Artificial Intelligence in K-12 Education: An Investigation of Educators' Stages of Concern, Perception, and Adoption

by

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Abstract

Generative artificial intelligence is transforming K-12 education, creating new advantages and significant challenges for educators. Guided by the Concerns-Based Adoption Model (CBAM), this quantitative study examined K-12 educators' stages of concern regarding AI integration in education; differences in concerns by educator characteristics; the relationships among the stages of concern, perceptions of AI benefits and challenges in education, and adoption intentions. Participants included certified educators from a single public school district in the western United States who completed an adapted version of the Stages of Concern Questionnaire (SoCQ), along with additional survey items on demographics, AI tool use, and two open-ended questions. Quantitative data were analyzed using the SoCQ manual (George et al., 2006), descriptive statistics, Pearson correlations, independent-samples t tests, and one-way analyses of variance. Qualitative responses were analyzed using content analysis.

Results indicated that most educators remained in the early stages of concern. AI experience showed stronger relationships with stages of concern than traditional demographics. Educators who reported being in the advanced stages of concern also reported increasingly positive perceptions of AI's instructional benefits, greater willingness to adopt AI tools designed for educators, and more unease as it relates to ethical AI use. The findings suggest that educators' responses to AI represent an evolving process rather than simple acceptance or resistance to innovation, even though a cross-sectional design methodology was employed. This study provides

several AI implementation recommendations for school leaders, as well as several directions for further research. By applying the Concerns-Based Adoption Model to the emerging field of artificial intelligence, this study contributes to the growing body of knowledge on AI implementation in K-12 framework to support educators through a significant technological innovation.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, the following Artificial Intelligence (AI) tools were used: ChatGPT (OpenAI) and Grammarly. These tools were used primarily for outlines and editorial assistance, specifically to improve clarity, organization, grammar and style of written text as well as refine the presentation of statistical results. Ai was used to assist in editing and following APA style requirements. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain scholarly integrity of this research.

Digital Accessibility Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure this document complies with federal requirements: Microsoft Word Accessibility Checker. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

Acknowledgments

This dissertation is dedicated to my husband, Marcus, and my beloved children. To Marcus, thank you for your unwavering love, encouragement, patience, and support throughout this journey. You believed in me even when the path seemed overwhelming, and your steadfast confidence gave me the strength to persevere. I am blessed to share this life with you, and I could not have accomplished this milestone without you. To my children, I hope this accomplishment inspires you to pursue your dreams with determination, perseverance, and integrity. Never stop learning and never underestimate the power of education.

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[1] To protect the anonymity of the participating school district and its employees, the school district is referred to throughout this study as School District A.

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List of Abbreviations

AI Artificial Intelligence

AIEd Artificial Intelligence in Education

SoCQ Stages of Concern Questionnaire

CBAM Concerns-Based Adoption Model

Chapter 1 Introduction

Background of the Study

Artificial Intelligence (AI) in Education has the potential to enrich instructional methods and tailor learning to the needs of individual students (Durak et al., 2024).AI tools in the educational context include adaptive learning platforms, automated formative assessment tools, and language translation services, which can be incorporated into the classroom to enhance learning environments (Chounta et al., 2022). However, AI integration in the K-12 setting is currently haphazard and lacks consistency (Alm & Ohashi, 2024). Educators are confronting a barrage of challenges, including little professional development on the topic, valid concerns about ethical implications, and a lack of data on AI's impact on student learning outcomes (Viberg et al., 2024). Amid the challenges and opportunities that AI in Education offers, educators' perceptions, readiness, and willingness to integrate these tools into their classrooms may be an important factor in deciding AI's effectiveness in K-12 education.

Since the arrival of OpenAI's ChatGPT in 2022, the use of AI in education and research on this new technology have increased exponentially (Alm & Ohashi, 2024). A 2024 bibliometric study on AI’s role in transforming teaching and learning shows that the number of studies conducted in the field of AI in Education (AIEd) has dramatically increased over the last 10 years and has become the center of attention for many researchers in recent years (Durak et al., 2024). As AI in education is still in its early stages, more research should be done to ensure that integrating AI into education is thoughtful, research-based, and optimized for improved academic outcomes while minimizing AI's challenges. According to Long and Magerko (2020), “there is a need for additional research investigating a) what competencies users need in order to effectively interact with and critically evaluate AI and b) how to design learner-centered AI technologies that foster increased user understanding of AI."

Additionally, the research surrounding K-12 educators' perceptions and concerns regarding AI integration in the classroom is currently limited (Alm & Ohashi, 2024). For example, some concerns teachers have pertain to data privacy and a fear that AI could pose a threat to their employment (Hur, 2024; Kaplan-Rakowski et al., 2023). There also appears to be a need for more empirical data on how teachers' backgrounds, such as their technological savvy or professional development opportunities, could sway their attitudes and approaches to AI adoption (Ho et al., 2022). "To explore teacher preparedness and readiness to adopt AI in classrooms, it is necessary to examine the underlying variables that contribute to teachers' ability and willingness to incorporate these innovative technologies effectively" (Woodruff et al., 2023). These early adoptions may be critical, considering that the future development of AI tools depends on the frameworks, policies, and needs of schools (Pham & Sampson, 2022). Given this gap in our understanding--and the coevolving nature of AI programs based on usage needs--policymakers and educational leaders are in an early and critical stage of how to implement guidelines for AI use in schools.

Therefore, this study aims to explore the perceptions, experiences, and concerns of K-12 educators regarding the adoption and integration of AI in the classroom. Using the Concern- Based Adoption Model (CBAM), the research will study the stages of concern and levels of use of AI among K-12 educators from a varied demographic. The study aims to illustrate insights that could inform professional development and training and assist with policy creation to support effective AI integration in the K-12 education setting, which could contribute to the use of AI in learning environments in a positive and impactful way.

Using a quantitative approach, this study will provide quantitative data to analyze the distribution of teachers across different stages of concern to provide valuable insight into the factors shaping their attitudes. Findings from this study aim to inform school leaders, policymakers, and professional development providers on how to better support teachers in adopting AI tools.

Statement of the Problem

Integrating Artificial Intelligence in Education has the potential to enrich instructional methods and tailor learning to the needs of individual students (Woodruff et al., 2023). However, educators' perceptions, readiness, and willingness to integrate these tools into their classrooms will be the main factors in deciding AI's effectiveness in K-12 education (Woodruff et al., 2023). While there is increasing research on AI's potential in education, the research surrounding K-12 educators' perceptions and concerns regarding AI integration in the classroom is limited (Alm & Ohashi, 2024). There also appears to be a lack of empirical data on how teachers' backgrounds, such as their savviness regarding technology or professional development opportunities, could sway their attitudes and approaches to AIEd technology adoption (Ho et al., 2022). Due to this gap in knowledge, policymakers and educational leaders are challenged in how to implement guidelines for AI use in schools (Woodruff et al., 2023).

Therefore, this study aims to explore the perceptions, experiences, and concerns of K-12 educators regarding the adoption and integration of AI in the classroom.

The research will use the Concern-Based Adoption Model (CBAM) to study the stages of concern and levels of use of AI among K-12 educators from a varied demographic. The study aims to illustrate insights that could inform professional development, training, and assist with policy creation to support effective AI integration in the K-12 education setting.

Purpose of the Study

The purpose of this study is to describe and explore the stages of concern among K-12 educators regarding the integration of Artificial Intelligence (AI) into the classroom in a public school district setting. Using original survey research, the study seeks to examine how demographic factors, such as years of experience, subject area, and prior exposure to technology, may associate with these concerns. The findings from this study aim to inform school leaders, policymakers, and professional development providers about how to better support teachers in adopting AIEd technology tools.

Research Questions or Hypotheses

Presented are the following research questions for the study:

RQ1.) What stages of concern do K–12 educators report regarding AI integration?

RQ2.) Do stages of concern differ according to educator characteristics?

RQ3.) What is the relationship between stages of concern and perceptions of AI?

RQ4.) What is the relationship between stages of concern and perceived challenges and adoption of AI?

Theoretical or Conceptual Framework

The Concerns-Based Adoption Model (CBAM) is a theoretical framework developed in the 1970's (Hall, 1979). It was designed to measure, describe, and explain teachers' concerns and the process of change when new technology, curricula, or instructional practices are implemented (Hall, 1979). This model has been used to monitor and lead the educational change process and change-related research (Fan & Zhao, 2023). The CBAM is based on theory and prior research on technology adoption, specifically in the educational context, making it an ideal research framework (Alm & Ohashi, 2024).

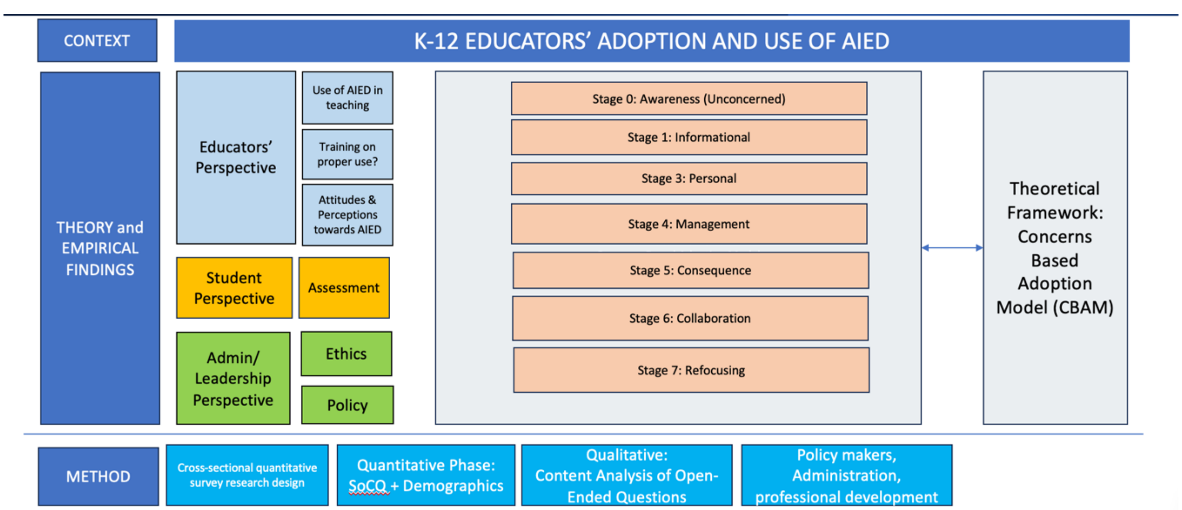

Figure 1. Concept Map of K-12 Educators' Adoption and Use of AIEd Technology

Significance of the Study

This study is significant in several important ways, listed below.

Informing Professional Development and Support Initiatives

Because the technology is new and evolving, it is possible that many teachers do not understand its full potential for assisting them in the classroom (Perkel, 2025). By identifying specific concerns that teachers experience at each stage of adopting AI, this study can guide the development of tailored professional development programs. Such programs would directly address teachers' unique needs, from foundational knowledge about AI to practical strategies for implementing AIEd technology tools in various subjects. Understanding teachers' concerns also helps school leaders and policymakers prioritize resources and support for effective AI integration (Woodruff et al., 2023).

Guiding Policy and Resource Allocation

A recent study from the NEA reported that more than 1 in 4 educators say their schools have no ChatGPT policy in place (NEA, 2024). Additionally, emerging polls show teachers do want more guidance and policy around AI in education (Singson, 2025). This study's findings can help inform district and state-level policies by providing data on the practical and emotional challenges teachers face when introducing new technologies like AI Insights into these challenges are especially critical in rural settings, where resource allocation and access to technology may be limited. Policymakers could use this information to craft policies that account for these disparities, ensuring that rural teachers are included in the AI adoption process.

Enhancing Teacher Retention and Job Satisfaction

An April 2024 Pew Research study showed that over 8 out of 10 teachers state they do not have enough time in the workday to accomplish all that they are required to do (Lin, Parker & Horowitz, 2024). Studies continue to sound the alarm about teacher burnout and difficulties with teacher retention (Modan, 2024). Implementing AI in the classroom could significantly impact teachers' workload, classroom management, and instructional methods (Merod, 2024). By understanding teachers' concerns, this study contributes to ideas for addressing these impacts in a way that minimize stress and increases support. Addressing these concerns could lead to higher levels of job satisfaction, reduce teacher burnout, and improve teacher retention.

Contributing to Educational Research on Technology Adoption

Even without AI, technology has moved from a facilitator in the classroom to shaping education environments and interactions between student and teacher (Vorobyov, 2024). Digital literacy is arguably as critical as traditional literacy in this new area, and it is essential to prepare students for a digital future (Vorobyov, 2024). This study adds to the existing knowledge on technology adoption in education by applying the Concerns-Based Adoption Model (CBAM) specifically to AI integration. By examining AI through the CBAM framework, the study provides a structured understanding of teachers' concerns. It contributes new insights into the psychological and practical aspects of adopting emerging technologies in the classroom.

Advancing Student Learning and Preparing Future-Ready Classrooms

While we know the drawbacks to AI in the classroom, like academic dishonesty and lack of critical thinking, we also know there are some uses AI can have in the classroom for major personalized learning opportunities (Perkel, 2025). It will be up to educators to guide effective AI integration in the classroom (Perkel, 2025). By identifying and addressing teachers' concerns, this study indirectly supports the creation of AI-enhanced classrooms where students can benefit from personalized learning, increased engagement, and relevant skills for a technology-driven world. Ensuring teachers are prepared and comfortable with AI helps foster a learning environment that prepares students for future careers and challenges (Perkel, 2025). In sum, this study's significance lies in its ability to address the human and systemic aspects of AI integration in education, providing insights that support effective and sustainable adoption of AI in high school classrooms. The findings will be valuable for educators, administrators, and policymakers alike, creating pathways for successful AI integration that meet the needs of teachers and students alike.

Scope and Delimitations

The study population consisted of K-12 educators employed by School District A, a rural public school district serving elementary, middle, and high schools in the western United States. This study follows a quantitative design involving a discrete quantitative phase followed by integrated analysis. It spans approximately 3 months, starting with data collection for the quantitative phase and concluding with a comprehensive analysis and interpretation.

Assumptions

Teachers' Concerns Can Be Systematically Categorized

The study assumes that the Concerns-Based Adoption Model (CBAM), specifically the Stages of Concern Questionnaire (SoCQ), is valid for categorizing and measuring teachers' concerns regarding AI integration. It presumes that teachers' feelings, apprehensions, and needs can be effectively mapped onto the seven stages of concern, accurately representing their readiness for and responses to AI adoption.

Quantitative Design Offers Objectivity, Repeatability and Efficiency

This study assumes that using purely quantitative data from the SoCQ and demographic survey will yield a more objective understanding of teachers' concerns than a mixed-method or purely qualitative design. While it is sometimes true that qualitative designs can add nuance and contextualize quantitative findings, the extreme “newness” of AI in education may render qualitative findings unreliable. A quantitative design using a proven survey in a defined school district can also be repeated more easily, varying for district demographics. Finally, the quantitative approach is efficient, leading to concrete data that can be expanded on at a future date with mixed-method and/or qualitative designs.

Teachers Will Provide Honest and Accurate Responses

The study assumes that teachers will answer the SoCQ and interview questions truthfully and accurately, offering genuine insights into their concerns and perspectives. This assumption is critical for the validity of both quantitative and qualitative data and assumes that any social desirability bias will be minimal or manageable through careful data interpretation.

Contextual Factors Impact Teachers' Stages of Concern

Given that this study focuses on a single school district, it assumes that the specific setting and characteristics of the school (e.g., access to technology and professional development opportunities, as well as socio-economic factors) may influence teachers' stages of concern. The assumption is that certain environmental and contextual factors affect teachers' readiness for AI adoption and may create concerns distinct from those in more distinctly different settings (rural v. suburban v. urban; public v. private v. charter, etc.).

AI-Specific Concerns Can Be Captured Within the CBAM Framework

The study assumes that the CBAM framework, although general in nature, is flexible enough to capture concerns specific to AI (such as data privacy, ethical considerations, and the impact on teaching roles). It presumes that any additional concerns unique to AI will emerge naturally in the qualitative data and can be analyzed and understood within or alongside the CBAM framework.

The Researcher's Role and Potential Bias Are Manageable

It is assumed that any researcher bias can be minimized through established procedures such as reflexivity, coding verification, and peer review. This is particularly relevant for the qualitative component, where the researcher's interpretation plays a significant role. The assumption is that the researcher's potential biases will not significantly impact data collection, analysis, or interpretation.

The Findings Will Be Transferable to Similar Contexts

While generalizability may be limited due to the single-site design, the findings are assumed to be transferable to similar contexts, such as other schools with comparable resources and teacher demographics. This assumption holds that other schools with similar characteristics may face comparable challenges and concerns, allowing insights to inform AI integration strategies beyond this setting.

Limitations

Single-Site Limitation

The study was conducted in a single school district, which may limit the generalizability of findings. Teachers' concerns about AI integration in this particular school district may not fully represent those in other rural, suburban, or urban settings. Consequently, results might not apply to schools with different resources, student demographics, or varying access to technology.

Self-Reported Data

Both the Stages of Concern Questionnaire (SoCQ) and interview data rely on self-reported information, which may be subject to bias. Teachers may respond in ways they believe are socially desirable or may underreport concerns about AI due to perceived professional expectations. This could impact the accuracy of the results regarding their actual levels of concern.

Stage of Concern Measurement

While the SoCQ is a widely used tool, it may only capture some nuances of teachers' concerns specific to AI integration, as it is a general tool for assessing concerns about innovations. Teachers may have AI-specific concerns (e.g., data privacy, ethical implications) that must align neatly with the CBAM stages, potentially limiting the insights into AI-related challenges.

Sample Size and Representation

Although the study aims to include a large portion of the districts' teaching staff, variations in response rates could lead to underrepresenting specific subgroups (e.g., teachers with less experience or those in non-technical subjects). A lower response rate could also impact the robustness of statistical analyses, limiting the study's ability to detect significant relationships.

Time Constraints and Cross-Sectional Design

The study captures teachers' concerns simultaneously, which may not fully reflect the evolving nature of their attitudes toward AI integration. Teachers' concerns could change as they gain more experience or as the school's support systems adapt, but a cross-sectional design does not capture this progression.

Potential Researcher Bias

While this study primarily employed a quantitative research design, researcher bias remains a potential limitation in the analysis of the two open-ended survey questions. The identification and categorization of themes through content analysis required researcher judgment, which may have influenced the interpretation of participant responses. Because the qualitative analysis was intended to complement and provide context for the quantitative results rather than serve as the primary source of evidence, the potential influence of researcher bias on the overall findings was limited.

Limited Exploration of External Influences

The study focuses primarily on teachers' personal, management, and consequence-related concerns about AI. However, it may need to fully capture the impact of broader educational policies or community attitudes toward AI. External factors like district policies or community support for technology in education may shape teachers' concerns but fall outside the scope of this study. These limitations highlight areas where caution should be taken in interpreting findings and suggest directions for future research, such as multi-site studies, longitudinal designs, or instruments tailored to AI-specific concerns in education.

Summary

Artificial Intelligence in Education (AIEd) has exciting potential for educators and students to vastly improve the educational experience. However, educators' perceptions, readiness, and willingness to integrate these tools into their classrooms will be the main factors in deciding AI's effectiveness in K-12 education. The next chapter provides a review of relevant literature on the topic of Artificial Intelligence in Education, including its potential benefits and challenges, the concept and importance of AI Literacy for educators, the importance of understanding educators' perceptions of AI in education, and a discussion of the gaps in the literature currently.

Chapter 2 Literature Review

Introduction

Artificial Intelligence technologies are being integrated into every facet of our lives. One area where it is growing exponentially is Education (Woodruff et al., 2023). Particularly since the arrival of open AI technologies, such as ChatGPT in 2022, AI in education is a rapidly growing area of research (Durak et al., 2024). AI in education has the potential for many benefits but also serious challenges (Wang et al., 2024). Before the benefits of AI can be harnessed in the classroom, educators' will need to successfully integrate this new technology into their pedagogy and curriculum. Educators' willingness to incorporate these tools is largely dependent on their perceptions and trust of AI tools and technology (Nazaretsky et al., 2021). These perceptions are shaped by various factors, including their general familiarity with technology, the perceived benefits and downsides, and how difficult or easy these tools are to incorporate into their pedagogy (Hur, 2024). Investigating these perceptions is important for professional development, policymaking and designing AI tools that respond to the needs of teachers and students. The following literature review intends to explore the existing research on AI in Education with a focus primarily on teachers' perceptions. Key themes such as the potential benefits and challenges of AI in the classroom, the importance of AI literacy, professional development opportunities and teachers' concerns with AI adoption are discussed. The summary of these findings establishes a foundation for the study which aims to investigate how educators in K-12 education perceive and eventually adapt to AI, framed within the concern-based technology adoption model.

AI in Education: An Overview

Definition of Artificial Intelligence

The term “artificial intelligence” was originally used in 1955 by Dartmouth College assistant professor John McCarthy in the title of a workshop for the Rockefeller Foundation. McCarthy defined it as “making a machine behave in ways that would be called intelligent if a human were so behaving” (McCarthy et al., 1955). 63 years later, Ferràs-Hernández defined Artificial Intelligence as “a new generation of technologies capable of interacting with the environment by (a) gathering information from outside (including from natural language) or from other computer systems; (b) interpreting this information, recognizing patterns, inducing rules, or predicting events; (c) generating results, answering questions, or giving instructions to other systems; and (d) evaluating results of their actions and improving their decision systems to achieve specific objectives” (Ferràs-Hernández, 2018).

AI has the potential to dramatically alter numerous aspects of life, including the structure of the workforce, the functioning of organizations, job roles, decision-making processes, and knowledge management (Glikson and Wooolley, 2020). AI can perform tasks similar to learning, recognizing situations, problem-solving and communicating in a natural language as humans do. What differentiates AI from other previous computer technologies is its ability to self-learn (Darayseh, 2023). Because of its relatively recent arrival, the exact way these areas will change is still very much to be determined, which means there is much need for research and data collection (Cope et al., 2020). Artificial Intelligence encompasses a wide-ranging spectrum within computer science surrounding the development of “smart machines” which can take on tasks like those performed by humans (Durak et al., 2024). Artificial Intelligence can also be defined as "that activity devoted to making machines intelligent… [where] intelligence is that quality that enables an entity to function appropriately and with foresight in its environment" (Nilsson, 2009). Thus, computers are programmed with 'intelligence', allowing them to perform 'thinking' and learn through programmed algorithms to mimic human thinking and actions (Durak et al., 2024). Artificial Intelligence is an incredible innovation as it allows computer systems to accomplish tasks and activities that have historically relied on human cognition, such as natural language processing and reasoning (Nazaretsky et al., 2021).

According to Karakose and Tülübas (2024), AI systems fall into four main categories: "conversational (capable of engaging in human-like conversations, both voice and text-based such as repetitive client queries or chatbots), biometric (those systems that can capture people's fingerprints, facial images, retinas, or hand geometry as well as their behavioral traits like the use of voice or gestures), algorithmic (capable of making decisions and executing actions by processing a predefined set of instructions and large volumes of data, mostly via machine/deep learning), and robotic (physical robots that can assist people to perform complex or automated tasks". AI is vastly implemented across virtually all sectors of society, including business, finance, military, health, and medicine (Kaplan-Rakowski *et al.,* 2023).

Definition of Artificial Intelligence in Education (AIEd)

Since the invention of the computer, there has been a continuous focus on enhancing education through adaptive learning tools (Wang et al., 2024). Computer-based learning started in a linear fashion and was constrained to pre-programming with minimal adaptability (Wang et al., 2024). As technology evolved, efforts were concentrated on creating adaptive learning experiences influenced by human tutoring concepts, aptitude-treatment interaction effects, and now the rise of artificial intelligence (Wang et al., 2024). This has led to the development of intelligent tutoring systems across various subjects. These systems, such as Carnegie Learning's Cognitive Tutor or Pearson's MyLab, aim to replicate one-on-one human tutoring, considered highly effective, and customize content based on learner, subject and environmental variables (Wang et al., 2024).

Artificial Intelligence has already had a transformative impact on the education sector (Durak et al., 2024). AI in education has promised a whole new epoch of personalized learning, heightened participation, and improved data and feedback to enhance students' educational experiences and instill a sense of hope and optimism in educators (Durak et al., 2024).

AI in adaptive learning can modify the presentation, curriculum, navigation, and learning support based on predictive machine learning models (Darayseh, 2022). A bibliometric analysis of AIEd literature of 1,726 academic studies from 2013 to 2023 showed how much AI in education has evolved. The study revealed a stable publication rate from 2013 to 2017, followed by an explosion of research after 2017 (Durak et al., 2024). This steep growth not only demonstrates the increasing interest in AIEd, but also keeps the audience informed and up to date about the recent technological advancements in AI and its potential in education, as well as the global demand for AI educational solutions and policy (Durak et al., 2024). Additionally, research regarding adaptive learning has been especially on the rise since 2015 (Wang et al., 2024).

Impressive large language models (LLMs) can generate human-like text, images, and music (Alm & Ohashi, 2024). A foundational LLM was GPT, which stands for Generative Pretrained Transformer, created by OpenAI in 2018. The release of the open generative AI, ChatGPT, in 2022, brought this technology mainstream, including into education (Kaplan-Rakowski et al., 2023). AI tools, processes, and services have also developed in education, but educators' enthusiasm for adopting these new tools has been seen as slower than in other fields (Kaplan- Rakowski et al., 2023). These tools include learning management systems, transcription and evaluation services, grammar checkers, and plagiarism detectors (Kaplan-Rakowski et al., 2023). Generative AI chatbots like ChatGPT can generate and summarize texts and translate language (Kaplan-Rakowski et al., 2023). AI can facilitate adapting content to students' knowledge levels and provide personalized recommendations for learning materials that address students' specific needs (Chounta et al.,2022). In the context of K-12 education, AI can be used as a teacher's tool to help design lesson plans, personalized learning, scaffolding strategies, and assessments (Chounta et al.,2022; Perkel, 2025).

Because AI is computer-based, it can never be human intelligence (Cope et al., 2021). The term AI includes a large area of computer processing, including machine learning, deep learning, natural language processing, neural networks, and computer vision (Cope et al., 2021; Hur, 2024).

The research in AIEd in K-12 contexts can be divided into two main categories: The first is how to teach students AI knowledge, literacy, and skills through formal or informal AI curricula. The second category uses AI to support learning and teaching in various subjects (Jong, 2022). The advances in generative AI have been exciting for the possibilities it provides in problem-solving and content creation but also terrifying in its possibility of diminishing human creativity, critical thinking and academic integrity (Kaplan-Rakowski et al., 2023).

While technology has been used in education for decades, the arrival of AI in Education is unique. As a relatively new and complex technology with such a vast array of different, possible applications, AI distinguishes itself from other new technologies, sparking intrigue and engagement among the audience (Kaplan-Rakowski et al., 2023).

Educators are labeling AI in education as a "double-edged sword" (Mohammmadkarimi, 2023) because of the exciting possibilities it provides for learning but the terrible misuse by students to have AI do the work for them and plagiarize. The popularity is outpacing administrations' ability to formalize policy and provide training to teachers (Mohammmadkarimi, 2023). This is also why research needs to be done on the topic. From 2023 on, there has been a surge of scholarly articles on the topic of AI in education for both students and teachers (Li et al., 2023; Magrill & Magrill, 2024; Abdelhalim, 2024; Al Darayseh, 2023). This demonstrates how important and relevant the topic of AI in education is at the moment.

AIEd Technology and Tools Currently Used in the Classroom

In education, AI is being used as a tool to assist teachers and students improve learning (Perkel, 2025). The current consensus seems to agree that AI will not replace teachers, but adopting AI can design a new form of education by incorporating its powerful uses (Cope et al., 202; Perkel, 2025).

Potential Benefits of AI in Teaching and Learning

AI can perform adaptive learning, enhanced personalization, automation of routine tasks, data-driven insights, and real-time feedback to students (Ayeni et al., 2024). Among the most important areas where AI tools can be used are:

1. Individualized teaching, which involves using AI tools to create activities that are compatible with the students' academic level and provide constructive and immediate feedback (Ayeni et al., 2024).
2. Adaptive learning environments: This allows a wide range of content to be taught at each students' learning methods and preferences (Al Nabhani, Hamzah, & Abuhassna, 2025).
3. AI-based assessments: AI can be used to help design and correct assessments (U.S. Department of Education, 2023).
4. Virtual Reality technology: This allows for integrating multi-sensory information and providing learners with an interactive and engaging learning environment (Al Darayseh, 2023).

According to IBM, a “neural network is a machine learning program, or model, that makes decisions in a manner similar to the human brain, by using processes that mimic the way biological neurons work together to identify phenomena, weigh options and arrive at conclusions” (IBM, 2024). When integrated into technology used in the classroom, research shows that these neural networks, mimicking human brain activity, can be trained to correctly determine whether students are actively engaged in various types of instruction, from whole group to small group to students working individually (Mulvihill & Martin, 2024). In addition, neural networks can also precisely evaluate the nature of teacher questioning during lessons, use of academic language, student explanation and justification, teacher feedback and uptake of students’ contributions (Banihashem et al., 2022). AIEd tools can allow teachers to monitor a dashboard visually displaying real time information about individual lessons, chapters within lessons and cumulative practices across multiple lessons and in general display how students are performing in the classroom (Mulvihill & Martin, 2024).

AI tools offer personalized student-centered learning by using learner performance information, demographics, and behavior data to customize student learning (Kaplan-Rakowski et al., 2023). AI Chatbots provide students with real-time support in an interactive, conversational style, answering questions immediately. This not only saves time but also makes the learning process more efficient. Teachers stated that AI could help them be creative, organize the students by knowledge level, and organize their learning materials by difficulty level (Chounta et al., 2022).

Adaptive learning models have existed for some time now, but the development of AI tools is vastly improving their capacity for personalized learning (Want et al., 2024).

In the earlier forms of adaptive learning, tools could only provide 'limited parameterization' (Wang et al., 2024). Adaptive learning is 'an emerging learning technology that dynamically adjusts instructional content to provide interactive and personalized learning paths to the individual to facilitate learning' (Martin et al., 2020 from Wang et al., 2024). Adaptive learning includes instructional materials that can be 'branched' using different pathways based on learner characteristics and interactions within these systems. Such pathways can now be automatically created using AI solutions focusing on learner deficiency and mastery of instructional content. Without AI, these pathways would have to be predesigned, and decisions about instructional delivery would be based on outcomes of assessments or other predetermined traits (CITE). Therefore, integrating AI can potentially make adaptive learning a more responsive and powerful learning tool. However, such integration also brings more challenges and risks because of the nature of its complexity. These risks include potential biases in the AI algorithms, data privacy concerns, and the need for continuous teacher training to effectively use AI tools (Wang et al., 2024).

For language teachers, generative AI can provide conversational practice, language input, personalized vocabulary notes, and comprehension questions (Alm & Ohashi, 2024). Teachers currently use AI to create learning materials, give assessments and feedback, and encourage self-study (Alm & Ohashi, 2024). AI provides students with personalized scaffolding, giving them the support they need to feel confident and independent in their learning. It also provides teachers with data on student performance. AI can facilitate content adaption to students' knowledge levels and provide personalized recommendations for learning materials that address students' specific needs. For example, ChatGPT can assign hierarchical assignments according to the student's cognitive level. In the second case, AI is used to facilitate and support the analysis and visualization of students' data and to provide indicators related to various aspects of learning, such as performance, knowledge state, affective state, cognition and metacognition (Fan & Zhao, 2023). In Mohammadkarimi's 2023 study, 79% of university educator participants agreed that AI was an excellent resource for students, and 83% of the participants were aware that their students used it for academic purposes. Studies are being done now on how AI can benefit various subject areas like math, science, and language learning. Many studies indicate that AI is quite versatile and can adapt to many different academic disciplines (Durak et al., 2024).

AI’s role in promoting differentiated instruction and formative assessment

AI can grade homework and perform everyday administrative tasks such as reporting. It can also provide support with lesson planning and monitor students. AI can provide support in terms of personalized feedback and instruction and finding and adapting appropriate learning material (Chounta et al., 2022). In addition, AI can provide language-translation services for learning materials (Chounta et al., 2022).

For example, a typical assessment task requires critical thinking, logical reasoning, and understanding texts written in a free language. Therefore, grading and assessing are usually associated with human-only capabilities. AI-Grader is a Natural Language Processing and AI- powered assessment technology that analyzes constructed responses to open-ended questions and creates an automated score based on an analytic grading rubric (Nazretesky et al., 2022).

AI powered chatbots are tools that recognize and understand speech and respond to the learner appropriately, thereby providing personalized learning support (Al Darayseh, 2023). AI applications can receive, store and process information as well as promote self- learning which can assist teachers to take into account individual differences among students and improving the quality of learning and education (Al Darayseh, 2023).

Challenges of AI Integration in Education

Several challenges related to using AI in education include ethical considerations, bias, data privacy, and accountability. Perhaps the biggest concern with generative AI is plagiarism and teachers' difficulty detecting misuse (Alm & Ohashi, 2024). In a 2023 study of 67 university EFL teachers, they unanimously agreed on the negative impact of AI on their students' academic integrity (Mohammmadkarimi, 2023). Many educators are spending more time trying to detect AI plagiarism in student work (Mohammmadkarimi, 2023). Meanwhile, students continue to be more 'innovative' in avoiding plagiarism detectors, such as using synonyms or rephrasing sentences. Examples of AI-powered tools that have made cheating easier include online essay generators, online essay mills, and custom writing services (Mohammmadkarimi, 2023). The advancement of these tools has made it increasingly challenging to identify incidents of academic dishonesty. Teachers are altering their techniques and evaluation methods to respond to academic dishonesty (Mohammmadkarimi, 2023). The advanced algorithms and natural language processing capabilities, which are part of AI tools, make it very difficult for educators to identify instances of plagiarism.

While plagiarism is 'bad' for several reasons, one of the most critical reasons is that it can lead to a significant loss in students' development of critical thinking, research, and creativity skills. These are crucial life skills for both professional and personal growth (Mohammmadkarimi, 2023).

There are other concerns about integrating AI into education. As the technology evolves, chatbots have been reported to respond problematically to students, either in a hostile way or generating nonsensical answers (Kaplan-Rakowski et al., 2023). Teachers have also raised concerns that AI could diminish the human element of education. They have also wondered whether AI could have humans' flexibility, creativity, and responsiveness (Chounta et al., 2022). While AI could be used to provide recommendations on learning materials and lesson plans, there is a significant risk that by over-prescribing automated solutions to teachers, the role of the teacher could be undermined (Chounta et al., 2022). There can be serious accountability issues if the AI provides incorrect, inappropriate, or harmful responses (Chounta et al., 2022). There is a danger in the 'mindless implementation of new technologies that uncritically ingest yesterday's mistake' (Bridle, 2018). There have been instances of inaccurate responses. There is also a risk of cultural bias in the responses (Alm & Ohashi, 2024). All of these challenges make teaching users AI literacy critical if it is to be used successfully.

Technical limitations

Several technical limitations are currently delaying the implementation of AI in education such as lack of teacher training, infrastructure, and accessibility. Teachers' knowledge levels of AI can be minimal, thereby making teachers unprepared to use AI tools in the classroom (Kaplan-Rakowski et al., 2023). In a study of 130 K-12 teachers, 82% of the respondents stated they have limited or fair knowledge of AI and 0% claimed to be experts in AI (Chounta et al., 2022). There is a potential issue that teachers who claim to know a lot about AI actual struggle to use it because of false perceptions and teachers who do not see themselves as knowledgeable do not use AI even though they have the required skills (Chounta et al., 2022). Several studies teachers are concerned about the amount of time and effort required to learn how to use AI and have expressed trust issues with AI (Chounta et al., 2022).

AI Literacy

Given that AI will be integral to numerous future jobs, the need for education on AI, its functionality, and its applications is as pressing as traditional literacy skills such as reading and writing (Hur, 2024). However, there is a significant public misunderstanding that needs to be addressed due to the novelty of this technology (Long & Magerko, 2020). The design of the AI in question can lead to misunderstanding, if the algorithms are "black box" with opaque rules. Often, users do not even know when they are interacting with AI (Long & Magerko, 2020), and most people lack technical knowledge of how AI functions, even with open AI This can cause misconceptions (Long & Magerko, 2020), such as students assuming AI-generated content is always accurate. "Research has shown that students assume that computers think like humans and want to make connections between human theories of cognition and machine learning. Students are also surprised that machine learning requires human decision-making and is not entirely automated. Finally, students often have difficulty identifying the limits of machine learning and identifying constraints that may make ML unsuitable for solving a particular problem "(Long & Margeko, 2020).

Students should be familiar with AI functions, critically evaluate how AI works, and consider ethical concerns (Hur, 2024). Since "AI Literacy" is a relatively new realm, there currently is no agreed-upon definition (Hur, 2024). Long and Magerko (2020) define AI literacy as "a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace." "Learners should be able to critically examine data with 'skepticism and interpretation" (Long & Magreko, 2020).

Research shows that teachers with a more realistic understanding of AI perceived more benefits and fewer concerns and ultimately reported more trust (Viberg et al., 2024). Therefore, educating teachers about AI can foster more trust at all stages and across all domains. Activities that enhance self-efficacy could be integrated into professional development. Rather than make teachers AI engineers, it can assist in developing a realistic understanding of AI as a tool, how it might benefit them, what concerns are warranted, and it can assist with their willingness to try it out in the classroom (Viberg et al., 2024).

Research shows that teachers need an understanding of AI to move from unrealistic visions of AI as autonomous robots to realistic ones (e.g., algorithms to support decision- making based on big data). Teacher training and professional development should strive to improve basic understanding of AI rather than provide in-depth courses on AI foundations and techniques (Viberg et al., 2024).

Lack of AI knowledge: AI literacy should improve teachers' AI literacy but not necessarily turn them into AI experts. They do not need technical details and jargon but concepts, standard procedures, and common practices, such as rubric development, expert tagging, accuracy, etc. Teachers should be able to interpret and justify automated results and communicate them to students. (Nazaretsky et al., 2022).

All education stakeholders – students, educators, admin, policymakers, and parents should become AI literate. More research is being done regarding AI literacy for these various stakeholders, while working groups are working on guidelines for how to teach AI literacy at each age, from young learners to college students (Long & Magerko, 2020). In order for educators to realize the full potential of AI in education, they must know the pedagogical contributions of AI-based tools. They should also collaborate with peers to see others' learning progress and outcomes and learn from other teachers' methods (Fan & Zhao, 2023). This collaboration is not just beneficial, but essential for the effective integration of AI in education.

Research has confirmed that end-users need to have basic data literacy to use learning analytics effectively (i.e., critically interpreting the results rooted in big data analysis and making data-informed decisions). In addition, knowing how the data is collected, stored, and processed in AI-powered systems is critical in developing students' and instructors' trust in AIEd technology. Research has also shown that although K-12 teachers consider AIEd technology a potentially powerful means for improving their instruction, they might avoid incorporating it into their daily teaching routines. One reason for this resistance is teachers' lack of knowledge about AI (e.g., how AIEd technology learns and makes decisions and what kind of information it can provide (Nazaretsky et al., 2022).

The Concern-Based Adoption Model (CBAM) Framework

Frameworks considered

For decades, the perceptions, concerns and attitudes of teachers towards technology adoption has been studied through various theoretical models and constructs. Studies are being done now on teachers' perceptions of AI through a variety of models and constructs (Viberg et al., 2024). The Technology Acceptance Model (TAM) framework has been used to study faculty's attitudes toward AI in higher education (Kaplan-Rakowski et al., 2023). This model was developed to explain behavior surrounding the use of technology and the factors associated with its acceptance and claims that behavioral intentions are determined by two types of factors: expected benefits and ease of use (Al Dayaseh, 2023). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model has been used to study English as a Foreign Language (ESL) students' motivation and use of generative AI tools (Zheng et al., 2024). The "Adaptive Source or Learner Model" is built on the learner's characteristics on what the learner knows and does. The learner model includes cognitive, affective and behavioral characteristics of the learner and includes variables such as learner attributes, learner preferences, learner knowledge and proficiency, motivational or emotional aspects of learner behavior and individual differences that are used to adapt the learning (Wang et al., 2024).

Since cultural and demographic differences can affect an individual's adoption and use of technology, another framework which has been used to study technology adoption is Hofstede's model of cultural values, developed in 2010 to conceptualize and study culture. The cultural values that came out of these findings showed that uncertainty, avoidance, power distance, masculinity v. femininity and collectivism v. individualism are important predictors of technology adoption (Hofstede et al., 2010). This model has been used to study cultural differences in both students' and teachers' attitudes towards technology use in educational settings, including AI technologies (Viberg et al., 2024).

While there are positive aspects of conducting research through a variety of theoretical lenses, the variety in theoretical and methodological approaches can mean that generalizing findings across studies is not possible (Viberg et al., 2024).

Origins and Evolution of CBAM

The Concerns-Based Adoption Model (CBAM) is a theoretical framework that was developed in the 1970's (Hall, 1979). The Concerns Based Adoption Model (CBAM) was designed to measure, explain and clarify teachers' concerns when new technology, curricula and/or instructional practices are implemented (Hur, 2024). The CBAM framework has been and continues to be widely utilized to measure and lead the educational change process and carry out change-related research (Fan & Zhao, 2023). In particular, the CBAM framework can provide valuable insights into the concerns that individuals experience during the technology adoption process (Hur, 2024). According to Hall (1979), concern is defined as a "composite representation of feelings preoccupation, thought and consideration" (p 5). The CBAM has been used in many studies throughout the years to understand the teacher technology adoption process, whether it is for hardware like physical computers to software tool (Alm & Ohashi, 2024). While both the TAM (Technology Acceptance Model) and the CBAM theory have solid theoretical foundations that can extend to the context of studying teachers' perceptions, the TAM only looks at two factors, benefits and ease of use, while the CBAM measures more factors through the scale of stages of concern and therefore provides a more complete picture of where teachers' might be in their acceptance of AI The CBAM is based in theory and prior research on technology adoption, specifically in the educational context (Alm & Ohashi, 2024). The CBAM Framework is ideally suited to conduct this research.

Key components of CBAM

The CBAM is comprised of three key diagnostic dimensions: Stages of Concern, Levels of Use and Innovation Configuration. The Stages of Concern relate to teachers' perceptions and feelings. The Levels of Use pertains to actual implementation of the technology. Innovation Configuration relates to how the technology is implemented (Fan & Zhao, 2023).

The Stages of Concern framework describes the progression of an individual's concerns in response to technological innovation. There are seven stages, each representing a different level of concern related to technology adoption. Stage 0 is the Awareness or Unconcerned Stage, Stage 1 is the Information Stage, Stage 2 is the

Personal Stage, Stage 3 is the Management stage, Stage 4 is the Consequence Stage, Stage 5 is the Collaboration Stage and Stage 6 is the Refocusing Stage (Hall, 1979).

However, other researchers have categorized the stages into 5 theoretical categories of teachers' concerns, which Jong (2022) defines as:

1. Consequence (C) pertains to the concerns about the impacts on student learning and teacher professional development brought by the innovation.
2. Evaluation (E) pertains to the concerns about the worthiness and possibility of introducing the innovation to schools.
3. Information (I) pertains to the concerns about the involved tasks and demands related to the innovation.
4. Management (M) pertains to the concerns about the practical issues related to the actual implementation of the innovation.
5. Refocusing (R) pertains to the concerns about the further improvement and enhancement of the innovation" (Jong, 2022).

Those respondents falling into the Evaluation, Innovation and/or Management stages can lean toward 'discouraging concerns' indicating that teachers may not be ready or willing to adopt the innovation. However, respondents falling into the stages of Consequence and Refocusing are 'encouraging concerns' indicating that teachers have a positive attitude toward adopting the new technology (Jong, 2022). Additionally, a respondent can demonstrate traits of more than one stage at a time. Hall developed a 35-item questionnaire to assess the intensity of concerns at various stages. This questionnaire has been widely used in education to measure teachers' concerns on a variety of technology adoption issues (Fan & Zhao, 2023).

Application of CBAM in Educational Technology

Research has shown that over half of teachers surveyed are currently in the Consequence Stage of the Concerns-Based Adoption Model (CBAM), indicating that they are beginning to consider the potential benefits and challenges of AI specifically for their students, rather than focusing solely on the technology itself (Alm & Ohashi, 20224). A significant number of teachers were also found to be in the Management Stage, where concerns center on the practical aspects of integrating AI tools into their instructional routines. These findings suggest that while many educators are moving beyond initial awareness, they have not yet fully implemented AI into their teaching practice. This reflects the broader reality that technology adoption in schools is often a gradual process, and that both educators and students are receiving uneven levels of guidance and support, which remains a critical area for policy and professional development attention.

Complementary findings from other studies indicate that many K-12 teachers recognize the growing importance of AI in education and have begun to explore its characteristics, classroom impacts, and the conditions necessary for effective implementation (Fan & Zhao, 2023). High levels of concern related to the Management Stage further underscore that most teachers have not yet deployed AI tools but are actively evaluating how to do so. In addition, teachers continue to express concerns about the effects of AI on students and their own professional roles, signaling the need for clearer implementation frameworks and ethical guidance (Fan & Zhao, 2023).

Teacher Perceptions of AI in the Classroom

Overview of Teacher Perceptions in Technology Adoption

Teachers' willingness to adopt AI in education is deeply influenced by human-centered factors such as trust, perceived reliability, and cognitive biases. Trust is a particularly decisive element in shaping whether educators are open to following automated recommendations, and that trust is in turn shaped by their attitudes, prior beliefs, and understanding of how AI functions (Nazaretsky et al., 2022; Viberg et al., 2024). When teachers harbor misconceptions about AI or lack foundational knowledge about how it operates, their adoption of AI in education technologies can be significantly slowed. As Viberg et al. (2024) note, teacher beliefs about functionality, helpfulness and reliability help determine whether the perceived benefits outweigh the concerns – a conceptual framework that helps explain varying levels of enthusiasm or hesitation.

Teachers who recognize AI's potential to enhance learning outcomes and productivity may still resist implementation if they are concerned about reliability or the potential erosion of interpersonal communication and social interaction, as seen in a study of K-12 teachers in Estonia (Chounta et al., 2022). These concerns reflect broader patterns seen across other domains of automated technology: when algorithms make mistakes, users tend to lose trust more quickly than they would with human error – a phenomenon known as algorithm aversion (Nazaretsky et al., 2022). This same skepticism is carried into educational contexts, where teachers may show greater forgiveness for human error than for similar failures from AI systems.

Moreover, well-documented cognitive biases such as confirmation bias and belief perseverance further entrench skepticism toward AIEd. These biases can lead educators to dismiss evidence that contradicts their existing beliefs or to maintain resistance even in the face of promising outcomes (Nazaretsky et al., 2022). Taken together, these finding suggest that building trust, correcting misconceptions, and addressing human judgment biases are essential steps in fostering the effective integration of AI into educational practice.

Key factors affecting teacher perceptions

One of the most critical factors influencing teachers' willingness to adopt AI technologies in the classroom is trust, particularly in relation to the uncertainty and vulnerability inherent in using unfamiliar systems. Trust in AI involves the belief that the technology will support educational goals in a context where outcomes may be unpredictable (Nazaretsky et al., 2022; Viberg et al., 2024). This trust is shaped not only by teachers' understanding of AI, but also by their self-efficacy, or confidence in their ability to use and discuss AI tools effectively. Teachers with greater AI self-efficacy and quotidian understanding of AI tend to perceive more benefits and express fewer concerns (Viberg et al., 2024).

Beyond trust and self-efficacy, several studies underscore the influence of perceived ease of use, workload, and institutional support in shaping teacher attitudes. For example, real-world integration of adaptive learning platforms has been associated with teachers' perceptions of ownership, ease of use, and access to community support (Cukurova et al., 2023). Teachers who believe that AI tools align with their pedagogical values and reduce their cognitive load are more inclined to adopt such technologies (Al Darayseh, 2023; Ayub et al., 2015). Moreover, professional development emerges as a key lever for increasing teacher trust and reducing misconceptions. Targeted training programs have been shown to improve not only knowledge of AI-powered assessments but also openness to data-informed decision-making and creative classroom integration (Nazaretsky et al., 2021).

Interestingly, teacher characteristics such as years of teaching experience and prior exposure to technology in education play a nuanced role. More experienced teachers often report fewer concerns about AI, though they may not necessarily see more benefits (Viberg et al., 2024). In contrast, demographic variables such as age, gender, education level or subject taught have not seemed to appear, for the moment, to significantly affect AI-related perceptions (Viberg et al., 2024).

Together, these findings suggest that fostering trust, building AI competence, and providing robust professional development are central to encouraging AI adoption in education. Rather than focusing solely on demographic traits, efforts should prioritize enhancing teachers' understanding of AI and reinforcing their confidence and autonomy in using these tools.

Teachers' Concerns with AI Integration

While many educators are curious about the potential of AI tools like Chat GPT, current research reveals a landscape of mixed feelings characterized by enthusiasm, uncertainty and mild to grave concern. A common and significant worry among teachers is the fear of being replaced by AI, particularly in subject areas where generative AI can mimic instructional language and content. One-third of teachers surveyed who had used generative AI tools at least once expressed concern about AI replacing educators altogether (Kaplan-Rakowski et al., 2023). This anxiety was echoed in a large-scale international survey of language educators, where one respondent voiced that “the development of AI at a higher level could replace the language teaching profession itself” (Alm & Ohashi, 2024).

In addition to job security, teachers expressed low confidence in their ability to use AI effectively – especially in areas such as creating lesson plans, guiding students in independent learning, or designing automated assessments (Alm & Ohashi, 2024). Even though the majority of teachers in that study had not yet used ChatGPT for educational purposes, many reported a strong interest in doing so, particularly for tasks related to lesson planning. However, they were notably less enthusiastic about using AI for assessments, highlighting broader hesitation around high-stakes applications.

Other studies similarly show that teachers are in the process of evaluating AI’s role in their classrooms, with attitudes often shaped by exposure, experience, and institutional support. For example, among teachers who had used AI tools even once, a majority reported positive perceptions – 82% agreed that generative AI could be a valuable instructional tool, and more than half said they were likely to use it in the future (Kaplan-Rakowski et al., 2023). Still, despite these optimistic trends, concerns about student misuse, ethical considerations, and the erosion of human interaction remain prevalent, particularly in the early phases of AI integration (Alm & Ohashi, 2024).

Interestingly, familiarity appears to correlate with more positive attitudes. Research suggests that teachers who have more experience using tools like ChatGPT are more likely to see the potential benefits, including increased efficiency, support for formative assessments and facilitation of self-directed learning (Alm & Ohashi, 2024). Even in contexts where teachers had limited AI knowledge – such as a study of K-12 educators in Estonia – there was a generally positive outlook on AI's potential, tempered by a clear recognition of the need for more support and understanding (Chounta et al., 2021).

In the ensemble, these findings suggest that while many teachers are still in the early stages of AI adoption, their interest is growing, alongside a desire for professional development, clarity around ethical usage, and tools that align with pedagogical values.

Concerns regarding AI's pedagogical effectiveness, ethical considerations, and student data privacy

Across recent studies, a consistent theme has emerged: teachers express significant concerns about the unintended consequences of integrating AI into education practice, especially regarding its impact on student learning behaviors, academic integrity and equity. One of the most frequently cited concerns is that AI tools may undermine traditional learning processes and reduce students' engagement with core academic skills such as critical thinking and creativity (Alm & Ohashi, 2024; Kaplan-Rakowski et al., 2023). Teachers are concerned that students are becoming overly reliant on generative AI, sacrificing deeper learning for convenience and potentially eroding their intellectual autonomy.

Concerns about plagiarism and academic dishonesty are especially prominent. Teachers have expressed fear that AI makes it easier for students to bypass authentic learning tasks, raising the risk of misconduct. In one study, 25% of teachers noted that AI use will lead students to neglect traditional resources and engage in plagiarism (Kaplan-Rakowski et al., 2023). Similar findings were echoed in Mohammadkarimi’s (2023) study, where teachers unanimously agreed that AI negatively impacted students’ commitment to academic honesty, and many voiced concerns about their ability to detect AI-generated assignments.

Another widespread issue relates to teachers’ limited understanding of AI and the practical challenges of implementation. Teachers report anxiety about how to incorporate AI meaningfully into their instruction, manage its technical components, and keep up with evolving tools (Jong, 2022; Hur, 2024). For example, participants in Jont’s (2022) study were unsure whether AI was even appropriate for their schools and cited time, training and workload required to use it effectively. Similarly, preservice teachers who initially felt unconcerned about AI became more apprehensive after completing an AI literacy course, particularly as it pertained to concerns about job security and academic misconduct (Hur, 2024).

Equity-related concerns also surfaced in multiple studies. Teachers have raised alarms that widespread AI integration might widen existing inequalities in educational access and outcomes. In Sharma and Sharma’s (2024) research, 44% of participants agreed that AI could exacerbate social stratification unless designed and deployed with equity in mind.

Taken together, these findings reveal that teachers' concerns extend far beyond technical limitations or unfamiliarity with AI. They focus on ethical, pedagogical, and social implications, including the erosion of academic honesty, the loss of critical thinking skills, increased workload for teachers, and equity issues. Addressing these fears will require not only technical training but also clear ethical guidelines and policies, inclusive design practices and serious professional development suited to educators' evolving roles in the age of AI.

Levels of Use and Adoption of AI in Education

The more that teachers are aware of AI, the more often they use it. In Kaplan-Rakowski et al., (2023), half of the respondents reported that they could think of specific learning tasks to use AI or that they were comfortable using AI. Moreover, research on human trust in AI has identified several technology characteristics that can help foster trust in AI: tangibility (e.g., physical presence), transparency (e.g., revealing its processes), reliability (e.g., making few mistakes), immediacy behaviors (e.g., responsiveness, adaptiveness, and pre-social behaviors), and anthropomorphism (e.g., human-likeness) (Glikson & Woolley, 2020). According to the Concerns-Based Adoption Model theory, if teachers are in the discouraging concern phases, they will not be willing to incorporate AI into the classroom until these concerns are addressed (Jong, 2022). Perceived value and ease of integration will help teachers to integrate AI into their teaching practices (Kaplan-Rakowski et al., 2023).

Factors Influencing Teachers' Perceptions and Concerns

Professional Development and Training

Professional Development can increase educator’s trust in incorporating AI into learning (Kaplan-Rakowski et al., 2023). Teachers need training in developing AI knowledge and skills (Hur, 2024). Professional Development can equip teachers with relevant knowledge about AIEd and address common misconceptions about AI (Viberg et al., 2024). Teaching K-12 teachers about AI can be daunting as it poses a complex task, and it is not yet prevalent in formal school settings. Professional Development should emphasize providing teachers with technological and pedagogical knowledge about AIEd to support effective adoption in K-12 settings and ultimately improve students’ learning outcomes (Viberg et al., 2024).

New research is showing that training programs and interventions can help mitigate AI- related concerns and improve decision making-process by increasing teachers AI knowledge (Nazaretsky et al., 2022). For example, there have been calls to overhaul medical education to correct it to the age of AI in the medical domain by teaching medical students about machine learning and AI In higher education settings, research shows that relevant training programs that increase users’ understanding of AI and learning analytics are crucial in adoption success (Nazaretsky et al., 2022).

As teachers become more refined in their use and understanding of AI, they can propose innovative ways to integrate AI into their classrooms and use it for making data-driven decisions (Nazaretsky et al., 2022).

Successful models of Professional Development for AI Adoption

Research has shown that Professional Development should focus on a concrete pedagogical task and AI-powered tool that is considered by teachers as helpful and worth an effort to learn (Nazaretsky et al., 2022). The usefulness of the tool can be used to juxtapose humans' ability to perform a similar task and/or the effort required to complete the task. For example, in the case of manually grading, the value proposition of an AI grading tool can be quite discernable. Teachers should be shown how useful AI tools can be and how easy they can be to use, which are important factors influencing a teachers' willingness to adopt technology in general. If possible, teachers should be shown data from real students as this creates a situation of vulnerability: teachers will feel they have a genuine stake in the AIEd decisions. Second, as previously described in the AI literacy section, professional development should include educating the teachers with a basic understanding of AI-common procedures and practices.

Teachers should be able to judge for themselves the validity of any kind of automated results. This will provide them with a perspective to what kind of errors the system can make. Finally, it is very important to introduce teachers to the expected accuracy in the context of the presented tasks and acknowledge that disagreements can occur between human and machine gradings.

Finally, teachers should have the control to review and overwrite automated grading and feedback as this assures human agency in AI technology use and will improve teachers' trust in the adoption (Nazaretsky et al., 2022). The question of how much technical knowledge is enough for trust is still open.

Leadership Support and Institutional Readiness

Research has shown that teachers will not adopt a new technology unless they believe it is important and that they feel confident using the new technology (Etmer, 2005, Hur, 2024, Hur et al., 2016).

Educational leadership models have evolved significantly, due to the need for schools to improve student outcomes. Whereas the traditional models were created with a leader-centered view, current leadership models involve a more shared/distributed form of leadership. The modern school is too complex to be led by a single leader (Karakose & Tülübas, 2024). Studies focusing on the influence of digital technologies on educational management have shown that leadership in the age of AI requires more shared efforts than that of a single principal. For instance, a study found that teachers' willingness to adopt new digital technologies into their classrooms was closely linked to their shared leadership efforts for that matter (Karakose & Tülübas, 2024). Studies recommend that modern day principals should be open to collaboration by involving the whole school community, including students, in working out how AI technology can be best integrated into education (Karakose & Tülübas, 2024).

AI technologies have also provided the educational landscape with extraordinary ability to use large-scale predictive modeling and data analytics. Developments in big data and learning analytics have already become an integral part of educational policymaking. Similarly, learning analytics, or educational data mining, allows for gaining data from students' educational activities, and monitoring their academic growth and attainments across a period, making it possible to take preventive actions and provide customized education. By focusing on the technical and social implications of these developments, school leaders can access more objective and comprehensive results regarding student outcomes and growth and making these results more intelligible and vivid to various stakeholders (Karakose & Tülübas, 2024).

School leaders will need to promote AI use by teachers by changing their attitudes and behaviors. Even if the school leaders equip schools with AI technologies, without the serious efforts of the school staff, technology adoption by teachers won't happen. Therefore, school leaders need to support professional development opportunities in AIEd tools, allowing teachers to take a central place in decision-making and strategic actions. School leaders also need to create a culture of trust and innovation (Karakose & Tülübas, 2024).

Socio-cultural and Contextual Factors

Comparative studies across different educational systems and regions. Studies prior to the release of OpenAI showed that principals have a high willingness to adopt artificial intelligence education, but only 16.3% of schools have implemented AI (Hao & Yan, 2021) This statistic may change dramatically after the release of OpenAI. Studies show that obstacles to the implementation of artificial intelligence in schools currently is lack of teachers, knowledgeability, funding, hardware, software resources and teaching materials is the main reason for the low development rate of artificial intelligence education (Hao & Yan, 2021).

Influence of socio-cultural norms, classroom culture, and external pressures on adoption.

There seems to be a dearth of studies on the influence of socio-cultural factors on AI Adoption. “Socio-cultural factors” relate to the intertwined nature of social issues and culture, so sociocultural factors are those issues arising out of socioeconomic and cultural differences. Research has shown that cultural values are found to motivate perceptions of risk and self- efficacy when dealing with new technologies such as Artificial Intelligence (Ho et al., 2022). The data is still unclear regarding which socio-demographic factors are found to be important predictors for technology acceptance. For example, male gender, higher income, and higher educational level are often found to predict a more tolerant attitude toward new technologies (Ho et al., 2022). In particular, men have been found to be more accepting of AI/Robots. Meanwhile, women can sometimes display more apprehension and perceive more risks in new technologies. In terms of socio-economic level, people in higher income levels tend to have more trust toward new technologies. Inversely, a recent study of AI technophobia among the US population reveals people from lower income levels, non-white groups or female are far more likely to feel concerned by new Technologies (Ho et al., 2022).

When it comes to age/ generational attitudes toward smart technologies such as AI, the results are also murky. A recent study reported Gen Z has the most multifaceted relationship with AI as their attitudes range from uncertain, to enthusiastic, to fearful. Meanwhile, the authors found Millennials and Baby Boomers said they had a more trusting and tolerant acceptance of A.I (Ho et al., 2022). However, Oracle conducted a worldwide study on 12,000 Gen Z participants in 11 countries and 84% of them expressed a preference for chatbots over humans for mental health support, as opposed to 77% for Millennials. Likewise, a small-scale study reported Gen Z was far more engaged with AI compared to Millennials (Ho et al., 2022).

For example, 40% of Gen Z in the workforce articulated a need for daily interactions with their boss and if not, they often worried there was something wrong. Similarly, another study found that Gen Z employees had a strong desire for constant supervisory feedback, implying technologies that support automated feedback such as AI may in fact be considered useful by Gen Z participants.

The current literature on societal attitudes toward certain AI technologies reveals inconsistencies, most likely due to its novelty. First, decisive evidence on the effects of socio- demographic factors such as gender, social class, or region is deficient. Second, it is difficult to account for cross-cultural differences in understanding technological acceptance. Further research should address demographic factors, cross-cultural (religions and regions) and perhaps even political factors to understand technology acceptance.

Addressing Teacher Concerns and Supporting AI Integration

Frameworks for Addressing Teachers' Concerns

Academic Integrity is a serious issue with the rapid availability of AI. Teachers are having to address it, but schools, districts and policy makers need to address academic integrity policies to decide whether students' actions would be considered academic misconduct or not. These policies need to be updated to consider the arrival of ChatGPT and other generative AI tools that are readily available. Additionally, with some reports of inaccuracy in ChatGPT prompts, teachers should corroborate, and fact-check

AI generated content. However, because the technology is so new, administration may need guidance themselves (Alm & Ohashi, 2024; Mohammmadkarimi, 2023)). In general, teachers with or without guidance from Administration are now required to stay educated on AI capabilities, promote ethical behavior in the classroom and be totally proactive about interventions (Mohammmadkarimi, 2023). Additionally, teachers need to emphasize instruction in proper citations and how to reference work in order to assist students in understanding why plagiarism is intolerable. Teachers will need to use tools like Turnitin to detect plagiarism, use AI to generate essays and compare with student work, and require students to turn in a rough and final draft of their writing (Mohammmadkarimi, 2023). Comprehending how teachers currently understand, use and perceive generative AI tools could assist in informing policy. Empirical research should track teachers' perceptions to inform policy, professional development and pedagogical methods (Alm & Ohashi, 2024).

Gaps in the Literature and Future Research Directions

Gaps in empirical research on CBAM and AI adoption

There is a research gap in examining how well AI-enabled adaptive learning interventions can improve students' learning performance overall, which is crucial since learning performance is a shared common goal across various adaptive learning interventions with AI technology integrated (Wang et al., 2024).

Despite the widespread availability of AI tools for K-12 education, there is a serious lack of studies on integrating AI into teacher education programs (Hur, 2024). Because the generative feature of AI is relatively recent, the research on incorporating

GAI into teaching practices and learning is still nascent but will grow as the world becomes aware of generative AI uses (Kaplan-Rakowski et al., 2023).

Many ethical questions remain about AI in education. Should teachers independently learn how to integrate ChatGPT into their classrooms or should the school promote the technology and provide training to educators? Is it ethically acceptable to allow a chatbot to grade a students' work? If teachers are concerned about students' misuse, how would students feel about teachers doing the same?

Future research should be done on the research already completed in the realm of Professional Development for teachers in terms of AI literacy, particularly in terms of examining teacher attitudes and responses to Professional Development with more nuanced measures of teacher understanding, controlling for their prior knowledge and experience in AI as well as in other grade levels, including primary and secondary school settings (Viberg et al., 2024).

Research is demonstrating that professional development can positively affect teachers' attitudes towards integrating AIEd technology into their classrooms. However, what information exactly teachers should know about AI to understand the nature of AI, is still an active area of research (Nazaretsky et al., 2022). Given the above gaps in the literature – including limited understanding of teachers concerns about AI integration, insufficient exploration of how these concerns impact instructional practices and perceptions of student learning, and a lack of research using a quantitative approach grounded in the Concerns Based Adoption Model – there remains a critical need to examine how K-12 educators perceive and respond to the integration of artificial intelligence in their classrooms. For this reason, the current study aims to address the following research questions:

RQ1.) *What stages of concern do K–12 educators report regarding AI integration?*

RQ2.) *Do stages of concern differ according to educator characteristics?*

RQ3.) *What is the relationship between stages of concern and perceptions of AI?*

RQ4.) *What is the relationship between stages of concern and perceived challenges and adoption of AI?*

By addressing these questions, this study seeks to build upon the existing literature by providing a more nuanced, empirically grounded understanding of teacher concerns and adoption behaviors related to AI in education, ultimately informing professional development, policy and support strategies.

Potential for Future Studies

Suggested methodologies for further exploration

A quantitative approach is ideal for further research. Quantitative data can tell us which teachers are using AI, how much, if at all and how they are using it. It can measure perceptions and concerns and provide immediate feedback on a data-based, statistical level.

Despite an increase in scholarly research published recently on the topic of AI in education, there is a gap in the literature on teachers' reflections on the issue, in how they perceive it's use in the classroom and their level of trust in AI. Since teachers will be the ones to integrate AI into their classrooms, further research needs to be done on teachers' personal experiences, perspectives and strategies (Viberg et al., 2024). Some examples of teachers' perceptions include teachers' perceptions toward the use of AI technologies, the impact of AI on the commitment to academic integrity, and strategies to deter AI-driven academic dishonesty. Studies should examine teachers' trust level in AI technologies and what factors influence this trust (Viberg et al., 2024).

Potential Policy Impact

Artificial Intelligence (AI) in K-12 education has the potential to bring about both benefits and challenges (Durak et al., 2024). From a benefit perspective, Artificial Intelligence in Education has the potential to enrich instructional methods and tailor learning to the needs of individual students. However, AI integration in the K-12 setting is currently haphazard and lacks consistency. Educators are confronting a barrage of challenges, including little professional development on the topic, valid concerns about ethical implications, and a lack of data on AI's impact on student learning outcomes. Because AI in education is emerging, its unregulated use raises concerns about academic integrity, ethical considerations and student data privacy.

Many school districts either lack a clear policy on appropriate AI use or have avoided the conversation altogether (Woodruff & Arnone, 2023). This has left educators unsure about how to integrate AI responsibly, thus creating a wild west atmosphere as individual teachers or groups of teachers attempt to learn how to integrate AI into their classrooms. Additionally, without formal guidelines on AI-generated content, student plagiarism, misinformation and over-reliance on AI tools for assignments could be negatively affecting student learning outcomes. Schools must establish clear policies to help teachers, students, administrators and parents navigate AI use while ensuring academic integrity and the development of critical thinking skills.

Conclusion

AIEd technology tools have the potential to provide a variety of benefits to teachers, to assist them in educating students and improving learner outcomes. While many teachers are aware of AIEd tools, many have chosen not to integrate these tools into their teaching, for a variety of reasons. Teacher perceptions of AI are a significant factor in why they have or have not integrated AI into the classroom. As the literature showed, many teachers perceive of the positive applications for learning in the classroom, but many teachers have concerns about ethical considerations, data privacy, plagiarism and more as a real problem preventing them from using AI The research has shown that many teachers haven’t received formal training on AI yet and often the policies do not reflect the arrival and widespread use of AI.

The goal of this study is to learn about teachers’ perceptions and attitudes towards using AIEd technology through the CBAM framework and what factors may change their perceptions.

Using the CBAM as an analytical framework, this study intends to identify teachers’ specific concerns regarding the integration of AI into the classroom. Further research about teachers’ perceptions and concerns about AI is critical to designing and delivering professional development related to AI in education.

Chapter 3 Methodology

Introduction

This chapter describes the methodology used to examine K-12 educators' concerns, perceptions, and experiences regarding the integration of artificial intelligence (AI) in education. The chapter presents the research design, research questions, population and sampling procedures, instrumentation, data collection procedures, data analysis procedures, ethical considerations, and limitations of the methodology.

Research Overview

This study employed a cross-sectional quantitative survey research design with supplemental qualitative content analysis of open-ended survey responses. The study was descriptive and exploratory in nature, with correlational and group comparison analyses used to examine relationships among educators' stages of concern, demographic characteristics, perceptions of AI, and experiences with AI implementation. The study was guided by the Concerns-Based Adoption Model (CBAM) framework and utilized the Stages of Concern Questionnaire (SoCQ) to assess educators' concerns regarding AI integration.

Research Questions

1. *What stages of concern do K–12 educators report regarding AI integration?*
2. *Do stages of concern differ according to educator characteristics?*
3. *What is the relationship between stages of concern and perceptions of AI?*

4. *What is the relationship between stages of concern and perceived challenges and adoption of AI?*

Research Setting and Participants

Research Setting

The study was conducted in District A, a rural public school district serving elementary, middle, and high school students. School District A includes nine schools and enrolls just over 9,000 students. The student composition predominantly White (75%) and Hispanic (21%), with 26% of students categorized as economically disadvantaged and 11% categorized as English Language Learners (ELL).

Population and Sampling

The target population consisted of all certified K-12 educators employed by the School District A during the 2025–2026 academic year. A census sampling approach was utilized, whereby all eligible educators were invited to participate. Approximately 414 full-time equivalent educators were employed by the district during the study period. Based on this population size, approximately 203 responses would provide a 95% confidence level with a ±5% margin of error.

Participant Selection Criteria

1. Current Employment: Participants must have been full-time teachers employed at the selected school district.

2. Teaching Experience: All levels of teaching experience, from novice to veteran teachers, were included to capture a broad range of concerns and experiences with AI.

3. Subject Area Diversity: Teachers across different subject areas (e.g., STEM, humanities, arts) were included to ensure diverse perspectives on AI integration.

4. Technology Experience: Teachers with varying levels of familiarity and comfort with technology, including those with minimal prior experience with AI, were considered.

Instrumentation

The primary instrument was the Stages of Concern Questionnaire (SoCQ), a validated instrument within the Concerns-Based Adoption Model framework. The SoCQ consists of 35 items measuring seven stages of concern: Awareness, Informational, Personal, Management, Consequence, Collaboration, and Refocusing. Responses are recorded on a scale from 0 (irrelevant) to 7 (very true of me now). The questionnaire measured teachers' levels of concern on a scale of 0 to 6, with 0 being the "Awareness stage" (or Unconcerned) to the "Refocusing stage," illustrated in Table 1.

Table 1. CBAM Levels of Stages of Concern

0	Awareness	Little concern or involvement with the innovation
1	Informational	General awareness and interest in learning more
2	Personal	Uncertainty about demands, role, and potential personal impact
3	Management	Concerns about time, logistics and implementation
4	Consequence	Focus on student outcomes and impact of the innovation
5	Collaboration	Interest in working with others using the innovation

6	Refocusing	Exploring ways to improve or replace the innovation

Adapted from the Stages of Concern Questionnaire, American Institutes for Research, 2025 (George et al., 2006)

Since its development, the SoCQ has been employed extensively across a variety of educational reform initiatives, instructional innovations, and organizational change efforts, providing substantial evidence of its validity and reliability (George et al., 2006).

Evidence supporting the construct validity of the SoCQ was established during the instrument's development through extensive factor analytic studies and longitudinal investigations examining the developmental progression of concerns associated with educational innovations (Hall et al., 1977; George et al., 2006). The instrument's seven stages of concern—Awareness, Informational, Personal, Management, Consequence, Collaboration, and Refocusing—have demonstrated conceptual coherence and have been replicated across numerous studies involving educators and educational change initiatives.

The developers of the SoCQ reported acceptable internal consistency reliability estimates across the seven stages of concern. Cronbach's alpha coefficients for the seven scales ranged from approximately .64 to .83 during instrument development studies, indicating moderate to strong reliability across the stages of concern (George et al., 2006). In addition, test-retest reliability studies demonstrated stability coefficients ranging from approximately .65 to .86 across stages over short administration intervals, providing evidence of temporal stability.

The SoCQ has subsequently been applied across numerous educational contexts and innovations, including curriculum reforms, instructional technologies, professional development initiatives, and organizational change efforts, with studies generally reporting reliability estimates consistent with those reported by the instrument developers (George et al., 2006).

For the present study, internal consistency reliability estimates were calculated for each stage of concern using Cronbach's alpha coefficients. Although the developers of the Concerns-Based Adoption Model emphasize the interpretation of concern profiles rather than reliance on individual scale scores, reporting internal consistency estimates provides additional evidence regarding the reliability of the instrument within the current sample.

Instrument Adaptation

Because the SoCQ was originally developed to assess concerns associated with educational innovations broadly rather than artificial intelligence specifically, the wording of the instrument was adapted by replacing references to "the innovation" with references to "artificial intelligence." This approach is consistent with the intended application of the CBAM framework to emerging educational innovations while preserving the underlying theoretical structure of the instrument (George et al., 2006). In addition, two open-ended questions asked participants to describe perceived advantages and challenges associated with AI integration.

Data Collection Procedures

Approval was obtained from the Auburn University Institutional Review Board and the School District A prior to data collection. Surveys were administered electronically using Qualtrics. District administrators distributed invitation emails to all certified educators. The survey remained open for approximately four weeks, and one reminder email was distributed. Participation was voluntary and anonymous. Respondents who wished to enter a gift-card drawing were directed to a separate survey link to preserve anonymity.

Data Analysis Procedures

Prior to conducting the primary analyses, survey data were screened for completeness, missing responses, and data quality. Responses with no usable survey data or only demographic information were removed. Missing data patterns were examined using a missing response count and a binary missingness indicator. Little's MCAR test was conducted in Jamovi to assess whether data were missing completely at random. Because missingness was not completely random, analyses were conducted using available data where appropriate, with listwise deletion used for inferential analyses involving missing variables. As a result, sample sizes varied across analyses.

Reliability analyses were conducted before creating composite variables. Cronbach's alpha coefficients were calculated for each of the seven Stages of Concern Questionnaire constructs. Additional reliability analyses were conducted for AI perception items. Items measuring student learning perceptions were combined into a composite score. Items measuring instructional benefits were also combined into a composite benefit score. Because the perceived challenge items demonstrated poor internal consistency, they were analyzed separately rather than combined.

Research Question 1: What stages of concern do K–12 educators report regarding AI integration?

To answer Research Question 1, responses to the Stages of Concern Questionnaire were scored according to the procedures outlined in the SoCQ manual. Raw scores were calculated for each of the seven concern stages: Awareness, Informational, Personal, Management, Consequence, Collaboration, and Refocusing. Raw scores were then converted to percentile scores using the SoCQ percentile conversion chart.

Descriptive statistics were used to identify the overall group concern profile. The highest percentile stage was interpreted as the dominant stage of concern for the sample. Individual profiles were also examined to identify each respondent's peak concern stage, second-highest concern stage, and elevated concern patterns. Consistent with the SoCQ interpretation procedures, individual profiles were reviewed for high-stage and low-stage patterns, including elevated Stage 0 concerns, advanced concern profiles, and tailing-up patterns.

Research Question 2: Do stages of concern differ according to educator characteristics?

To answer Research Question 2, group comparison analyses were conducted using the seven SoCQ stage scores as dependent variables. Educator characteristics served as grouping variables, including age, gender, years of teaching experience, technology comfort, teaching level, subject area, AI training status, and self-reported AI experience level.

Prior to conducting group comparisons, assumptions of normality and homogeneity of variance were evaluated. Shapiro-Wilk tests and Q-Q plots were used to examine normality. Levene’s tests were used to evaluate homogeneity of variance. Independent-samples t-tests were used for two-group comparisons, including gender and AI training status. One-way analyses of variance were used for variables with more than two groups, including age, years of teaching experience, technology comfort, teaching level, subject area, and AI experience level. When statistically significant ANOVA results were identified, Tukey HSD post hoc tests were conducted to examine pairwise group differences.

Because multiple group comparisons were conducted, findings were interpreted cautiously to account for possible Type I error inflation. Given the modest sample size and small subgroup sizes, attention was also given to possible Type II error. Therefore, effect sizes were reported and interpreted alongside statistical significance. Cohen’s d was reported for independent-samples t-tests, and eta squared was reported for ANOVA analyses.

Research Question 3: What is the relationship between stages of concern and perceptions of AI?

To answer Research Question 3, Pearson product-moment correlation analyses were conducted. The seven SoCQ stage scores were correlated with composite measures of AI perceptions.

First, correlations were calculated between each stage of concern and the Student Learning Perceptions composite. This composite included survey items measuring educators' perceptions of AI's impact on student motivation, independent thinking, engagement, and learning effectiveness. Second, correlations were calculated between each stage of concern and the instructional benefit composite. This composite included items measuring perceptions that AI can support differentiation and reduce teacher workload.

In addition to correlation analyses, descriptive comparisons were conducted to examine perceived benefit scores across elevated concern profile groups. These profile-based descriptive analyses were used to provide additional context for interpreting the relationship between concern profiles and positive perceptions of AI.

Research Question 4: What is the relationship between stages of concern and perceived challenges and adoption of AI?

To answer Research Question 4, Pearson product-moment correlation analyses were conducted between the seven SoCQ stage scores and measures of perceived AI-related challenges and adoption intentions.

Because the perceived challenge items did not demonstrate adequate internal consistency, they were analyzed separately. Correlations were calculated between each stage of concern and three challenge variables: perceptions that students use AI unethically, perceptions that AI creates equity-related challenges, and perceptions that AI makes assessment of student learning more difficult.

Additional correlations were conducted between each stage of concern and educators' reported preference for using AI tools designed specifically for educators. This item was used as an indicator of AI adoption intention. Descriptive analyses were also conducted to examine mean challenge perceptions across elevated concern profile groups.

Analysis of Open-Ended Responses

Open-ended responses were analyzed using content analysis to provide supplemental context for the quantitative findings. Responses to the two open-ended questions regarding advantages and challenges of AI were reviewed multiple times. Initial codes were generated inductively from participants' written responses. Similar responses were grouped into broader thematic categories. Because participants often expressed more than one idea in a single response, responses could be assigned to more than one category.

Frequency counts were calculated to summarize the most common themes, and representative quotations were selected to illustrate major categories. The researcher served as the sole coder. Because the open-ended responses were used to supplement and contextualize the quantitative findings rather than serve as an independent qualitative phase, formal interrater reliability was not calculated.

Ethical Considerations

Prior to data collection, approval was obtained from the Auburn University Institutional Review Board and from the participating school district. In addition, school-level permission was requested from principals before the survey was distributed to educators at each school. Data collection did not begin until all required institutional, district, and school-level approvals had been secured.

Participation in the study was voluntary. Educators were invited to participate through an electronic recruitment message distributed through district communication channels. The recruitment message explained the purpose of the study, the approximate time required to complete the survey, the voluntary nature of participation, and participants' right to discontinue the survey at any time without penalty.

The study was designed to minimize risk to participants. The primary risk was the possibility that educators could feel uncomfortable reporting concerns about AI use, district practices, or instructional technology. To reduce this risk, the survey was administered anonymously through Qualtrics. No names, employee identification numbers, school email addresses, or other directly identifying information were collected as part of the survey responses. Results were reported in aggregate form, and individual responses were not attributed to specific participants.

Because the study was conducted within a single district and some educator subgroups were small, additional care was taken when reporting demographic comparisons. Results were summarized at the group level, and findings involving small subgroups were interpreted cautiously to reduce the possibility of indirect identification. Open-ended responses were reviewed before inclusion in the dissertation, and representative quotations were selected in a way that avoided identifying individual educators, schools, students, or district personnel.

To protect participant confidentiality, survey data were stored securely and accessed only for research purposes. Data exported from Qualtrics were maintained in password-protected files. Any incentive information was collected through a separate link that was not connected to survey responses, preventing the researcher from linking participant identities to survey data.

Overall, the study posed minimal risk to participants. Ethical safeguards included prior IRB and district approval, voluntary participation, anonymous data collection, secure data storage, separation of incentive information from survey responses, and aggregate reporting of findings.

Limitations

Several methodological limitations should be considered when interpreting the findings of this study. First, this study employed a cross-sectional survey design, which captured educators' concerns and perceptions regarding artificial intelligence at a single point in time. Consequently, the study cannot determine how educators' stages of concern evolve over time. Longitudinal research would be needed to examine developmental changes in educators' concerns regarding AI integration.

Second, the study was conducted within a single rural public school district in the Western United States. Although participants represented a range of grade levels, subject areas, years of experience, and levels of AI familiarity, the findings may not be generalizable to educators working in other districts, states, or educational contexts. Differences in organizational culture, technology infrastructure, professional development opportunities, educational policy environments, and the degree of AI implementation may influence educators' concerns and experiences with artificial intelligence.

Third, the study experienced a modest response rate and evidence of non-random missingness. Although the obtained response rate compares favorably with many online survey studies, nonresponse bias remains a potential concern. Additional analyses suggested that patterns of missingness were associated with certain respondent characteristics, indicating that the results may disproportionately reflect the experiences and perceptions of educators who chose to participate and complete the survey. Consequently, findings should be interpreted cautiously and viewed as exploratory rather than definitive.

Fourth, the study relied exclusively on self-reported survey data. Self-report measures are subject to several potential sources of bias, including social desirability effects, differences in participants' interpretation of survey items, recall error, and inaccuracies in self-assessing technology use and instructional practices. Although self-report measures are appropriate for examining perceptions and concerns, responses reflect participants' subjective experiences rather than direct observations of classroom practice.

Fifth, although the Stages of Concern Questionnaire (SoCQ) has demonstrated substantial evidence of validity and reliability across numerous educational innovations and organizational change initiatives, the instrument was originally developed to assess concerns regarding educational innovations broadly rather than artificial intelligence specifically. For this study, references to “the innovation” were adapted to refer to artificial intelligence while preserving the structure and intent of the original instrument. Although this adaptation is consistent with the intended application of the Concerns-Based Adoption Model, the instrument may not fully capture all dimensions of educators’ experiences with contemporary generative AI technologies.

Finally, the qualitative component of the study consisted of content analysis of two open-ended survey questions rather than in-depth qualitative methods such as interviews, focus groups, or observations. Although these responses provided valuable context and enriched the interpretation of the quantitative findings, they did not permit follow-up questioning, clarification, or deeper exploration of participants’ experiences. Therefore, the qualitative findings should be interpreted as complementary to the quantitative analyses rather than as a comprehensive examination of educators’ experiences with AI integration.

Despite these limitations, the study provides an important exploratory examination of educators’ concerns regarding artificial intelligence in K-12 education and offers a foundation for future research examining how educators experience and adapt to emerging educational technologies.

Chapter 4 Results

Introduction

This chapter presents and analyzes survey results from a study investigating K-12 educators' Stages of Concern regarding the emergence of artificial intelligence (AI) in education. This study aims to examine educators' concerns related to AI adoption, examine differences in concerns across demographic characteristics, and explore relationships among stages of concern, perceptions of AI, and reported AI use. Specifically, this study aims to answer the following research questions:

RQ 1: What stages of concern do K–12 educators report regarding AI integration?

RQ 2: Do stages of concern differ according to educator characteristics?

RQ 3: What is the relationship between stages of concern and perceptions of AI?

RQ 4: What is the relationship between stages of concern and perceived challenges and adoption of AI?

The survey included the validated Stages of Concern Questionnaire (Hall, 1979), adapted to the context of AI use in education, as well as demographic questions, and two open-ended response questions. Quantitative analyses included conversion of raw scores to percentiles per the SoCQ manual (George et al., 2006), descriptive statistics, tests for missing data, reliability analyses, independent samples t-tests, one-way analyses of variance (ANOVA), and Pearson correlation analyses. Open-ended responses were analyzed using content analysis to identify recurring themes related to the perceived benefits and challenges of AI integration in education.

This chapter begins with a description of data preparation procedures, including analyses of missing data and instrument reliability. Next, demographic characteristics and patterns of AI use are presented. The results are then organized according to the research questions, examining relationships among Stages of Concern, AI use, perceptions of student engagement and learning, and perceived benefits and challenges of AI. The chapter concludes with findings from the open-ended responses and a summary of key results.

Results: Sample

Data were collected through an online survey administered to K-12 educators within one public, rural-designated school district in the western United States. Permission to distribute the survey was requested from the principals of all ten schools in the district, which collectively employed 414 full time teachers for the 2025-2026 school year, according to the State's Board of Education. Four schools declined participation; therefore, the survey was distributed to educators at the remaining six schools, representing approximately 280 full time educators.

Table 2. Sample and Scope Participation

Name of School	Number of Teachers Employed 2025-2026 School Year	Participated?
Elementary School 1	46	Declined to Participate
Elementary School 2	32	Agreed to Participate
Elementary School 3	44	Declined to Participate
Elementary School 4	32	Declined to Participate
Elementary School 5	32	Agreed to Participate
Middle School 1	43	Agreed to Participate
Middle School 2	47	Agreed to Participate
District A Online Middle School	12	Declined to Participate

District A Alternative High School	12	Agreed to Participate
District A High School	114	Agreed to Participate
	Total FTE Teachers in the School District A, 2025-2026 School Year: 414	Total FTE Teachers in the School District A participating in study: 280
		Total Responses: 71 Total Complete Responses: 55 Complete Response Rate: 19.6%

The resulting sample yielded 55 complete observations, a response rate of 19.6%. While this rate is higher than the general average of published online research surveys of this size (Wu, Zhao, and Fils-Aime 2022), it may nonetheless introduce systematic bias based on common characteristics amongst non-responders, and so, results should be taken with caution. Missingness is investigated more thoroughly in the Data Cleaning and Missing Data Analysis section below.

Summary of Results: Respondent Characteristics

Table 3. Sample Demographic Characteristics

	N	%
Gender		
Male	27	38.0
Female	44	62.0
Age		
18-34	13	18.3
35-44	25	35.2
45-54	23	32.4
55+	10	14.1
Years Teaching		
0-3 years	13	18.3
4-6 years	8	11.3
7-10 years	6	8.5

11-15 years	16	22.5
16-20 years	15	21.1
21+ years	13	18.3
Teaching Level		
Elementary (K-5)	11	15.7
Middle School (6-8)	24	34.3
High School (9-12)	35	50
Technology Comfort		
Very Uncomfortable	5	7.1
Somewhat Uncomfortable	1	1.4
Neutral	12	17.1
Comfortable	38	54.3
Very Comfortable	14	20
Subject Area		
English Language Arts	14	20
STEM	19	27.1
Other	37	52.9
AI Experience Level (n=55)		
Non-user	9	16.4
Novice	20	36.4
Intermediate	16	29.1
"Old hand"	8	14.5
Past User	2	3.6
AI Training (n=55)		
Yes	13	23.6
No	42	76.4

Summary of Results: Years of Teaching Experience

Participants in the survey represented a range of teaching experience levels. The largest group of respondents reported 11-15 years of teaching experience (22.5%), followed by 16-20 years (21.1%). Educators with 0-3 years of experience comprised 18.3% of the sample, while those with 21 or more years of experience also represented 18.3% of respondents. A comparison with publicly available staffing data for the participating schools indicated that the sample was generally representative of the district's teaching workforce, although experienced educators were somewhat over-represented. In particular, 70.4% of survey respondents reported seven or more years of teaching experience compared to approximately 60% of teachers in the participating schools. Meanwhile, educators with 4-6 years of experience comprised 11.3% of the sample compared to 18% of the district workforce. These differences suggest that survey responses may reflect slightly greater representation from more experienced educators.

Summary of Results: Teaching Level

Table 4. Comparison of Teaching Levels Between Survey Respondents and Participating School Faculty

Teaching Level	Survey Respondents (n = 70)	Participating Schools' Faculty (n = 280)
Elementary (K-5)	11 (15.7%)	64 (23.0%)
Middle (6-8)	24 (34.3%)	90 (32.0%)
High School (9-12)	35 (50.0%)	126 (45.0%)

As shown in Table 4, the distribution of respondents generally reflected the instructional-level composition of the participating schools. Middle school representation was nearly identical to the faculty population, while high school educators were somewhat overrepresented and elementary educators were somewhat underrepresented.

Summary of Results: Primary AI Tool Used in Teaching Practice

Participants were asked to identify the AI tool they primarily used in their teaching practice. Among respondents who answered the question (n = 55), ChatGPT was the most frequently reported tool (36.4%), followed by SchoolAI (18.2%). Other AI tools, including MagicSchoolAI (3.6%), Grammarly (3.6%), and GPTZero (1.8%), were reported less frequently. Additionally, 12.7% of respondents selected "Other," while 23.6% indicated that they did not currently use AI tools in their teaching practice.

Table 5. Primary AI Tool Used by Participants (n=55)

AI Tool	n	Valid %
Chat GPT	20	36.4
School AI	10	18.2
Magic School AI	2	3.6
Grammarly	2	3.6
GPT Zero	1	1.8
Other	7	12.7
Do not use AI	13	23.6

Data Cleaning and Missing Data Analysis

Before conducting the primary statistical analyses, the dataset was examined for completeness, patterns of missing data and potential sources of systematic bias. Initial data cleaning procedures found 3 responses containing no usable survey data, and 4 additional responses that contained only demographic information with nearly all substantive survey items left unanswered. Consistent with common survey research practices, observations with insufficient data to contribute meaningfully to the analysis were excluded from subsequent analyses. Following this screening process, the dataset consisted of 71 respondents.

To address missing items, a missing data count variable (MISSING_COUNT) was created to calculate the total number of missing responses for each participant. In addition, a binary missingness indicator (MISSING_GROUP) was developed to classify overall response completeness. Participants with more than 50% missing responses across survey items were categorized as exhibiting high missingness, whereas those with less than 50% missing responses were classified as mostly complete. This classification was used to examine whether patterns of missingness were associated with systematic differences among participants. Examination of response patterns indicated that missing data frequently occurred in large blocks near the end of the survey, suggesting survey attrition rather than random or specific item omission.

To examine the nature of missing data, Little's Missing Completely at Random (MCAR) test was conducted using Jamovi software. This test evaluates whether the probability of missingness is independent of both observed and unobserved variables. Results indicated that the data were not missing completely at random, $D^2(459) = 1.14 \times 10^7$, $p < .001$; therefore, the assumption of MCAR was rejected and it can be assumed that some missingness is systematic.

Because Missing at Random (MAR) cannot be tested directly, additional diagnostic analyses were conducted to examine whether missingness was associated with observed participant characteristics. Missingness indicator variables were compared across demographic and key study variables to identify potential systematic patterns. These analyses indicated that missingness did covary with several observed variables, including age, teaching level, and selected survey responses, suggesting that certain patterns of survey attrition or omission may coincide with certain types of respondents.

Given the moderate sample size, the modest proportion of observations with missing responses (12%), and the nature of the missingness as drop-off rather than random or select omission, all available cases were retained for analysis where possible. As an exploratory analysis focused on describing patterns and relationships, descriptive analyses were conducted using available data, and inferential analyses were conducted using listwise omission of observations with missing data relevant to the analysis. As a result, sample sizes varied across analyses depending on the variables included, ranging from 55 to 71 participants. Results are to be interpreted with caution, given the potential for nonrandom missingness and small sample size.

Reliability of Stages of Concern Questionnaire

Reliability for internal consistency was assessed for each of the seven Stages of Concern Questionnaire (SoCQ) constructs using Cronbach's alpha. Reliability coefficients ranged from .528 to .809. Collaboration demonstrated the strongest internal consistency (α = .809), followed by Personal (α = .748) and Informational (α = .718). Management produced acceptable reliability (α = .670), while Awareness demonstrated marginal reliability (α = .601). Consequence (α = .536) and Refocusing (α = .528) exhibited lower levels of internal consistency.

Although reliability estimates varied across constructs, all items were retained and scored according to the established SoCQ framework to maintain consistency with the validated instrument and prior SoCQ research that uses SoCQ as a holistic measure (George et al., 2006). Lower reliability coefficients observed for the Consequence and Refocusing constructs indicate that scores for these scales may contain greater measurement error. Therefore, findings involving these constructs should be interpreted with caution. Reduced internal consistency may attenuate relationships with other variables and decrease the likelihood of detecting statistically significant effects (Fowler, 2014). Despite these limitations, all seven constructs were retained due to the theoretical structure and widespread use of the SoCQ in prior research.

Table 6. Reliability Coefficients for the Seven Stages of Concern Questionnaire Constructs

Construct	Number of Items	Original α	Sample α	Interpretation
Awareness	5	.63	.601	Questionable
Informational	5	.86	.718	Acceptable
Personal	5	.65	.748	Acceptable
Management	5	.73	.670	Acceptable
Consequence	5	.74	.536	Poor/ Questionable
Collaboration	5	.79	.809	Good
Refocusing	5	.81	.528	Poor/Questionable

Note: Original α refers to the most recent report from the SoCQ manual (George, et al., 2006, p. 21).

Reliability of Perception Measures

Reliability analyses were conducted to evaluate the internal consistency of survey items measuring teachers' perceptions of artificial intelligence (AI) in education prior to creating composite variables. Cronbach's alpha coefficients were calculated for groups of items representing student learning perceptions, perceived instructional benefits, and perceived challenges associated with AI use.

The four items measuring perceptions of AI's impact on student learning and engagement (POS_37–POS_40) demonstrated excellent internal consistency reliability (Cronbach's α = .933). Given the strong reliability coefficient, these items were combined into a composite Student Learning Perceptions score for subsequent analyses.

Reliability analysis was conducted on the two items measuring perceived instructional benefits of AI (POS_42 and POS_44). Because Cronbach's alpha may be unstable for two-item scales, the inter-item correlation was also tested. The two items demonstrated a moderate positive correlation, $r = .533$, $p < .001$, and acceptable internal consistency (Cronbach's $\alpha = .694$; Spearman-Brown coefficient = .695). Therefore, these items were combined to create a composite Benefit Score for subsequent analyses. into a composite Benefit Score for subsequent analyses.

In contrast, the three items measuring perceived challenges of AI implementation (ETH_41, ETH_43, and ETH_45) demonstrated poor internal consistency reliability (Cronbach's $\alpha = .138$), indicating that the items were not measuring a single underlying construct. Examination of the item-total statistics revealed weak and inconsistent relationships among the items, including a negative corrected item-total correlation. These findings suggest that the challenge items reflected distinct concerns rather than a unified dimension of perceived challenges. Consequently, the items were not combined into a composite score. Instead, each challenge variable was analyzed independently in subsequent analyses to preserve the unique dimensions represented by concerns related to academic integrity, equity of access, and assessment of student learning.

Table 7. Reliability of Perception Measures

Construct	Items	Cronbach's α	Decision
Student Learning Perceptions	POS_37–POS_40	.933	Combined into composite score
Instructional Benefits	POS_42, POS_44	.694	Combined into composite score

Perceived Challenges	ETH_41, ETH_43, ETH_45	.138	Analyzed separately

The following sections discuss the results of each of the four research questions.

Research Question 1: What stages of concern do K–12 educators report regarding AI integration?

Research Question 1 examined the stages of concern reported by K-12 educators regarding the integration of artificial intelligence into teaching and learning. Applying the recommendations of the Stages of Concern Questionnaire (SoCQ) manual (George et al., 2006), raw stage scores were converted to percentile scores to create a group profile of concerns. The conversion of raw stage scores to percentiles are detailed in the appendix. A summary of what the scores mean, according to the SoCQ Manual is provided in the Table 8 below:

Table 8. Summary of Each Stage of Concern, per the SoCQ Manual

Stage of Concern	Per the SoCQ Chapter 5, "Interpretation of Stages of Concern Questionnaire Data"
0 - Awareness	"Stage 0 scores provide an indication of the degree of priority the respondent is placing on the innovation and the relative intensity of concern about the innovation… Stage 0 addresses the degree of interest in and engagement with the innovation (AI) in comparison to other tasks, activities and efforts… A low score on Stage 0 is an indication that the innovation is of high priority and central to the thinking and work of the respondent. The higher the Stage 0 score, the more the respondent is indicating that there a number of other initiatives, tasks and activities that are of concern to him or her…"
1 - Informational	"A high score in Stage 1 indicates that the respondent would like to know more about the innovation…(they) want fundamental information about what the innovation (AI) is, what it will do and what its use will involve."
2 - Personal	"A high Stage 2 percentile score indicates ego-oriented questions and uncertainties. Respondents are most concerned about status, rewards and what effects the innovation might have on them…"

3 - Management	"A high Stage 3 score indicates intense concern about management, time and logistical aspects of the innovation (AI).
4 - Consequence	(A high Stage 4 score indicates) the individual focuses on the innovation's impact on students in his or her immediate sphere of influence…"
5 - Collaboration	"The individual focuses on coordinating and cooperating with others regarding the use of the innovation."
6 - Refocusing	"The individual focuses on exploring ways to reap more universal benefits from the innovation…"

While the SoCQ manual does not explicitly state what is considered "high" or "low" scores, for purposes of this study, the following metrics will be adopted:

Percentile	Interpretation
90–99	Very high concern (peak/elevated concern)
70–89	Moderately high concern
41–69	Moderate concern
20–40	Low concern
0–19	Very low concern

Table 9 presents the reliability coefficients, raw scale scores and corresponding percentile scores for each of the seven stages of concern. The resulting profile indicated that Awareness concerns were the highest at 96th percentile, followed by Informational concerns (80th percentile) and Personal concerns (80th percentile). Management concerns were moderate (60th percentile). Refocusing concerns were also moderately elevated (65th percentile). Finally, Consequence concerns (43rd percentile) and Collaboration concerns (40th percentile) were the lowest. Analysis of these results will be provided in the Discussion section.

Table 9. Reliability, Raw Scores, and Percentiles of SoCQ Stages

Stage	α	Raw Score	Nearest Raw Score	Percentile
0 -Awareness	.601	18.16	18	96
1 - Informational	.718	21.84	22	80
2 - Personal	.748	22.63	23	80
3 - Management	.670	16.38	16	60
4- Consequence	.536	23.12	23	43
5- Collaboration	.809	18.16	18	40
6- Refocusing	.528	20.26	20	65

Figure 2 plots these percentile scores, again demonstrating that the group profile indicated the highest concerns at Awareness, Informational and Personal stages, with comparatively lower concerns at Consequence and Collaboration stages.

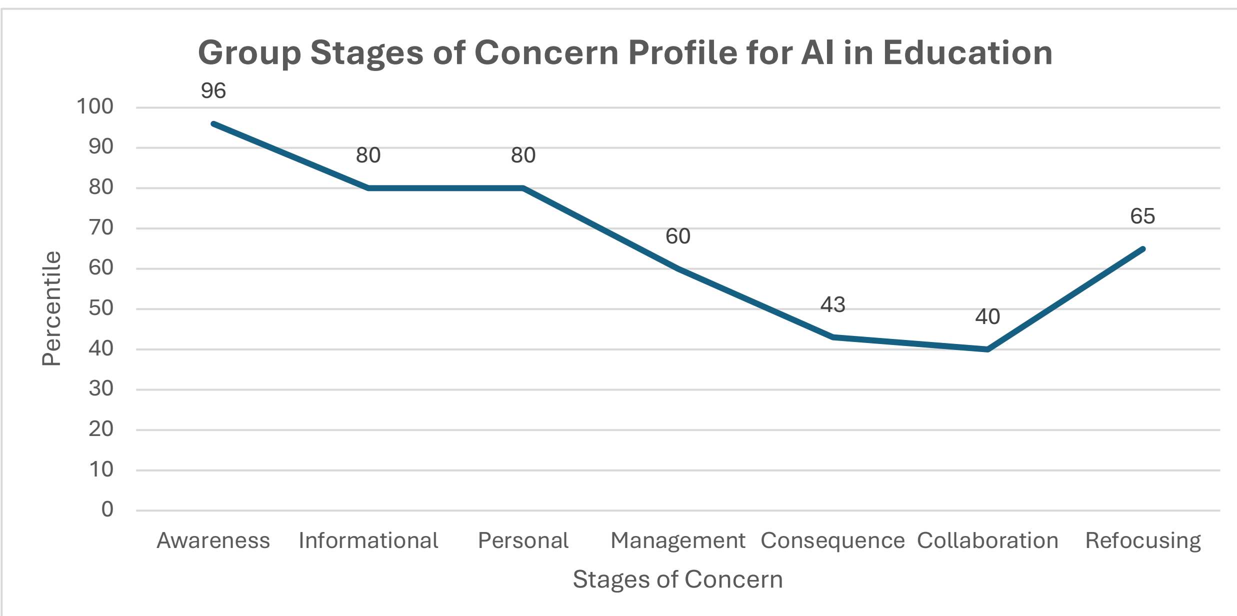

Figure 2. Group Stages of Concern Profile for AI in Education

Following the SoCQ interpretation procedure (George et al., 2006), the analysis of peak percentile stages is presented next. The percentiles are calculated by adding the Raw Score of each construct and then using Figure 4.3 of the Stages of Concern Raw Score: Percentile Conversion Chart for the Stages of Concern Questionnaire (George et al., 2006). The peak percentiles show that Awareness was the dominant concern stage among respondents, with 41 of 58 valid respondents (70.7%) demonstrating their highest concern in Awareness. Informational concerns were the second most common peak stage (13.8%), followed by Personal concerns (6.9%). No respondents demonstrated peak concerns in either the Management or Consequence stages.

Table 10. Distribution of Peak Percentile Stages of Concern

Peak Percentile Stage	N	%
Awareness	41	70.7
Informational	8	13.8
Personal	4	6.9
Management	0	0.0
Consequence	0	0.0
Collaboration	3	5.2
Refocusing	2	3.4

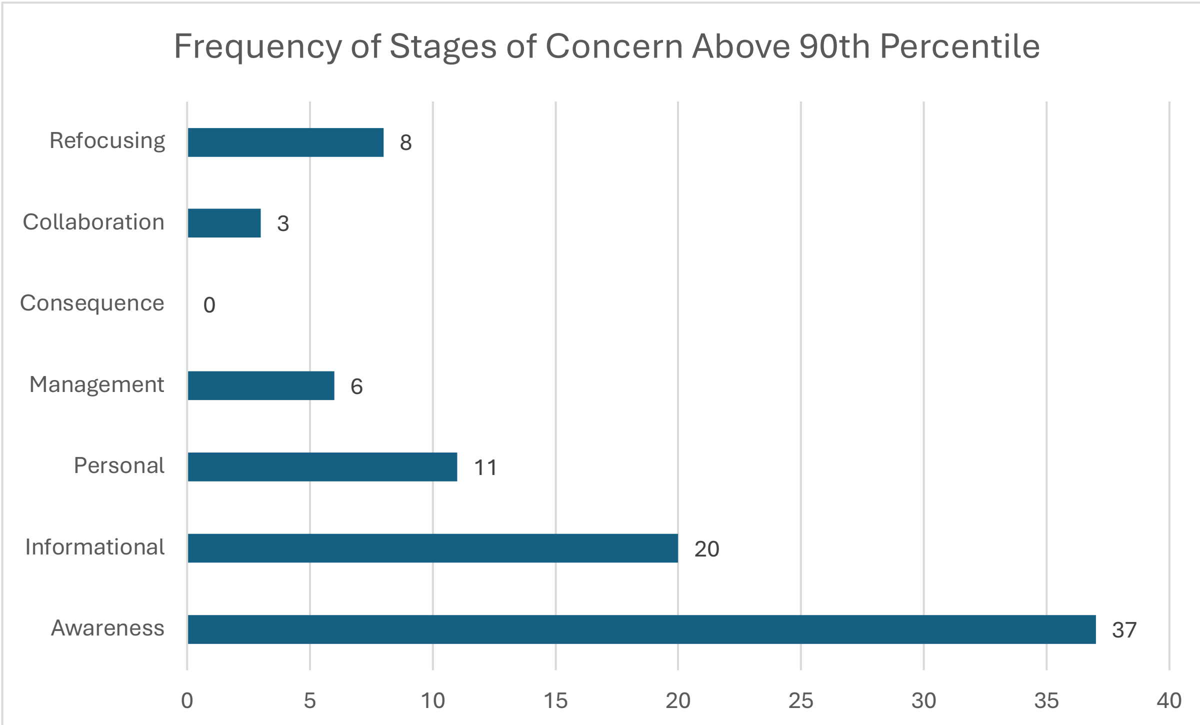

Figure 3. Frequency of Stages of Concern Above the 90th Percentile

The SoCQ interpretation guidelines also suggest comparing the second-highest stage of concern with the highest stage of concern, as presented in Table 11.

Table 11. Percent Distribution of Second Highest Stage of Concern in Relation to First Highest Stage of Concern

Highest Stage of Concern	Second Highest Stage of Concern								
	0	1	2	3	4	5	6	Row Pct.	Row No.
0 Unconcerned	0	34	21	7	0	2	9	72	42
1 Informational	3	0	7	0	0	2	2	14	8
2 Personal	2	2	0	0	0	0	2	5	3
3 Management	0	0	0	0	0	0	0	0	0
4 Consequence	0	0	0	0	0	0	0	0	0
5 Collaboration	0	2	3	0	0	0	0	5	3
6 Refocusing	0	0	3	0	0	0	0	3	2
								Total	58

Finally, per the SoCQ manual (George et al., 2006), interpretation guidelines for various profiles were applied to the study data. Individual concern profiles were examined to identify respondents who met specific interpretation criteria outlined in the manual, including high (Figure 3: 90th percentile or above) and low stage scores, combinations of high and low stage scores, and tailing-up patterns. The number and percentage of respondents meeting each interpretation criterion were then calculated and are presented in Table 12.

Table 12. SoCQ Profile Interpretation Summary Based on Manual Interpretation Guidelines

SoCQ Profile Interpretation Summary Based on Manual Interpretation Guidelines			
n	%	Scores (High or Low)	Interpretation per the SoCQ manual
Stage 0: High and Low Scores			
42	72%	High Stage 0 only (Over 90th Percentile)	Respondent is “not concerned about the innovation
1	2%	Low Stage 0 – High Other Stages	Respondent has “intense involvement with the innovation.”
0	0%	Low Stages 0-3	Respondent is “an experienced user who is still actively concerned about the innovation.”
Stages 1 and 2: High and Low Scores			
8	14%	High Stage 1	Respondent would like to have more information about the innovation.
3	5%	Low Stage 1	Respondent feels they already know enough about the innovation.
3	5%	High Stage 2	Respondent has “intense personal concerns about the innovation and its consequences for them. Although these concerns reflect uneasiness regarding the innovation, they do not necessarily indicate resistance”
0%	0%	Low Stage 2	Respondent does not feel threatened in relation to the innovation.
0	0	High Stage 1 – Low Stage 2	Respondents want more information and are “generally open to and interested in the innovation”
0	0	Low Stage 1 – High Stage 2	Respondent has self-concerns and “may be more negative toward the innovation and not open to information about it.”
Stage 3 and 4: High and Low Scores			
0	0	High Stage 3	“Indicates concerns about logistics, time and management”
12	21%	Low Stage 3	Respondent has “minimal to no concerns about managing use of the innovation”
0	0	High Stage 4	Respondent has concerns “about the consequences of use of the innovation for the students”

24	41%	Low Stage 4	Respondent has "minimal concerns about the effects of the innovation on students"
Stage 5: High Scores			
1		High Stage 5 only	Respondent is "concerned about working with others in relation to use of the innovation
2		High Stage 5 with Some Combination of Stages 3, 4, and 6 Also High	Respondent has concerns about a "collaborative effort in relation to the other stages with high scores"
0	0	High Stage 5 – High Stage 1	Respondent wants to "learn from what others know and are doing."
Stage 6: High Scores			
0	0	High Stage 6 - Low Stage 1	Respondent is "not interested in learning more about the innovation… likely feel(s) that he or she already knows all about the innovation and has plenty of ideas for improving the situation."
0	0	High Stage 6 - High Stage 3 - Low Stages 0-2	Respondent "has become frustrated with not having Management concerns resolved."
6	10%	Stage 6 Tailing-Up for Stage 0	Respondent has "strong ideas about how to do things differently. These ideas may be positive but are more likely to be negative toward the innovation."

Note: This table follows the profile interpretation framework presented in the Stages of Concern Questionnaire (SoCQ) manual. Because individual respondents may exhibit multiple profile characteristics simultaneously (e.g., a high Stage 0 score together with low Stage 3 and Stage 4 scores), respondents may be represented in more than one interpretation category. Consequently, frequencies do not sum to the total number of respondents.

Table 13. Most Common Elevated Concern Profile Patterns (greater than or equal to 90th percentile)

Profile Pattern	n	%
Awareness Only	18	31.0
Awareness + Informational	5	8.6
Awareness + Informational + Personal + Refocusing	3	5.2
Informational Only	3	5.2
Nothing above 90^{th} percentile	13	22.4
Other patterns	16	27.6

When examined further, Awareness concerns were most frequently elevated, with 37 respondents exceeding the 90th percentile. Informational concerns were the second most frequently elevated stage ($n = 20$), followed by Personal concerns ($n=11$). No respondents demonstrated Consequence concerns above the 90th percentile.

Research Question 2: Do stages of concern differ according to educator characteristics?

Following the analysis of the overall profile of teachers' stages of concern, this section examines whether these concerns differ across educator characteristics. These analyses are intended to explore potential patterns of variation across demographic and experiential variables. Because subgroup sizes varied and were relatively small for some comparisons, particularly for variables with multiple categories, the following analyses are interpreted as exploratory. Emphasis is therefore placed on effect sizes and overall patterns of results in addition to statistical significance.

RQ2 Assumptions

Before conducting independent samples t-tests and one-way analyses of variance (ANOVA) for the purposes of answering Research Question 2, assumptions of normality and homogeneity of variance were evaluated. Shapiro-Wilk tests were conducted to assess the normality of the seven Stages of Concern Questionnaire (SoCQ) construct scores, along with visual inspections of distributional (Q-Q) plots (Fowler, 2014). As shown in Table 14, all Shapiro-Wilk tests were non-significant ($p > .05$), which, alongside distributional plots, indicated that no substantial violations were detected (Fowler, 2014).

Homogeneity of variance was evaluated using Levene's test. Results indicated that all Levene statistics were non-significant ($p > .05$), indicating no evidence of unequal variances across groups. Additional Levene's tests conducted for independent samples t-tests examining differences by sex and AI training status were also non-significant ($p > .05$). Independent samples t-tests and ANOVAs are generally robust to moderate deviations from normality, particularly with similar group sizes, so independent samples t-tests and one-way analyses of variance (ANOVA) were used to examine differences in stages of concern across educator demographic characteristics.

Table 14. Tests of Normality and Homogeneity of Variance for SoCQ Constructs

Stage of Concern	Shapiro-Wilk W	Shapiro-Wilk p	Levene Statistic	Levene Statistic p	Assumptions Supported?
Awareness	.971	.122	1.318	.275	Yes
Informational	.982	.432	2.990	.057	Yes
Personal	.979	.328	0.801	.454	Yes
Management	.982	.448	0.222	.801	Yes
Consequence	.972	.138	2.085	.133	Yes
Collaboration	.974	.191	0.810	.449	Yes
Refocusing	.975	.208	0.909	.408	Yes

RQ2 Consideration of Type I and Type II Error

Since multiple independent samples t-tests and one-way analyses of variance (ANOVA) were conducted to examine differences in stages of concern across educator characteristics, the potential for Type I error inflation is acknowledged here. Conducting numerous statistical tests increases the likelihood of obtaining statistically significant findings by chance alone (Fowler, 2014). Therefore, significant results were interpreted cautiously and considered in conjunction with the overall pattern of findings, rather than on statistical significance alone.

In addition, the potential for Type II error should be considered. Given the moderate overall sample size and smaller subgroup sizes in several analyses, statistical power to detect differences may have been limited. As a result, non-significant findings do not necessarily indicate the absence of meaningful differences between groups (Fowler, 2014). Accordingly, results are interpreted with attention to effect sizes and patterns of findings, and non-significant results are considered cautiously.

RQ2: Educator Age versus Stages of Concern

Given the assessment of assumptions above, the analysis begins with a series of one-way analyses of variance (ANOVAs) to examine differences in stages of concern across four age groups (18–34, 35–44, 45–54, and 55 years and older). Levene's tests indicated that the assumption of homogeneity of variance was satisfied for all seven constructs (all $p > .05$).

Results revealed no statistically significant differences among age groups for Awareness, $F(3, 62) = 1.92$, $p = .136$, $\eta^2 = .085$; Informational, $F(3, 62) = 2.08$, $p = .112$, $\eta^2 = .092$; Personal, $F(3, 62) = 0.60$, $p = .619$, $\eta^2 = .028$; Management, $F(3, 62) = 0.84$, $p = .475$, $\eta^2 = .039$; Consequence, $F(3, 62) = 0.99$, $p = .406$, $\eta^2 = .046$; Collaboration, $F(3, 62) = 1.04$, $p = .381$, $\eta^2 = .048$; or Refocusing concerns, $F(3, 62) = 1.76$, $p = .165$, $\eta^2 = .078$.

Table 15. Stages of Concern Questionnaire Raw Scores and Percentile Scores by Age Group

Stage of Concern	18-34 Raw	18-34 %	35-44 Raw	35-44 %	45-54 Raw	45-54 %	55+ Raw	55+ %
Awareness	15.88	91	17.32	94	18.62	97	21.25	99
Informational	17.33	63	21.05	75	23.38	84	23.13	84
Personal	23.67	83	22.58	80	22.76	80	21.63	78
Management	16.67	65	17.25	65	16.57	60	13.5	47
Consequence	22.00	38	23.55	48	23.95	48	21.22	33
Collaboration	17.00	36	19.15	44	19.05	44	14.89	28
Refocusing	20.13	65	21.55	69	20.50	65	17.00	52

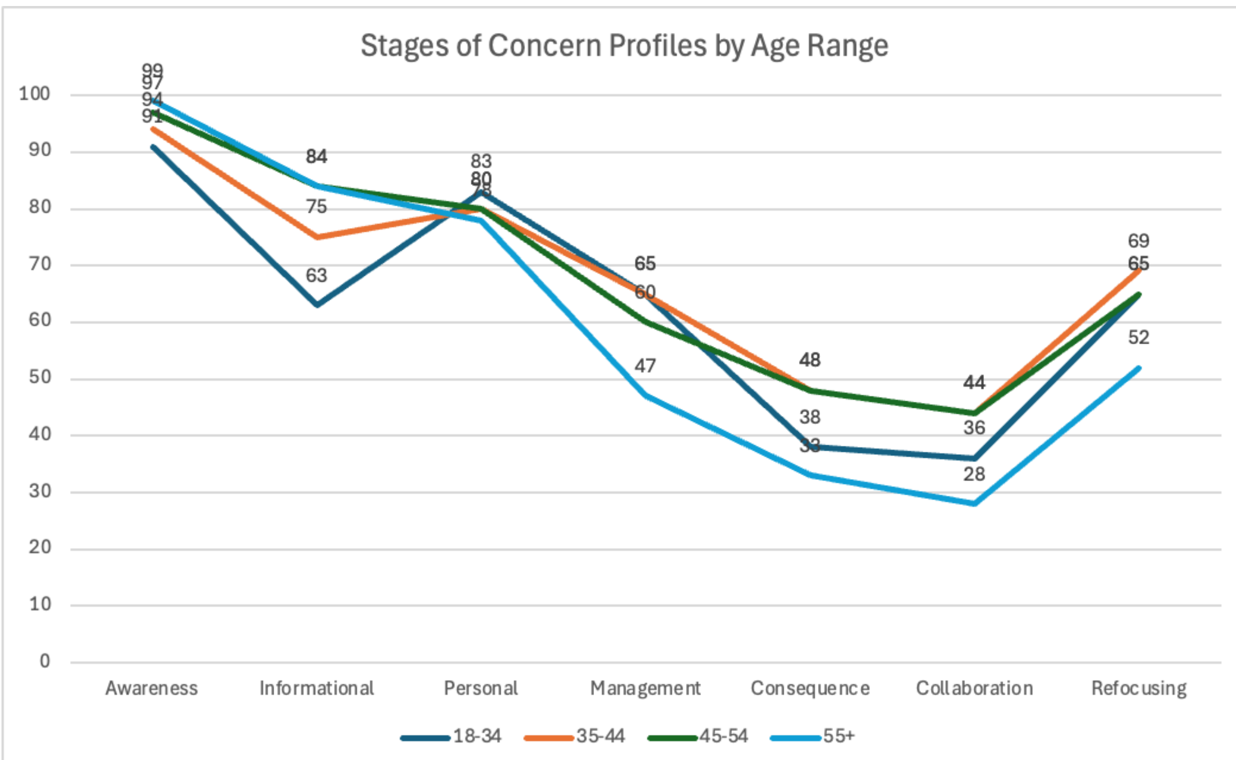

Figure 4. Stages of Concern Profiles by Age Range

RQ2: Educator Gender versus Stages of Concern

Independent-samples t-tests were next conducted to determine whether teachers' concerns regarding AI in education differed by gender. Results indicated no statistically significant differences between male and female teachers across any of the seven Stages of Concern constructs. Specifically, no significant gender differences were observed for Awareness, $t(64) = 1.65$, $p = .104$, Informational, $t(64) = -0.20$, $p = .839$, Personal, $t(64) = -0.06$, $p = .955$, Management, $t(64) = -1.00$, $p = .322$, Consequence, $t(64) = -0.42$, $p = .680$, Collaboration, $t(64) = -0.25$, $p = .808$, or Refocusing concerns, $t(64) = 1.05$, $p = .299$. Effect sizes ranged from negligible to small (Cohen's $d = -.252$ to $.416$), indicating minimal practical differences between male and female teachers' concerns regarding AI integration.

Table 16. Independent Samples t-Test Results by Gender

Stage of Concern	Male M (SD)	Female M (SD)	t(df)	p	Cohen’s d
Awareness	3.73 (1.19)	3.26 (1.09)	1.65 (64)	.104	.416
Informational	4.21 (1.17)	4.27 (1.36)	-0.20 (64)	.839	-.051
Personal	4.60 (1.26)	4.62 (1.12)	-0.06 (64)	.955	-.014
Management	3.10 (1.22)	3.40 (1.15)	-1.00 (64)	.322	-.252
Consequence	4.75 (1.00)	4.87 (1.20)	-0.42 (64)	.680	-.104
Collaboration	3.45 (1.47)	3.54 (1.37)	-0.25 (64)	.808	-.062
Refocusing	4.17 (0.94)	3.88 (1.18)	1.05 (64)	.299	.264

Note. Cohen's d values represent effect sizes.

RQ 2: Years Teaching versus Stages of Concern

Next, a series of one-way analyses of variance (ANOVAs) were conducted to examine differences in Stages of Concern scores across years of teaching experience. Results indicated no statistically significant differences among experience groups for Awareness, $F(5, 60) = 1.69$, $p = .151$, $\eta^2 = .123$; Informational, $F(5, 60) = 1.52$, $p = .197$,

$\eta^2 = .112$; Personal, $F(5, 60) = 0.61$, $p = .695$, $\eta^2 = .048$; Management, $F(5, 60) = 0.74$, $p = .593$, $\eta^2 = .058$; Consequence, $F(5, 60) = 0.55$, $p = .737$, $\eta^2 = .044$; Collaboration, $F(5, 60) = 0.45$, $p = .815$, $\eta^2 = .036$; or Refocusing concerns, $F(5, 60) = 0.26$, $p = .932$, $\eta^2 = .021$.

Although no statistically significant differences were identified, Awareness ($\eta^2 = .123$) and Informational ($\eta^2 = .112$) demonstrated the largest effect sizes among the constructs. However, the observed differences did not reach statistical significance.

Table 17. One-Way ANOVA Years of Teaching Experience v. 7 SoCQ Constructs

Stage of Concern	F	P	η^2
Awareness	1.689	.151	.123
Informational	1.521	.197	.112
Personal	.607	.695	.048
Management	.744	.593	.058
Consequence	0.552	.737	.044
Collaboration	0.445	.815	.036
Refocusing	0.262	.932	.021

Table 18. Stages of Concern versus Years of Teaching Experience

Stage of Concern	Early Career (0–6) Raw Score	Early Career (0–6) Percentile	Mid-Career (7–15) Raw Score	Mid-Career (7–15) Percentile	Veteran (16+) Raw Score	Veteran Percentile
Awareness	16	91	18	96	20	98
Informational	22	80	19	69	24	88
Personal	23	80	21	76	23	80
Management	18	69	16	60	15	56
Consequence	23	43	24	48	23	43
Collaboration	18	40	18	40	18	40
Refocusing	20	65	21	69	20	65

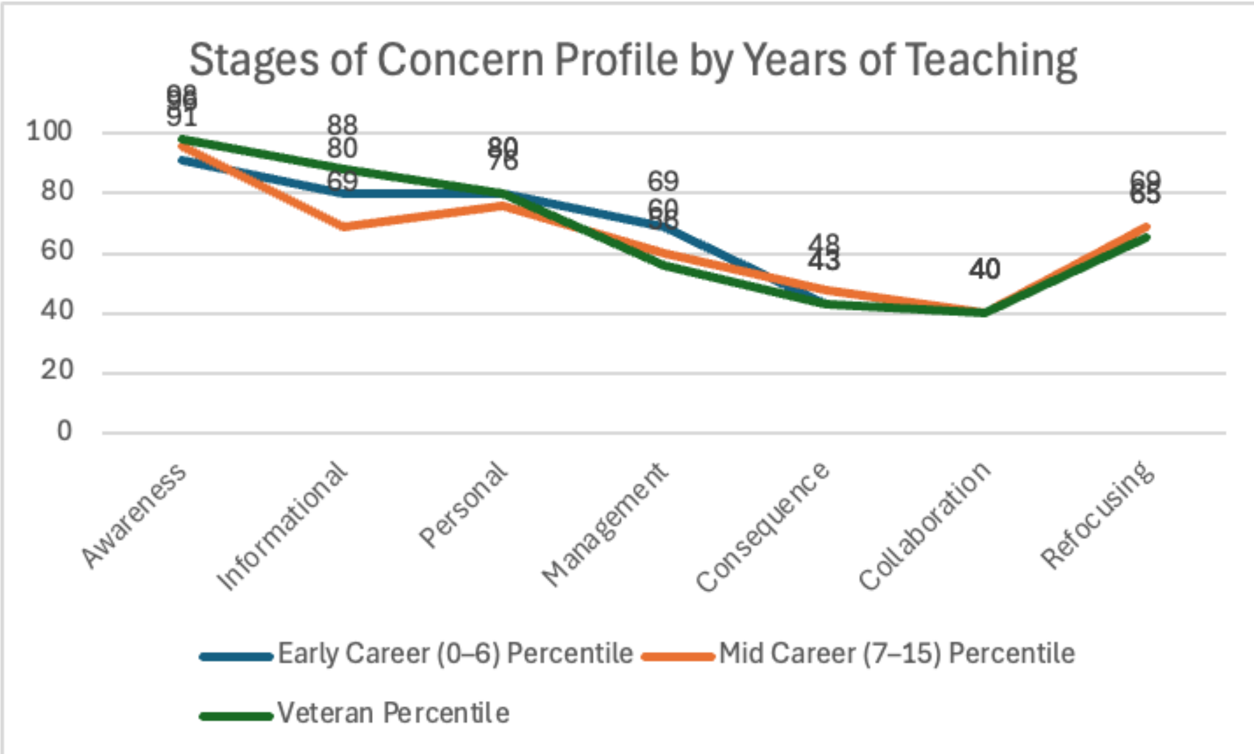

Figure 5. Stages of Concern Profiles by Years of Teaching

RQ2: Technology Comfort versus Stages of Concern

A series of one-way analyses of variance (ANOVAs) were conducted to examine differences in Stages of Concern scores across technology comfort groups (low comfort, neutral, and high comfort). Results indicated no statistically significant differences among technology comfort groups for Awareness, $F(2, 63) = 0.49$, $p = .615$, $\eta^2 = .015$; Informational, $F(2, 63) = 0.45$, $p = .638$, $\eta^2 = .014$; Personal, $F(2, 63) = 1.26$, $p = .291$, $\eta^2 = .038$; Management, $F(2, 63) = 0.52$, $p = .598$, $\eta^2 = .016$; or Consequence concerns, $F(2, 63) = 0.26$, $p = .770$, $\eta^2 = .008$. Collaboration concerns, $F(2, 63) = 2.89$, $p = .063$, $\eta^2 = .084$ and refocusing concerns, $F(2, 63) = 2.67$, $p = .077$, $\eta^2 = .078$ approached statistical significance and demonstrated moderate effect sizes.

Although the omnibus ANOVA for Collaboration concerns did not reach statistical significance, Tukey HSD post hoc analyses indicated that educators with low technology comfort reported significantly higher Collaboration concerns than educators with neutral technology comfort (MD = 1.74, $p = .050$). No other pairwise comparisons were statistically significant.

Table 19. One-way ANOVA Stages of Concern Constructs v. Technology Comfort

Stage of Concern	F	df	p	η^2
Awareness	0.49	(2, 63)	.615	.015
Informational	0.45	(2, 63)	.638	.014
Management	0.52	(2, 63)	.598	.016
Personal	1.26	(2, 63)	.291	.038
Consequence	0.26	(2, 63)	.770	.008
Collaboration	2.89	(2, 63)	.063	.084
Refocusing	2.67	(2, 63)	.077	.078

Table 20 and Figure 6 present Stages of Concern profiles by technology comfort level. Although the overall pattern of concerns was generally similar across groups, some differences were observed in Collaboration and Refocusing concerns. Educators reporting low technology comfort showed higher Collaboration (64th percentile) and Refocusing (84th percentile) concerns than educators reporting neutral or high technology comfort. Note that the omnibus ANOVAs for Collaboration and Refocusing concerns were not statistically significant, and any profile differences should be interpreted descriptively and with caution. In addition, the low technology comfort group included only five participants, further limiting interpretation.

Table 20. Stages of Concern Profile by Technology Comfort Level

Stage of Concern	Low Technology Comfort Level Raw Score	Low Technology Comfort Level SoCQ Percentile	Neutral Technology Comfort Level Raw Score	Neutral Technology Comfort Level SoCQ Percentile	High Technology Comfort Level Raw Score	High Technolog y Comfort Level SoCQ Percentile
Awareness	16.5	94	19.7	98	17.95	96
Informational	23.8	88	20.6	75	21.9	80
Personal	26.4	87	21.8	78	22.36	78
Management	19	73	16.5	65	16.03	60
Consequence	25.8	59	21.4	33	23.21	43
Collaboration	23.8	64	16.1	31	17.98	40
Refocusing	24.8	84	18.4	57	20.17	65

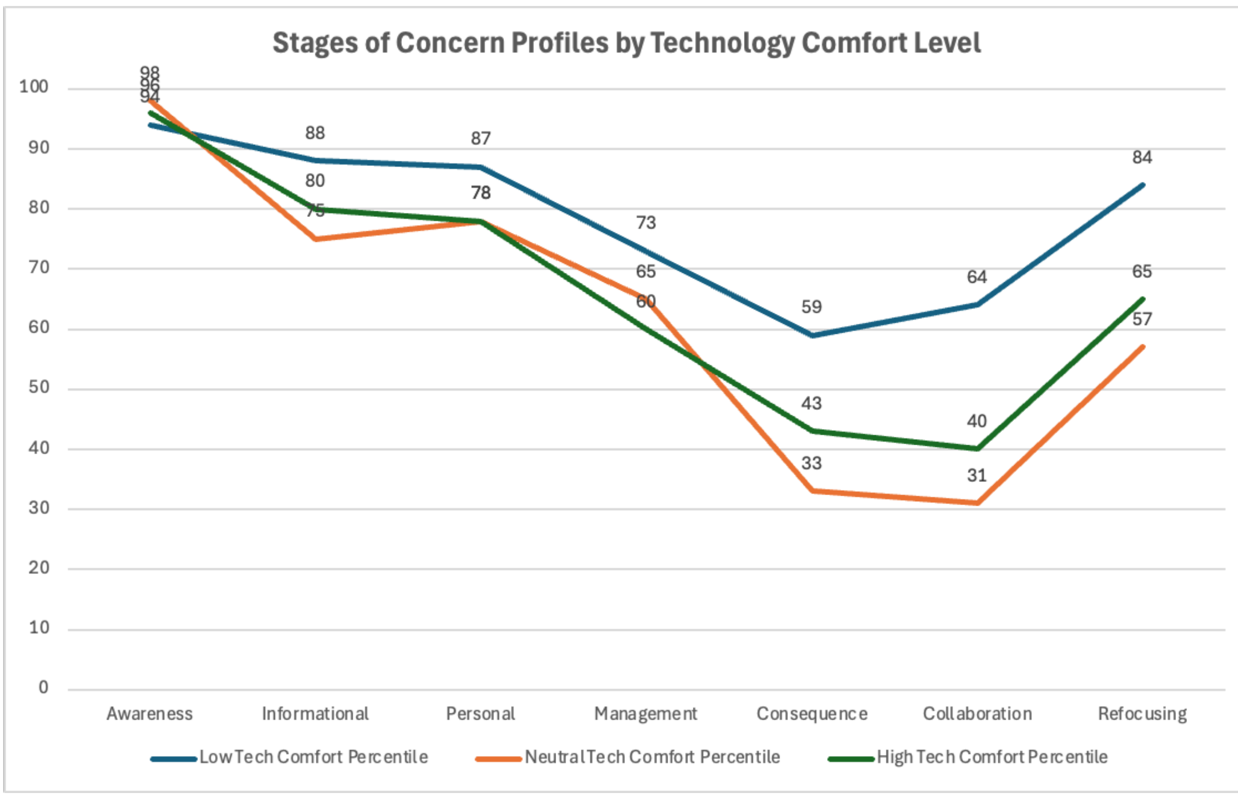

Figure 6. Stages of Concern by Technology Comfort Level

Figure 7 below illustrates the differences in elevated concern profiles across technology comfort groups. Educators reporting neutral technology comfort demonstrated the highest proportion of Awareness-only profiles (50%) and no advanced concern profiles. In contrast, educators reporting high technology comfort exhibited a broader distribution of elevated concern profiles, including Informational, Collaboration and Refocusing concerns.

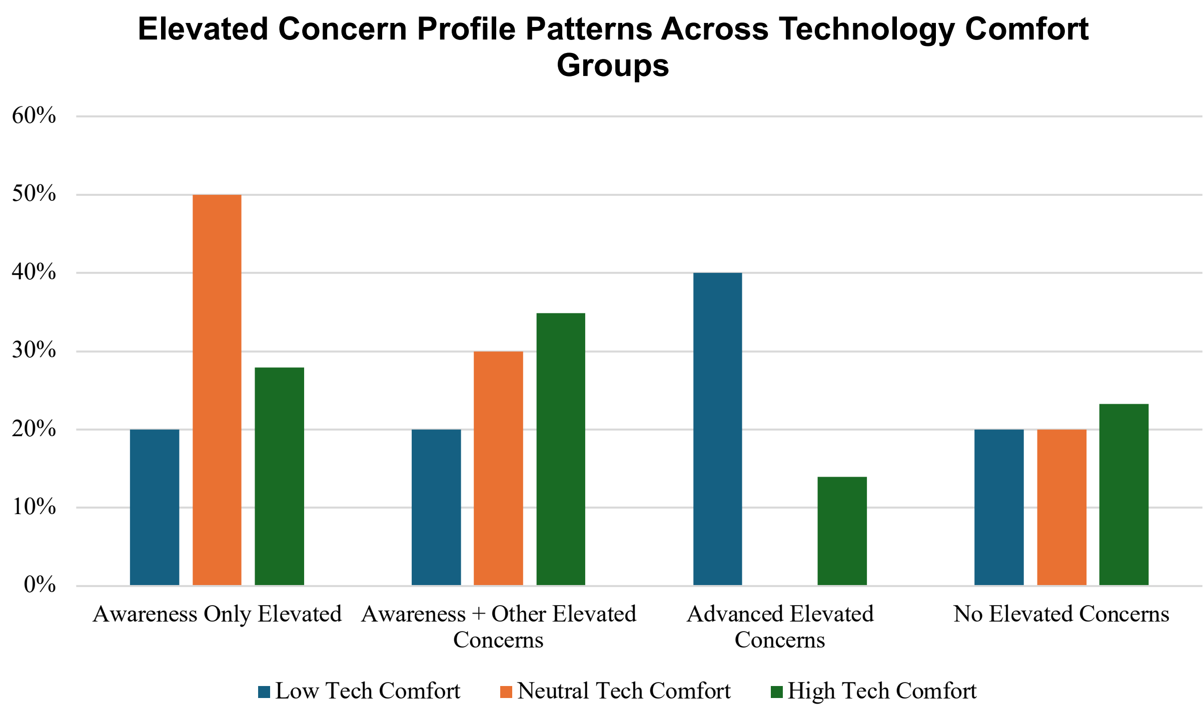

Figure 7. Elevated Concern Profile Patterns Across Tech. Comfort Groups

RQ2: Teaching Level versus Stages of Concern

A series of one-way analyses of variance (ANOVAs) was conducted to examine differences in Stages of Concern construct scores across teaching levels (elementary, middle school, and high school). Results indicated no statistically significant differences among teaching levels for Awareness, $F(2, 63) = 0.39$, $p = .680$, $\eta^2 = .012$; Informational, $F(2, 63) = 0.27$, $p = .766$, $\eta^2 = .008$; Personal, $F(2, 63) = 0.11$, $p = .899$, $\eta^2 = .003$; Management, $F(2, 63) = 0.58$, $p = .561$, $\eta^2 = .018$; Consequence, $F(2, 63) =$

0.17, p = .842, η^2 = .005; Collaboration, F(2, 63) = 0.23, p = .794, η^2 = .007; or Refocusing concerns, F(2, 63) = 0.35, p = .705, η^2 = .011.

Table 21. Stages of Concern Profiles by Teaching Level

Stage of Concern	Elementary (K-5) Raw Score	Elementary (K-5) Percentile	Middle School (6-8) Raw Score	Middle School (6-8) Percentile	High School (9-12) Raw Score	High School (9-12) Percentile
Awareness	19	97	17	94	18	96
Informational	23	84	22	80	21	75
Personal	23	80	23	80	22	78
Management	18	69	17	65	15	56
Consequence	23	43	23	43	23	43
Collaboration	20	48	17	36	18	40
Refocusing	20	65	21	69	20	65

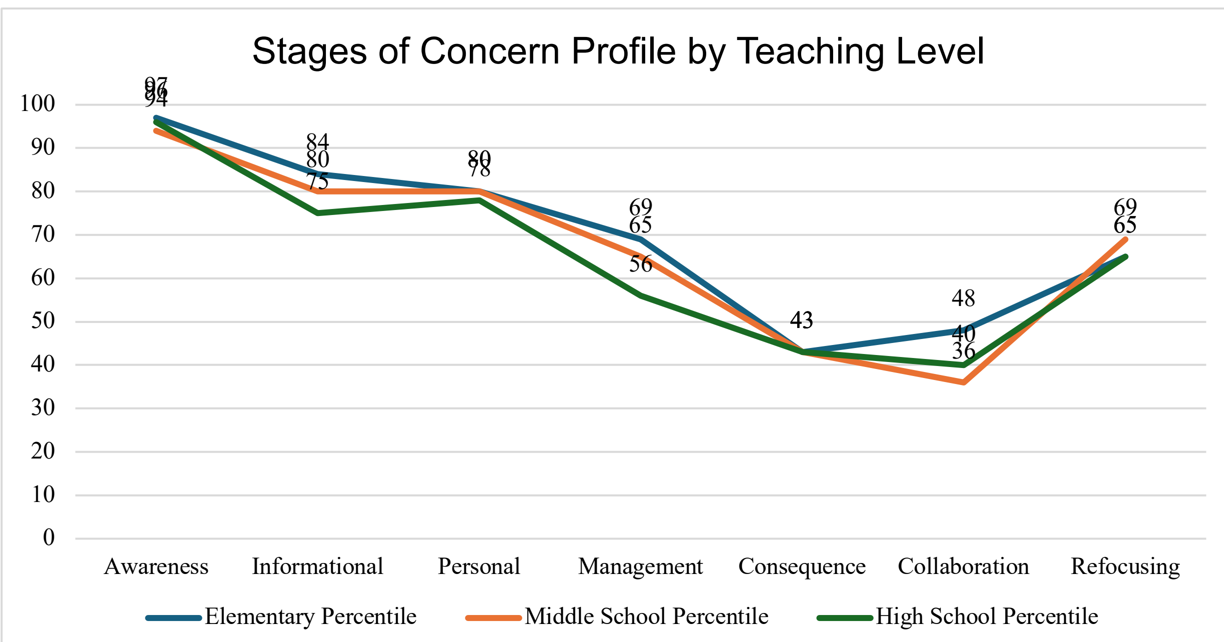

Figure 8. Stages of Concern Profile by Teaching Level

RQ 2: Educator Subject Area versus Stages of Concern

A series of one-way ANOVAs was conducted to determine whether teachers' concerns regarding AI differed by subject area. As shown in Table 22, no statistically significant differences were found for Awareness, Informational, Personal, Management, Consequence, Collaboration, or Refocusing concerns (all $p > .05$). Although Management ($\eta^2 = .065$) and Consequence ($\eta^2 = .056$) demonstrated the largest effect sizes, the observed differences did not reach statistical significance.

Table 22. One-Way ANOVA between Subjects Taught versus 7 SoCQ Constructs

Stage of Concern	F (df)	p	η^2
Awareness	$F(2, 63) = 1.04$	.359	.032
Informational	$F(2, 63) = 0.86$	.429	.027
Personal	$F(2, 63) = 0.22$	.801	.007
Management	$F(2, 63) = 2.20$	.119	.065
Consequence	$F(2, 63) = 1.87$	.163	.056
Collaboration	$F(2, 63) = 0.34$	.712	.011
Refocusing	$F(2, 63) = 1.32$	.274	.040

Note. η^2 = eta squared effect size.

Table 23. Stages of Concern Profiles by Subjects Taught

Stage of Concern	ELA/Social Studies Raw Score	ELA/Social Studies Percentile	STEM Raw Score	STEM Percentile	Other Raw Score	Other Percentile
Awareness	16	91	20	98	19	97
Informational	23	84	20	72	22	80
Personal	24	83	22	78	22	78
Management	14	52	18	69	17	65
Consequence	22	38	25	54	23	43
Collaboration	17	36	16	31	19	44
Refocusing	21	69	21	69	19	60

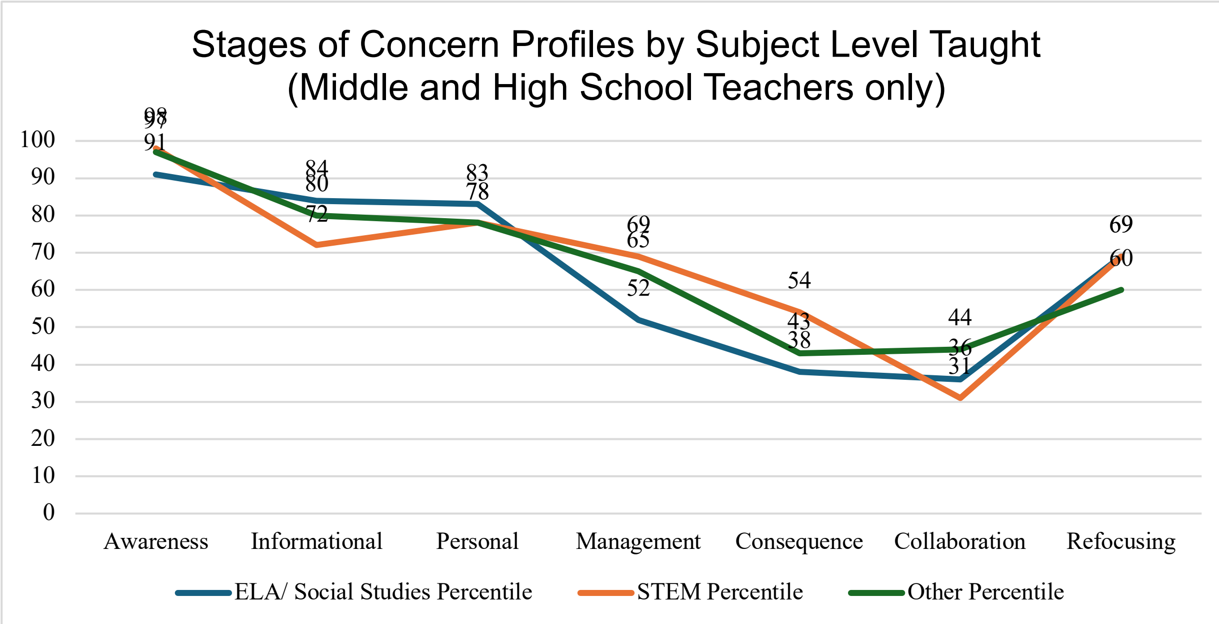

Figure 9. Stages of Concern Profiles by Subject Level Taught

RQ2: Educators With and Without AI Training and Stages of Concern

Independent-samples t-tests were conducted to examine differences in Stages of Concern construct scores between educators who reported receiving AI-related training and those who did not. Results indicated a statistically significant difference in Personal concerns, with educators who had received AI training ($M = 6.12$, $SD = 1.02$) reporting higher Personal concern scores than educators who had not received AI training ($M = 5.37$, $SD = 1.17$), $t(53) = 2.08$, $p = .042$, $d = 0.66$. The effect size was moderate, suggesting a meaningful difference between groups.

No statistically significant differences were observed between trained and untrained educators on Awareness, Informational, Management, Consequence, or Collaboration concerns (all $p > .05$). No statistically significant difference was observed for Refocusing concerns, $t(53) = 1.72$, $p = .092$, $d = .55$. Although the effect size was moderate, the difference did not reach statistical significance.

Overall, the findings suggest that AI-related training was associated primarily with educators' Personal concerns regarding AI integration, while differences in other concern constructs were minimal.

Table 24. Independent Samples t-Test Results Comparing Educators with and without AI Training on Stages of Concern Constructs

Construct	AI Training Mean (SD)	No AI Training Mean (SD)	t	df	p	Cohen's d
Awareness	4.38 (1.17)	4.64 (1.09)	-0.71	53	.478	-0.23
Informational	5.32 (0.91)	5.38 (1.22)	-0.16	53	.875	-0.05
Personal	6.12 (1.02)	5.37 (1.17)	2.08	53	0.042	0.66
Management	4.34 (0.90)	4.26 (1.21)	0.22	53	.824	0.07
Consequence	5.55 (0.89)	5.63 (1.05)	-0.25	53	.806	-0.08
Collaboration	4.32 (1.38)	4.70 (1.34)	-0.89	53	.376	-0.28
Refocusing	5.49 (0.96)	4.91 (1.10)	1.72	53	.092	0.55

Note: $p < 0.05$ indicated in bold.

Comparison of the Stages of Concern profiles by AI training status revealed generally similar patterns across groups. Educators who had received AI training demonstrated higher Personal concern scores (87th percentile) than educators who had not received training (78th percentile), consistent with the statistically significant difference identified in the independent samples t-test analysis. The trained group also exhibited somewhat higher Refocusing concerns (73rd vs. 65th percentile), although this difference was not statistically significant.

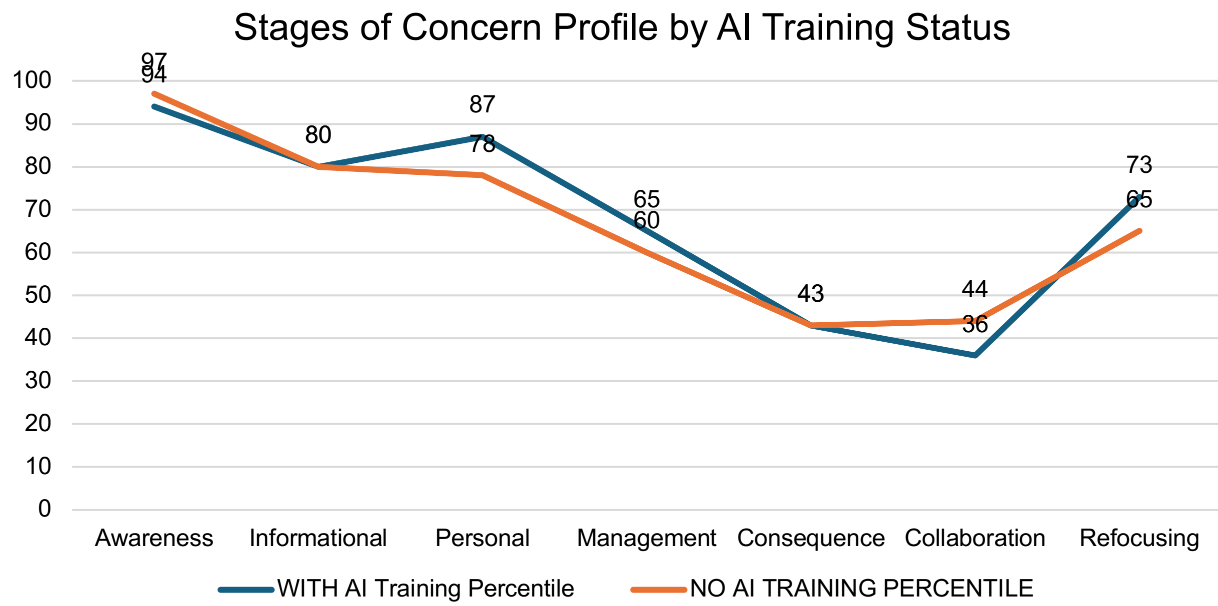

Figure 10. Stages of Concern Profiles by AI Training Status

Further examination of percentile concern profiles suggested notable differences between educators who had and had not received AI-related training. Educators without AI training were more likely to demonstrate Awareness-only profiles, whereas Educators with AI training more frequently exhibited profiles that included Personal and Refocusing concerns. These patterns align with the independent-samples t-test findings, which indicated significantly higher Personal concern scores among educators who had received AI training.

RQ2: Stages of Concern versus Self-Reported AI Experience Level

A series of one-way analyses of variance (ANOVAs) were conducted to examine differences in stages of concern across self-reported AI experience levels (non-user, novice, intermediate, old hand and past user). Results indicated statistically significant differences in Awareness concerns F (4, 50) = 2.68, p = .042, η^2 = .176; Informational concerns, $F(4, 50) = 4.20$, $p = .005$, $\eta^2 = .251$; and Collaboration concerns, $F(4, 50) = 4.34$, $p = .004$, $\eta^2 = .258$. No statistically significant differences were observed for Personal concerns, $F(4, 50) = 0.88$, $p = .482$, $\eta^2 = .066$; Management concerns, $F(4, 50) = 0.75$, $p = .563$, $\eta^2 = .057$; Consequence concerns, $F(4, 50) = 0.90$, $p = .472$, $\eta^2 = .067$; or Refocusing concerns, $F(4, 50) = 0.44$, $p = .777$, $\eta^2 = .034$.

Table 25. One-Way ANOVA Stages of Concern v. Self-Reported AI Experience Level

Construct	F	df	p	η^2
Awareness	2.676	(4, 50)	.042	.176
Informational	4.197	(4, 50)	.005	.251
Personal	0.881	(4, 50)	.482	.066
Management	0.749	(4, 50)	.563	.057
Consequence	0.899	(4, 50)	.472	.067
Collaboration	4.338	(4, 50)	.004	.258
Refocusing	0.442	(4, 50)	.777	.034

Note: $p < 0.05$ indicated in bold.

Post hoc Tukey (HSD) analyses were conducted for the three significant ANOVA findings. For Awareness concerns, novice users reported significantly higher Awareness concerns than intermediate users ($MD = 1.00$, $p = .046$). For Informational concerns, novice users ($MD = 1.55$, $p=.004$) and intermediate users ($MD = 1.35$, $p = .023$) reported significantly higher informational concerns than non-users. For Collaboration concerns, novice users ($MD = 1.44$, $p=.033$), intermediate users ($MD = 1.57$, $p=.023$) and old-hand users ($MD = 1.97$, $p=.012$) reported significantly higher collaboration concerns than non-users. These findings suggest that educators with greater AI experience exhibited stronger informational and collaborative concerns regarding AI integration than educators who did not use AI.

Examination of the SoCQ profiles showed meaningful differences across self-reported AI experience levels. Informational concerns were highest among novice and intermediate users. Collaboration concerns increased steadily from non-users to experienced users. Awareness concerns were greatest among non-users and novice users and declined among intermediate and old-hand users. This progression is consistent with the Concerns-Based Adoption Model.

Table 26. Stages of Concern Profiles versus Self-Reported AI Experience Level

Stage of Concern	Non-User Raw Score	Non-User Percentile	Novice Raw Score	Novice Percentile	Intermediate Raw Score
Awareness	19	97	20	98	16
Informational	16	60	24	88	23
Personal	20	72	23	80	24
Management	15	56	18	69	15
Consequence	21	33	23	43	25
Collaboration	12	19	19	44	20
Refocusing	18	57	21	69	21

Stage of Concern	Intermediate Percentile	Old Hand Raw Score	Old Hand Percentile	Past User* Raw Score	Past User* Percentile
Awareness	91	16	91	20	98
Informational	84	20	72	21	75
Personal	83	21	76	26	87
Management	56	16	60	12	60
Consequence	54	23	43	22	38
Collaboration	48	22	55	11	17
Refocusing	69	20	65	21	69

Note: $p < 0.05$ in bold.

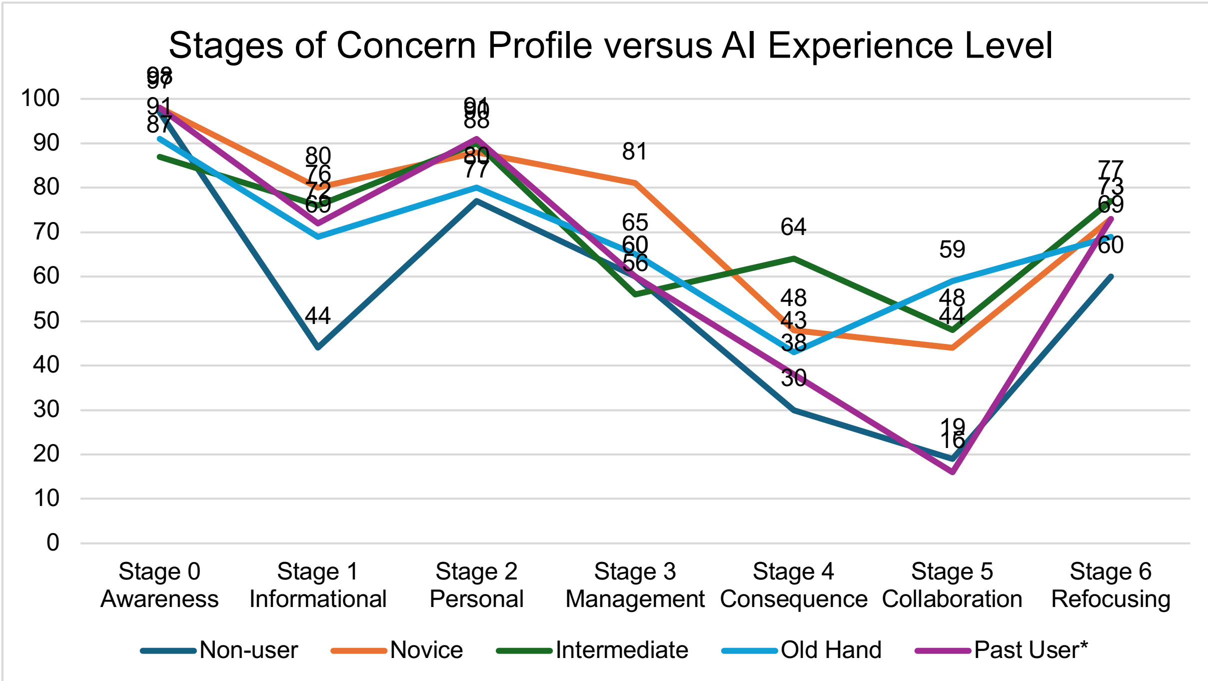

Figure 11. Stages of Concern Profiles versus AI Experience Level

Figure 12 below shows that as AI experience increases, elevated concern profiles shift away from Awareness and toward Informational, Collaboration and Refocusing concerns.

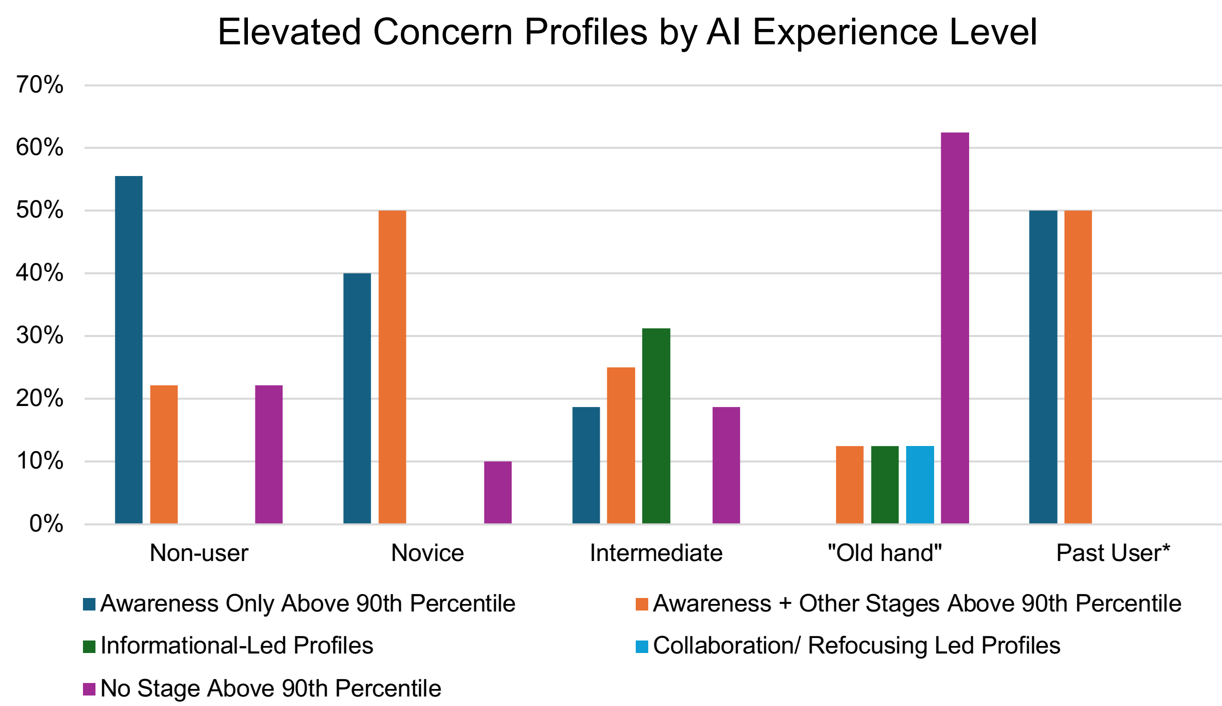

Figure 12. Elevated Concern Profiles by AI Experience Level

Table 27. Summary of Statistically Significant and Notable Demographic Differences in Stages of Concern

Demographic Variable	Construct	Test	Statistic	P	Effect Size	Statistically Significant
AI Training	Personal	t-test	t (53) = 2.079	.042	d=.660	Yes
AI Training	Refocusing	T-test	t (53) = 1.17	.092	D = .545	No
AI Experience Level	Awareness	ANOVA	F (4, 50) = 2.676	.042	η^2 = .176	Yes
AI Experience Level	Informational	ANOVA	F (4,50) = 4.197	.005	η^2=.251	Yes
AI Experience Level	Collaboration	ANOVA	F (4,50) = 4.338	.004	η^2=.258	Yes
Technology Comfort Level	Collaboration	ANOVA	F (2,63) = 2.893	.063	η^2=.084	No
Technology Comfort Level	Refocusing	ANOVA	F (2,63) = 2.674	.077	η^2=.078	No

Examination of the SoCQ percentile profiles provided additional insight into educators' concern patterns. Although many demographic comparisons did not reach statistical significance, several descriptive differences emerged. Veteran educators showed higher Awareness concerns than less experienced educators, while early-career educators reported somewhat higher Management concerns. Educators with lower technology comfort showed higher Collaboration and Refocusing concerns as compared with educators reporting greater comfort with technology. The most distinct concern profiles were observed across self-reported AI experience levels, where novice users demonstrated particularly high informational concerns and experienced users demonstrated higher Collaboration concerns. These profile differences are consistent with the CBAM framework and suggest meaningful variation in how educators experience AI adoption, even when statistical differences are not detected.

Research Question 3: What is the relationship between stages of concern and perceptions of AI?

Relationship Between Stages of Concern and Student Learning Perceptions

Research question 3 begins with Pearson correlation analyses to examine the relationships between teachers' stages of concern regarding artificial intelligence and their perceptions of AI's impact on student learning and engagement. Significant positive relationships were found between Informational concerns and Student Learning Perceptions, $r(53) = .296$, $p = .002$, Management concerns and Student Learning Perceptions, $r(53) = .267$, $p = .049$ and Collaboration concerns and Student Learning Perceptions, $r(53) = .647$, $p < .001$.

The strongest relationship observed in the study was between Collaboration concerns and Student Learning Perceptions. This strong, positive correlation suggests that teachers who expressed greater interest in collaborating with colleagues regarding AI implementation were substantially more likely to report favorable perceptions of AI's impact on student learning and engagement.

No statistically significant relationships were found between Student Learning Perceptions and Awareness concerns, r (53) = -.071, p = .608, Personal concerns, r (53) = .147, p = .285, or Refocusing concerns, r (53) = .027, p = .846.

Table 28. Pearson Correlations Between Stages of Concern and Student Learning Perceptions

Variable	R	p
Awareness	-0.071	.608
Informational	.406	.002
Personal	.147	.285
Management	.296	.028
Consequence	.267	.049
Collaboration	.647	<.001
Refocusing	.027	.846

Note: N = 55. p < .05 in bold.

Relationship Between Stages of Concern and Perceived Benefits of AI

Pearson product-moment correlation analyses were conducted to examine the relationships between teachers' stages of concern regarding artificial intelligence and their perceptions of the instructional benefits of AI. Significant positive relationships were found between Informational concerns and perceived benefits of AI, r (53) = .428, p = .001; Management concerns and perceived benefits of AI, r (53) = .330, p = .014; Consequence concerns and perceived benefits of AI, r(53) = .281, p = .037 and Collaboration concerns and perceived benefits of AI, r(53) = .684, p < .001.

The strongest relationship was observed between Collaboration concerns and perceived benefits of AI. This strong positive correlation suggests that teachers who expressed greater interest in collaborating with colleagues regarding AI implementation were substantially more likely to perceive AI as beneficial for instruction.

No statistically significant relationships were found between perceived benefits of AI and Awareness concerns, $r(53) = -.060$, $p = .665$, Personal concerns, $r(53) = .176$, $p = .199$ or Refocusing concerns, $r(53) = .057$, $p = .678$.

Table 29. Pearson Correlations Between Stages of Concern and Perceived Benefits of AI

Variable	R	p
Awareness	-.060	.665
Informational	.428	.001
Personal	.176	.199
Management	.330	.014
Consequence	.281	.037
Collaboration	.684	<.001
Refocusing	.057	.678

Note: N = 55. Pearson product-moment correlations reported. p < .05 in bold

Elevated Stages of Concern Profiles by Average Perceived Benefits

Average perceived benefit scores increased across concern profiles, with educators exhibiting advanced concern profiles reporting the most favorable perceptions of AI.

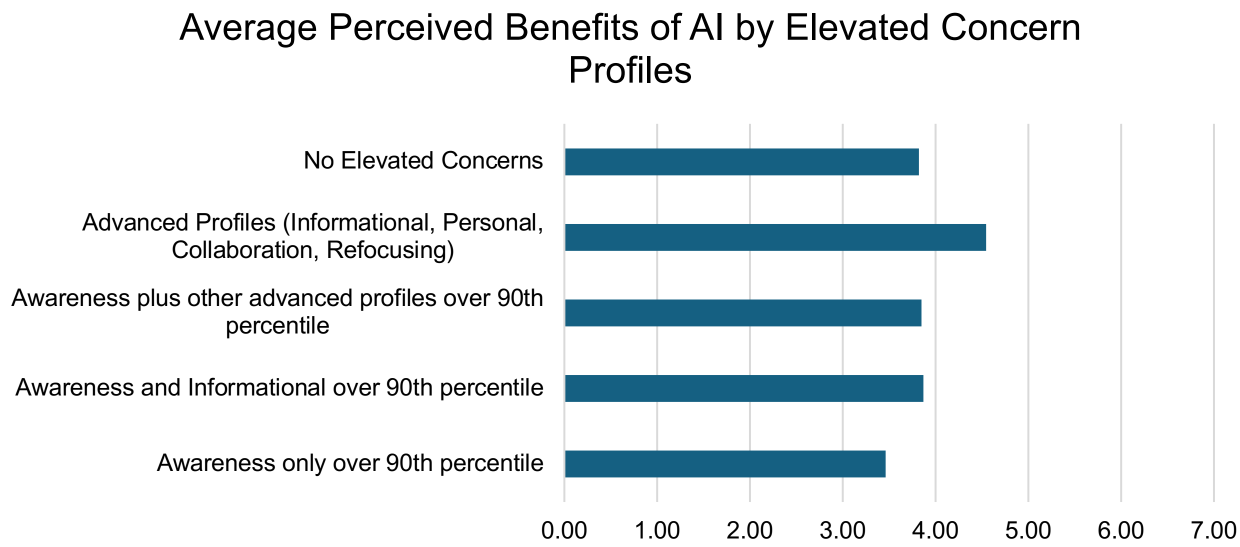

Figure 13. Average Perceived Benefits of AI by Elevated Concern Profiles

Table 30. Average Perceived Benefits of AI by Elevated Concern Profile

Over 90th Percentile Concerns	Increased motivation	Independent thinking	Increased student engagement
Awareness only over 90th percentile	3.59	2.65	3.71
Awareness and Informational over 90th percentile	3.80	3.40	4.00
Awareness plus other advanced profiles over 90th percentile	3.62	2.69	3.85
Advanced Profiles*	4.75	3.25	5.25
No Elevated Concerns	3.83	2.67	4.42

	More effective learning	Differentiation	Reduce teacher workload	Average Benefit Score
Awareness only over 90th percentile	2.88	3.76	4.18	3.46

Awareness and Informational over 90th percentile	3.00	4.80	4.20	3.87
Awareness plus other advanced profiles over 90th percentile	3.23	4.46	5.23	3.85
Advanced Profiles*	3.50	5.38	5.13	4.54
No Elevated Concerns	2.75	4.50	4.75	3.82

Research Question 4: What is the relationship between stages of concern and perceived challenges and adoption of AI?

Pearson correlation analyses were conducted to examine relationships between teachers' stages of concern regarding AI and perceptions of AI-related challenges. Because reliability analysis indicated poor internal consistency among the challenge items, each challenge variable was analyzed separately.

Relationship Between Stages of Concern and Perceptions of Unethical Student AI Use

Pearson correlation analyses were conducted to examine the relationships between teachers' stages of concern regarding artificial intelligence and perceptions that students are using AI unethically (e.g., plagiarism). Significant positive relationships were found between Personal concerns and perceptions of unethical AI use, r (52) = .322, p = .018, Consequence concerns and perceptions of unethical AI use, r (52) = .344, p = .011, and Refocusing concerns and perceptions of unethical AI use, r (52) = .357, p = .008. These findings indicate that teachers who expressed greater concerns about the personal implications of AI, its impact on students, and potential modifications to AI implementation were more likely to perceive unethical student use of AI as a challenge.

No significant relationships were found between perceptions of unethical AI use and Awareness concerns, $r(52) = .147$, $p = .290$, Informational concerns, $r(52) = .065$, $p = .643$, Management concerns, $r(52) = .080$, $p = .566$, or Collaboration concerns, $r(52) = .037$, $p = .792$.

Relationship Between Stages of Concern and Perceptions of Equity

Pearson correlation analyses were conducted to examine relationships between teachers' stages of concern regarding AI and perceptions that AI presents equity-related challenges. No statistically significant relationships were identified between equity concerns and any of the seven stages of concern, including Awareness, Informational, Personal, Management, Consequence, Collaboration, and Refocusing concerns (all $p > .05$). Management concerns demonstrated a small positive relationship with equity concerns, $r(52) = .260$, $p = .057$; however, the relationship was not statistically significant.

Relationship Between Stages of Concern and Difficulty in Assessing Students

Pearson correlation analyses were conducted to examine the relationship between teachers’ stages of concern regarding artificial intelligence and perceptions that AI makes student assessment more difficult. Significant positive relationships were identified between Personal concerns and assessment related challenges $r(52) = .290$, $p = .003$;Consequence concerns and assessment-related challenges, $r(52) = .290$, $p = .033$; and Refocusing concerns and assessment-related challenges, $r(52) = .445$, $p <$

.001.These findings suggest that teachers who expressed greater concerns regarding the personal implications of AI, its impact on students and potential modifications to AI implementation were more likely to perceive AI as creating challenges for assessment and evaluation of student learning.

No statistically significant relationships were found between assessment-related challenges and Awareness concerns, r (52) = .060, p=.667; Informational concerns, r (52) = .171, p = .217; Management concerns, r (52) = .090, p=.517; or Collaboration concerns, r (52) = .139, p = .315.

Table 31. Pearson Correlations Between Stages of Concern Constructs and Perceived Challenges of AI Integration

Stage of Concern	Plagiarism	Equity Concerns	Assessment Difficulties
Awareness	.147 (.290)	.020 (.888)	.060 (.667)
Informational	.065 (.643)	.067 (.631)	.171 (.217)
Personal	.322 (.018)	.091 (.514)	.438 (<.001)
Management	.080 (.566)	.260 (.057)	.090 (.517)
Consequence	.344 (.011)	.081 (.562)	.290 (.033)
Collaboration	.037 (.792)	.055 (.691)	.139 (.315)
Refocusing	.357 (.008)	-.057 (.682)	.445 (<.001)

Note: Values represent Pearson correlation coefficients (r), with p-values in parentheses. p < .05 in bold.

Descriptive Analyses of Elevated Concern Profiles

Descriptive analyses of elevated concern profiles revealed meaningful differences in perceptions of AI-related challenges. Concerns regarding unethical student use of AI (plagiarism) were consistently high across all concern profiles, with mean scores ranging from 5.08 to 6.20. In contrast, perceptions of equity-related challenges demonstrated substantial variability and no clear pattern across profiles, consistent with the non-significant correlation findings reported previously. Assessment-related challenges demonstrated the clearest profile differences. Educators with awareness-only profiles and those with no elevated concerns reported the lowest levels of concern regarding assessment difficulty (M = 4.00), whereas educators with more complex concern profiles involving Informational, Personal, Management, Collaboration, or Refocusing concerns reported higher levels of assessment-related concern (M = 4.50–5.23).

Table 32. Mean Challenge Perceptions by Elevated Concern Profile

Elevated Concern Profile	Plagiarism Concerns	Equity Concerns	Assessment Difficulty
Awareness Only above 90th percentile	5.38	4.00	4.00
Awareness + Informational	6.20	2.60	5.20
Awareness + Advanced Concerns	5.92	4.92	5.23
Advanced Profiles Only	5.88	4.38	4.50
No Elevated Concerns	5.08	3.58	4.00

Relationship Between Stages of Concern and AI Tool Adoption

Pearson correlation analyses were conducted to examine the relationships between teachers' stages of concern regarding artificial intelligence and their likelihood of adopting AI tools specifically designed for educators. Significant positive relationships were identified between Informational concerns and adoption intentions, $r(53) = .305$, $p=.024$; Management concerns and adoption intentions, $r(53) = .359$, $p = .007$.

These findings suggest that educators who are interested in learning more about AI, managing its implementation and collaborating with colleagues regarding its use were more likely to express intentions to adopt AI tools designed specifically for educational settings.

No statistically significant relationships were found between adoption intentions and Awareness concerns, $r(53) = -.096$, $p=.485$; Personal concerns, $r(53) = .127$, $p=.355$; Consequence concerns, $r(53) = .158$, $p=.249$; or Refocusing concerns, $r(53) = .050$, $p=.718$.

Table 33. Pearson Correlations Between Stages of Concern Constructs and Preference for Educator-Specific AI Tools

Stage of Concern	r	p
Awareness	-.096	.485
Informational	.305	.024
Personal	.127	.355
Management	.276	.041
Consequence	.158	.249
Collaboration	.359	.007
Refocusing	.050	.718

Note: $p < 0.05$ in bold.

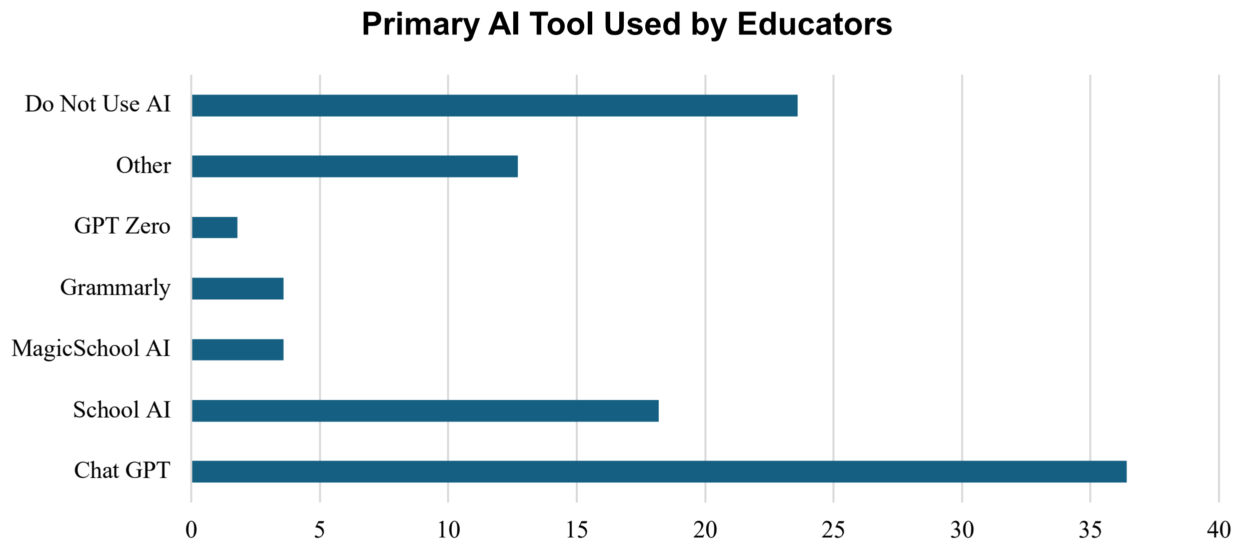

Figure 14. Primary AI Tool Used by Educators

Additional Context: Open-Ended Responses: Advantages and Challenges of AI in Education

To provide additional context to the responses at hand, open-ended questions regarding the advantages and challenges of AI in K–12 education were analyzed using content analysis.

Content Analysis Procedure

Responses to the two open-ended survey questions were analyzed using content analysis. The researcher served as the sole coder and carefully reviewed all responses multiple times to become familiar with the responses. Initial codes were generated inductively from the survey participants' written responses. Those answers that were similar were grouped into broader thematic categories and themes were refined by repeatedly reviewing the data. Frequency counts were then calculated to identify the most commonly reported advantages and challenges associated with AI use in K-12 education.

To increase trustworthiness and coding consistency, responses were reviewed multiple times during the coding process and coding decisions were applied consistently across all responses. Representative participant comments were retained to illustrate the themes during the analysis. Because the open-ended questions were included to provide supplemental context to the quantitative findings, formal interrater reliability was not calculated.

Open-Ended Responses: Advantages of AI in Education

Several recurring themes emerged from participant responses. The most frequently identified advantage was the reduction of teacher workload. Participants frequently described AI as a tool that could assist with lesson planning, grading, resource development, routine communication, and other time-consuming tasks. A second prominent theme involved differentiation and personalized learning. Respondents noted that AI could assist teachers in adapting materials to meet diverse student needs, provide language support for multilingual learners, and offer individualized learning opportunities. Lesson planning and instructional resource creation also emerged as common benefits, with participants describing the use of AI to generate prompts, worksheets, activities, and instructional materials.

Additional themes included increased student engagement and learning opportunities, support for creativity and idea generation, and enhanced access to information and research resources. Several participants emphasized that AI could help teachers generate new instructional approaches and provide students with opportunities for personalized feedback. A small number of participants expressed skepticism regarding the value of AI and reported that they did not perceive significant advantages associated with its use in education.

Table 34. Themes Identified in Responses Regarding the Advantages of AI in K–12 Education (Question 46)

Theme	Frequency	Example Response
Teacher workload reduction	25	"Teacher workload," "less time to create lesson plans," "decrease workload"
Differentiation and personalized learning	15	"Differentiation," "different levels," "personalized feedback"
Lesson planning and resource creation	13	"Writing prompts," "creating worksheets," "lesson planning"
Student learning and engagement	10	"Increase engagement," "support student learning," "motivate students"
Idea generation and creativity	8	"Brainstorm ideas," "creative activities," "new teaching techniques"
Research and information access	5	"Research," "quick information," "finding resources"

Open-Ended Responses: Challenges of AI in Education

Responses to the open-ended question regarding challenges associated with AI integration in K–12 education were analyzed using content analysis. The most frequently cited concern involved student dependence on AI and the potential reduction of critical thinking skills. Many participants expressed concern that students may rely on

AI as a substitute for problem solving, writing, and independent learning rather than using it as a support tool.

Academic integrity emerged as a second major theme. Participants frequently referenced concerns related to cheating, plagiarism, and students using AI to complete assignments without demonstrating their own learning. Ethical concerns were also commonly reported and included issues related to privacy, data security, misinformation, deep fakes, and the responsible use of student information.

Additional themes included the need for teacher training and professional development, concerns regarding equitable access to AI technologies, and broader environmental and societal impacts. Several participants emphasized the importance of learning how to integrate AI effectively while maintaining opportunities for authentic student thinking and human interaction.

Table 35. Themes Identified in Responses Regarding Challenges of AI in K–12 Education (Question 47)

Theme	Frequency	Example Response
Student dependence/loss of critical thinking	24	"Students use AI as a crutch," "replaces thinking," "limits critical thinking"
Academic integrity/cheating	14	"Cheating," "plagiarism," "shortcutting learning"
Ethical concerns/privacy/security	10	"Ethics," "student information," "ID scams," "deep fakes"
Teacher training and implementation challenges	7	"Need more training," "learning curve," "how to use it effectively"
Equity and access concerns	3	"Not all families have equal access to technology"

Environmental and societal concerns	5	"Environmental impact," "AI psychosis," "loss of human interaction"

**Frequencies are approximate because many responses contained multiple themes and were coded into more than one category. Responses were coded into all applicable categories.*

Chapter 5 Discussion

Introduction

In 2022, OpenAI released a free, publicly accessible version of ChatGPT, which led to the rapid integration of artificial intelligence across nearly every sector, industry, and area of the economy. The education sector saw particularly rapid adoption, as students began using AI tools for academic work (CITE). Educators were confronted with the challenge of adapting to this technological innovation with minimal training and were expected to respond quickly. This study attempts to determine the current position of teachers within the AI in Education adoption process. To maintain the scope of this chapter, the discussion will focus on the major findings associated with each research question.

Purpose of the Study

The purpose of this quantitative study was to examine K-12 educators' stages of concern regarding the integration of generative artificial intelligence (AI) in education through the lens of the Concern-Based Adoption Model (CBAM). As generative AI technologies have become increasingly available to educators and students, schools have faced the task of determining how AI should be used in teaching and learning. To take on this task, schools need to understand how teachers perceive and respond to this rapidly emerging innovation. Understanding educators' concerns is important because they will influence whether and how innovations are adopted, implemented, and sustained (Hall, 1979).

Using the Stages of Concern Questionnaire (SoCQ), a validated instrument to measure educators' concerns about new innovations in education, this study investigated the relationship between educators' stages of concern and their experience of AI in the classroom, perceptions of AI's instructional benefits and challenges, adoption intentions, and demographic variables. Four research questions guided this investigation: (a) the current stages of concern of K-12 educators regarding AI, (b) do stages of concern differ according to educator characteristics? (c) What is the relationship between stages of concern and perceptions of student learning and instructional benefits? (d) What is the relationship between stages of concern, perceived challenges, and adoption of AI?

The Concerns-Based Adoption Model provided the conceptual structure for interpreting teachers' responses to AI as an educational innovation. Rather than viewing AI adoption as a simple decision to accept or reject the technology, the CBAM frames implementation as a developmental process in which educators progress through evolving stages of concern. The framework served as the foundation for examining where educators currently reside along the AI adoption 'scale' and how those stages relate to their perceptions of AI in academic environments.

Summary of Major Findings

Based on the Concerns-Based Adoption Model, four research questions were developed to guide the study, each helping in a greater understanding of how K-12 educators are experiencing the arrival of AI as an educational innovation.

The survey included the validated Stages of Concern Questionnaire along with a series of typical demographic questions and two open-ended questions exploring educators' perceptions of the advantages and challenges of AI in education.

The first research question aimed to address the more general inquiry: What stages of concern do K-12 educators report regarding AI integration? The findings showed that the majority of respondents are in the early-stage concerns, with Stage 0 Awareness (Unconcerned) emerging as the dominant stage of concern for nearly three-fourths of respondents. Consistent with the Concerns-Based Adoption Model, Informational concerns frequently emerged as the second-highest stage of concern, suggesting that many educators were beginning to move from Awareness (Unconcerned) stage toward information-seeking. As advised in the SoCQ manual, peak stages, elevated-concern profiles, and profile-interpretation patterns were also analyzed. All of these results suggested that relatively few educators had progressed beyond the early stages of concern. Few respondents identified Collaboration plus Refocusing as their greatest concern, and none identified Management or Consequence as their highest stage of concern.

The findings related to the first research question indicate that most educators remain in the initial stages of AI adoption, as described by the Concerns-Based Adoption Model, with some progressing from basic awareness to information-seeking. Few educators are currently focused on implementation, collaboration, or refinement of AI use in school environments.

The second research question investigated whether stages of concern differed according to educator characteristics. Consistent with the Concerns-Based Adoption Model and the SoCQ manual (George et al., 2006), relatively few differences were seen across traditional demographic variables such as age, sex, years of teaching experience, and grade level taught. In contrast, educators' experience with AI demonstrated more meaningful relationships with stages of concern than demographic characteristics alone. Although a cross-sectional study, the results appear to support the CBAM statement that an individual's "developmental state in relation to an innovation is more influential than demographic characteristics in affecting responses to new technology in education" (George et al., 2006).

The third research question examined the relationship between educators' stages of concern and their perceptions of AI, particularly its potential benefits, such as increased student engagement and reduced teacher workload. The results showed that instructors with more advanced concern profiles reported increasingly positive perceptions of AI's instructional benefits. The Collaboration stage showed the strongest positive relationship with perceived instructional benefits. Informational, Management, and Consequence concerns were also positively associated with positive perceptions of AI. The open-ended responses further supported these conclusions. Participants frequently identified reductions in teacher workload, chances for differentiation, and increased student engagement as major advantages of AI. The data show that teachers are progressively recognizing AI's instructional potential as they move through the stages of concern.

The fourth research question examined the relationship between educators' stages of concern, perceived challenges, and AI adoption. Educators with stronger Informational, Management, and Collaboration concerns were significantly more likely to report intentions to adopt AI tools specifically designed for educators. At the same time, educators with stronger Personal, Consequence, and Refocusing concerns reported significantly greater concerns regarding plagiarism and assessment. Open-ended responses reinforced the results, noting student dependence on AI, reduced critical thinking, concerns about academic integrity, and ethical issues as the most frequently reported implementation challenges. Interestingly, concern about plagiarism appeared to be widespread among educators regardless of their stage of concern, while later-stage educators expressed even stronger concern about ethical implementation and assessment. In contrast, perceptions of equity-related challenges were not significantly associated with any stages of concern.

Finally, according to the SoCQ manual, analysis of concern profiles provided additional viewpoints on educators' AI readiness. Although most participants exhibited elevated Stage 0 Awareness concerns, instructors with more advanced concern profiles consistently reported stronger perceptions of instructional benefits while also expressing greater concerns about assessment difficulties and ethical use. Rather than showing simple acceptance or resistance toward AI, these results indicate that educators develop increasingly balanced perspectives as they gain experience with the innovation. Together, these outcomes support the Concerns-Based Adoption Model by suggesting that educators' responses to AI represent a process rather than a simple dichotomy of acceptance or resistance.

Discussion of Research Question 1

The first major finding of this study was that most educators remained in the earliest stages of concern regarding the integration of artificial intelligence into education. Stage 0 Awareness or Unconcerned emerged as the dominant stage of concern, with nearly three-fourths of respondents reporting it as their highest stage. In addition, Informational concerns frequently appeared as the second-highest stage, which is consistent with the Concerns-Based Adoption Methodology framework (George et al., 2006)

According to the SoCQ manual, a high Stage 0 score may either indicate that an individual is a non-user of the innovation or that the individual is using the innovation but is not currently concerned about it and may be concerned about other issues. Although 16% of respondents identified themselves as non-users of AI, 84% reported using AI at some level. Because Stage 0 Awareness remained the highest stage of concern for approximately 72% of respondents, that could indicate that many educators displaying high Stage 0 concerns were already using AI. Therefore, for most participants, high Awareness scores appear to reflect limited concern with AI integration rather than a complete absence of AI use. These results indicate that AI is still a relatively new educational innovation for many teachers, with most participants still trying to understand the technology rather than focusing on its implementation, its impact on student learning, or concerns about working with others.

According to the developmental assumptions of the Concerns-Based Adoption Model, individuals encountering an innovation typically progress from self-oriented concerns, such as Awareness/Unconcerned and Information, to task-related concerns involving implementation, and eventually to impact-related concerns focused on student outcomes (Consequence) and working with others (Collaboration). While this study presents a snapshot in time, the concern profiles observed closely reflected this pattern. Rather than indicating resistance to AI, the predominance of Awareness and Informational concerns suggests that many educators remain in the earliest stages of understanding a rapidly emerging innovation.

The predominance of Informational concerns as the second-highest stage provides additional evidence supporting the assumptions of the Concerns-Based Adoption Model. Rather than remaining fixed in Stage 0 - Awareness, many educators appear to be moving toward a desire to learn more about AI. This progression suggests curiosity rather than resistance and reflects the natural sequence of concern proposed by Hall and colleagues.

The absence of respondents whose highest stage was Management or Consequences suggests that relatively few educators had progressed to concerns with the day-to-day logistics of AI implementation or its effects on student learning. According to the SoCQ manual, these stages usually emerge after individuals have gained sufficient experience using an innovation. Given the relatively recent emergence of generative AI in schools, this finding is consistent with expectations that most educators remain in earlier stages of adoption.

Although only a small proportion of respondents reported Collaboration and Refocusing as their highest stages of concern, these profiles could be especially noteworthy. The SoCQ manual describes high Collaboration concerns as characteristic of educators interested in coordinating implementation with colleagues; while Refocusing concerns reflect individuals who are already considering improvements or options to the innovation (George et al., 2006). The results show that a small group of educators within the district had progressed beyond initial implementation and were beginning to think strategically about the future use of AI in teaching and learning.

An additional finding emerged from the profile interpretation analysis. Approximately 9% of respondents demonstrated a Stage 6 tailing-up pattern following a dominant Stage 0 profile. The SoCQ manual (George et al., 2006) suggests that this pattern may indicate that respondents already possess alternative ideas regarding the innovation and, in some cases, may be resistant to its proposed implementation. In the context of AI, however, this finding may reflect the quickly evolving nature of generative AI technologies. Rather than resisting AI altogether, these educators may already have developed preferences for alternative AI tools, instructional approaches, or implementation strategies. Future research ought to explore whether Stage 6 tailing-up among AI users reflects resistance, innovation, or both.

These findings closely align with prior Concerns-Based Adoption Model research that describes AI adoption as an emerging innovation. Consistent with Alm and Ohashi (2024), Fan and Zhao (2023), and Hur (2024), most educators in this study demonstrated early-stage concerns centered on Awareness and Informational, rather than on classroom implementation or student impact. These results indicate that although AI has become highly visible in education, many educators are still in the early readiness phase described within the CBAM framework.

These findings also align with the broader AI in Education literature, which shows that educators are in the early stages of AI adoption and wish to seek greater understanding of AI technologies before fully integrating them into instruction (Chounta et al., 2022; Kaplan-Rakowski et al., 2023; Hur, 2024). Similarly, Fan and Zhao (2023) reported that teachers were mostly concerned with understanding AI and determining proper implementation strategies rather than focusing on instructional refinement or student outcomes. The studies cited in Chapter 2 and the findings of this study suggest that AI integration into education remains an emerging educational innovation requiring continued educator support.

Overall, these outcomes indicate that educators vary in their readiness to integrate AI into teaching and learning. Rather than reflecting simple acceptance or resistance, teachers' concerns span a readiness continuum, as outlined by the Concerns-Based Adoption Model. Most educators remain in the early phases of awareness and information-seeking, while a smaller group has advanced toward collaboration, refinement, and planned implementation. These results illustrate the utility of CBAM in understanding educators' responses to AI and suggest that professional learning initiatives should be developed to support educators' progression through the various stages of concern, rather than assuming uniform preparedness for AI implementation.

Discussion of Research Question 2

The second research question examined whether educators' stages of concern differed according to educator characteristics. Overall, relatively few differences were seen across traditional demographic variables, including age, sex, years of teaching experience, grade level, and subject area. These outcomes closely correspond to the Concerns-Based Adoption Model and the SoCQ manual (George et al., 2006), which note that standard demographic characteristics have historically shown limited relationships with stages of concern. Hall et al. (2006) argued that "there have been no outstanding relationships between standard demographic variables and Stages of Concern data," implying instead that an individual's relationship to the innovation is more influential than demographic characteristics alone.

The absence of meaningful demographic differences provides additional support for one of the central assumptions of the CBAM framework- that concerns develop primarily as a function of individuals' experience with an innovation rather than demographic characteristics. These outcomes are consistent with Hall et al.'s assertion that programs and implementation experiences are stronger predictors of concerns than age, gender, or years of teaching experience.

The present study provides additional support for this proposition within the context of artificial intelligence in education.

Although demographic characteristics showed relatively weak associations with stages of concern, educators' experience with AI was consistently associated with more advanced profiles of concern. Educators with greater AI experience reported significantly different Awareness-, Informational-, and Collaboration-related concerns than those with less AI experience. These data show that an educator's stage of concern is influenced less by who educators are than by where they are in their experience with the innovation. These findings closely mirror the findings of the literature review studies, such as Viberg et al. (2024), who reported that educators' understanding of AI and prior experience were stronger predictors of positive perceptions than traditional demographic variables such as age or gender. Similarly, Nazaretsky et al. (2022) argued that one of the most critical factors influencing teachers' willingness to adopt AI technologies is trust. The literature review findings showed that trust in using AI in education is shaped not only by teachers' understanding of AI, but also by their self-efficacy, or confidence in their ability to use and discuss AI tools effectively. Teachers with greater AI self-efficacy and quotidian understanding of AI tend to perceive more benefits and express fewer concerns (Viberg et al., 2024). Therefore, rather than demographic characteristics, educators' experience with AI – both formal training and how much they report using it - appears to shape their readiness for implementation.

Surprisingly, formal AI training demonstrated relatively modest relationships with stages of concern. Although educators who had received AI training reported significantly greater personal concerns, training was not associated with significant differences across the remaining stages of concern. One possible explanation is that professional development related to AI often consists of isolated workshops or introductory sessions rather than sustained opportunities for implementation and reflection. Within the Concerns-Based Adoption Model, educators progress through stages of concern as they gain experience using an innovation over time rather than through a single exposure (George et al., 2006). Consequently, short-term professional development may increase awareness of AI without substantially advancing educators toward later stages characterized by collaboration, student impact, and refinement of practice. This result suggests that a single professional development experience may increase educators' awareness of the personal implications of AI implementation without necessarily advancing them through later stages of concern. Consistent with CBAM, concern development may require sustained experience with an innovation rather than isolated training opportunities.

As hypothesized in the Concerns-Based Adoption Model, the user's stage appears to be significantly more important than standard demographic variables in determining how the user will respond to an innovation. The findings of this study closely align with previous CBAM research demonstrating that educators' concerns are shaped more by their experiences with an innovation than by demographic characteristics. George et al. (2006) noted that age, gender, and years of experience have historically demonstrated limited relationships with stages of concern, whereas an individual's experience with the innovation is a much stronger predictor of responses to educational change. The present findings extend this conclusion to the context of artificial intelligence, suggesting that educators' experiences with AI are more influential than demographic characteristics in shaping their concerns regarding AI integration. Accordingly, professional learning initiatives should focus less on demographic differences and more on assisting educators as they progress through successive stages of concern.

These findings support recommendations in the AI-in-Education literature that professional development should emphasize AI literacy, practical classroom applications and opportunities for educators to gain authentic experience with AI technologies.

Viberg et al., (2024) claimed that improving educators' understanding of AI fosters greater trust and more positive perception of AI, while Hur (2024) concluded that professional development should focus on building educators' confidence and practical competence with AI, instead of assuming that demographic characteristics determine readiness for adoption. The findings of this study support the findings of the literature review: implementation efforts should emphasize the importance of AI literacy, authentic implementation experiences, ongoing professional learning as well as prioritizing educators' readiness and experience rather than traditional demographic characteristics (George et al., 2006; Hur, 2024; Viberg et al., 2024).

Discussion of Research Question 3

The third research question examined the relationship between educators' stages of concern and their perceptions of AI. Overall, the data show that perceptions of AI became increasingly positive depending on how advanced their stage of concern. Within the stages of Information, Management, and Collaboration, educators have stronger beliefs that AI could positively influence student learning and provide meaningful instructional benefits. This evidence could suggest that positive perceptions of AI develop alongside increasing experience and engagement with the innovation, rather than precede them.

Collaboration consistently revealed the strongest relationships with educators' perceptions of AI. Educators who expressed a greater inclination toward collaborating with colleagues on AI implementation were substantially more likely to perceive AI as beneficial for student learning and instruction. Within the CBAM framework, Collaboration represents a shift from self-centered concerns to concerns focused on improving implementation with others. Educators' recognition of AI's potential learning benefits had the strongest correlation with the Collaboration: this result suggests that once educators begin engaging with colleagues about AI, they may become better positioned to recognize its instructional potential.

The strong relationship between Collaboration concerns and positive perceptions of AI also reflects prior research emphasizing the importance of professional learning communities and collaborative exploration when implementing AI technologies (Fan & Zhao, 2023; Karakose & Tülübas, 2024), which argued that educators develop greater confidence and instructional competence when AI implementation occurs collaboratively rather than individually.

Consequence concerns demonstrated a particularly interesting pattern. Instructors with stronger Consequence concerns were more likely to perceive AI as beneficial. Simultaneously, instructors with stronger Consequence concerns were more likely to express greater concern regarding plagiarism and assessment. This evidence suggests that educators who have progressed to thinking about AI's effects on students do not adopt purely negative views of the technology. Rather, they appear to develop increasingly balanced perspectives that acknowledge both the potential benefits and risks of AI integration.

Analysis of elevated concern profiles further supported the correlated findings. Educators demonstrating only Awareness concerns generally reported lower perceptions of AI's instructional benefits than the educators possessing more advanced concern profiles. Participants whose elevated concern profiles included Collaboration, Personal, Refocusing, or multiple advanced stages consistently reported more favorable perceptions of AI across several measures of instructional benefit. The results could suggest that the more exposure educators have to AI in Education, and therefore an elevated stage of concern, the more positive their perceptions of AI.

The results of Research Question 3 suggest that educators' perceptions of AI are closely linked to their readiness for AI integration. As seen in the literature review, beyond trust and self-efficacy, several studies underscore the influence of perceived ease of use, workload, and institutional support in shaping teacher attitudes. For example, real-world integration of adaptive learning platforms has been associated with teachers' perceptions of ownership, ease of use, and access to community support (Cukurova et al., 2023). Teachers who believe that AI tools align with their pedagogical values and reduce their cognitive load are more inclined to adopt such technologies (Al Darayseh, 2023; Ayub et al., 2015).

Rather than expressing fixed or polarized attitudes toward technology, perceptions of AI evolve as educators acquire experience, move through successive stages of concern, and become more engaged in implementation. This supports prior literature stressing the importance of professional learning communities, AI literacy, and joint implementation in building teacher confidence and trust in AI technologies. These outcomes also correspond to Research Question 2, indicating that perceptions of AI are more strongly associated with an educator's position on the stage of concern continuum than with traditional demographic characteristics.

The open-ended findings supported the quantitative findings. When asked to describe the advantages of AI in education, participants most frequently identified reductions in teacher workload, opportunities for differentiation and personal learning, support for lesson planning, and increased pupil engagement. One participant described AI simply as "less time creating lesson plans." These themes closely mirror the constructs examined quantitatively with the perceived advantages and student learning measures. Participants also described AI as a useful means for generating instructional ideas, increasing creativity, and providing individualized feedback for students, with one educator stating, "AI helps me differentiate assignments much faster."

These qualitative findings support previous research describing AI's instructional advantages. Participants most frequently identified reductions in teacher workload, support for lesson planning, differentiation and increased student engagement, all of which have been repeatedly identified as major benefits of AI in education (Ayeni et al., 2024; Chounta et al., 2022; Durak et al., 2024; Wang et al., 2024). Likewise, Alm and Ohashi (s0s4) found that educators viewed AI as valuable for generating instructional materials and supporting individualized learning.

These outcomes carry important ramifications for professional learning. Efforts to improve educators' perceptions of AI may be more successful when they focus on where teachers are in the stages of concern, rather than attempting to persuade educators of AI's value. As teachers become more informed, collaborate with colleagues, and gain implementation experience, positive perceptions of AI may develop naturally as part of the adoption process.

Interestingly, many of the benefits identified through the content analysis reflected practical classroom applications rather than abstract technological advantages. This finding further supports the conclusion that educators who report being in a more advanced stage of concern increasingly view AI as a tool that can improve instructional practice and student learning when used prudently.

Discussion of Research Question 4

The fourth research question examined the relationship between educators' stages of concern and both their adoption of AI and their perceptions of AI-related challenges. Regarding adoption, educators demonstrating stronger Informational, Management, and Coordinative concerns were significantly more likely to report that they would adopt AI tools designed specifically for educators. These data suggest that educators become increasingly willing to integrate AI into instruction as they progress through the stages of concern. Additionally, these findings relate back to the literature review, where previous research showed that the more that teachers are aware of AI, the more often they use it (Kaplan-Rakowski et al.,2023). The study findings, along with the literature review findings, both suggest that professional development should focus on helping educators move from the Awareness (Unconcerned) phase to further stages of concern for AI adoption to occur.

Additionally, the literature review research on human trust in AI has identified several technology characteristics that can help foster trust in AI: tangibility (e.g., physical presence), transparency (e.g., revealing its processes), reliability (e.g., making few mistakes), immediacy behaviors (e.g., responsiveness, adaptiveness, and pre-social behaviors), and anthropomorphism (e.g., human-likeness) (Glikson & Woolley, 2020). According to previous studies as seen in the literature review, if educators are in the discouraging concern phases, they may not be willing to incorporate AI into the classroom until these concerns are addressed (Jong, 2022). Perceived value and ease of integration will help teachers to integrate AI into their teaching practices (Kaplan-Rakowski et al., 2023).

Within the Concerns-Based Adoption Model, these stages represent a progression from simple awareness to active implementation and joint effort, indicating increasing readiness for AI integration. While this study is cross-sectional, this result is consistent with the CBAM assumption that individuals become more engaged with an innovation as they progress through successive stages of concern (George et al., 2006).

Regardless of the stage of Concern, educators generally rated students' use of AI unethically, notably regarding plagiarism, as a substantial challenge associated with AI in education. Mean plagiarism results were consistently high. However, Pearson correlational analyses also indicated that instructors with stronger Personal, Consequence, and Refocusing concerns had substantially greater concerns about unethical AI use and plagiarism than instructors with lower scores on these stages. Taken together, the results may show that while plagiarism worries are nearly universal amongst educators, those who have progressed to later stages of concern may be experiencing these problems more distinctly.

These findings strongly support the literature review, which identified plagiarism and academic integrity as a principal concern of educators' regarding generative AI in education. Kaplan-Rakowski et al. (2023), Alm & Ohashi (2024), and Mohammadkarimi (2023) also reported widespread concern that students are misusing AI to complete assignments without demonstrating authentic learning.

Unlike perceptions of instructional benefits, which became increasingly positive the later the reported stage of concern, apprehension regarding academic integrity appeared to remain consistently high across all stages of concern. Teachers whose concern profiles reflected only Stage 0 Awareness concerns, teachers with more advanced concern profiles, and even those with no elevated concerns all identified plagiarism as a substantial challenge associated with AI. These results indicate that academic integrity represents a shared concern among educators regardless of their stage of concern.

The open-ended responses provided additional context for the results. Academic integrity emerged as one of the most frequently reported challenges, with participants expressing concerns about cheating, plagiarism, and students relying on AI to complete assignments rather than demonstrating their own learning. One educator was cited as saying, "Students use AI as a crutch." Even more frequently, participants described concerns that AI may reduce students' critical thinking and encourage dependence on technology, with one educator stating, "It replaces critical thinking." These themes suggest that educators' concerns extend beyond academic dishonesty to broader questions about authentic learning and cognitive development. The finding that educators were even more concerned about diminished critical thinking than plagiarism closely reflects concerns repeatedly expressed throughout the literature. Previous studies have warned that excessive reliance on AI may reduce students' critical thinking, creativity, problem solving skills and independent learning (Kaplan-Rakowski et al., 202; Mohammadkarimi, 2023; Alm & Ohashi, 2024). The quantitative and qualitative findings along with the review of literature underscore the conclusion that educators view cognitive dependence as one of AI's most significant educational challenges.

Unlike plagiarism and assessment concerns, perceptions regarding AI and equity did not vary according to educators' stages of concern. A third challenge, difficulty in student assessment, was strongly correlated with those educators in the Personal, Consequence, and Refocusing stages.

Although equity did not show statistically significant relationships with stages of concern, a small number of participants nevertheless identified unequal access to AI technologies as a challenge in their open-ended responses. Additional qualitative themes – including privacy, data security, misinformation, deepfakes, and broader ethical issues – illustrate that educators are navigating multiple dimensions of responsible AI implementation. Similarly, concerns regarding privacy, misinformation, deepfakes, and responsible AI use have been identified as recurring implementation challenges throughout the AI-in-education literature (Chounta et al., 2022; Wang et al., 2024). While these challenges were not explicitly examined quantitatively in the present study, their emergence in open-ended responses highlights the broader ethical landscape surrounding AI implementation in education, and they emphasize the complex educational environment in which AI adoption is occurring.

Examination of elevated concern profiles further supported the correlational analyses. Although concern regarding plagiarism was consistently elevated across nearly all concern profiles, educators with more advanced concern profiles generally reported the highest levels of concern regarding plagiarism and assessment. These results indicate that concerns about academic integrity are widespread among educators, while those who have progressed to later stages of concern may perceive these challenges with greater intensity and complexity.

An important qualitative finding that went beyond the quantitative survey was educators' widespread concern that AI may reduce students' independent thinking and increase dependence on technology. Because this concern emerges more frequently than plagiarism in the open-ended responses, future inquiry should examine student cognitive dependence as a distinct dimension of educators' concerns regarding AI integration.

A higher stage of concern appears to alter the nature of both an educator's trepidations and perceived benefits rather than diminish them. As educators acquire experience with AI, their concerns shift from general awareness to increasingly nuanced considerations, including ethical use, assessment, collaboration, benefits for student learning and outcomes, and AI adoption. The open-ended question results reinforce this conclusion. Participants identified numerous instructional benefits – including lowered teacher workload, differentiation, lesson planning, and student engagement – while also expressing major concerns about plagiarism, critical thinking, ethics, and assessment. Rather than viewing AI as either wholly 'good' or wholly 'bad', educators described a balanced perspective that acknowledged both its opportunities and its risks. This merging of quantitative and qualitative findings strengthens the conclusion that educators' responses to AI constitute a process marked by increasingly sophisticated understandings of AI's promise and challenges.

Summary of Findings by Research Question

Table 36. Summary of Findings by Research Question

Research Question	Principal Finding	Literature Review Support	Practical Implication
RQ1	Majority of educators are in Stage 0 – Awareness (Non-user or Unconcerned)	• Chounta et al. (2022) • Fan & Zhao (2023) • Hur (2024) • Kaplan-Rakowski et al. (2023)	Teachers need introductory AI in the classroom and/or general AI literacy
RQ2	Experience was more significant than typical demographics	• Hur (2024) • George et al., 2006 • Kaplan-Rakowski et al. (2023) • Nazaretsky et al. (2022) • Viberg et al. (2023)	Professional Development should be differentiated not by typical demographics (like teaching level or years of experience) but by how much experience with AI.
RQ3	Collaboration had strongest correlation with positive perceptions of AI	• Alm & Ohashi (2024) • Chounta et al. (2022) • Durak et al. (2024) • Fan & Zhao (2023) • Karakose & Tülübas, 2024 • Wang et al. (2024)	Encourage collaborative AI learning communities

RQ4	Advanced Stages of Concern recognize both benefits and challenges	• Alm & Ohashi (2024) • Chounta et al. (2022) • Kaplan-Rakowski et al. (2023) • Mohammadkrimi (2023) • Wang et al. (2024)	Prepare educators for responsible AI implementation

Implications for Educational Leaders

1. Educational leaders should acknowledge that educators possess varying levels of readiness.

A key finding of this study is that educators demonstrate differing levels of readiness for AI integration, necessitating tailored responses from educational leaders. In alignment with the Concerns-Based Adoption Model, educators expressed a range of concerns, with most participants situated in the initial Awareness (Unconcerned) and Informational stages. Districts should avoid assuming uniform professional development needs among teachers. Instead, AI implementation efforts should consider educators' stages of concern and previous experience with AI to deliver differentiated support.

2. Professional development should be differentiated

The findings indicate that professional development should correspond to educators' specific levels of concern, rather than being delivered as a uniform district-wide training session. For instance, educators in the Awareness (Unconcerned) stage may benefit from introductory information about AI, whereas those in the Informational stage may require opportunities to observe AI in classroom contexts. In subsequent stages, professional learning should focus on classroom implementation, present evidence of student learning, and facilitate collaboration among colleagues. Table 5.2 outlines a potential framework for structuring professional development according to educators' stages of concern.

Table 37. Professional Development Recommendations

Stage of Concern	Professional Development Focus	Professional Development: Practical Application
Awareness	What is AI?	Build knowledge of AI through introductory sessions explaining what AI is (and isn't), what it can and cannot do and why this is important in education.
Informational	Demonstrations	Show classroom applications through hands-on examples, lesson demonstrations, opportunities to explore AI tools and examples of how students may be using AI.
Personal	Address fears	Address teacher concerns regarding ethics, job security, academic integrity, confidence and responsible AI use.
Management	Classroom implementation	Provide practical and differentiated implementation strategies, including lesson planning, classroom management, assessment design and integration into day-to-day teacher workload
Consequence	Student learning evidence	Share evidence of AI's positive impact on student learning, engagement, differentiation and instructional effectiveness.
Collaboration	PLC's	Establish Professional Learning Communities (PLC's) and peer mentoring to encourage collaborative exploration and sharing of effective practices.
Refocusing	Innovation	Encourage innovation by empowering experienced educators to pilot new approaches, evaluate emerging tools and mentor colleagues.

Again, the literature review reinforces this recommendation. Studies in Chapter 2 show that professional development emerges as a key lever for increasing teacher trust and reducing misconceptions. Targeted training programs have been shown to improve not only knowledge of AI-powered assessments but also openness to data-informed decision-making and creative classroom integration (Nazaretsky et al., 2021). Similarly, Viberg et al. (2024) and Hur (2024) argued that effective AI professional development should emphasize AI literacy, practical classroom applications, and opportunities for educators to build confidence through authentic experiences.

3. AI implementation should incorporate district standards and policies

Educators across all stages of concern reported significant apprehension regarding ethical AI use, plagiarism, and academic integrity. Educational leaders should prioritize the development of district guidelines that address ethical AI use, academic integrity, assessment practices, student disclosure of AI use, privacy, consequences of unethical use, and responsible digital citizenship. Establishing clear expectations may reduce uncertainty and support educators' readiness for AI.

Similarly, Alm & Ohashi (2024) and Mohammadkarimi (2023) recommend that schools establish clear policies regarding plagiarism, ethical AI use, academic integrity, and responsible classroom implementation, especially as AI evolves in the education setting.

4. AI should be regarded as organizational change rather than solely as technology

The findings, interpreted through the Concerns-Based Adoption Model framework, indicate that successful AI implementation is influenced more by educators' readiness to embrace educational change than by the technology itself. Educational leaders should approach AI as an organizational change initiative rather than exclusively as a technology initiative. School leaders are encouraged to provide ongoing professional learning, opportunities for collaboration, continuous coaching, and time for reflection.

5. AI adoption should be conceptualized as an evolving journey rather than a singular professional development event.

Educators advance through the stages of concern as they integrate innovations such as AI into the classroom. By addressing needs at each stage of concern, school leaders can promote greater confidence, enhanced collaboration, and improved instructional effectiveness while also responding to valid concerns about ethics, assessment, and academic integrity.

Recommendations for Future Research

The findings of this study point to several important directions for future research regarding artificial intelligence in education, including its successful adoption by educators and its positive, ethical use.

First, this study was limited in that it employed a cross-sectional design, providing only a snapshot of educators' concerns about AI integration in education. Future research should employ longitudinal designs to examine how educators' stages of concern evolve over time as artificial intelligence becomes more prevalent in K-12 education. The Concerns-Based Adoption Model (CBAM) conceptualizes concerns as developmental; therefore, longitudinal studies could examine how educators progress through the stages of concern. One benefit of this is that professional training could be appropriately adapted in response to the updated results.

Second, future research could investigate the impact of certain artificial intelligence professional development on educators' stages of concern using a quasi-experimental pretest-posttest design. The study found that educators were primarily in the Awareness (Unconcerned) stage, which includes non-users. Researchers could therefore administer the Stages of Concern Questionnaire, along with accompanying measures of AI-perceived benefits and challenges, and adoption intentions before and after a structured AI professional development program. A comparison group of educators who do not participate in the professional development would allow researchers to determine whether targeted AI training facilitates movement through the developmental stages of concern. Because the present study found that an educator's stage of concern was more closely related to one's experience with AI than to demographic characteristics, this research could provide valuable evidence regarding how targeted professional development supports educators' readiness for AI integration, depending on where they are in the stage of concern. Additionally, differentiated professional development programs could emerge from this research.

Third, this study was conducted within a single public school district in the western United States. Therefore, future studies should replicate this research across multiple school districts, states, and types of schools (rural vs. densely populated, public vs. private, etc.). Replication across diverse educational contexts would strengthen the generalizability of the findings and could identify organizational and contextual factors that influence educators' concerns regarding AI implementation.

Fourth, a limited number of qualitative results were produced in this study through the open-ended questions. However, qualitative and mixed-methods research could provide a deeper understanding of educators' stages of concern and the reasons behind them. The anonymous survey design does not permit follow-up interviews. Future qualitative studies could explore why educators are experiencing their particular concerns, how they have implemented AI into the classroom, and what motivates them to move from one stage of concern to the next. Such research could provide explanations for the quantitative relationships identified in the present study.

Fifth, future research should investigate educators who simultaneously exhibit multiple elevated stages of concern. While traditional interpretation of the Stages of Concern Questionnaire often emphasizes the highest stage of concern, the present study found that many educators exhibited multiple elevated concern profiles. Examining how these complex concern patterns relate to classroom implementation, AI adoption, instructional decision-making, and professional learning may extend current applications of the Concerns-Based Adoption Model and provide a more comprehensive understanding of educators' experiences with emerging educational innovations.

Sixth, our comprehension of the impact of AIEd on student learning and outcomes is only in the very early stages. The adoption of AIEd in K-12 schools is not yet ubiquitous. The dramatic increase in use in schools started in earnest in 2022 with the arrival of open AI tools. Empirical studies on student learning outcomes are lacking (Viberg et al., 2024). Studies on students should also be done to discover their perceptions, concerns and uses. If AI indeed has a net positive impact on student learning, and this can be demonstrated through research, educators will most likely be more open to integrating AI into the classroom.

Finally, future research should continue exploring the concept of educators' readiness for AI integration, since the current study is a cross-sectional design, which quantified educators' concerns at a moment in time rather than over time. The findings of the present study suggest that educators' perceptions of AI, willingness to adopt AI, and recognition of implementation challenges evolve alongside their stages of concern. A future longitudinal methodological approach could examine how developmental readiness interacts with educators' AI knowledge, instructional practices, professional learning experiences, and leadership support. Such work has the potential to extend the application of the Concerns-Based Adoption Model to generative artificial intelligence and other rapidly emerging educational innovations while informing the design of more effective implementation strategies for schools and districts.

The current study is the foundation upon which these recommendations for further research could be built. As AI continues to evolve, research based on the Concerns-Based Adoption Model can assist both educational practice and implementation theory, which can ultimately support more effective, practical and responsible integration of AI in K-12 education.

Limitations of Research

Single School District

This study was conducted within a single public, rural-designated school district in the western United States. Organizational culture, district policies, and professional learning opportunities, including those related to AI, vary across districts and states.

Cross-sectional Design

As data were collected at a single point in time, the study provides only a snapshot of educators' concerns regarding AI, rather than capturing how these concerns change over time. To fully leverage the Concerns-Based Adoption Model, which conceptualizes concerns as developmental, a longitudinal approach would be preferable for examining how educators progress through the stages of concern as AI becomes more integrated into education.

Self-report Data

Educators self-reported their perceptions of AI use, benefits, challenges, and adoption. As with all self-report instruments, responses may have been influenced by recall bias or by participants' interpretations of survey items.

Rapidly Changing AI Environment

Artificial Intelligence is advancing at an unprecedented rate. AI tools, school policies, educator adoption, student use, and professional development opportunities are all evolving rapidly. Educators' stages of concern are likely to change as AI technologies become more widespread and integrated into educational settings.

Anonymous Survey

Because responses were collected anonymously, individual follow-up interviews could not be conducted. The Stages of Concern Questionnaire manual indicates that results can be interpreted at both the group and individual levels. However, anonymity limited the ability to investigate why specific educators exhibited particular profiles of concern.

Quantitative Design

This study used quantitative techniques and analyses to identify significant relationships among stages of concern, perceptions, and AI adoption. However, qualitative research could offer a deeper understanding of how educators are responding to AI in education.

Standards Around AI Use

This study's findings suggest that school districts and leaders should lay out clear expectations for responsible AI use by both teachers and students. Respondents in the study overall identified academic integrity, ethical use, assessment, and student over-reliance as serious concerns. Educational leaders should develop AI literacy policies that define appropriate classroom practices, clarify what constitutes plagiarism, set expectations for student disclosure of AI use, and outline assessment practices and responsible digital citizenship.

Conclusion

Since the introduction of OpenAI's generative Artificial Intelligence in 2022, the educational landscape has undergone rapid transformation. Educators have been at the forefront of this innovation, addressing both its opportunities and the significant challenges it presents in classroom settings. Therefore, it is essential to systematically examine educators' concerns regarding AI in education to ensure effective classroom implementation. Using the Concerns-Based Adoption Model (CBAM) as a framework, this study analyzed the stages of concern reported by K-12 educators, both collectively and by specific educator characteristics. The study also explored educators' perceived benefits and challenges of AI, as well as their intentions to adopt these technologies.

The results indicate that most educators remain in the early stages of concern, with Awareness concerns being most prevalent, followed by Informational concerns. Cautiously, one can compare the results of this study to outcomes typically seen within the CBAM framework, which consistently demonstrates that educators progress through stages when adopting new innovations. Furthermore, the study found that experience with Artificial Intelligence was more influential on perceived benefits, challenges, and readiness to adopt AI than traditional demographic factors such as age or years of teaching experience. As educators advanced to later stages of concern, they reported more favorable perceptions of AI's instructional benefits and a reduction in teacher workload, as well as a greater willingness to adopt AI tools for educational purposes. Despite these positive trends, most educators, regardless of their stage of concern, expressed apprehension about ethical use, plagiarism, and the impact of AI on students' critical thinking abilities. Notably, educators in more advanced stages of concern reported even greater worries, suggesting that they may be confronting these issues more directly than those in the Awareness stage.

The primary contribution of this study is the demonstration that educators' responses to AI cannot be characterized merely as acceptance or resistance. Rather, educators' concerns evolve as they acquire greater knowledge and experience with AI. Both quantitative and qualitative findings illustrate that educators recognize AI's potential to reduce teacher workload, support differentiated instruction, and enhance learning outcomes, while simultaneously expressing concerns about plagiarism, critical thinking, assessment, and ethical considerations. Consequently, the integration of AI should be conceptualized as an organizational change process rather than simply the adoption of a new technology.

There are important implications for educational leaders responsible for implementing AI initiatives or developing AI use policies. Rather than providing uniform professional development for all educators, school leaders should recognize that educators are in different stages of concern regarding the use of AI in education. During this period of rapid innovation and adoption, school leaders should provide professional development opportunities, district policies, and implementation strategies designed to address educators' evolving concerns. A professional training for an educator in the Awareness stage should not look like a professional training for an educator in the Collaboration stage, for example. The research here suggests that supporting educators in this way will lead to more effective, ethical, and positive AI integration into the classroom.

The findings of this study closely align with the rapidly expanding body of literature examining AI in education while extending previous work through the application of the Concerns-Based Adoption Model to K-12 educators' readiness for AI integration.

Artificial Intelligence is evolving, and educators' concerns will evolve with it. By applying the Concerns-Based Adoption Model to the emerging field of artificial intelligence in education, this study contributes to the growing body of knowledge regarding implementation in K-12 education. This study also aims to provide educational leaders with strong guidance in supporting educators as they navigate one of the most significant educational innovations of the twenty-first century.

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Appendix

Table 38. Adapted SoCQ Questionnaire and Additional Demographic Questions

The items were developed from typical responses of school and college teachers who ra
from no knowledge at all about various programs to many years' experiences using them
Therefore, many of the items on this questionnaire may appear to be of little relevance o
irrelevant to you at this time. For the completely irrelevant items, please circle "0" on the
Other items will represent those concerns you do have, in varying degrees of intensity, a
should be marked higher on the scale.

For example:

This statement is very true of me at this time.	0	1	2	3	4	5	6	7
This statement is somewhat true of me now.	0	1	2	3	4	5	6	7
This statement is not at all true of me at this time.	0	1	2	3	4	5	6	7
This statement seems irrelevant to me.	0	1	2	3	4	5	6	7

Please respond to the items in terms of your present concerns, or how you feel about yo
involvement with AI in Education. We do not hold to any one definition of AI in Education
please think of it in terms of your own perception of what it involves. Phrases such as "th
approach" and "the new system" all refer to AI in Education. Remember to respond to ea
in terms of your present concerns about your involvement or potential involvement with t
Education.

Thank you for taking time to complete this task.

1. I am concerned about students' attitudes toward AI.	0	1	2	3	4	5	6	7
2. I now know of some other approaches that might work better.	0	1	2	3	4	5	6	7
3. I am more concerned about another innovation besides AI.	0	1	2	3	4	5	6	7
4. I am concerned about not having enough time to organize myself each day.	0	1	2	3	4	5	6	7

5. I would like to help other faculty in their use of AI.	0 1 2 3 4 5 6 7
6. I have a very limited knowledge of AI.	0 1 2 3 4 5 6 7
7. I would like to know the effect of AI on my professional status.	0 1 2 3 4 5 6 7
8. I am concerned about conflict between my interests and my responsibilities.	0 1 2 3 4 5 6 7
9. I am concerned about revising my use of AI.	0 1 2 3 4 5 6 7
10. I would like to develop working relationships with both our faculty and outside faculty using AI.	0 1 2 3 4 5 6 7
11. I am concerned about how AI affects students.	0 1 2 3 4 5 6 7
12. I am not concerned about AI at this time.	0 1 2 3 4 5 6 7
13. I would like to know who will make the decisions concerning AI.	0 1 2 3 4 5 6 7
14. I would like to discuss the possibility of using AI.	0 1 2 3 4 5 6 7
15. I would like to know what resources are available if we decide to adopt AI.	0 1 2 3 4 5 6 7
16. I am concerned about my inability to manage all that AI requires.	0 1 2 3 4 5 6 7
17. I would like to know how my teaching or administration is	0 1 2 3 4 5 6 7

supposed to change.

18. I would like to familiarize other departments or persons with the progress of AI.	0	1	2	3	4	5	6	7
19. I am concerned about evaluating my impact on students.	0	1	2	3	4	5	6	7
20. I would like to revise AI's approach.	0	1	2	3	4	5	6	7
21. I am preoccupied with things other than AI.	0	1	2	3	4	5	6	7
22. I would like to modify our use of AI based on the experiences of our students.	0	1	2	3	4	5	6	7
23. I spend little time thinking about AI.	0	1	2	3	4	5	6	7
24. I would like to excite my students about their part in this approach.	0	1	2	3	4	5	6	7
25. I am concerned about time spent working with nonacademic problems related to AI.	0	1	2	3	4	5	6	7
26. I would like to know what the use of AI will require in the immediate future.	0	1	2	3	4	5	6	7
27. I would like to coordinate my efforts with others to maximize AI's effects.	0	1	2	3	4	5	6	7

28. I would like to have more information on time and energy commitments required by AI.	0 1 2 3 4 5 6 7
29. I would like to know what other faculty are doing in this area.	0 1 2 3 4 5 6 7
30. Currently, other priorities prevent me from focusing my attention on AI	0 1 2 3 4 5 6 7
31. I would like to determine how to supplement, enhance, or replace AI.	0 1 2 3 4 5 6 7
32. I would like to use feedback from students to change the program.	0 1 2 3 4 5 6 7
33. I would like to know how my role will change when I am using AI.	0 1 2 3 4 5 6 7
34. Coordination of tasks and people is taking too much of my time.	0 1 2 3 4 5 6 7
35. I would like to know how AI is better than what we have now.	0 1 2 3 4 5 6 7
36. I am more likely to use AI tools that are specifically designed for educators.	0 1 2 3 4 5 6 7
37. I believe that using AI in the classroom will increase student motivation.	0 1 2 3 4 5 6 7

38. I believe that using AI in the classroom will increase student's ability to think independently. 0 1 2 3 4 5 6 7

39. I believe that responsible use of AI can increase student engagement with course content. 0 1 2 3 4 5 6 7

40. I believe students learn more effectively when using AI tools in class. 0 1 2 3 4 5 6 7

41. I believe students are using AI unethically (e.g., plagiarism) 0 1 2 3 4 5 6 7

42. I see AI as a valuable tool to help differentiate instruction based on student needs. 0 1 2 3 4 5 6 7

43. I believe that a challenge with AI tools is that they are not equitable across student populations (e.g., access, digital literacy). 0 1 2 3 4 5 6 7

44. I believe that an advantage of AI tools is that they can reduce teacher workload by automating routine tasks. 0 1 2 3 4 5 6 7

45. I believe that a challenge with AI tools is that it makes it difficult to assess student learning. 0 1 2 3 4 5 6 7

46. What do you see as the main advantages of using AI tools in K-12 education? (Ex: student learning, teacher workload, differentiation or other factors.)

47. What concerns or challenges do you associate with integrating AI tools into your teaching practice? (Ex: You may consider issues related to ethics, effectiveness, student behavior or equity)

48. What AI tools are you actively using in your teaching practice?

__ Chat GPT

__ School AI,

__ MagicSchoolAI,

__ Grammarly,

__ GPTZero,

__ Other

__ I do not use AI in my teaching practice

DEMOGRAPHIC QUESTIONS:

49. Age

__ 18-24

__ 25-34

__ 35-44

__ 45-54

__ 55-64

__ 65+

51. How many years have you been teaching?

__ 0-3 years

__ 4-6 years

__ 7-10 years

__ 11-15 years

__ 16-20 years

__ 21+ years

52. How would you self-report your comfort level with new technology?

__ Very uncomfortable

__ Somewhat uncomfortable

__ Neutral/ Neither comfortable nor uncomfortable

__ Comfortable

__ Very comfortable

53. What level do you teach?

__ Elementary

__ Middle School (6th through 8th)

__ High School

53B. If Middle or High School, what subject(s) do you teach:

__English Language Arts

__STEM (Science, Technology, Engineering, Math)

__Other

54. How long have you been using AI in your teaching practice, not counting this school year?

___Never

___ 1 year

___2 years

___3 years

___4 years

___5 years or more

55. In your use of the AI in education, do you consider yourself to be a:

___Non-user

___ Novice

___Intermediate

___Old Hand

___Past User

56. Have you received formal training regarding AI in education (workshops, courses)?

___ Yes

___ No