	150	0.221		

*significant at 0.05 level

The One-Way Analysis of Variance (ANOVA) revealed an F-ratio of 1.284 with a corresponding p-value of 0.282. Since the p-value (0.282) is greater than the significance level of 0.05, the null hypothesis is accepted.

This indicates that there is no statistically significant difference in the overall level of AI readiness when science teachers are grouped according to their Highest Educational Attainment (Bachelor's, Master's, Doctorate). This suggests that holding an advanced degree does not automatically translate into a higher perceived readiness for AI integration. AI readiness appears to be a factor driven more by specific training and access to resources (as seen in the low scores for those dimensions) rather than general academic attainment.

Post Hoc Analysis (Tukey HSD Test)

While the ANOVA test revealed no overall significant difference across the groups, a Post Hoc Tukey HSD test was conducted to formally assess pairwise comparisons between the levels of Highest Educational Attainment, as presented in Table 5. This test serves to confirm the absence of specific differences.

Table 5. Post Hoc Comparisons - Group (Tukey HSD Test) for AI Readiness by Highest Educational Attainment

		Mean Difference	SE	t	p-value
Bachelor's	Master's (Earned Units)	-0.088	0.217	-0.408	0.977
	Master's	0.075	0.078	0.962	0.771
	Doctorate	-0.040	0.241	-0.165	0.998
Master's (Earned Units)	Master's	0.164	0.218	0.751	0.876
	Doctorate	0.049	0.315	0.154	0.999
Master's	Doctorate	-0.115	0.242	-0.476	0.964

The results from the Tukey HSD test further confirm the findings of the ANOVA. As shown in Table 5, none of the pairwise comparisons yielded a statistically significant difference (all p-values are far greater than 0.05). This robustly supports the conclusion that simply holding a higher academic degree, such as a Master's or Doctorate, does not independently translate into a higher perception of AI readiness or competence compared to having a Bachelor's degree. This underscores the hypothesis that specific, targeted AI training is a more potent predictor of readiness than general academic achievement.

4 DISCUSSION

This chapter interprets the results of the study, linking the findings on AI readiness among science teachers in Compostela, Davao de Oro, to the research objectives and relevant academic literature.

Overall AI Readiness and Teacher Disposition

The study revealed an overall level of AI readiness among science teachers that is interpreted as Agree (Mean=3.57). This general positive disposition is heavily driven by the high scores in Attitudes Towards AI in Education (Mean=4.04), which was the highest-rated dimension. This finding aligns with global and national literature, which consistently reports that educators express optimism and a positive behavioral intention towards adopting AI technologies (Uygun, 2024). Teachers are receptive to the idea that AI can enhance teaching effectiveness and support twenty-first-century skills. Similarly, the high score in Perceived Competence in AI (Mean=3.84) suggests that teachers feel they possess a foundational understanding of AI concepts relevant to education. This level of confidence is a critical first step for technology adoption, yet its interpretation must be carefully balanced against the significantly lower scores in the implementation-focused dimensions.

The Implementation Gap: Resources and Professional Development

A key finding is the significant 'implementation gap' highlighted by the lowest means for Professional Development and Training (Mean = 3.10, Moderate Readiness) and Access to Resource and Infrastructure (Mean = 3.17, Moderate Readiness). These results indicate a fundamental disconnect: while teachers are willing and feel competent in theory, the institutional support and logistical necessities for effective integration are insufficient or highly inconsistent. The " Moderate Readiness " interpretation for resources strongly suggests that the rural setting of Compostela, Davao de Oro, faces challenges consistent with the documented urban-rural digital divide in the Philippines (Co, 2025; Rodrigo & Talandron-Felipe, 2024). Lack of reliable internet, up-to-date AI tools, and necessary technical support creates a systemic barrier, rendering the teachers' positive attitudes and competence practically ineffective in the classroom.

The low score for Professional Development further accentuates this issue. The current training landscape is perceived as neither satisfactory nor consistently available, indicating that professional growth in AI is likely self-initiated rather than institutionally mandated or sustained. This lack of tailored and practical training prevents teachers from translating their positive attitudes into robust pedagogical practices.

The Influence of Demographics

Age and Experience

The finding of a weak, but statistically significant, negative correlation between Age and Overall AI Readiness (r = -0.178, p = 0.028) is consistent with generational studies on technology adoption. Younger teachers tend to exhibit higher comfort and self-efficacy with emerging technologies. However, the absence of a significant relationship between Years in Service and readiness suggests that mere classroom experience does not necessarily predict AI readiness. A veteran teacher of 20 years who has received recent, high-quality training may be more ready than a 10-year veteran who has not. This points to targeted training as a more critical predictor than simple chronological age or tenure.

Highest Educational Attainment

The One-Way ANOVA revealed no statistically significant difference in Overall AI Readiness based on the teacher-respondents' Highest Educational Attainment (p =0.282). This is a crucial finding, as it debunks the assumption that advanced academic qualifications (Master's or Doctorate degrees) automatically equip teachers with the skills necessary for AI integration. It underscores that AI readiness is a specific, learned skill set that requires dedicated technological and pedagogical training, not merely general academic achievement. Policy interventions must therefore focus on embedding AI literacy into professional development mandates rather than relying on existing post-graduate credentials.

5 CONCLUSION

The study concluded that the Science teachers in the Division of Davao de Oro exhibit an Overall High Readiness for integrating AI into their teaching practice, largely driven by a strong positive Attitude and Intention toward AI adoption. However, the moderate ratings in the Resources and Infrastructure and Professional Development and Training dimensions are critical constraints. The enthusiasm and competence of the teaching force are currently not being matched by adequate institutional support, hardware, software, or targeted training programs. This gap between positive attitude and poor structural support is a common impediment to technology implementation globally (Zhao et al., 2022).

Furthermore, the study established a statistically significant, albeit small, negative relationship between Age and AI Readiness, implying that policies designed to promote AI literacy should particularly target the older, more experienced demographic to ensure equitable adoption. Crucially, academic degrees (Highest Educational Attainment) were not a differentiating factor in AI readiness, as confirmed by both the ANOVA and Post Hoc analysis.

These findings suggest that the Davao de Oro Division should pivot its AI strategy from fostering positive attitudes (which are already high) to investing heavily in three key areas: infrastructure provision, dedicated technical support, and the implementation of subject-specific, hands-on AI literacy training programs. Future research should focus on developing a localized AI literacy framework based on the TPACK model tailored to the Philippine context.

6 Acknowledgement

I would like to express my sincere thanks to all those who contributed to the completion of this research. Special thanks to my mentor and peers for their insightful feedback and encouragement throughout the process. Finally, I thank my family and friends for their unwavering support and patience while I conducted this study.

7 Authors' Biography

Clyde Evan Gines is a dedicated educator and researcher currently serving as a full-time Science teacher at Corazon C. Aquino National High School. Committed to professional growth and the advancement of science pedagogy, he is presently pursuing a Master of Science in Teaching (MST) with a specialization in Biology at Davao del Norte State College.

His current academic interests lie at the intersection of technology and education, specifically focusing on the integration of Artificial Intelligence (AI) within the Philippine basic education sector. His recent research efforts, such as assessing the AI readiness of Science teachers in the Division of Davao de Oro, aim to provide empirical evidence to bridge the digital divide and improve instructional effectiveness in non-urban settings. Through his work in the classroom and his graduate studies, Mr. Gines strives to contribute to the development of a technologically adept and ethically grounded teaching force

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