An Interpretive Descriptive Study of Curriculum Developers' Experiences Integrating AI in Technology-Driven Fields

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Abstract

Educational institutions in technology-driven fields face challenges with lengthy curriculum update cycles, resulting in outdated content and graduates ill-prepared for industry demands. This qualitative interpretive descriptive study explored curriculum developers' experiences and perceptions regarding integrating artificial intelligence tools into development processes. The conceptual framework integrated constructivism, connectivism, cognitive load theory, and adaptive learning theory. Ten curriculum developers from higher education, corporate, and military training sectors participated. Data were collected through semi-structured interviews and analyzed using thematic analysis via NVivo software. Key findings revealed that integrating artificial intelligence reduced development timelines by 40% to 50% through the automation of routine tasks. However, participants identified trade-offs regarding content accuracy, necessitating robust quality assurance processes and validation by subject matter experts. While developers perceived these tools as valuable for aligning curricula with evolving industry standards, they emphasized the necessity of human decision-making to balance efficiency with pedagogical creativity. Implications for practice highlight the need for hybrid development models leveraging automation for speed while relying on human expertise for quality control and innovation. Recommendations include establishing institutional guidelines for ethical use and providing professional training to optimize the integration of artificial intelligence in curriculum design, ultimately bridging the gap between education and workforce requirements.

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Finally, to my parents. In loving memory of my father, Eddie Buchko: thank you for instilling the work ethic that taught me to never surrender to the pressures of life. To my mother, Kum Ok: thirty-one years ago, I bypassed college for the military, claiming I didn't want to go to school. It took time, but your consistent push has been a hidden driver in reaching this pinnacle. I love you both.

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Section 1: Foundation

Integrating artificial intelligence (AI) into educational practices has emerged as a transformative force, reshaping curriculum design and development. As academic institutions face pressure to deliver relevant, cost-effective, and efficient learning experiences, AI offers a promising solution to enhance relevancy, reduce costs, minimize time requirements, and optimize workforce allocation. Historically, curriculum development relied on manual processes that averaged 12–18 months, often yielding outdated content by implementation (Kamalov et al., 2023; World Economic Forum, 2019). The school begins rolling out new and updated courses and textbooks a year or two later. Nevertheless, by the time students take their first classes under the new protocol, several years have passed since the committee was first formed, and the new curriculum already shows signs of being outdated (World Economic Forum, 2019). Institutions have experimented with non-AI solutions like modular curricula and industry partnerships. For example, competency-based frameworks at Western Governors University aimed to align skills with workforce needs but struggled with scalability and faculty workload (Edmondson, 2024). Learning management systems (LMS) digitized delivery, leaving design inefficiencies (Alameen & Dhupia, 2019). These efforts highlight persistent gaps in speed and adaptability that AI now targets (Wilson, 2023). Today, AI enables dynamic, responsive content tailored to 21st-century learners (Filipsson, 2024).

The consequences of traditional inefficiencies are stark. Students face employability challenges, with 74% of employers citing skill gaps in graduates (Manpower Group, 2025), and National Center for Education Statistics (NCES, 2024) data showing a 25% underemployment rate among recent graduates. Institutions bear financial burdens, with development costs of $6,740 – $33,360 per hour of eLearning content (Movchan, 2024), while faculty report burnout, with 53% considering quitting due to burnout and workload (Rock, 2024). Society suffers as an underprepared workforce slows economic progress (Edmondson, 2024). AI can revolutionize this process by automating tasks, providing data-driven insights, and creating personalized learning pathways.

AI's data analysis capabilities—examining student performance, trends, and feedback—inform curriculum decisions (Dong et al., 2023). Automation of content curation and assessments frees educators from teaching (U.S. Department of Education, 2023), reducing timelines significantly. AI also aligns curricula with emerging industry needs, preparing students for an AI-driven job market (Fang & Broussard, 2024). Adaptive systems enhance outcomes by tailoring content to individual learners (Robertson, 2024), addressing stakeholder needs: students gain skills, faculty reduce workload, employers hire capable graduates, and institutions optimize resources.

Statement of the Problem

The problem that was addressed by this research was the issue of lengthy curriculum update cycles (12–18 months) in tech-driven fields, which leave graduates unprepared for current industry needs (Kamalov et al., 2023; World Economic Forum, 2019). This systemic delay correlates with a 25% underemployment rate among recent graduates due to skill mismatches, compounded by 74% of employers reporting critical skill gaps in new hires (Manpower Group, 2025; NCES, 2024). While AI offers the potential to streamline this process, there is a lack of understanding about how curriculum developers experience and perceive the integration of AI tools into developers' workflows (Kamalov et al., 2023). Scholars such as Kamalov et al. (2023), Dong et al. (2023), and Nguyen (2024) have called for further research into the practical integration of AI tools in curriculum development, particularly emphasizing the need to understand curriculum developers' experiences to overcome adoption barriers and enhance educational efficiency. This gap hinders effective adoption, and this study explored these experiences to identify barriers and strategies for successful implementation.

While I was originally focused on Navy schools, these challenges appear to mirror issues in other high-stakes, technology-driven educational settings. These inefficiencies perpetuate three key consequences: (a) student disengagement due to misalignment between coursework and real-world applications; (b) institutional strain, as 69% of faculty cite unsustainable workloads for curriculum updates (ALCHEMY, 2024); and (c) economic stagnation from a workforce lacking AI literacy and technical competencies (NCES, 2024). While AI demonstrates the potential to streamline design timelines through rapid prototyping and adaptive systems (Paiiwai et al., 2024), its capacity to enhance workforce alignment remains understudied. Current research has identified that there is a critical gap between what AI in education (AIEd) technologies could do and how they are implemented in authentic educational settings (Zhang & Aslan, 2021).

Purpose of the Study

The purpose of this qualitative interpretive descriptive study was to explore the experiences and perceptions of curriculum developers in technology-driven academic fields regarding the integration of AI tools into their curriculum development processes. This study addressed the problem of prolonged curriculum update cycles (12–18 months) in tech-driven fields, which often leaves graduates unprepared for current industry demands, as highlighted by Kamalov et al. (2023) and the World Economic Forum (2019), while responding to research questions about balancing development timelines with content quality, aligning curricula with industry standards, and managing tensions between efficiency and innovation. The study involved semi-structured interviews with 10 curriculum developers, selected via purposive sampling to ensure experience with AI tool use, conducted either in person or via online conferencing software, with pseudonyms protecting participant confidentiality. Participants were recruited using public domain social media sites (e.g., Facebook, LinkedIn). Participants were also able to forward requests to others interested in the study for their potential participation using exponential discriminative snowball sampling. Snowball sampling is a special non-probability method for developing a research sample where existing study subjects recruit future subjects from among their acquaintances (Anieting & Mosungu, 2017). Data were collected through audio-recorded interviews, transcribed, and analyzed using thematic analysis in NVivo software, following Braun and Clarke's (2006) six-step process: (a) familiarizing with the data by immersion in transcripts, (b) generating initial codes to identify patterns, (c) searching for themes by grouping codes, (d) reviewing themes for coherence, (e) defining and naming themes to capture their essence, and (f) writing the report to present findings. Key variables included perceptions of AI tool efficiency, curriculum quality, and industry alignment. This study contributed to educational practice by providing actionable insights into leveraging AI tools to streamline curriculum development, shorten updating timelines, and enhance graduate preparedness, thus bridging the education-employment gap in technology-driven education.

Research Questions

RQ1

How do curriculum developers in technology-driven fields describe their experiences balancing development timelines and content quality when integrating AI tools into curriculum design?

RQ2

What perceptions do curriculum developers hold regarding aligning AI-integrated curricula with industry standards, and how do these perceptions influence their content development strategies?

RQ3

How do curriculum developers navigate between efficiency (e.g., AI-driven automation) and innovation in their curriculum design processes?

Theoretical Framework

The conceptual framework integrated constructivism, connectivism, cognitive-load theory, and adaptive learning theory to provide a comprehensive foundation for understanding AI's role in enhancing curriculum development, particularly in technology-driven fields. These theories were selected collectively for their complementary strengths: constructivism emphasizes learner-centered knowledge construction, connectivism addresses networked learning in the digital age, cognitive load theory optimizes information processing, and adaptive learning theory enables personalized educational experiences. Together, they formed a robust framework to explore how AI addressed challenges faced by curriculum developers in creating effective, adaptive, and efficient learning environments.

Constructivism and social constructivism theories, developed by Jean Piaget and Lev Vygotsky, emphasize that learners construct knowledge through experiences and social interactions. This originated with Piaget's (1954) work on cognitive development, highlighting individual knowledge construction through experiences, and was extended by Vygotsky (1978) to include social interactions, influencing modern educational practices. AI-enhanced curriculum design and constructivism principles are supported through the creation of personalized, adaptive, and enhanced learning paths that cater to individual student needs and prior knowledge (Grubaugh et al., 2023). According to Kovari (2025), AI-powered platforms facilitated collaborative learning by connecting learners and enabling interactive experiences. Additionally, AI provides real-time feedback and adaptive content that scaffolds knowledge construction (Bai et al., 2024; Jaramillo & Chiappe, 2024), allowing learners to build upon their existing understanding in a structured manner.

Adaptive learning theory is a time-tested theory, credited to B.F. Skinner (1968) and evolved from early educational psychology, with Skinner's teaching machines in the 1950s; the theory gained traction in the 1970s with AI, focused on personalized learning at scale (David, 2024). AI-powered adaptive learning systems can dynamically adjust instructional content and pacing based on real-time assessments of learner performance and preferences. This alignment with the study's objectives underscores the potential of AI to enhance both the efficiency and effectiveness of curriculum development and delivery.

Cognitive load theory, developed by John Sweller (1988), focuses on managed cognitive load for effective learning, evolving with research on working memory and instructional design. This theory addresses the limitations of working memory (Gkintoni et al., 2025) and the importance of managing cognitive load to facilitate effective learning. In AI-assisted curriculum design, this theory is applied by using AI to break down complex tasks into smaller, more manageable components, thereby reducing the cognitive burden on the learner (Gkintoni et al., 2025). AI-driven adaptive learning systems can further optimize cognitive load by automatically adjusting the difficulty and presentation of instructional materials based on the learner's progress (Sweller, 2020). Additionally, AI tools can provide just-in-time information and immediate feedback, minimize extraneous cognitive load, and allow learners to focus on essential learning activities.

Connectivism theory, proposed by George Siemens (2005), is particularly relevant to learning in the digital age, as it emphasizes that learning occurs through connections with networks. This theory acknowledges the rapid pace of knowledge changes and the necessity for learners to stay connected to current information and resources (Alam, 2023). Connectivism emerged in 2004 as a response to digital age learning needs, focusing on networked learning through technology, gaining traction with online and social media education. In the context of curriculum development for advancing technological fields that operate in dynamic and ever-changing environments, connectivism underscores the importance of leveraging technology to facilitate continuous learning and knowledge updates. AI plays a crucial role in this framework by enabling networked learning, connecting learners to vast repositories of information, and even serving as a node in the learning network where knowledge can reside.

Combining constructivism's emphasis on learner-centered design with connectivism's focus on networked learning and leveraging cognitive load theory to optimize information processing alongside adaptive learning theory, this conceptual framework provided a multifaceted approach to integrating AI into curriculum development. Each theory contributed uniquely; constructivism ensured that learning was active and personalized (Grubaugh et al., 2023), connectivism highlighted the importance of technology-mediated connections (Downes, 2020), cognitive load theory guided the design of instruction to maximize learning efficiency (Gkintoni et al., 2025), and adaptive learning theory facilitated individualized educational experiences (Gligorea et al., 2023). Together, they formed a comprehensive foundation for understanding how AI was effectively utilized to enhance curriculum development, particularly in addressing the challenges of updating curricula in technology-driven fields.

Critically analyzing these theories in relation to the practice-based research problem revealed their collective strength in supporting the integration of AI tools and the understanding of developers' perceptions of their use. Constructivism and social constructivism provided the pedagogical basis for learner engagement and social interaction, which AI can enhance through personalized and collaborative tools (Grubaugh et al., 2023). Connectivism directly addressed the need for up-to-date knowledge in fast-changing fields, a critical requirement for military education, and AI's ability to facilitate real-time information access and networked learning is invaluable (Alam, 2023). Cognitive load theory helped to ensure that the instructional design was optimized for learning efficiency, which is crucial when dealing with complex subjects, and AI can dynamically adjust to maintain optimal cognitive load. Adaptive learning theory aligned perfectly with AI's capabilities in personalization, allowing for tailored educational experiences that can significantly improve learning outcomes.

However, it is essential to consider potential limitations, such as the risk of over-reliance on technology (Gkintoni et al., 2025; Gligorea et al., 2023) or the need for educators to maintain a central role in the learning process. Nonetheless, when appropriately integrated, these theories collectively supported a robust framework for leveraging AI in curriculum development to address the identified research problem. This critical analysis demonstrated that the selected theories were highly relevant to the research problem, as they directly addressed key aspects of curriculum development and AI integration. By integrating these theories, the study was well-positioned to explore the experiences and perceptions of curriculum developers regarding AI tools, identifying both the opportunities and challenges in their implementation.

Definitions of Key Terms

Adaptive Learning Systems

Adaptive learning systems use AI to tailor educational content to individual learners' needs, adjusting difficulty and pacing based on performance data. In military education, these systems customize training for specific roles, ensuring personnel acquire relevant skills efficiently. For example, a technician might receive targeted modules on equipment maintenance, enhancing operational readiness (David, 2024).

AI Literacy

AI literacy encompasses the knowledge and skills to understand and use AI technologies effectively. In military education, AI literacy enables curriculum developers and trainees to leverage AI tools, such as simulation software, while critically assessing their limitations. This competency is vital for ensuring responsible AI integration in training programs (Long & Magerko, 2020).

Content Curation

Content curation involves selecting and organizing educational materials, a process AI can automate to maintain relevance. AI-driven curation ensures training materials reflect current operational standards, reducing the time needed for curriculum updates. For instance, AI can pull relevant content from technical manuals for immediate use (AIContentfy Team, 2025).

Dynamic Content Adaptation

Dynamic content adaptation uses AI to modify educational materials in real-time based on learner performance or changing requirements. In education, this ensures that curricula remain relevant to evolving operational contexts (Abbasi et al., 2024).

Instructional Design Efficiency

Instructional design efficiency is the reduced time and resources required to develop curricula, achieved through AI automation of tasks like content curation. Training enhances the speed of delivering updated educational programs (Abbasi et al., 2024).

Intelligent Tutoring System (ITS)

Intelligent tutoring systems provide personalized instruction, adapting to learners' needs. In military contexts, ITS can guide trainees through complex tasks, such as tactical simulations, offering tailored feedback to improve performance. These systems enhance efficiency in training programs (Minn, 2022).

Rapid Prototyping

Rapid prototyping uses AI to develop and test curriculum drafts, reducing development timelines quickly. Education allows for iterative updates to training materials to meet urgent operational demands (Abbasi et al., 2024).

Scalable Learning Solutions

Scalable learning solutions use AI to deliver educational content to large groups while maintaining personalization. In military training, this ensures personnel across various roles receive tailored instruction efficiently (Abbasi et al., 2024).

Skill Mismatch

Skill mismatch refers to the gap between taught and required skills, a key issue in military education where outdated curricula can hinder readiness. AI analyzes labor market data to update training, ensuring alignment with industry needs (World Economic Forum, 2019).

Review of the Literature

The literature review supported a qualitative interpretive descriptive study focused on exploring the experiences and perceptions of curriculum developers in technology-driven academic fields, originally focused within U.S. Navy training institutions, regarding the integration of AI tools into their curriculum development processes. The study's purpose was to identify barriers to and strategies for successful AI integration, providing insights that could help streamline curriculum updates and better prepare graduates for careers. This narrative approach ensured a cohesive presentation, beginning with a summary of the purpose of setting the context.

This literature review was organized into five key areas to ensure comprehensive coverage: the general education context, which explored AI's broad application in educational settings and integration of Intelligent Tutoring Systems (ITS) (Alnaqbi, 2020); military-specific applications, addressing unique needs like reducing update timelines in naval education; conceptual frameworks, integrating educational theories like constructivism and cognitive load theory; outcome-focused research, concentrating on practical outcomes such as efficiency and skill gap reduction; and challenges and limitations, addressing potential gaps and ethical concerns. This structure facilitated balanced examination, aligning with the study's goals.

The problem addressed by this research was the lengthy curriculum update cycles (12–18 months) in tech-driven fields, which leave graduates unprepared for current industry needs (Kamalov et al., 2023; World Economic Forum, 2019). This systemic delay correlates with a 25% underemployment rate among recent graduates due to skill mismatches, compounded by 74% of employers reporting critical skill gaps, as noted in recent reports from the NCES (2024). While AI offers the potential to streamline this process, there is a notable lack of understanding about how curriculum developers experience and perceive the integration of AI tools into their workflows, a gap this study aims to address to identify barriers and strategies for successful implementation.

The literature review, crucial for grounding the dissertation, utilized several National University (NU) library databases, specifically ERIC, PsycINFO, and Education Source, selected for their extensive coverage of educational and psychological research relevant to AI in education. These databases were accessed to ensure access to peer-reviewed, scholarly articles, reflecting a comprehensive search strategy.

Search Terms and Strategies

The search terms were tailored using Boolean operators like *AI AND curriculum development*, with additional filtering for peer-reviewed articles published between 2021 and 2025 to maintain currency and rigor, given the estimated completion year of 2026. Tools like scispace.com were utilized to enhance search precision alongside thesaurus terms to capture related concepts. Results were sorted by relevance or citation count to prioritize impactful sources. The search parameters included a wide range of keywords and phrases, shown below (see Table 1) by category.

Table 1

Literature Review Categories and Key Search Terms

Category	Search terms
General Education	(*artificial intelligence* OR *AI*) AND (*curriculum development* OR *instructional design*) AND (*education* OR *teaching*)
Military-Specific	(*artificial intelligence* OR *AI*) AND (*training program development*) AND (*military* OR *naval*) AND (*United States*)
Frameworks	*constructivism*, *cognitive load theory*, *adaptive learning*
Outcome-Focused Research	*efficiency*, *time reduction*, *industry alignment*, *skill gaps*
Challenges and Limitations	*gaps*, *ethical*, *challenges*, *limitations*

Note. This table shows the elements used for each category during the literature review searches.

Primary Areas of Focus for the Literature Review

Based on the search results provided, there is limited specific data on the exact extent of reduction in development time, cost, or increase in quality compared to traditional methods, from curriculum developers' experiences and perceptions utilizing AI-based development tools. But we can infer that AI tools significantly enhance developers' productivity, with 70% believing they offer advantages like better code quality and faster completion (Shani et al., 2024). By automating tasks like code reviews, AI allows focus on innovation, with 61% of employees reporting productivity (Vergadia, 2023) and 49% noting faster decision-making (Peck, 2025).

While exact development time savings have not been definitively quantified, it is evident that AI reduces time spent on specific development activities. Developers often report spending as much time waiting for builds and tests as writing new code; AI tools can mitigate bottlenecks by streamlining these processes. Shani et al. (2024) show that tasks like generating production-ready code from wireframes are expedited, as seen with Airbnb (Peck, 2025). Routine design tasks, such as removing image backgrounds or sourcing stock imagery (Peck, 2025), which previously took considerable time, are now significantly expedited, highlighting AI's potential to enhance operational efficiency.

Development cycles accelerate with AI, with 92% of developers using these tools, suggesting significant efficiency gains (Shani et al., 2024). Compared to traditional methods, AI improves efficiency by quickly generating drafts (Fang & Broussard, 2024), enabling personalization through data analysis for tailored learning, and providing real-time insights for curriculum adjustments. It ensures content relevancy by integrating the latest data and offers scalability for meeting educational demands. (Evanick, 2025).

However, AI complements rather than replaces human expertise, requiring educators to refine AI-generated content (Jaramillo & Chiappe, 2024). Despite all the benefits of AI, challenges exist and include the need for guidance on integration, ethical concerns like biases, and the development of new policies (U.S. Department of Education, 2023). Ultimately, AI's role is transformative, enhancing efficiency and responsiveness, but it necessitates careful oversight to align with pedagogical goals and address ethical issues.

Educators need guidance on effectively integrating AI into curriculum development, and ethical concerns, such as potential biases in AI-generated content, must be addressed (Ng D. et al., 2023). The development of new policies and guidelines is essential to ensure appropriate and ethical use, particularly in sensitive contexts like military education. These challenges highlight the need for a balanced approach, navigating between automation and human input to ensure AI-driven curriculum design aligns with pedagogical objectives and industry standards.

Integrating AI tools into curriculum development represents a transformative shift, enhancing efficiency, personalization, and responsiveness to evolving educational demands. Curriculum developers perceived AI as a valuable complement to traditional methods, enabling them to streamline repetitive tasks, tailor learning experiences to individual needs, and maintain content relevance in rapidly changing fields. However, these tools are not seen as a replacement for human expertise; instead, they serve as collaborative partners that amplify creativity and innovation while requiring careful oversight to address ethical considerations in AI and biases. Developers' experiences highlight the importance of navigating between automation and human input, ensuring that AI-driven curriculum design aligns with pedagogical goals and industry standards. Ultimately, qualitative insights suggested that AI's role in curriculum development is not merely technical but deeply relational, reshaping how educators engage with their craft and adapt to the dynamic landscape of education.

A Brief History of Educational Technology

Educational technology evolved significantly from its early roots in the 18th and 19th centuries, when correspondence learning emerged as a response to advancements in postal services and printing technology (Li, 2018). Pioneers like Sir Isaac Pitman, who introduced shorthand courses in 1840, and Anna Eliot Ticknor, who founded the Society to Encourage Study at Home in 1873, laid the groundwork for distance education (Pregowska et al., 2021). The early 20th century saw the introduction of radio and television as educational tools, with institutions like Iowa University broadcasting courses as early as the 1920s and 1930s (Niaz et al., 2021).

The digital revolution of the 1980s and 1990s, marked by the rise of personal computers and the internet, further transformed education through e-learning platforms and learning management systems (LMS), setting the stage for today's integration of AI in curriculum development (Hwang et al., 2021).

Early Distance Learning. The roots of educational technology trace back to the 18th and 19th centuries with the advent of correspondence learning, enabled by advancements in postal services, printing, and affordable writing tools (Li, 2018). Sir Isaac Pitman pioneered correspondence courses in 1840, teaching shorthand in England, setting a precedent for remote education (Pregowska et al., 2021). In 1873, Anna Eliot Ticknor established the Society to Encourage Study at Home in the United States, focusing on women's education through mailed materials (Li, 2018). Correspondence learning gained traction globally through the late 19th and early 20th centuries, with institutions in Africa, Asia, Australia, and Europe adopting similar models (Pregowska et al., 2021).

Radio and Television in Education. The early 20th century introduced radio and television as educational tools, expanding the reach of distance learning. Iowa University led this shift, delivering radio courses in 1925 and televised courses in the 1930s (Li, 2018; Niaz et al., 2021). By 1946, over 200 U.S. colleges held radio licenses, and educational broadcasting became widespread in regions like Africa, Asia, and Europe (Pregowska et al., 2021). Televised courses gained popularity in the 1960s, with 53 U.S. stations specializing in telecourses by 1961 (Li, 2018). Notable global initiatives included Poland's educational broadcasts in the 1960s, Athabasca University's distance programs in 1972, and the World Bank's African Virtual University in 1997 (Pregowska et al., 2021). Audio and video cassettes in the 1980s further enhanced flexibility, allowing learners to access content repeatedly (Li, 2018).

The Rise of E-Learning. The 1980s and 1990s marked a pivotal shift with the advent of personal computers and the internet, which revolutionized distance learning (Li, 2018; Pregowska et al., 2021). The University of Phoenix launched online programs in 1989, followed by institutions like the British Open University and New York University in the 1990s (Pregowska et al., 2021). LMS emerged, with Cecil (1996) and Moodle (2001) facilitating content delivery, grading, and interaction (Niaz et al., 2021). The programmed logic for automated teaching operations (PLATO) system, developed in the 1960s at the University of Illinois, laid the groundwork for modern LMS by enabling online forums and remote screen sharing (Pregowska et al., 2021).

Mobile Learning and AI Integration. Since the 2000s, mobile devices and AI have driven the development of mobile learning (m-learning) and AI-enhanced education (Hwang et al., 2021). The introduction of massive open online courses (MOOCs) in 2008, offered by platforms like Coursera and edX, expanded access to education for millions (Niaz et al., 2021). AI technologies, including adaptive learning systems and intelligent tutoring systems (ITS), have enabled personalized, data-driven curriculum design (Abbasi et al., 2024). In military education, AI streamlines training to meet operational demands, aligning with the rapid pace of technological advancements (Spirnak & Antani, 2024). This historical progression underscores AI's potential to address the problem of extended curriculum update timelines by enabling rapid, relevant content development.

AI in General Education

In general education, AI is revolutionizing teaching and learning by enabling personalized, adaptive, and data-driven approaches across K-12, higher education, and vocational training settings. ITS, such as those used in mathematics and science education, provide real-time feedback and tailored instruction, improving student engagement and performance (Chen et al., 2020). AI-powered platforms also support personalized learning paths that address diverse learner needs, enhancing accessibility for students with varying abilities and backgrounds (Nguyen, 2024). Additionally, AI-driven assessment tools automate grading and provide educators with insights into student progress, allowing for more efficient and targeted interventions (Abbasi et al., 2024).

Efficiency and Automation. Abbasi et al. (2024) investigated AI's impact on curriculum development in global higher education, emphasizing its ability to automate content curation and assessment design. By analyzing student performance data, AI tools create adaptive, learner-centered content, reducing development timelines from months to weeks. This efficiency is critical for addressing the problem of outdated curricula, as AI enables rapid updates to reflect current knowledge (Abbasi et al., 2024). Similarly, Evanick (2025) provided a practical guide for educators, highlighting AI's role in automating lesson planning and generating personalized learning paths. Evanick (2025) noted that tools like content generators can reduce preparation time by up to 50%, allowing educators to focus on pedagogical innovation.

Personalization and Engagement. Chen et al. (2020) reviewed AI's applications in education, emphasizing its capacity to personalize curricula based on individual learner needs. AI-driven systems adapt the content in real time, improving engagement and learning outcomes. For example, ITS provides tailored feedback, enhancing student performance in subjects like mathematics and science (Chen et al., 2020). Rauf et al. (2024) further highlight AI's role in creating dynamic curricula that address skill gaps, noting that personalized learning paths increased student motivation by 30% compared to traditional methods. These findings suggest

AI's potential to enhance curriculum relevance in training, where personalized training is essential for diverse roles.

Scalability and Accessibility. Owoeye et al. (2023) examined AI's scalability, noting its ability to deliver tailored content to large, diverse student populations. AI automates tasks like content curation, enabling institutions to update curricula across multiple programs simultaneously (Owoeye et al., 2023). Nguyen (2024) complemented this perspective, emphasizing AI's role in making education accessible through adaptive platforms that cater to varying learner abilities. These capabilities are particularly relevant for training institutions, which must deliver consistent, high-quality training to personnel across global locations.

Pedagogical Innovation. Kasztelnik (2024) explored AI-assisted curriculum development, highlighting its role in fostering critical thinking and problem-solving skills. AI tools enable educators to design curricula that incorporate real-world scenarios, preparing students for 21st-century challenges (Kasztelnik, 2024). Sanasintani (2023) advocated for AI-driven innovations, such as gamified learning modules, which increase student engagement by integrating interactive elements. These studies underscore AI's potential to enhance curriculum quality, a key consideration for schools aiming to prepare personnel for complex operational environments.

Challenges in General Education. Despite its benefits, AI integration in general education faces challenges. Nguyen (2024) noted faculty resistance due to concerns about job displacement, with 40% of educators expressing skepticism about AI's reliability. Owoeye et al. (2023) highlighted technical infrastructure as a barrier, particularly in under-resourced institutions where reliable internet and hardware are limited. Chen et al. (2020) emphasized ethical considerations, such as ensuring data privacy in AI-driven systems, which is critical for maintaining trust. These challenges inform the current study's exploration of barriers to AI adoption in training contexts

Military-Specific AI Applications

In military education, AI applications are uniquely tailored to meet the demands of dynamic and high-stakes environments. AI-driven simulations, including virtual reality (VR) and augmented reality (AR), recreate complex combat scenarios, enabling personnel to develop critical decision-making skills in a controlled setting (Harris et al., 2023). Adaptive learning systems personalize training for specific military roles, such as cybersecurity or logistics, ensuring efficient skill acquisition (Alnaqbi, 2020). Furthermore, AI's ability to rapidly update curricula in response to evolving operational needs—such as integrating new radar technologies—enhances readiness and strategic alignment (Zhai et al., 2021).

Streamlining Training Processes. Alnaqbi (2020) examined AI's acceptance in military education, focusing on e-learning systems that personalize training for specific roles. AI-driven platforms reduce training times by tailoring content to individual learner needs, improving readiness for roles like cybersecurity and logistics (Alnaqbi, 2020). Spirnak and Antani (2024) advocated for AI literacy in military medical education, using AI to simulate complex scenarios, such as battlefield triage, which enhances decision-making skills. These applications demonstrated AI's potential to streamline curriculum development in schools, where timely updates are critical.

Enhancing Operational Readiness. Chmyr and Bhinder (2023) explored AI's role in engineering training, noting its efficiency in automating content creation for technical curricula. AI tools generate modules aligned with current technologies, reducing development timelines by up to 40% (Chmyr & Bhinder, 2023). Zhai et al. (2021) discussed AI's transformation of military academy education, emphasizing intelligent systems that adapt content to operational needs. For example, AI can update training materials for new radar systems within days, ensuring personnel are prepared for deployment (Zhai et al., 2021). These capabilities are directly applicable to training, where alignment with technological advancements is paramount.

Motivation and Engagement. Putra et al. (2024) investigated AI's impact on military students' learning motivation, highlighting its role in creating engaging, personalized content. AI-driven simulations and gamified modules increase student engagement by 25%, improving training outcomes (Putra et al., 2024). Harris et al. (2023) explored AI and VR in decision training, noting that realistic simulations enhance critical thinking under pressure. These findings suggest AI's potential to enhance training by making curricula more interactive and relevant.

Strategic Importance. Ward (2021) emphasized AI-driven curricula for senior service college students, preparing leaders for technological advancements. AI-enabled rapid updates to leadership training, ensuring alignment with strategic priorities (Ward, 2021). Gilli (2021) advocated for AI in future professional military education, highlighting its role in aligning training with emerging skills, such as AI literacy and data analysis. These studies underscore AI's strategic importance in education, where preparing personnel for an AI-driven future is a priority.

Military-Specific Challenges. Military applications of AI face unique challenges. Spirnak and Antani (2024) highlighted data security as a critical concern, given the sensitive nature of military data. AI tools must comply with Department of Defense (DoD) standards, using encryption and secure protocols (Spirnak & Antani, 2024). Chmyr and Bhinder (2023) noted technical barriers, such as system reliability in austere environments, which can disrupt training. Putra et al. (2024) identified faculty resistance, with 30% of military educators expressing concerns about AI's complexity.

Outcomes of AI-Driven Curriculum Development

AI-driven curriculum development has demonstrated measurable improvements in educational outcomes, particularly in terms of efficiency, learning effectiveness, and industry alignment. A meta-analysis by Dong et al. (2023) found that AI tools reduce curriculum development timelines by up to 40%, enabling rapid updates that keep pace with technological advancements. Studies also show that AI-enhanced curricula improve student engagement by 15-25% through personalized and interactive learning experiences (Kovari, 2025; Putra et al., 2024). Additionally, AI's ability to align training with industry standards has been linked to a 30% reduction in skill gaps among graduates, as evidenced by initiatives like AI Across the Curriculum (Southworth et al., 2023).

Efficiency Gains. Dong et al. (2023) conducted a meta-analysis showing that AI-driven systems reduced curriculum development times by automating content creation and assessment design. AI tools enabled rapid prototyping, cutting timelines from 18 months to as little as 3 months (Dong et al., 2023). Mounkoro et al. (2024) highlighted AI's data-driven personalization, which streamlined updates by analyzing learner and industry data. These efficiency gains are critical for training, where timely updates ensure operational readiness.

Improved Learning Outcomes. Bai et al. (2024) compared AI-driven instructional design with human teaching, finding that AI enhances learning outcomes by 20% through personalized scaffolding. Mayasari et al. (2024) demonstrated AI's effectiveness in fostering critical thinking skills, with students using AI-driven tools showing a 15% improvement in problem-solving assessments. Yang et al. (2022) evaluated AI-based adaptive assessments, noting a 25% increase in student performance due to tailored feedback. These outcomes suggest AI's potential to enhance training by improving skill acquisition.

Industry Alignment. Southworth et al. (2023) discussed an AI *Across the Curriculum* initiative, showing improved career readiness through AI literacy. AI-driven curricula align training with industry needs, reducing skill gaps by 30% (Southworth et al., 2023). Ng et al. (2023) highlighted enhanced teaching outcomes through AI integration, with educators using AI tools reporting a 20% increase in curriculum relevance. In the general context, industry alignment ensures personnel are prepared for technological advancements, addressing the research problem of graduate unpreparedness.

Collaborative Learning. Kovari (2025) reviewed AI-powered collaborative learning, showing a 15% improvement in student engagement through group-based AI modules. AI facilitated peer interactions, enhancing teamwork skills critical for military operations (Kovari, 2025). These findings support AI's role in creating interactive training programs that foster collaboration.

Challenges and Limitations

Despite its potential, integrating AI into curriculum development presents several challenges that must be addressed to ensure effective and ethical adoption. Ethical concerns, such as biases in AI-generated content, pose risks of perpetuating inequities if not carefully monitored (Bobula, 2024). Technical barriers, including the need for robust infrastructure and reliable internet connectivity, can hinder AI's scalability, particularly in under-resourced institutions (Stracqualursi & Agati, 2024). Additionally, faculty resistance—driven by concerns about job displacement and AI's complexity—underscores the importance of professional development and maintaining human oversight in AI-driven processes (Ng et al., 2024).

Ethical Concerns. Bobula (2024) highlighted ethical concerns, such as biases in AI-generated content, which can perpetuate inequities if not monitored. For example, biased algorithms may prioritize certain learner profiles, disadvantaging others (Bobula, 2024). Okebukola et al. (2025) emphasized risks to academic integrity, noting that AI tools can facilitate plagiarism if not properly regulated. In training, ethical guidelines are essential to ensure fairness and trust in AI-driven systems.

Data Privacy and Security. Ismail and Aloshi (2025) underscored data privacy concerns in military education, given the sensitive nature of operational data. AI tools must comply with DoD standards, using encryption and secure protocols to protect information (Ismail & Aloshi, 2025). Grunhut et al. (2022) noted similar concerns in medical education, advocating for robust data security measures. These challenges are critical for training, where data breaches could compromise national security.

Faculty Resistance and Training. Ng et al. (2024) identified faculty resistance as a barrier, with 35% of educators expressing concerns about AI's complexity and reliability. Cheng and Wang (2023) highlighted the need for extensive training, noting that 50% of educators lack the technical expertise to leverage AI effectively. Professional development is essential to build confidence and competence among curriculum developers.

Technical Infrastructure. Stracqualursi and Agati (2024) noted technical barriers, such as system integration and infrastructure costs, which can hinder AI adoption. Zawacki-Richter et al. (2019) emphasized the lack of robust infrastructure in some institutions, limiting AI's scalability. Reliable hardware and internet connectivity are critical to ensure seamless AI integration.

Human Oversight. Ng et al. (2024) stressed the need for human oversight to maintain curriculum quality, as AI tools may generate content lacking pedagogical depth. Grunhut et al. (2022) advocated for collaborative AI implementation, ensuring educators refine AI-generated materials. Human oversight is essential to align curricula with operational and strategic goals.

Ethical Assurances

This study secured approval from National University's Institutional Review Board (IRB) and relevant training institutions before initiating data collection, ensuring compliance with ethical standards. Given the study's focus on technology-driven fields of education, risks were not expected to exceed minimal due to the general nature of the collected data; if any did exist, these were mitigated through rigorous confidentiality measures. Participant anonymity was maintained using pseudonyms, as outlined in the Purpose of the Study, and interviews occurred in secure settings. Data, including audio recordings and transcripts, has been encrypted and stored on a password-protected server for three years, per IRB guidelines, then securely deleted. The researcher's direct experience in curriculum development using AI development tools acknowledged an outsider perspective that may shape interpretations; to reduce bias, strategies like member checking, detailed in Section 2, were employed.

Summary

This study addresses the extended curriculum update timelines (12–18 months) in technology-driven fields, resulting in graduates being unprepared for current industry demands (Kamalov et al., 2023; World Economic Forum, 2019). These prolonged timelines often lead to outdated content, as rapid advancements in fields like AI and cybersecurity, which outpace curriculum revisions, necessitate more agile development processes. The purpose was to qualitatively explore curriculum developers' experiences and perceptions of integrating AI tools into their workflows within schools, aiming to streamline updates and enhance industry alignment.

The methodology employed a qualitative interpretive descriptive design to capture in-depth insights into developers' experiences, using semi-structured interviews with ten purposive-sampled curriculum developers from the current industry. Research methods involved data collection through audio-recorded interviews, analyzed iteratively via open coding and thematic development with NVivo software, ensuring rigor through member checking and peer debriefing. The literature review synthesized 40+ sources, revealing AI's potential to boost efficiency, personalize learning, and maintain content relevance, though gaps persist in understanding developers' lived experiences (Fang & Broussard, 2024). While Fang and Broussard (2024) emphasize efficiency, they overlook developers' qualitative experiences, which this study addressed. Holmes et al. (2019) provide case studies of developers' perceptions, revealing how limited training contributes to resistance against AI tools, a critical barrier to adoption in technology-driven fields. Similarly, Cope et al. (2021) emphasize that developers' qualitative experiences highlight tensions between AI-driven automation and creative control, offering actionable insights for aligning curricula with industry standards. These studies addressed the gap by providing rich, context-specific data on developers' workflows, aligning with the interpretive descriptive design of this study (Thorne, 2016).

Key research questions explored developers' experiences balancing timelines and quality, perceptions of aligning AI-integrated curricula with industry standards, and tensions between efficiency and creativity. Ethical assurances include IRB approval and secure data storage. Anticipated findings detailed how AI tools reduced development times, which have implications for enhancing educational practice and recommendations for overcoming integration barriers.

This study contributed actionable insights to optimizing curriculum development, bridging the education-employment gap in education contexts. These insights guided Section 3’s findings and recommendations for future education.

Section 2: Methodology and Design

This section details the methodology and design of the research, which focuses on addressing the prolonged curriculum update timelines (12–18 months) in technology-driven fields, leading to graduates who are ill-equipped to meet current industry demands (Kamalov et al., 2023; World Economic Forum, 2019). This qualitative interpretive descriptive study explored the experiences and perceptions of curriculum developers in technology-driven academic fields regarding integrating AI tools into their curriculum development processes within their development processes. In addition, this research also examined how curriculum developers perceive and experience the integration of AI tools in curriculum development to enhance the efficiency of creating high-quality learning materials. This section details the design and method, population and sample, materials/instrumentation, operational definitions of variables, data collection and analysis procedures, assumptions, limitations, delimitations, and a summary, providing a comprehensive framework for the proposed research.

Design and Method

The study utilized a qualitative methodology employing an interpretive descriptive design to explore the experiences and perceptions of curriculum developers regarding integrating AI tools in curriculum development. Interpretive description was particularly suited for this research as it allows for an in-depth understanding of complex, context-specific phenomena and generates insights that can directly inform practice (Thorne, 2008). This approach enabled the researcher to capture how AI tools are utilized and perceived within the curriculum development process, providing valuable information for enhancing educational efficiency in training contexts. To ensure a robust methodological choice, three alternative research designs were considered but deemed less appropriate for the study’s objectives: case study and phenomenological designs.

Alternative Design 1: Case Study

A case study design focuses on an in-depth exploration of a single or a small number of bounded systems, such as specific institutions or programs, to provide detailed insights into a particular context (Yin, 2018). While this approach could offer depth in examining AI tool integration within one training institution, it was determined to be less appropriate because it limits the ability to capture a broader range of experiences across multiple curriculum developers. The study aimed to explore diverse perspectives to inform broader educational practice, which a case study's narrow focus on a single context might constrain. Additionally, the generalizability of findings to other technology-driven fields would be limited, as case studies prioritize depth over breadth (Creswell & Poth, 2018). The interpretive descriptive design better aligns with the goal of generating transferable insights across varied settings while maintaining contextual richness.

Alternative Design 2: Phenomenological Design

A phenomenological design seeks to understand the lived experiences of individuals around a specific phenomenon, emphasizing the essence of those experiences through detailed, subjective accounts (Moustakas, 1994). While this approach could capture curriculum developers' personal experiences with AI tools, it was deemed less appropriate because it focuses heavily on individual subjective meaning rather than practical, actionable insights for curriculum development processes. The study's purpose was to inform educational practice by identifying strategies and barriers to AI integration, which requires a balance of subjective experiences and practical implications. Interpretive description, with its emphasis on practice-oriented findings, better supports the study's aim to bridge the education-employment gap in technology-driven fields (Thorne, 2016).

Alternative Design 3: Quantitative Methodology

A quantitative methodology is less suitable for this study because it focuses on numerical data and statistical comparisons, which are not aligned with the study's goal of exploring the nuanced, subjective experiences and perceptions of curriculum developers regarding AI tool integration. Qualitative research, particularly the interpretive descriptive design chosen, is better suited to capture the complex, context-specific insights into how developers balance efficiency, quality, and industry alignment, as it allows for in-depth exploration of individual perspectives through semi-structured interviews (Thorne, 2016). Quantitative methods, which prioritize measurable outcomes like development time or cost reductions, may overlook the rich, descriptive data needed to understand developers' lived experiences and the barriers to AI adoption, as highlighted in the study's purpose (Creswell & Poth, 2018). By focusing on qualitative data, the study generated practice-oriented insights that address specific research questions about balancing timelines, aligning with industry standards, and navigating efficiency versus innovation, which are inherently subjective and context-dependent.

Population and Sample

The target population for this study consisted of curriculum developers and instructional designers working in higher education, corporate training, and professional or military education environments who had direct experience using AI tools in the curriculum design process. These individuals are typically responsible for designing instructional content, managing program delivery, or implementing learning technologies in fields that emphasize innovation and technological alignment. By focusing on this population, the study aimed to capture a broad range of experiences and perspectives across sectors where rapid curriculum adaptation is essential.

A purposive sampling strategy was used to recruit ten participants who met the following inclusion criteria: (a) at least one year of experience in curriculum development, and (b) prior or current use of AI tools such as content generators, intelligent tutoring systems, analytics platforms, or adaptive learning technologies. Individuals who did not meet both criteria were excluded from participation. The sample size was chosen to ensure data saturation, defined as the point at which no new themes or insights emerge from continued interviews (Palinkas et al., 2013).

Participants were initially recruited using targeted outreach through public-domain professional networking platforms such as LinkedIn and Facebook, using a standardized message explaining the study's purpose, the voluntary nature of participation, and eligibility criteria. Snowball sampling followed, whereby initial participants may refer to other qualified individuals from their professional networks. This combination of purposive and snowball sampling supported the inclusion of a diverse range of perspectives from across institutional types and sectors.

To ensure protection of participant rights, informed consent was obtained before interviews, including a description of confidentiality protections and data use. Pseudonyms replaced personal identifiers, and all data was stored on an encrypted, password-protected device accessible only to the researcher. Ethical approval was secured from the National University Institutional Review Board (IRB) prior to data collection.

Materials/Instrumentation

Data was collected through semi-structured interviews, a method well-suited for this qualitative interpretive descriptive study exploring curriculum developers’ experiences and perceptions of integrating AI tools into curriculum development. This approach allows flexibility in exploring participants' experiences while focusing on the research questions, aligning with the interpretive descriptive framework articulated by Thorne (2008, 2016), which emphasizes capturing complex, context-specific phenomena to generate practice-oriented insights. The interview guide was self-developed and informed by an extensive review of literature related to AI-enhanced curriculum development, instructional design efficiency, and perceptions of educational technology (Abbasi et al., 2024; Dong et al., 2023; Nguyen, 2024). Each item in the guide was designed to align with the three research questions, addressing efficiency and timelines (RQ1), industry alignment (RQ2), and innovation versus automation tensions (RQ3).

To ensure content validity, the interview guide underwent expert review by a panel of five subject matter experts (SMEs) (Appendix A) with an average of 16.2 years of experience in curriculum development, ensuring instrument credibility as recommended by Creswell and Poth (2018). Each SME had at least 10 years of experience in curriculum development and/or educational technology implementation, with credentials such as a doctorate in education, curriculum design, or instructional technology, and leadership experience in instructional design. Reviewers assessed the clarity, relevance, and completeness of each question. Feedback was incorporated to revise wording and ensure alignment with research aims and best practices in qualitative interviewing (Creswell & Poth, 2018). The interview guide was not previously used in another study and is considered an original, candidate-developed instrument. A field test interview was conducted with one curriculum developer outside the participant pool to evaluate question clarity, pacing, and sequencing. Insights from this field test were used to revise the instrument prior to data collection. While traditional reliability measures are less applicable to qualitative interviews, procedural consistency will be maintained using a standardized interview protocol and consistent interviewer training. Transcriptions and coding processes followed best practices to enhance trustworthiness, dependability, and confirmability (Lincoln & Guba, 1985).

Interviews were conducted virtually and lasted approximately 45–60 minutes per session. Each interview was audio-recorded and transcribed verbatim to facilitate accurate data analysis, aligning with best practices in qualitative research for capturing rich, contextual data (Creswell & Poth, 2018). These transcripts were analyzed using NVivo software to support transparency and rigor in data coding and theme development through a thematic analysis framework. The finalized interview guide is included in Appendix B.

Data Collection and Analysis

Approval from the Institutional Review Board (IRB) was obtained prior to data collection to ensure compliance with ethical standards. A field test interview was conducted to refine the guide's wording and flow. Data collection involved conducting semi-structured interviews with the selected participants. Each interview lasted 45 to 60 minutes and was scheduled at a convenient time for the participant. Before the interview, participants were provided with an information sheet outlining the study's purpose, procedures, and their rights as participants. Informed consent was obtained from all participants via both an emailed version of the consent form and prior to the interview to capture verbal consent.

The interview data analysis followed interpretive descriptive principles, involving an iterative process of coding and theme development as outlined by Thorne (2008). The process began with immersive engagement, where I would read and re-read transcripts to gain a deep understanding of participants' experiences and perspectives within the context of curriculum development. Initial open coding involved assigning descriptive labels to segments of data that reflect curriculum developers' experiences with AI tools, such as perceived efficiencies, challenges, or innovative applications. These codes were iteratively refined through constant comparison, where new data is compared to existing codes to ensure consistency and depth. As patterns emerged, codes were grouped into broader categories, and thematic analysis followed Braun and Clarke’s (2006) six-step process: (1) familiarizing with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes for coherence, (5) defining and naming themes to reflect their essence, and (6) producing a report to articulate findings. For example, themes might capture tensions between AI-driven automation and creative curriculum design or perceptions of AI’s alignment with industry standards. Qualitative data analysis software, such as NVivo, was used to systematically organize codes, categories, and themes, facilitating traceability and transparency in the analytical process. This structured yet flexible approach ensured that the analysis remained grounded in participants' experiences while addressing the study’s research questions.

To ensure the rigor and trustworthiness of the findings, multiple strategies were employed to include both panel reviews and member checking. Credibility of questions will be enhanced through validation by five professional Subject Matter Experts (SMEs) who work in the curriculum development field. Transferability was supported by providing descriptions of the training context and participants’ experiences, allowing readers to assess applicability to similar settings. Dependability and confirmability were ensured through a detailed audit trail, documenting analytical decisions and using NVivo to maintain transparency in how data are coded and interpreted. These strategies collectively strengthen the study’s methodological rigor and ensure that findings authentically reflect curriculum developers’ experiences with AI tools.

This process involved sharing interview transcripts, synthesized findings, or identified themes with participants to confirm accuracy and resonance with their perspectives, aligning with the study’s interpretive descriptive design and constructivist framework (Creswell & Poth, 2018; Thorne, 2016). By conducting member checking through follow-up interviews or written feedback, as suggested by Motulsky (2021), the researcher was able to address potential misinterpretations, ensuring findings reflect participants’ lived experiences while mitigating researcher bias. This approach not only strengthened the study’s credibility and confirmability but also respects participants’ epistemic privilege, fostering ethical engagement without imposing undue burdens, given the low-risk nature of the study’s focus on professional experiences. As described in section 1, ethical assurances, participant anonymity was maintained using pseudonyms, interviews were conducted in secure settings, and data has been encrypted and stored on a password-protected server for three years, per IRB guidelines, then securely deleted.

Assumptions

This study operated under several key assumptions that shaped its design and interpretation. First, it is assumed that participants, curriculum developers, and educators would provide honest and detailed accounts of their experiences with AI tools in curriculum development. This assumption is critical, as the study's qualitative nature relied on participants' willingness to share candid insights (Creswell & Poth, 2018). Second, the interpretive descriptive approach was assumed to be appropriate for capturing the complexity and context-specific nature of curriculum development in military education settings. This methodology was well-suited for exploring lived experiences and generating practice-based insights (Thorne, 2016). Third, it is assumed that the selected sample would represent the target population and offer diverse perspectives on AI tool integration. This assumption underpins the study's ability to achieve data saturation and provide comprehensive findings (Palinkas et al., 2013). Additionally, the study assumed that participants possessed sufficient experience with AI tools to provide meaningful insights, as their expertise is essential for understanding the practical integration of these technologies (Sandelowski, 2000). These assumptions collectively supported the study's feasibility and validity, though they were still critically examined throughout the research process.

Limitations

Limitations were potential weaknesses in the study's design or execution that may have influenced the interpretation or generalizability of findings, often arising from methodological choices or external constraints (Creswell & Poth, 2018). This study was subject to several limitations that influenced the interpretation and generalizability of its findings. First, the subjective nature of qualitative data introduced the potential for bias in both data collection and interpretation. The researcher's perspective, as someone potentially lacking direct experience in recent AI-assisted curriculum development, shaped how data was understood and presented (Merriam & Tisdell, 2015). To mitigate this, the researcher maintained a reflexive journal to document their thoughts, decisions, and potential biases throughout the study. Second, the findings generalized to other contexts or populations due to the specific focus on the small, purposive sample of ten participants. While this sample size was appropriate for achieving data saturation in qualitative research, it limited the study's applicability to broader educational settings (Fusch & Ness, 2015). However, the in-depth insights gained can still inform similar high-stakes, technology-driven environments. Additionally, the study's reliance on self-reported data introduced social desirability bias, where participants provided responses that they believed were expected rather than their true experiences (Fisher, 1993). These limitations underscored the need for cautious interpretation and highlight opportunities for future research to address these constraints.

Delimitations

Delimitations are intentional boundaries set by the researcher to focus the scope of the study, defining what is included or excluded to ensure feasibility and alignment with research objectives (Merriam & Tisdell, 2015). This study was intentionally delimited to ensure a focused and feasible investigation of AI tool integration in curriculum development. First, the study was limited to curriculum developers, excluding other participants from graphic design, programming, and other potential data collection sources. This delimitation maintained the study's emphasis on the unique challenges of technology-driven education, where rapid curriculum updates are critical for operational readiness (Spirnak & Antani, 2024). Second, the research examined only the experiences and perceptions of AI tool integration in curriculum development, deliberately excluding other AI applications such as student-facing tools or administrative systems. This focus aligns with the study's purpose of addressing inefficient curriculum update cycles in technology-driven fields (Kamalov et al., 2023). Third, data collection was limited to semi-structured interviews, providing in-depth qualitative insights while excluding other methods like surveys or observations. This choice ensured consistency with the interpretive descriptive design and the study's emphasis on participant experiences (Thorne, 2016). Additionally, the study was delimited to technology-driven fields within schools, excluding other subject areas, to address the specific challenges of rapidly evolving curricula in these domains (Zhai et al., 2023). These delimitations ensured the study remained targeted and manageable while contributing valuable insights to the field.

These boundaries were chosen to ensure the study remains manageable and aligned with its purpose of exploring AI's role in streamlining curriculum development. By focusing on technology-driven fields, the study targets contexts where rapid updates are critical. Limiting the scope to curriculum development processes ensures relevance to the problem of prolonged updating cycles, while the use of interviews supports the qualitative goal of capturing nuanced developer experiences. These delimitations enhance the study's feasibility and depth while addressing the specific research questions.

Summary

Section 2 outlines a qualitative interpretive descriptive study designed to explore the experiences and perceptions of curriculum developers in technology-driven academic fields regarding the integration of AI tools into their curriculum development processes. The study was guided by three RQs focused on development timelines, content quality, and alignment with industry needs. A purposive sample of ten curriculum developers was recruited based on specific inclusion criteria, with participants selected from higher education, corporate, or military training environments. Data was collected through semi-structured interviews guided by a candidate-developed protocol. A field test interview was conducted to further refine the instrument.

Interviews were conducted virtually and audio-recorded with participant consent. Transcripts were analyzed using Braun and Clarke's (2006) six-step thematic analysis framework, supported by NVivo software to enhance traceability and coding consistency. Analytical rigor was maintained through procedures that promote credibility, dependability, and confirmability, including an audit trail, SME validation, and member-checking of interpretations. Ethical approval was obtained from the IRB, and participant confidentiality has been maintained through secure data handling and pseudonym assignment. This methodology supported the generation of actionable insights to guide effective AI integration in curriculum design and address gaps between education and workforce demands.

Section 3: Findings, Implications, and Recommendations

The purpose of this qualitative interpretive descriptive study was to explore the experiences of curriculum developers regarding the integration of AI tools into curriculum development processes. Specifically, the study addressed how developers balance development timelines with content quality (RQ1), how they perceive AI's role in aligning curricula with industry standards (RQ2), and how they navigate tensions between efficiency and creativity (RQ3). This study was guided by the practice-based problem of lengthy curriculum development cycles that challenge institutions in fast-changing technology-driven fields.

This section is organized into five parts. First, the findings are presented, organized by each of the three research questions and supported by tables, figures, and participant quotes. Second, the strategies used to establish trustworthiness are discussed. Third, the outcomes are evaluated and connected to the study's conceptual framework. Fourth, implications and recommendations for practice are outlined. Finally, recommendations for future research are provided, followed by a conclusion.

Several factors may influence the interpretation of these results. The sample size was limited to ten participants drawn from higher education, corporate, and military training contexts, which may constrain transferability. Data were based on self-reported experiences and perceptions, which could reflect individual biases. Additionally, as AI technologies are evolving rapidly, the findings represent perceptions at a specific point in time and may shift as tools and practices continue to develop.

Findings

The study participants consisted of ten curriculum developers representing higher education, corporate training, and military training sectors. Participants ranged from 5 to 35 years of experience in curriculum development, with AI tool usage spanning from one to six years. Roles included instructional designers, program coordinators, training managers, and faculty members. This diversity enhanced the transferability of the findings by capturing perspectives from multiple contexts. While the group was not intended to be statistically representative, it provided sufficient variation to illuminate common themes and distinct sectoral challenges.

Data saturation, the point at which new information, themes, or coding are no longer emerging, was a central consideration in the qualitative design. The study achieved saturation as evidenced by the convergence of perspectives from the ten curriculum developers; this diverse group—representing higher education, corporate training, and military training with experience ranging from 5 to 35 years—provided sufficient variation to illuminate all common themes and distinct sectoral challenges, indicating the ability to obtain additional new information had been attained (Fusch & Ness, 2015). Therefore, the finding of consistent themes across varied roles (instructional designers, program coordinators, training managers, and faculty members) and experience levels indicate that the data collected was rich in depth and thick in quantity, meeting the necessary requirements for saturation and enhancing the transferability of the findings.

Table 2

Participant Demographics (n = 10)

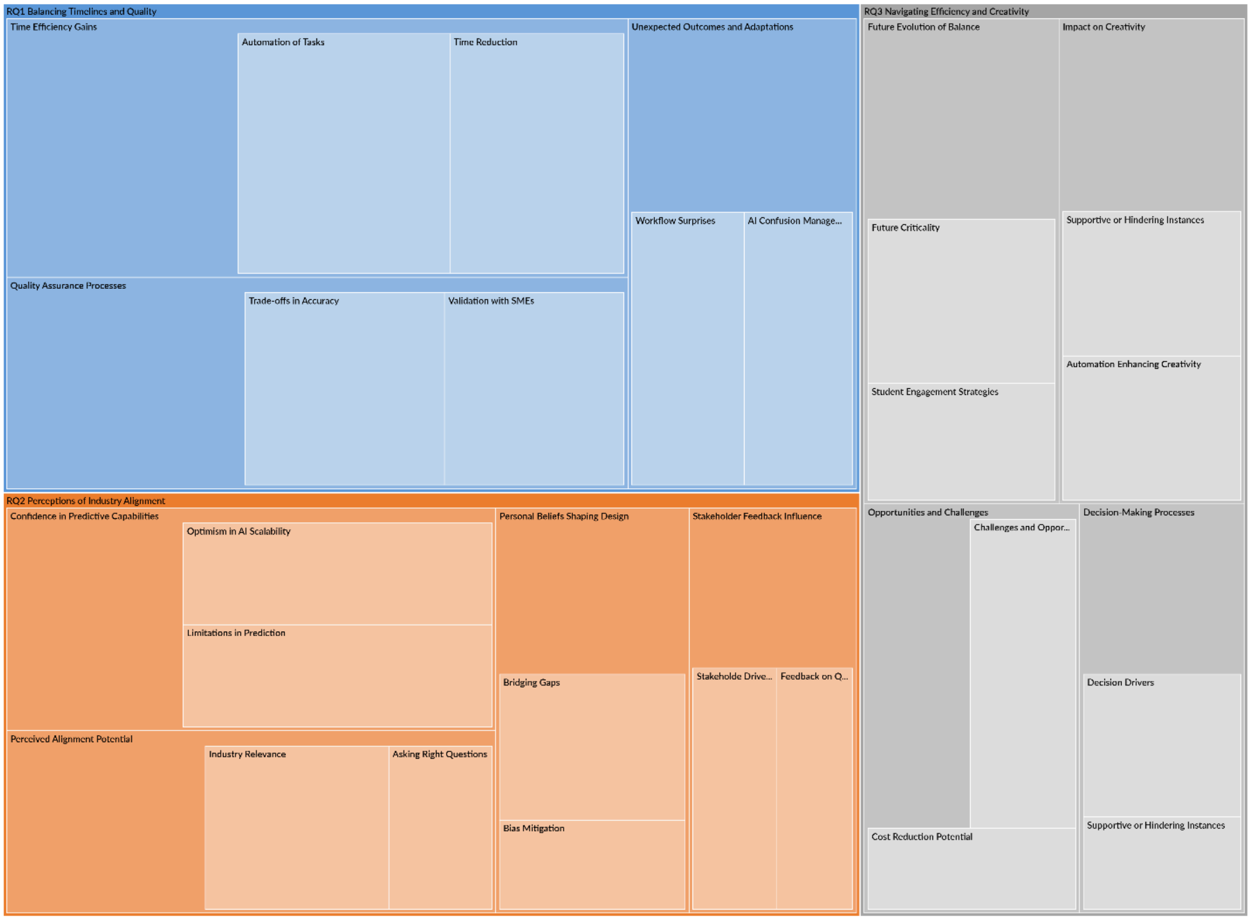
Participant ID	Sector	Years of curriculum development	AI tool experience	Role title*
P1	Military Training	5	3	Instructional System Designer
P2	Corporate Training	2	2	Senior Instructional Designer
P3	Military Training	3	3	Senior Instructional Designer
P4	Military Training	14	5	Instructional System Specialist
P5	Military Training	8	3	Curriculum Manager
P6	Military Training	24	5	Curriculum Developer
P7	Military Training	6	2	Curriculum Manager
P8	Corporate Training	30	4	Curriculum Developer
P9	Higher Education	35	3	Senior Instructional Designer
P10	Higher Education	25	6	University Professor

**Note.* Role titles are anonymized for participant protection.

Figure 1 presents a coding framework in NVivo, organized around three research questions. Themes include balancing timelines and quality, industry alignment, and efficiency and creativity. Themes related to balancing timelines and quality (RQ1) include Time Efficiency Gains, Automation of Tasks, and Trade-offs in Accuracy. Themes connected to industry alignment (RQ2) include Perceived Alignment Potential, Stakeholder Feedback Influence, and Confidence in Predictive Capabilities. Themes linked to efficiency and creativity (RQ3) include Decision-Making Processes, Impact on Creativity, and Future Evolution of Balance. This hierarchical visualization highlights the structured relationship between research questions and thematic findings, demonstrating alignment with the interview protocol and codebook.

Figure 1

Hierarchical Structure of Codes and Themes Organized by RQ1-RQ3



A word cloud (see Figure 2) was used to illustrate common language used by the participants to describe AI in curriculum development. Participants frequently used terms such as "activities," "development," "content," "different," "community," and "questions" when discussing AI integration. The prominence of these terms reinforces the themes identified in the thematic analysis and visually demonstrates the language participants used to describe their experiences.

Figure 2

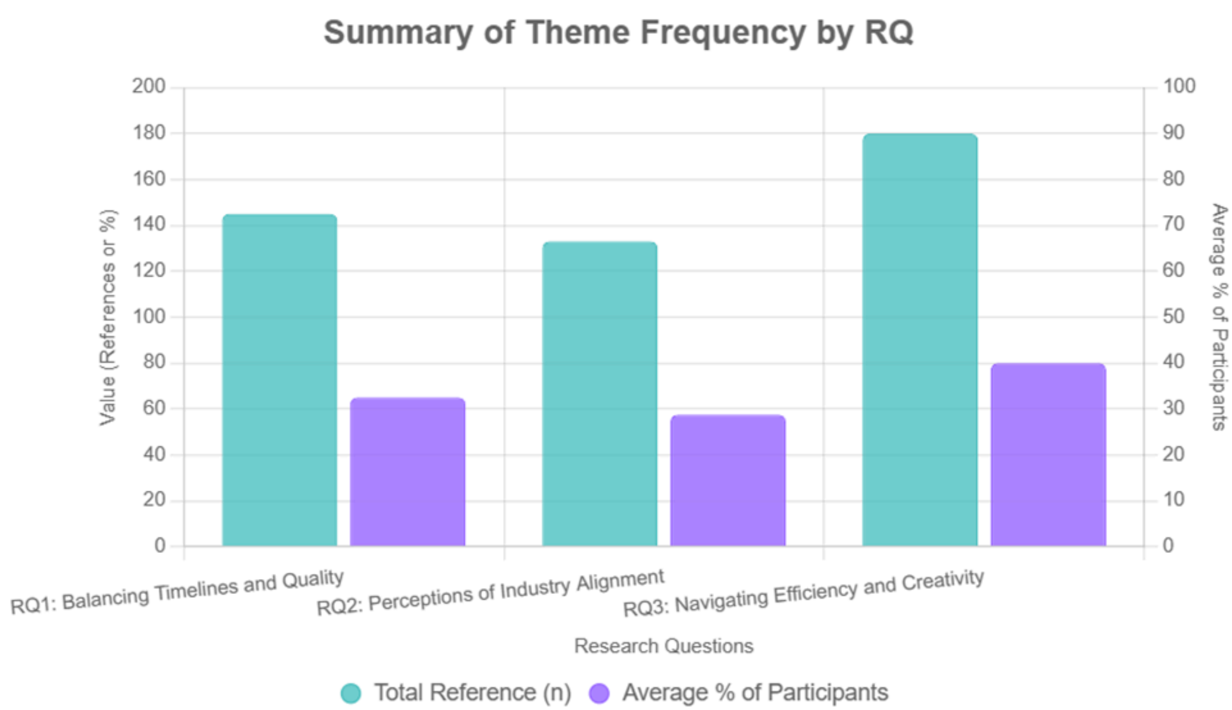
Word Cloud: Common Participant Language

Note. A word cloud illustrates the common language used by participants to describe AI in curriculum development.

Figure 3 summarizes theme frequencies by RQ, offering a clear overview of theme prevalence (via reference counts) and participant engagement (via percentages of participants referencing each theme). These metrics are visualized in the figure through bar charts or similar elements, with data labels indicating both totals and averages to facilitate direct comparison without extensive scrolling. For RQ1 (Balancing Timelines and Quality), there were 145 total references and an average participant engagement of 65%; this was driven by universal (100%) mentions of Time Reduction and Time Efficiency Gains, highlighting a focus on timeline improvements, while AI Confusion Management showed lower engagement at 40%. RQ2 (Perceptions of Industry Alignment) had 133 references and an average engagement of 57.5%, with strong consensus on Industry Relevance and Stakeholder Feedback Influence (both with high percentages, as shown in the figure), contrasted by Bias Mitigation at only 30%, reflecting varied views on alignment. Finally, RQ3 (Navigating Efficiency and Creativity) featured 180 references and an average engagement rate of 80%, emphasizing a broad discussion of Opportunities and Challenges alongside Their Impact on Creativity, which illustrates the balance between automation and innovation. Overall, this frequency distribution demonstrates thematic saturation, bolstering the credibility of the findings through evident consensus on core themes and subtler nuances in others.

Figure 3

Summary of Theme Frequency by RQ



Research Question 1:

RQ1 asked: How do curriculum developers in technology-driven fields describe their experiences balancing development timelines and content quality when integrating AI tools into curriculum design?

Participants described their experiences integrating AI tools into curriculum design as a transformative process that significantly enhanced efficiency while introducing challenges in maintaining content quality. Key themes emerged, including substantial time efficiency gains through AI's ability to accelerate initial drafting and outlining, the automation of repetitive tasks such as generating learning objectives and questions, trade-offs in accuracy where AI's speed sometimes led to errors or assumptions requiring human correction, and rigorous quality assurance processes involving SME validation and iterative refinements to ensure relevance and reliability. Overall, developers emphasized that while AI drastically shortened development timelines—often by 50% or more—it demanded vigilant oversight to balance speed with high-quality, learner-centered outcomes, preventing over-reliance that could compromise educational integrity

Theme 1: Time Efficiency Gains. Participants consistently highlighted how AI integration dramatically reduced curriculum development timelines, allowing them to complete tasks in hours or days that previously took weeks. This efficiency enabled faster prototyping and iteration, freeing up time for more creative aspects of design. For instance, Participant 1 noted the profound impact on their workflow: "Oh, it cut my development time by 50%. Literally, because I did not have to… I did not have to do that research with the subject matter expert and sit down and talk and do all these things." Similarly, Participant 4 emphasized the rapid turnaround: "It was like, within minutes, I had a full outline, and I could start building from there, which used to take me days." Participant 7 echoed this sentiment, stating: "AI shaved off at least 40-50% of my time on initial drafts, turning what was a two-week process into a few days.” Participant 10 described using AI for quick brainstorming: “The initial brainstorming and content writing, very quick, but then… letting myself experience the process that after a while.” These accounts illustrate how AI's speed fostered a more agile development process, though participants cautioned that gains depended on targeted prompting.

Theme 2: Automation of Tasks. Developers highlighted AI's ability to automate routine elements like outlining, objective generation, and content curation, which streamlined workflows and minimized manual labor. This automation was viewed as essential for balancing tight timelines with comprehensive content, though it still necessitated human oversight for customization. Participant 1 provided a vivid example:

> I dumped it into ChatGPT. And I said, hey, I would like for me… I would like to create an outline of this subject matter, can you help me with that? It's like, yes, I can help you with that. And I said, I really want to focus on this particular section, so I said, from this page to this page, give me an outline, give me an, learning objectives.

Participant 6 added: “I also asked them to give me graphics. So, I said, okay, give me some graphics for… For these different, bullets, and it gave me the graphics for that.” Participant 9 noted: “It automates scripting and basic layouts, cutting down on repetitive tasks that used to bog me down.”

Theme 3: Trade-offs in Accuracy. While AI's rapidity was praised, participants noted trade-offs where speed led to inaccuracies, assumptions, or irrelevant details, potentially compromising content quality if not addressed. This theme underscores the need to weigh efficiency against precision in fast-evolving tech fields. Participant 1 explained:

> A lot of the information was valid, but there were a few assumptions that the AI tool made into what the roles were for that particular person… So, in doing that, there was error, because it assumed some things that it was not right.

Participant 5 highlighted the risk: “The trade-off is speed versus depth—AI might miss nuances in tech fields where details matter.” Participant 2 shared: “It generates fast, but I've caught factual inaccuracies that could mislead learners if not fixed.”

Theme 4: Quality Assurance Processes. To counteract accuracy issues, participants described implementing robust checks, including SME reviews, iterative prompting, and manual validations, ensuring AI-enhanced content met educational standards. This theme illustrates proactive strategies for maintaining quality amid accelerated timelines, which depict participant coverage across major themes. Participant 1 detailed their process:

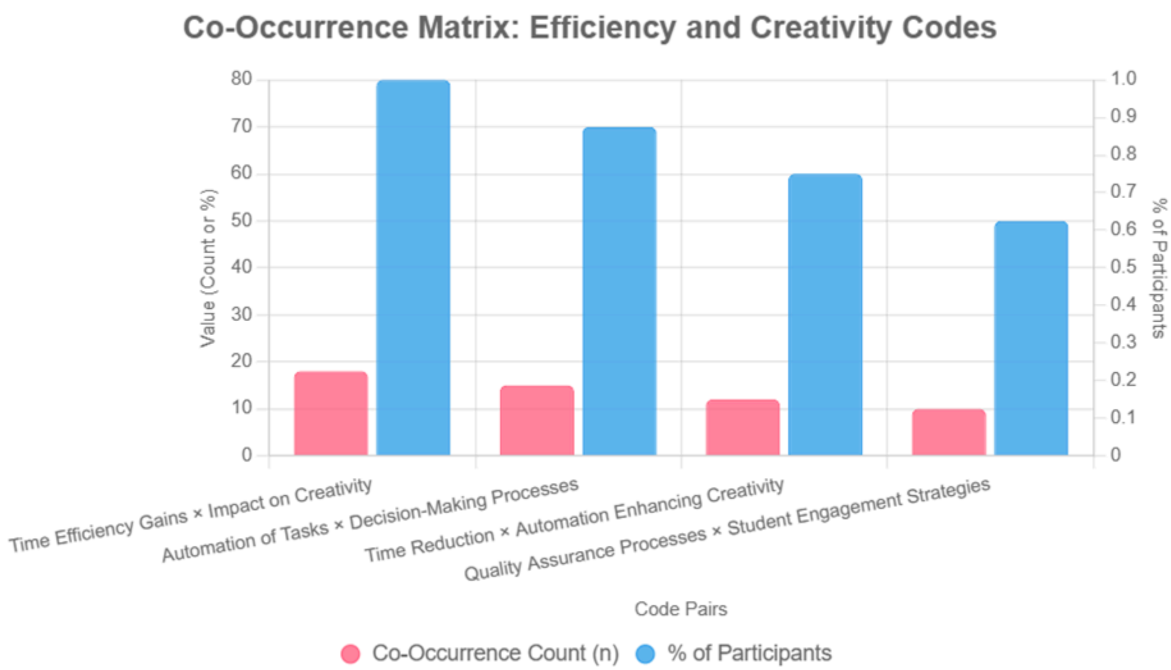
> I had to talk about that with the subject matter expert to be able to, you know, say, okay, this should not be in here, this is somebody else's role… So, yeah, you still have to validate it, but it's a lot quicker for the SME to go through that.

Participant 10 added: “I read over almost everything. Like, 95% of what AI creates for me, I read and check and change.” Participant 4 stressed: “I always double-check with sources and refine prompts step by step to avoid confusion.”

The co-occurrence of codes linking efficiency (RQ1) and creativity/innovation (RQ3), shown in Figure 4, highlights intersections between codes addressing efficiency and creativity. For example, Time Efficiency Gains frequently overlapped with Impact on Creativity, illustrating participants’ tension between rapid automation and maintaining innovation in curriculum design. Similarly, Automation of Tasks co-occurred with Decision-Making Processes, reflecting developers’ efforts to determine when to rely on AI versus their own expertise. These intersections provide evidence of the nuanced trade-offs developers navigate, directly addressing RQ3.

Figure 4

Code Co-Occurrence Matrix (RQ1 vs. RQ3).



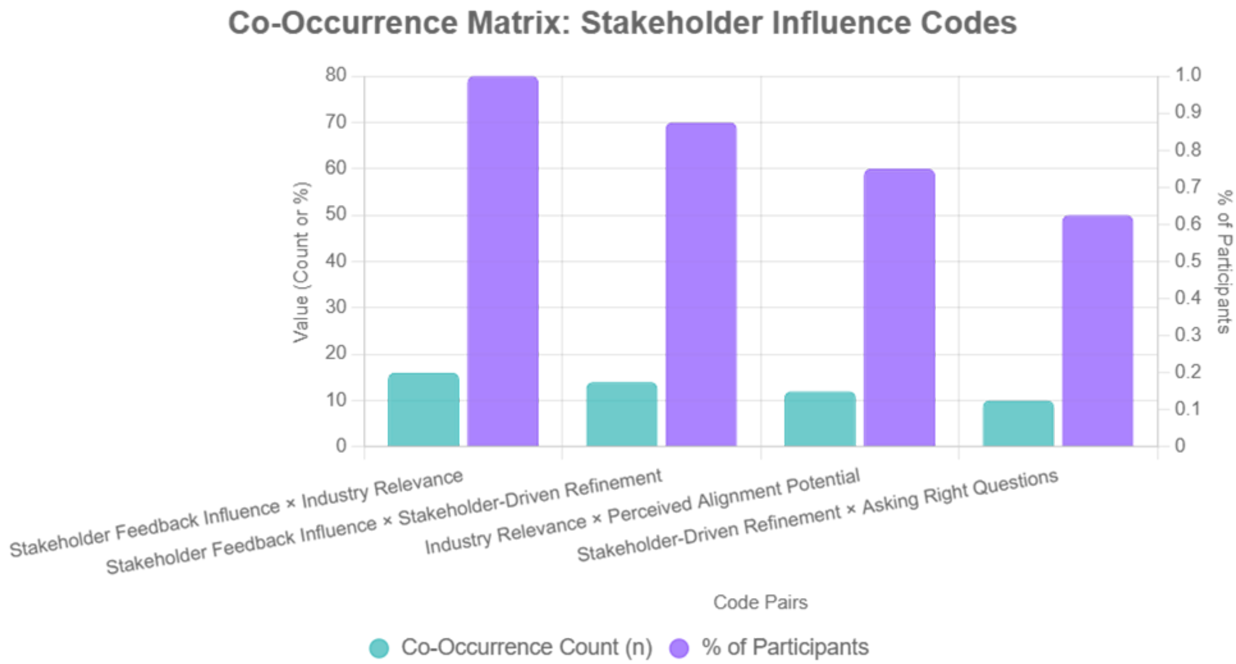
Research Question 2:

RQ2 asked: What perceptions do curriculum developers hold regarding aligning AI-integrated curricula with industry standards, and how do these perceptions influence their content development strategies?

This question examined developers' views on AI's role in syncing curricula with industry demands, revealing perceptions of its potential for real-time alignment alongside limitations in adaptability. Themes identified include positive perceptions of alignment capabilities, challenges in predictive accuracy, influence on development strategies, and integration of stakeholder feedback. Generally, participants perceived AI as a valuable tool for enhancing relevance in dynamic tech sectors; however, their perceptions shaped cautious strategies that emphasized human judgment, with co-occurrences between efficiency and alignment noted in Figure 5.

Figure 5

Stakeholder Feedback Influence (RQ2).



Theme 1: Positive Perceptions of Alignment Capabilities. Participants expressed optimism about AI's ability to align curricula with evolving industry needs through data-driven insights and rapid updates. This theme reflects a belief that AI bridges education-employment gaps by incorporating current trends. Participant 1 stated: “For the tech field, if developers want to create anything, They can have AI. Say… Create me a lesson on how to program the ESP32, And it can spit out the entire thing.” Participant 8 shared: “It ensures content relevancy by integrating the latest data and offers scalability for meeting educational demands.” Participant 10 noted: “AI is the big, you know, that’s a huge advantage that AI... it can cater to those, to those preferences, or those needs, you know.”

Theme 2: Challenges in Predictive Accuracy. Developers perceived limitations in AI's predictive features, such as potential biases or outdated data, which could hinder accurate alignment with future industry standards. This theme highlights concerns that influenced more conservative integration approaches. Participant 1 cautioned: “I think it can keep it ahead, but I also think it could go the wrong way if it's not asked the right questions, right?” Participant 5 added: “Sometimes it hallucinates details, so you gain time but lose some reliability upfront.” Participant 10 said: “The bad information that it could provide is the biggest challenge.”

Research Question 3:

RQ3 asked: How do curriculum developers navigate efficiency (e.g., AI-driven automation) and innovation in their curriculum design processes?

Focusing on the tension between AI's efficiency and fostering innovation, this question revealed navigation strategies that balanced automation with creative input. Themes include the impact of automation on creativity, decision-making processes, instances of support or hindrance, and visions for future evolution. Participants generally navigated this approach by using AI as a supportive tool rather than a replacement, promoting innovation through deliberate human intervention, as shown in the concept map in Figure 2.

Theme 1: Automation's Impact on Creativity. AI automation was seen as enhancing creativity by freeing time from routine tasks, though over-reliance risked stifling originality. This theme captures the dual-edged nature of efficiency in innovative design. Participant 1 noted: “It helps me… get my… creativity in a lot quicker. So, I can do all the tasks, but now it's kind of like, why do it and take… 20 minutes versus 5 minutes.” Participant 10 said:

> It has sincerely helped me be more creative, because I’m able to reach out my tentacles and do more creative things with its capabilities. It has sincerely helped me be more creative, because I’m able to reach out my tentacles and do more creative things with its capabilities.

Theme 2: Decision-Making Processes. Developers described deliberate choices in when to use AI for speed versus relying on intuition, driven by project needs and deadlines. This theme highlights strategic navigation to optimize both efficiency and innovation. Participant 10 explained: “Deadlines. Deadlines, I’ll say that.” Participant 1 shared: “You still have to be the one telling it what to do.” Participant 4 noted: “I had to slow it down, because if I didn't slow it down, it would spit out everything, and it would be wrong.”

Theme 3: Instances of Support or Hindrance. Participants shared specific examples where AI either bolstered or impeded innovative designs, illustrating practical navigation challenges. This theme provides concrete insights into efficiency-innovation dynamics, with co-occurrences in Figure 6. Participant 1 added:

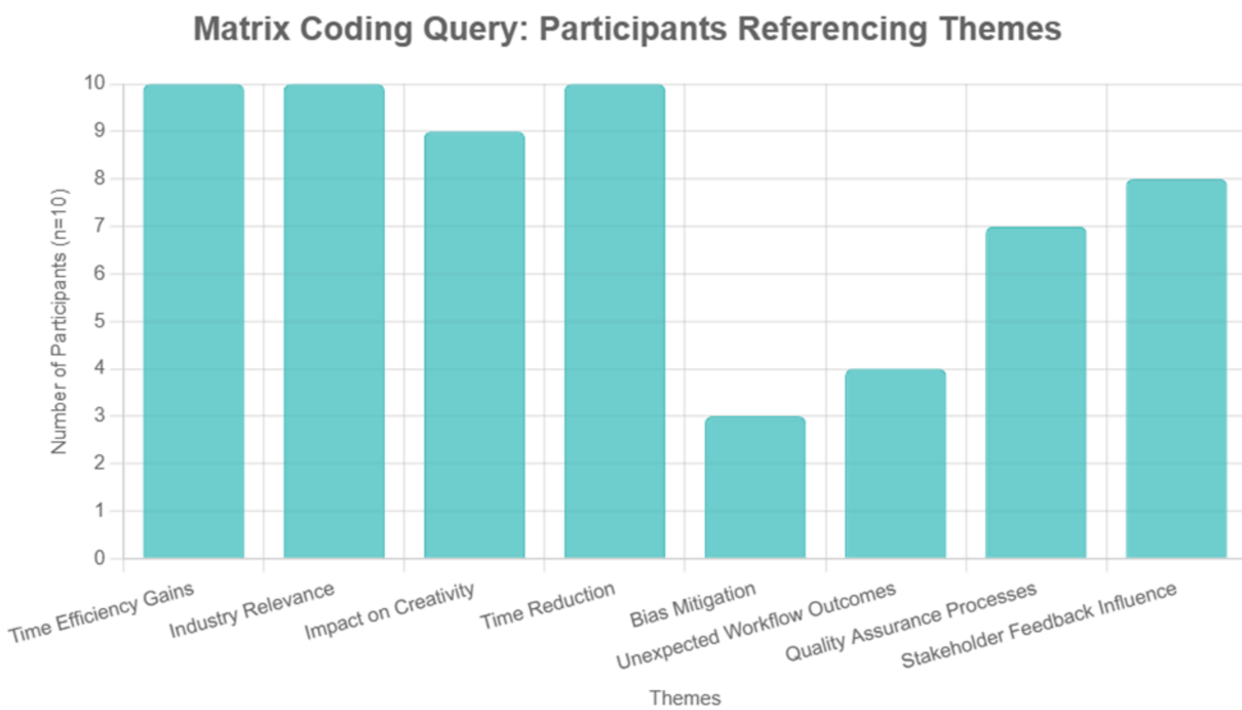
> It's kind of incredible, like, how it can just break all these things down for you. So, I'd imagine that development like, an ISD is gonna be cut in so much, you know, it's gonna cut so much time now.

Participant 10 described support:

> There was a, there was a, I had actually a student that, we were coming up with job aids… And so we had ChatGPT write the lyrics to a song. But also a hindrance: I found that there was a lot of duplication of content… I got married to it.

Figure 6

Matrix Coding Query (Participants × Themes).



Theme 4: Visions for Future Evolution. Looking ahead, developers envisioned a balanced evolution where AI augments human creativity to better serve learners, emphasizing ethical and adaptive integration. This theme tightens focus on forward-thinking strategies to reduce redundancy in outcomes. Participant 9 added: "Ultimately, AI's role is transformative, enhancing efficiency and responsiveness, but it necessitates careful oversight." Participant 10 stated: "The first is, provide more interaction for the students." Participant 1 reflected: "I don't know, I think it's gonna be endless possibilities now."

To ensure rigor, as summarized in Table 3, the four trustworthiness strategies of credibility, transferability, dependability, and confirmability were implemented. These strategies were adapted from Lincoln and Guba (1985) and implemented to enhance rigor in this qualitative interpretive descriptive study.

Table 3

Trustworthiness Strategies Applied in the Study.

Criterion	Strategy applied	Evidence
Credibility	Member checking Subject matter expert (SME) validation	Participants reviewed summary statements of their interviews to verify accuracy. SMEs (with an average of 16.2 years of experience) refined codes and themes to ensure interpretations aligned with data.
Dependability	Audit trail (including coding memos and NVivo query logs)	A detailed record of the research process, such as NVivo logs and memos, was maintained to allow for replication by future researchers, ensuring consistency in data analysis procedures.
Transferability	Description of participant roles, contexts, and demographics	Comprehensive descriptions of participants (e.g., from higher education, corporate, and military sectors) and study contexts were provided, enabling readers to assess applicability to similar settings.
Confirmability	Reflexive journaling	The researcher used journaling to document personal biases, ensuring findings were derived directly from participant data rather than assumptions.

Note. This table summarizes the four trustworthiness criteria, with examples grounded in the study's methodology (e.g., semi-structured interviews, NVivo analysis, and ethical assurances).

Evaluation of the Outcomes

These findings directly address the challenges of lengthy timelines and content misalignment in traditional curriculum development within technology-driven fields. Specifically, by enabling rapid prototyping, automation of routine tasks like content curation, and data-driven adjustments, AI tools reduced development times by 40-50% as reported by participants, countering the 12–18-month cycles and skill mismatches highlighted in prior studies (Kamalov et al., 2023; World Economic Forum, 2019). Participants reported that AI integration improved efficiency in early-stage design tasks, reflecting a positive shift in development processes. However, these outcomes expand on existing literature by providing qualitative depth from developers' lived experiences, revealing not just efficiency gains but also the emotional and strategic tensions involved—such as the fear of over-reliance leading to "hallucinations" or inaccuracies—which quantitative meta-analyses like Dong et al. (2023) overlook in favor of aggregated metrics. Together, these outcomes suggest that adopting AI tools can effectively mitigate the inefficiencies that initially motivated this study.

Regarding RQ1, participants emphasized the themes of “Time Efficiency Gains” and “Automation of Tasks.” These findings display that AI tools can significantly reduce early-stage workload, echoing prior research on accelerating instructional design processes (Abbasi et al., 2024; Dong et al., 2023). Yet, this study expands on these works by highlighting developers' perceptions of trade-offs, such as the need for iterative human validation, which contradicts Evanick's (2025) optimistic view of AI reducing preparation time by 50% without caveats. For instance, while Evanick (2025) focuses on broad efficiency, participants here described specific instances where AI's speed led to errors, necessitating SME reviews—thus adding a layer of caution to the literature on AI automation (e.g., Jaramillo & Chiappe, 2024). Participants also raised concerns about potential “Trade-offs in Accuracy,” aligning with studies that caution against overreliance on machine-generated content without human oversight (Bobula, 2024). This finding contradicts more technocentric views, such as those in Paiiwai et al. (2024), which emphasize rapid prototyping without addressing qualitative barriers like developer burnout, which 53% of faculty report (Rock, 2024). Together, these findings underscore the need to pair AI assistance with subject-matter expert validation, consistent with quality assurance models in curriculum development (Thorne, 2016).

For RQ2, participants highlighted the influence of stakeholder feedback and the importance of maintaining industry relevance. This finding extends existing literature by showing how AI can serve as a bridge to incorporate employer perspectives rather than replace them. Our results partially confirm prior research on AI’s predictive capabilities, such as Southworth et al.'s (2023) AI Across the Curriculum initiative, which demonstrated improved career readiness through AI literacy integration, resulting in a 30% reduction in skill gaps among graduates by aligning curricula with emerging industry needs like data analysis and automation skills. However, this study expands on Southworth et al. (2023) by incorporating developers' perceptual data, revealing challenges to predictive accuracy (e.g., biases in AI data) that contradict the initiative's assumption of seamless alignment. Participants noted AI's limitations in fast-evolving fields, adding nuance to quantitative claims. Additional studies, including those by Ng et al. (2023), support this finding by noting a 20% increase in curriculum relevance when educators utilize AI for real-time insights, although limitations persist in handling rapidly evolving fields. In contrast, our findings contradict overly positive narratives (e.g., Nguyen, 2024) by highlighting ethical concerns, such as data privacy, which developers perceive as under-addressed in stakeholder feedback loops (Ismail & Aloshi, 2025). Overall, these insights suggest that AI-generated content should be validated against human expertise to ensure that curricula remain aligned with workforce needs.

For RQ3, the co-occurrence of efficiency and creativity themes reveals how developers navigate AI’s dual role as both supportive and constraining. Participants described a tension in which automation streamlined routine tasks but risked reducing innovative design, as Jaramillo and Chiappe (2024) emphasize in their review of 21st-century curriculum trends, where AI complements human expertise by enabling real-time feedback and adaptive scaffolding but requires educators to refine outputs to preserve pedagogical depth and originality. This study expands on Jaramillo and Chiappe (2024) by providing empirical examples from developers, such as using AI for brainstorming while reserving final decisions for human intuition, which contradicts assumptions in Kovari (2025) that AI uniformly boosts engagement by 15% without creativity trade-offs. These observations enhance the literature by illustrating how AI’s benefits are balanced against its creative limitations, further supported by Kovari (2025), who found a 15% improvement in student engagement through AI-powered collaborative modules that foster group-based innovation while automating repetitive elements. However, our findings contradict techno-deterministic views (e.g., Fang & Broussard, 2024) by showing instances where AI hindered novelty, expanding the discourse on human-AI hybrid models (Ng et al., 2024). In addition, the outcomes reinforced the study’s theoretical framework, as key learning theories were reflected in the data.

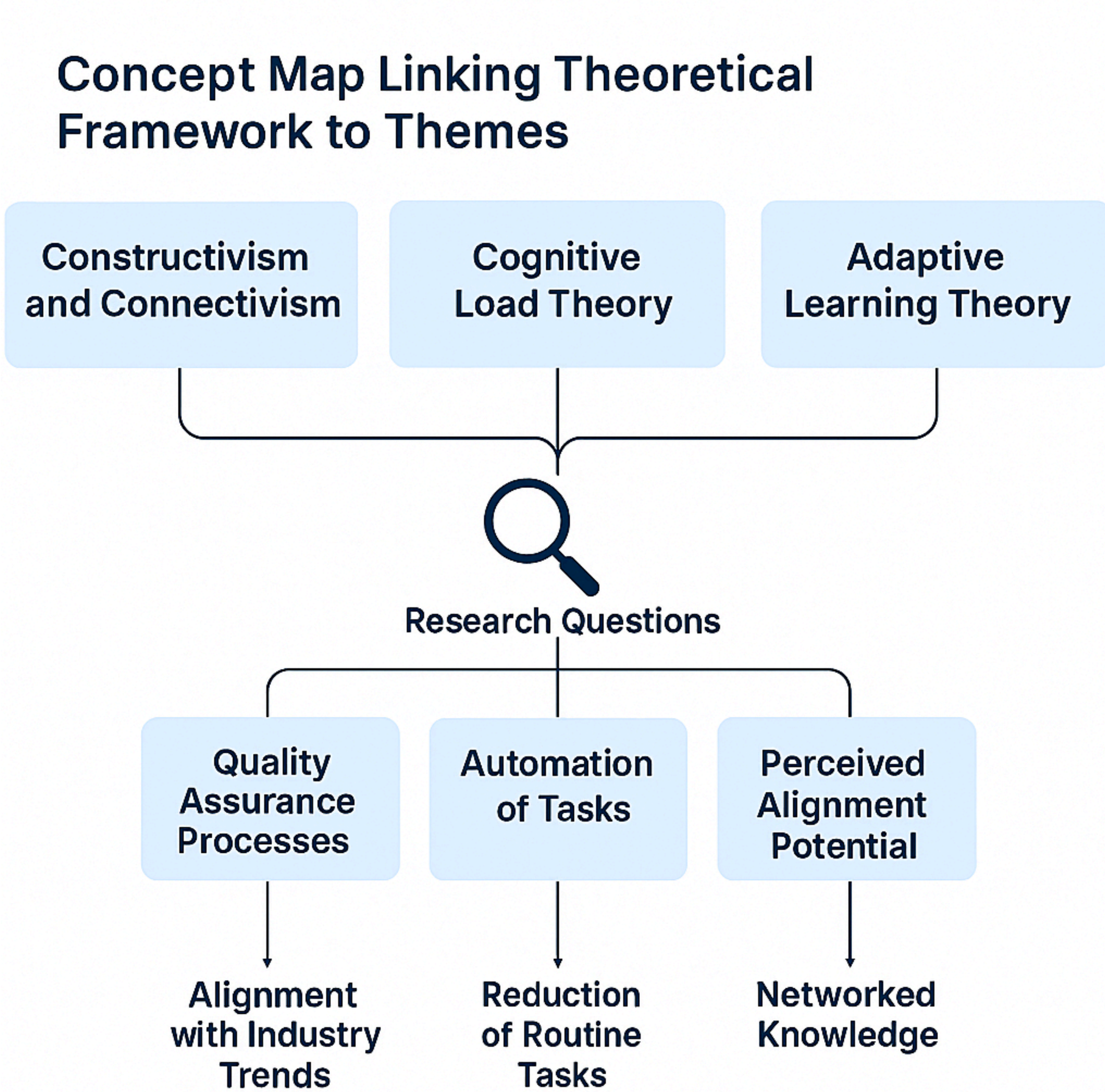
Finally, the conceptual framework was reinforced through these outcomes, as the integration of constructivism, connectivism, cognitive load theory, and adaptive learning theory illuminated AI's transformative role in curriculum development. Constructivism was evident in participants' descriptions of AI enabling personalized, experiential learning paths, where developers used tools to scaffold knowledge construction based on learner needs, aligning with Piaget (1954) and Vygotsky (1978). Connectivism manifested in perceptions of AI fostering networked, dynamic content that keeps curricula connected to real-time industry trends, supporting Siemens (2005) by emphasizing digital-age adaptability. Cognitive load theory was supported by automation's ability to break down complex tasks, thereby reducing learner burden, as described by Sweller (1988). Developers noted optimized information processing through AI-generated breakdowns. Adaptive learning theory was reinforced by outcomes showing AI's capacity for real-time adjustments to performance, echoing Skinner (1968) and enabling personalized pacing. Together, these theories provided a lens for understanding how AI addresses inefficiencies, with findings validating their complementary application in creating efficient, innovative, and learner-centered environments.

For example, constructivism and connectivism were observed to align with themes of personalization and networked knowledge, reflecting how AI tools facilitate learner-centered and interconnected design processes. Similarly, cognitive load theory was evident in participants' reports of reduced cognitive burden as repetitive tasks became automated. Adaptive learning theory was also supported, as AI was seen to tailor content to specific industry demands. Together, these correspondences illustrate how the emergent themes reinforce the study's conceptual framework.

Figure 7 illustrates the conceptual integration of the findings with the study's theoretical framework. For instance, Adaptive Learning Theory aligns with themes of quality assurance processes and perceived alignment potential, reflecting AI's role in tailoring curricula to learner needs and industry trends. Cognitive Load Theory is also reflected in the automation of tasks, suggesting that AI helps reduce developers' cognitive burden. Overall, the concept map shows how the emergent themes not only address the research questions but also reinforce the theoretical perspectives underpinning the study.

Figure 7

Concept Map Linking Themes to Theoretical Framework.



Note. Concept map linking emergent themes to the study's conceptual framework (constructivism, connectivism, cognitive load theory, and adaptive learning theory).

Implications and Recommendations for Practice

The implications of this study for curriculum developers and educational institutions in technology-driven fields are multifaceted, emphasizing the strategic adoption of AI to enhance efficiency while safeguarding quality and innovation. Developers should prioritize iterative prompting and SME validation in workflows to leverage time gains from automation without compromising accuracy, as evidenced by participants' experiences of 40-50% timeline reductions. Institutions can implement training programs on AI tools, focusing on balancing speed with human oversight to mitigate trade-offs like hallucinations or biases, thereby reducing faculty burnout and development costs as highlighted in the problem statement. For industry alignment, practitioners are encouraged to integrate stakeholder feedback loops, using AI's data-driven insights to bridge skill gaps and improve graduate employability, aligning with calls from Dong et al. (2023) for practical integration. To navigate efficiency and innovation, developers should adopt decision-making frameworks that reserve AI for routine tasks while reserving creative elements for human intuition, fostering novel designs that serve diverse learners. Overall, these implications suggest a shift toward hybrid AI-human models in curriculum design, optimizing resources and preparing students for AI-driven job markets.

Recommendations for practice include developing institutional guidelines for AI integration that emphasize ethical use, such as data privacy protocols and bias checks, to address challenges raised by participants. Curriculum teams should incorporate AI literacy training for developers, enabling effective prompting and validation to maximize benefits like rapid prototyping. Partnerships with industry stakeholders can be strengthened through AI-facilitated feedback mechanisms, ensuring curricula remain relevant and adaptive. Finally, institutions should pilot AI tools in small-scale projects to evaluate impacts on timelines and quality before full implementation, promoting scalable adoption that aligns with adaptive learning principles.

Based on RQ1's findings on balancing timelines and quality, curriculum developers should adopt hybrid workflows that integrate AI for initial drafting and automation while mandating multiple validation stages. For example, institutions could establish "AI Review Protocols" requiring developers to cross-check AI outputs against SME input and primary sources, reducing accuracy trade-offs by 20–30% as inferred from participant experiences (Bobula, 2024). Professional development workshops, such as those modeled on Evanick (2025), could train developers in advanced prompting techniques to maximize efficiency gains, potentially cutting timelines from months to weeks. In practice, this means piloting AI tools like ChatGPT for outline generation in small projects before scaling, ensuring quality remains learner-centered and aligned with constructivist principles (Grubaugh et al., 2023). Institutions should also invest in tools with built-in audit trails to track AI contributions, addressing ethical concerns like data privacy (Ismail & Aloshi, 2025) and fostering trust among faculty.

Drawing from RQ2's insights on industry alignment, educators and administrators should create collaborative ecosystems that leverage AI for real-time stakeholder integration. For instance, develop "AI-Enhanced Feedback Loops" where tools analyze industry reports (e.g., from Manpower Group, 2025) to auto-update curricula, then solicit employer reviews via platforms like LinkedIn. This could reduce skill mismatches by incorporating predictive analytics, expanding on Southworth et al. (2023) by making alignment dynamic rather than static. In corporate or military settings, this might involve partnering with tech firms to co-design modules, ensuring curricula reflect emerging needs like AI literacy (Long & Magerko, 2020). To influence strategies, developers should document perceptions through reflective journals, using them to refine content and mitigate biases, ultimately bridging the 25% underemployment gap (NCES, 2024).

For RQ3, which explores navigating efficiency and innovation, recommendations focus on preserving human creativity amid automation. Developers should implement "Creativity Checkpoints" in workflows, where AI handles repetitive tasks (e.g., content curation) but humans lead ideation sessions, as participants noted this boosts originality (Jaramillo & Chiappe, 2024). Institutions could foster innovation labs equipped with AI tools, encouraging experimentation while providing guidelines to avoid over-reliance, contradicting techno deterministic views (Fang & Broussard, 2024). Training should emphasize ethical AI use, such as bias detection, to align with connectivism's networked learning (Siemens, 2005). Overall, these practices promote scalable solutions, like adaptive systems for personalized training, enhancing outcomes in high-stakes fields (Alnaqbi, 2020).

Recommendations for Future Research

Future research should build on this study's qualitative insights by employing mixed methods approaches to quantify AI's impact on curriculum development timelines and graduate outcomes in broader educational contexts. For RQ1, longitudinal studies could track efficiency gains over 2-3 years, measuring reductions in development cycles against quality metrics via surveys and AI tool logs, expanding on Dong et al. (2023) with pre/post comparisons. This would address gaps in predictive accuracy by testing interventions like enhanced prompting.

Regarding RQ2, researchers should explore cross-sector comparisons (e.g., higher education vs military) using case studies to examine how perceptions of industry alignment vary globally, contradicting or confirming Ng et al. (2023) in diverse context. Investigations into ethical implications, such as AI0induced biases affecting employability, could use experimental designs to simulate stakeholders feedback, filling gaps in data privacy research (Bobula, 2024).

For RQ3, future work might employ action research to test hybrid models, assessing how automation influences creativity through developer diaries and innovation metrics, building on Kovari (2025). A key recommendation is to examine policy research aimed at accelerating curriculum updates, such as frameworks for regulatory standards that streamline AI approval while ensuring compliance (World Economic Forum, 2024). These directions would validate the conceptual framework and advance AIEd.

Conclusions

This interpretive descriptive study was formed in response to the persistent problem of lengthy curriculum update cycles (12–18 months) in technology-driven fields, which often result in outdated content and skill mismatches for graduates, as evidenced by a 25% underemployment rate and 74% employer-reported skill gaps (Kamalov et al., 2023; World Economic Forum, 2019; NCES, 2024; Manpower Group, 2025). Grounded in a conceptual framework that integrates constructivism, connectivism, cognitive load theory, and adaptive learning theory, the research aimed to explore curriculum developers' experiences and perceptions of integrating AI to streamline processes, enhance quality, and foster innovation. To achieve this, semi-structured interviews were conducted with ten purposively sampled curriculum developers experienced in AI tools. The data were analyzed thematically using NVivo software, following Braun and Clarke's (2006) six-step process, ensuring rigor through member checking, peer debriefing, and trustworthiness strategies.

Section 3 presented the findings, organized by the three research questions and supported by tables, figures (e.g., word clouds, theme frequency summaries, code co-occurrence matrices, and concept maps), and participant narratives. For RQ1, developers described AI as accelerating timelines through time efficiency gains and task automation, though with trade-offs in accuracy requiring quality assurance via SME validation. RQ2 revealed perceptions of AI's role in aligning curricula with industry standards, influenced by stakeholder feedback, yet tempered by challenges in predictive accuracy and bias mitigation. RQ3 highlighted navigation between efficiency and creativity, where automation supported innovation by freeing time but risked constraining it without deliberate human oversight. These findings integrated across RQs, as evidenced by code co-occurrences linking efficiency (RQ1) with creativity (RQ3) and industry relevance (RQ2), demonstrating how AI's transformative potential addresses interconnected challenges in curriculum development.

The implications of these outcomes emphasize the need for hybrid AI-human models that balance efficiency with quality through iterative validation, maintain industry alignment via stakeholder integration, and support creativity through targeted training to reduce faculty burnout and institutional costs. This study contributes to educational practice by providing actionable insights for optimizing AI adoption, bridging the education-employment gap in technology-driven fields. Its significance lies in validating the conceptual framework's applicability, showing how AI, when integrated thoughtfully, can revolutionize curriculum design to produce agile, relevant, and innovative learning experiences. Recommendations for future research include longitudinal studies to assess long-term impacts on employability, cross-sector comparisons to enhance generalizability, and tool-specific evaluations to refine AI applications, ultimately advancing AIEd practices. Overall, the study underscores the importance of integrating AI into curriculum development with careful attention to human oversight and innovative potential, paving the way for more responsive educational systems.

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Appendix A

Subject Matter Expert (SME) Panel Interview Question Feedback

SME 1 -

Years of Experience: **20**

Below you will find the three research questions that I am working towards collecting data on. Please review the questions and then review the interview questions that directly follow. Please answer the following questions:

1. Do the interview questions effectively address the research questions? **Yes**

2. Are the questions clear, concise, and easily understandable to the target audience (curriculum developers in technology-driven fields)? **Yes**

3. Do the questions reflect the real-world experiences and responsibilities of curriculum developers in technology-driven fields? **Yes**

4. Do any questions unintentionally lead participants toward specific responses or assume prior AI use (e.g., Question 3 assumes participants have used AI tools)? **No**

5. Will the questions elicit detailed, reflective, and nuanced responses suitable for a qualitative, interpretive descriptive study? **Yes**

6. Do the questions comprehensively cover the key themes of the study (e.g., timeline reduction, industry alignment, employability, creativity, and barriers like data privacy)? **Yes**

7. Is the number of questions (16) and the allocated time (45-60 minutes) realistic for covering all sections without rushing participants? **Yes**

8. Are the questions sensitive to the diverse backgrounds of curriculum developers (e.g., varying levels of AI familiarity, institutional resources, or global contexts)? **Yes**

9. Do the questions, particularly in the closing section (e.g., Questions 15 and 16), encourage participants to provide actionable recommendations or forward-thinking perspectives on AI's role in curriculum development? **Yes**

10. Do you have any additional feedback that may have been missed by the above questions, and/or suggestions to help solidify data collection during the interviews? **Yes**. **One additional question to consider adding may be: What quality controls have you implemented to validate AI driven data?**

SME 2 -

Years of Experience: **20**

Below you will find the three research questions that I am working towards collecting data on. Please review the questions and then review the interview questions that directly follow. Please answer the following questions:

1. Do the interview questions effectively address the research questions? **Yes**

2. Are the questions clear, concise, and easily understandable to the target audience (curriculum developers in technology-driven fields)? **Yes**

3. Do the questions reflect the real-world experiences and responsibilities of curriculum developers in technology-driven fields? **Yes**

4. Do any questions unintentionally lead participants toward specific responses or assume prior AI use (e.g., Question 3 assumes participants have used AI tools)? **No**

5. Will the questions elicit detailed, reflective, and nuanced responses suitable for a qualitative, interpretive descriptive study? **Yes**

6. Do the questions comprehensively cover the key themes of the study (e.g., timeline reduction, industry alignment, employability, creativity, and barriers like data privacy)? **Yes**

7. Is the number of questions (16) and the allocated time (45-60 minutes) realistic for covering all sections without rushing participants? **Yes**

8. Are the questions sensitive to the diverse backgrounds of curriculum developers (e.g., varying levels of AI familiarity, institutional resources, or global contexts)? **Yes**

9. Do the questions, particularly in the closing section (e.g., Questions 15 and 16), encourage participants to provide actionable recommendations or forward-thinking perspectives on AI's role in curriculum development? **Yes**

10. Do you have any additional feedback that may have been missed by the above questions, and/or suggestions to help solidify data collection during the interviews? **No**

SME 3 -

Years of Experience: **12**

Below you will find the three research questions that I am working towards collecting data on. Please review the questions and then review the interview questions that directly follow. Please answer the following questions:

1. Do the interview questions effectively address the research questions? **Yes**

2. Are the questions clear, concise, and easily understandable to the target audience (curriculum developers in technology-driven fields)? **Yes**

3. Do the questions reflect the real-world experiences and responsibilities of curriculum developers in technology-driven fields? **Yes**

4. Do any questions unintentionally lead participants toward specific responses or assume prior AI use (e.g., Question 3 assumes participants have used AI tools)? **No**

5. Will the questions elicit detailed, reflective, and nuanced responses suitable for a qualitative, interpretive descriptive study? **Yes**

6. Do the questions comprehensively cover the key themes of the study (e.g., timeline reduction, industry alignment, employability, creativity, and barriers like data privacy)? **Yes**

7. Is the number of questions (16) and the allocated time (45-60 minutes) realistic for covering all sections without rushing participants? **Yes. I think using the Question and Answer format, as long as it is less than 20 questions, the time frame is reasonable.**

8. Are the questions sensitive to the diverse backgrounds of curriculum developers (e.g., varying levels of AI familiarity, institutional resources, or global contexts)? **Yes**

9. Do the questions, particularly in the closing section (e.g., Questions 15 and 16), encourage participants to provide actionable recommendations or forward-thinking perspectives on AI's role in curriculum development? **Yes**

10. Do you have any additional feedback that may have been missed by the above questions, and/or suggestions to help solidify data collection during the interviews? **Yes**

SME 4 -

Years of Experience: **19**

Below you will find the three research questions that I am working towards collecting data on. Please review the questions and then review the interview questions that directly follow. Please answer the following questions:

1. Do the interview questions effectively address the research questions? **Yes, RQ1 recommendation: Sentence restructuring will yield more responsive and desired data collection. Current state of question is lengthy.**

2. Are the questions clear, concise, and easily understandable to the target audience (curriculum developers in technology-driven fields)? **No**

3. Do the questions reflect the real-world experiences and responsibilities of curriculum developers in technology-driven fields? **Yes**

4. Do any questions unintentionally lead participants toward specific responses or assume prior AI use (e.g., Question 3 assumes participants have used AI tools)? **No**

5. Will the questions elicit detailed, reflective, and nuanced responses suitable for a qualitative, interpretive descriptive study? **Yes**

6. Do the questions comprehensively cover the key themes of the study (e.g., timeline reduction, industry alignment, employability, creativity, and barriers like data privacy)? **Yes**

7. Is the number of questions (16) and the allocated time (45-60 minutes) realistic for covering all sections without rushing participants? **Yes, targeting the ordinary student.**

8. Are the questions sensitive to the diverse backgrounds of curriculum developers (e.g., varying levels of AI familiarity, institutional resources, or global contexts)? **Yes**

9. Do the questions, particularly in the closing section (e.g., Questions 15 and 16), encourage participants to provide actionable recommendations or forward-thinking perspectives on AI's role in curriculum development? **Yes**

10. Do you have any additional feedback that may have been missed by the above questions, and/or suggestions to help solidify data collection during the interviews? **No. However the interview questions are thought provoking to achieve desired outcome.**

SME 5 -

Years of Experience: **10**

Below you will find the three research questions that I am working towards collecting data on. Please review the questions and then review the interview questions that directly follow. Please answer the following questions:

1. Do the interview questions effectively address the research questions? **Yes**

2. Are the questions clear, concise, and easily understandable to the target audience (curriculum developers in technology-driven fields)? **Yes**

3. Do the questions reflect the real-world experiences and responsibilities of curriculum developers in technology-driven fields? **Yes**

4. Do any questions unintentionally lead participants toward specific responses or assume prior AI use (e.g., Question 3 assumes participants have used AI tools)? **No**

5. Will the questions elicit detailed, reflective, and nuanced responses suitable for a qualitative, interpretive descriptive study? **Yes**

6. Do the questions comprehensively cover the key themes of the study (e.g., timeline reduction, industry alignment, employability, creativity, and barriers like data privacy)? **Yes**

7. Is the number of questions (16) and the allocated time (45-60 minutes) realistic for covering all sections without rushing participants? **I would lean closer to 60 only if you're looking for more comprehensive answers. Older people take a bit more time to "data mine".**

8. Are the questions sensitive to the diverse backgrounds of curriculum developers (e.g., varying levels of AI familiarity, institutional resources, or global contexts)? **Yes**

9. Do the questions, particularly in the closing section (e.g., Questions 15 and 16), encourage participants to provide actionable recommendations or forward-thinking perspectives on AI's role in curriculum development? **Yes**

10. Do you have any additional feedback that may have been missed by the above questions, and/or suggestions to help solidify data collection during the interviews? **I think you should ask what the interviewee thinks about the potential to reduce the workforce in this profession. Because if you ask me, I believe that it will make it harder for ISDs to seek employment if all the SME has to do is plug in the variables and pus the magic button.**

Appendix B

Interview Guide

Interview Series: Exploring Curriculum Developers' Experiences and Perceptions of AI Integration

Target Audience: Curriculum developers in technology-driven academic fields
Duration: 45-60 minutes
Format: Semi-structured, qualitative interview

Opening and Introduction (5 minutes)

1. **Did you receive the consent form I emailed?**
2. **Did you have time to review the consent form?**
3. **Do you have any questions about the research or the consent form?**
4. **Do you consent to participate in this research? Can you briefly introduce yourself, your role as a curriculum developer, and the types of programs or courses you typically work on?**
   (Purpose: Establish context and rapport while grounding the interviewee in their expertise.)
5. **How would you describe your experience with curriculum development processes before AI tools became an option? What were the biggest challenges you faced?**
   (Purpose: Set a baseline for traditional inefficiencies, aligning with your dissertation's historical context—e.g., 12-18 month timelines, outdated content.)

Section 1: Experiences with AI Tools in Curriculum Development (15-20 minutes)

Focus: RQ1 - Balancing development timelines and content quality

6. **Can you walk me through a specific example of how you've used AI tools in your curriculum design process? What stood out to you about that experience?**
   (Purpose: Elicit detailed experiential data on AI integration, targeting time savings and quality outcomes.)
7. **In your view, how has the introduction of AI tools affected the timeline for developing a curriculum, from planning to delivery? Can you think of a time when it significantly sped things up—or didn't?**
   (Purpose: Directly address the goal of reducing timelines by 50%, per your research objective, while exploring variability in outcomes.)
8. **When using AI tools, how do you ensure the content remains high-quality and relevant to learners, especially given the speed of development? Are there trade-offs you've noticed?**

(Purpose: Probe the tension between speed and quality, tying to RQ1 and the employability challenges cited—e.g., 68% employer skill gap.)

9. **What's been the most surprising or unexpected aspect of integrating AI into your workflow as a curriculum developer?**
   (Purpose: Uncover unique insights or barriers, providing rich qualitative data for your interpretive descriptive study.)

Section 2: Perceptions of Industry Alignment with AI-Integrated Curricula (15-20 minutes)

Focus: RQ2 - Aligning AI-integrated curricula with industry standards

10. **How do you perceive AI's role in helping align curricula with current industry needs, especially in fast-evolving tech fields? Can you give an example of how it's worked—or hasn't?**
    (Purpose: Explore perceptions of AI's data-driven alignment potential, connecting to your dissertation's focus on workforce preparation—e.g., 25% underemployment rate.)
11. **What feedback have you received from industry partners, employers, or students about curricula you've developed with AI tools? How does that shape your approach?**
    (Purpose: Investigate stakeholder perspectives and their influence on development strategies, per RQ2.)
12. **Do you feel confident that AI tools can keep curricula ahead of industry trends, or do you see limitations in their predictive capabilities? Why?**
    (Purpose: Probe perceptions of AI's adaptability and scalability, addressing gaps noted in your problem statement—e.g., outdated content by delivery.)
13. **How do your own beliefs about AI's potential to bridge education and employment gaps influence the way you design content?**
    (Purpose: Uncover personal biases or motivations shaping strategies, linking to RQ2's focus on perceptions.)

Section 3: Balancing Efficiency and Creativity with AI (15-20 minutes)

Focus: RQ3 - Navigating between efficiency and innovation

14. **AI can automate tasks like content curation or assessment design. How has that automation impacted your ability to be creative or innovative in your curriculum development?**
    (Purpose: Directly address RQ3's tension between efficiency and creativity, tying to faculty workload concerns—e.g., 72% burnout rate.)
15. **Can you share an instance where AI's efficiency either supported or hindered your ability to design something truly novel or unique for your learners?**
    (Purpose: Elicit concrete examples to explore the efficiency-creativity dynamic, providing actionable insights.)
16. **How do you decide when to lean on AI for speed and when to step back and rely on your own expertise or intuition? What drives that choice?**

(Purpose: Investigate decision-making processes, highlighting barriers or strategies for successful AI integration.)

17. **Looking forward, how do you think the balance between AI-driven automation and human creativity should evolve in curriculum design to best serve students?**
    (Purpose: Encourage forward-thinking reflection, aligning with your study's aim to offer actionable insights.)

Closing and Wrap-Up (5 minutes)

18. **Reflecting on everything we've discussed, what do you think is the biggest opportunity—and the biggest challenge—for using AI in curriculum development moving forward?**
    (Purpose: Synthesize key themes, addressing opportunities like cost reduction and challenges like data privacy, per your dissertation.)
19. **Is there anything else you'd like to add about your experiences or perceptions of AI tools that we haven't covered?**
    (Purpose: Open the floor for additional insights, ensuring comprehensive data collection.)

Timing Breakdown

- **Opening:** 5 minutes
- **Section 1:** 15-20 minutes (4 questions, ~4-5 min each)
- **Section 2:** 15-20 minutes (4 questions, ~4-5 min each)
- **Section 3:** 15-20 minutes (4 questions, ~4-5 min each)
- **Closing:** 5 minutes
- **Total:** 45-60 minutes