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Artificial Intelligence as a University Graduation Requirement: Advantages, Disadvantages, and Opportunities

Barbara D. Klein
University of Michigan, Dearborn, bdklein@umich.edu

Rassule Hadidi
Metro State University, Rassule.Hadidi@metrostate.edu

Abstract

Universities have continually adapted curricula to equip students for the intellectual and professional demands of their era. The rapid diffusion of artificial intelligence now creates an inflection point, reshaping work, civic life, and everyday decision-making in ways that higher education cannot ignore. This article argues that institution-wide AI graduation requirements can advance core university aims by improving career readiness, strengthening ethical judgment, expanding equitable access to technological understanding across majors, and fostering interdisciplinary learning. It also examines practical and pedagogical concerns, such as already crowded degree plans and the substantial staffing, infrastructure, and support needed for effective implementation. Situating the debate within the historical evolution of general education and drawing lessons from earlier computer literacy requirements, the article proposes a flexible menu of approved courses that collectively develop AI concepts, skills, and critical perspectives. Emerging examples, including recent initiatives at Purdue University and The Ohio State University, illustrate how requirements can be embedded in curricula with workforce emphasis. Increasing AI adoption and use across a broad spectrum of professional domains tilt the case toward adopting artificial intelligence graduation requirements, provided the implementation of these requirements properly addresses capacity, equity, and ethical issues.

Keywords: artificial intelligence; university graduation requirements; general education; career readiness; workforce preparation; fairness in AI usage; privacy; bias in AI models; technological equity; interdisciplinary innovation in higher education

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1. Introduction

Universities have long sought to prepare students for the intellectual and professional demands of their time. General education and graduation requirements have shifted as the needs of society and the workplace have changed. As artificial intelligence becomes increasingly embedded in society and professional work, universities will continue this evolution and consider the extent to which graduation requirements can be and should be updated to reflect the need to prepare students for the AI-related challenges and opportunities that will arise in their personal, professional, and civic lives. The following sections will discuss an argument in favor of university AI graduation requirements, arguments against AI graduation requirements, the history of general education in the United States, the relationship between general education requirements and AI graduation requirements, a history of computer literacy graduation requirements, a workforce preparation justification for AI graduation requirements, existing approaches, and a proposed way forward.

2. An Argument in Favor of University AI Graduation Requirements

As artificial intelligence (AI) profoundly shapes the nature of work, society, and daily life, universities stand at a critical juncture (Bankins and Formosa, 2023; Hoffman et al., 2025). Naturally, consideration of graduation requirements across all majors may arise as institutions explore ways to ensure that all students gain foundational knowledge of AI technology, applications, and ethical issues. Potential advantages of adopting AI graduation requirements include improved workforce preparedness, enhanced critical thinking, improved ethical reasoning (Aston, 2024), the promotion of equity (Gayed, 2025), and multidisciplinary innovation.

Perhaps the most compelling advantage of AI graduation requirements is equipping graduates with skills directly relevant to current and future job markets. AI is found in everything from healthcare diagnostics and financial modeling to automated vehicles and smart personal assistants. By making AI education mandatory and universal, universities help bridge the gap between academia and industry needs. Students with AI literacy (Wang et al., 2025) are better prepared for roles in fields ranging from business and engineering to social sciences and the arts. Even if they do not become AI specialists, every graduate is likely to interact with automated systems, algorithms, and data-driven decision-making in their chosen profession. Students who are prepared with AI-related knowledge and skills are likely to compete more effectively in the labor market upon graduation and advance more rapidly in their careers.

While workforce preparation is an undisputed role of universities in society, an even more important aspect of a university education is preparing students for the ethical dilemmas they will face in their professions, as citizens, and as members of their families and communities. AI-based systems and algorithms introduce complex questions regarding fairness, privacy, bias, and accountability; and these issues will confront graduates entering all professions. AI graduation requirements ensure students are exposed to these ethical considerations, enabling them to question the societal impacts of new technologies. By integrating ethics into AI education, universities promote responsible innovation and informed citizenship. Students learn to ask about the impacts of AI-based algorithmic decisions. For example, questions of the causes, detection, effects, and reduction of bias can be considered (Daneshjou R, 2021). These debates are fundamental for a society that is increasingly governed by opaque and powerful algorithms.

Requiring AI literacy and preparation for all students democratizes access to technological knowledge while reducing disparities between technical and non-technical majors. It ensures humanities, arts, and social science students are not left behind as AI revolutionizes their fields. This broader approach promotes equity, making every graduate fluent in the language of contemporary technology as well as prepared to challenge, shape, and engage with AI rather than merely consume its outputs.

Finally, AI is inherently multidisciplinary. It intersects with linguistics, philosophy, psychology, law, medicine, and other academic disciplines (Dignum, 2019). Mandatory AI education fosters collaboration across diverse fields and encourages students to apply AI concepts in creative and meaningful ways. For example, a musician might use AI to analyze trends in composition, a political science major may use it to study public opinion, and a nurse may use AI to improve patient outcomes. Broad adoption of AI requirements helps cultivate a culture of interdisciplinary problem solving, which may, in turn, spark new ideas and innovative solutions that might not otherwise emerge.

Adopting AI graduation requirements offers universities far-reaching advantages such as aligning curricula with workforce needs, instilling ethical awareness, promoting technological equity, fostering interdisciplinary innovation, and enhancing institutional standing. In a world shaped by intelligent machines, such strategies help ensure that every graduate is prepared for a variety of roles in their professions and communities.

3. Arguments Against University AI Graduation Requirements

While there are advantages of AI graduation requirements, a consideration of potential drawbacks is needed before adoption. First, university graduation requirements often incorporate very little slack, and degree requirements can be packed. By the time students complete general education requirements, requirements of their majors, electives, and other requirements, they may have very few remaining credit hours available. This is especially true of transfer students who may have credits on their transcripts that do not directly meet any requirements. Federal financial aid regulations limit the extent to which students can receive financial aid for incremental credit hours beyond those required for degree completion. For students in some professional programs, such as engineering, incremental course requirements can lengthen the time needed for degree completion and may impose burdensome costs related to tuition, fees, and living expenses. Students may also prefer to devote any slack credit hours to the pursuit of personal interests rather than an additional AI-related graduation requirement.

Another potential downside of AI graduation requirements is the significant human and technological resources needed to implement the requirement. Faculty must be recruited and trained, and cutting-edge technology must be deployed to make the requirement meaningful and helpful to students post-graduation. An AI graduation requirement may also be unappealing to students who simply are not interested in the topic or even philosophically opposed to using AI tools (Chan and Hu, 2023).

4. The History of General Education in the United States

The role of general education graduation requirements in universities in the United States has evolved. In general, its goals have been to develop broad intellectual skills and knowledge in graduates, regardless of their field of study. As societal values and priorities, philosophies of education, and the labor market have evolved, so too have general education requirements (Zai, 2015).

In the early days of university education in colonial America, private universities such as Harvard and Yale adopted educational choices similar to those in Europe. Students focused on topics such as Greek, Latin, and mathematics, and much of the curriculum was what we would now call general education. Later, students were allowed more choice and intellectual freedom, and as land-grant universities developed, the curriculum continued to evolve to include topics such as engineering and agriculture. General education began to focus on what all students should study across a broad spectrum of specialized options. As general education requirements matured, the focus was often on knowledge in the humanities, social sciences, and natural sciences, as well as skills and dispositions such as critical thinking and preparation for community and national citizenship. Further evolution of general education requirements has broadened this component of the curriculum to include a wider range of perspectives, more integration across disciplines, ethical and critical thinking, and global issues and perspectives (Warner and Koeppel, 2009). Increasingly, students choose from a menu of courses that focus on learning outcomes related to these perspectives, and often a single course is allowed to fulfill two or even more general education requirements.

This framework for graduation requirements opens the door to consideration of AI graduation requirements, with one possible approach being the creation of a menu of course options addressing AI-related concepts, skills, and perspectives.

5. On the Relationship Between General Education Requirements and AI Graduation Requirements

General education requirements are designed to ensure that students attain a broad educational foundation that will enable them to participate as members of society and their chosen professions. Students receive a well-rounded education, including areas such as composition, mathematics, humanities, social sciences, natural sciences, critical thinking, cultural awareness, and so forth. As AI literacy becomes increasingly important in society and in the workplace, educational priorities may shift to include AI graduation requirements. Arguably, students will face an environment in which AI is present in the devices they use, the algorithms that affect them, and the jobs they perform. A well-rounded education will likely help students understand and navigate AI technologies.

As awareness of AI-related issues and competencies spreads, universities are debating and considering whether to implement formal AI graduation requirements. This requirement may be included in general education requirements, especially in the current environment in which many general education requirements can be satisfied through a menu of course options, some of which may count for major or other requirements. An approach that allows students to fulfill AI graduation requirements using a single course that also fulfills another graduation requirement may prepare students for their future roles without requiring additional credit hours, delaying graduation, or increasing costs. Furthermore, this approach may encourage faculty to design and deliver courses that focus on AI learning outcomes along with other goals and objectives of their courses. A course focused on social aspects of AI might simultaneously fulfill an AI graduation requirement and a social sciences requirement. Likewise, a machine learning course might simultaneously fulfill an AI graduation requirement and a quantitative thinking graduation requirement.

6. A History of Computer Literacy Graduation Requirements

University experiences with graduation requirements focused on computer literacy provide a lens through which AI graduation requirements can be viewed. As computers began to proliferate, it became clear that students would need to develop the skills needed to use this technology across many work domains (Hindi et al., 2002). In addition to basic digital skills, a focus on using computers for strategic advantage in the workplace emerged. Universities began by offering elective courses, often focused on computer programming. Over time, in part because of employer requests, universities incorporated computer literacy into mandatory parts of the curriculum in various ways. During the 1990s, as the Internet became more prominent in daily life, course requirements tended to shift toward the use of productivity software and navigation of the Internet. In some institutions, as this technology continued to mature, computer literacy instruction moved into majors and was customized to specific professional needs (Johnson et al., 2006). Many universities and majors no longer include explicit computer literacy graduation requirements because students bring a base level of competence from their earlier experiences, and computer-related fluency is an expected part of many required courses across the university.

7. A Workforce Preparation Justification for AI Graduation Requirements

While there are both advantages and disadvantages to AI graduation requirements, an increasingly AI-infused workplace shifts the argument toward such a requirement. As students enter a workplace in which collaboration with AI-agents will be common and employees will focus less on routine work and more on impactful work with strategic importance, AI-based competency emerges as an important aspect of education for all (Bonney, 2024). This shifts AI graduation requirements from an incremental curricular innovation to a necessity for future career preparation. AI-based agents and related algorithms will impact many job sectors, and students without preparation in this domain are likely to struggle to attain entry level positions and progress in their careers. As AI literacy becomes as critical as computer literacy once was, the justification for AI graduation requirements becomes clear.

Such a graduation requirement ensures that students across majors have access to this preparation. This opens opportunities for all and prepares students for an environment in which interdisciplinary innovation and collaboration will be essential aspects of the workplace. An AI graduation requirement also builds student adaptability and resilience as they contend with technologies that are rapidly changing. Graduates who have AI-related competencies will be better prepared to adapt to new jobs and careers as they learn new technologies and software and develop the ability to understand the inputs and outputs of AI. Additionally, AI graduation requirements promote ethical problem-solving. Students will be better prepared to consider issues of privacy and bias in AI systems. A basic understanding of the fundamentals of AI will help students consider these issues in more concrete ways rather than as abstractions. This, in turn, will help them understand and mitigate risks and foster a more calibrated understanding of trust in AI systems and algorithms. As employers increasingly list AI skills as requirements on job postings, universities with AI graduation requirements will help students meet the requirements of the workforce into which they will graduate.

8. Existing Approaches

Purdue University and The Ohio State University, among others, have recently adopted AI graduation requirements that embed AI education into the curriculum with a focus on workforce preparation.

Purdue University is introducing an “AI working competency” graduation requirement for undergraduate students effective Fall 2026. The requirement is aimed at workforce and employer needs and focuses on the development of critical thinking skills needed to understand and use AI effectively (Purdue unveils, 2026).

The Ohio State University has announced that it is incorporating AI into its curriculum and graduation requirements by integrating AI into its general education requirements through an initiative called the AI Fluency initiative (AI

Fluency, 2026). This initiative is effective with the class of 2029 and focuses on AI fluency from the perspective of professional preparation. Students will encounter AI in their first “Bookend” course, which is a 1-credit seminar that students take early in their program to fulfill a general education requirement (AI Fluency, 2026; The Ohio State University, 2026). Consistent with widely adopted general education strategies and practices, six learning outcomes related to AI have been defined and are listed below verbatim.

“Explain foundational concepts such as artificial intelligence, large language models, machine learning

Explore the potential benefits and limitations of common AI applications in the context of a chosen field

Evaluate the types of inputs and outputs foundational to AI systems — including data, prompts, commands and emerging modalities — and explain how input form and quality influence output quality, performance and reliability

Use AI tools to accomplish specific goals in the field of study, and critically assess outputs for accuracy and relevance to the task

Design innovative applications of AI within a discipline, supported by a rationale for the potential value and feasibility

Explore the implications (ethical, societal, environmental, legal, practical) of AI use cases and develop reasoned recommendations for responsible implementation within a field of study” (AI Fluency, 2026)

9. Conclusion

Universities have repeatedly revised graduation expectations to meet the changing intellectual and professional realities facing students, and the present moment calls for a similarly deliberate response to artificial intelligence. As AI systems increasingly mediate how people work, learn, communicate, and make consequential decisions, the question is no longer whether universities should address AI, but how to do so in a way that aligns with the purposes of general education. The case for an AI graduation requirement rest on more than labor-market signaling. Rather, it reflects the responsibility of higher education to ensure that all graduates can interpret, evaluate, and appropriately use AI-enabled tools and claims. Done well, such a requirement would support workforce preparation while also cultivating ethical reasoning, civic capacity, and informed participation in communities where the use of AI is becoming pervasive and mandatory rather than optional.

At the same time, the advantages of an AI requirement do not erase the real constraints institutions face. Degree programs often have limited room for additional mandates, and meaningful AI education demands substantial human expertise, technological infrastructure, and ongoing support. These implementation challenges are precisely why the most viable path forward may be a flexible general education model, such as a curated menu of courses spanning disciplines and levels that develops shared competencies while respecting program differences. Historical experience with computer literacy initiatives suggests that campus-wide requirements can succeed when they are adaptable, adequately resourced, and grounded in broad educational aims rather than narrow tool training. Early adopters, including Purdue University and The Ohio State University, indicate that embedding AI learning into existing curricula is feasible, especially when paired with clear outcomes focused on both practical capability and responsible judgment. In an increasingly AI-infused workplace and society, the balance of considerations ultimately supports moving toward an AI graduation requirement, provided institutions design it to be equitable, interdisciplinary, and ethically rigorous.

That said, similar to the evolution of computer literacy graduation requirements, AI graduation requirements may be a time-limited feature of university curricula as students, employers, and society adjust to AI-based technologies and the ethical and social issues they raise. While many students have some exposure to AI and use AI tools for some applications, AI-based graduation requirements may serve to boost skills and improve the future employability prospects of graduates. Additionally, AI graduation requirements may ensure that graduates across a wide variety of intellectual and professional domains are prepared to address ethical and social issues related to AI and craft a future in which the benefits of AI are shared across members of society and drawbacks are well managed and limited.

10. Overview of the Contents of this Issue

This issue of the journal includes three other articles. Steven Schilhabel, John Muraski, Meena Subedi, and Balaji Sankaranarayanan, in their timely and interesting article, examine the implications of using Generative AI (GenAI) for students' stress, anxiety, understanding, and perception of fairness during classroom instruction. The results of their analysis and results may serve as a roadmap for faculty interested in using GenAI in teaching and learning, as well as provide guidelines for faculty development and instructional design related to this area.

Katryna Johnson, in her timely and impactful article, examines the progressing function of GenAI in business education. Her article presents a three-dimensional framework for integrating GenAI in business education and provides a road map to do so.

Tood Little, in his interesting article, looks at the paradigm shift that is creating challenges to the established organizational knowledge management due to the vibe coding development and its implications. Based on an extensive literature review, the article suggests the need for further studies looking at vibe coding and general perspective of knowledge management.

We appreciate and wish to acknowledge the contributions of reviewers for this issue of the journal, including Queen Booker (Metropolitan State University), Mari Buche (Michigan Technological University), Omar El-Gayar (Dakota State University), Yi "Maggie" Guo (University of Michigan-Dearborn), Bryan Hosack (Penske Logistics), John Muraski (University of Wisconsin-Oshkosh), and Jeff Wall (Michigan Technological University).

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Author Biographies

Barbara D. Klein is Professor of Management Information Systems and Information Technology Management at the University of Michigan-Dearborn. She received her Ph.D. in Information and Decision Sciences from the University of Minnesota, her M.B.A. from the State University of New York at Albany, and her B.A. from the University of Iowa. Professor Klein has published in the *Journal of the Midwest Association for Information Systems*, *MIS Quarterly*, *Omega*, *Database*, *Information & Management*, *Information Resources Management Journal*, and other journals. Her research interests include information quality, artificial intelligence, user error behavior, and information systems pedagogy. Professor Klein has also worked in the information systems field at IBM, Exxon, and AMP.

Rassule Hadidi is Dean of the College of Business and Management, Metro State University, St. Paul - Minneapolis, Minnesota. His research areas of interest include online and blended teaching and learning pedagogy and its comparison with face-to-face teaching; curriculum development and quality assessment; cloud computing and its applications for small and medium-sized enterprises; the quality of online information; and the applications of AI in teaching and learning. He has served as president and At-Large Director of the Midwest Association for Information Systems. He is the founding Managing Editor of the *Journal of the Midwest Association for Information Systems,* is an AIS Distinguished Member – Cum Laude, and is a member of the Board of Directors of the Society for the Advancement of Management.

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Amplified Intelligence in the Classroom: An Exploratory Study of Generative AI's Psychological and Pedagogical Effects

Steven A. Schilhabel
University of Wisconsin – Oshkosh, schilhabels@uwosh.edu

John M. Muraski
University of Wisconsin – Oshkosh, muraskij@uwosh.edu

Meena Subedi
Carroll University, msubedi@carrollu.edu

Balaji Sankaranarayanan
University of Wisconsin – Whitewater, sankarab@uww.edu

Abstract

In this study, we employed a quasi-experimental design with a 2×2 factorial framework to investigate the effects of using Generative Artificial Intelligence (GenAI)-based tools on student stress, anxiety, understanding, and perceived fairness during authentic classroom learning experiences in higher education. We analyzed data from the validated and exploratory analyses in two stages. Across both analyses, results suggested that GenAI systems function as both cognitive and emotional supplements, enhancing users' mental health and deepening their understanding of the learning material. The results of the exploratory analysis also indicated improvements in perceived fairness and equity among peers. The results of this study could offer preliminary implications for higher education leaders and scholars. Our results offer insights into faculty development, instructional design, and curriculum changes to train students for a GenAI-mediated world of work.

Keywords: Generative AI; Higher Education; Prompt Literacy; Student Well-Being; Human-AI Collaboration; Technology Acceptance

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1. Introduction

The growing implementation of Generative Artificial Intelligence (GenAI) in educational tools prompts important discussions about how it affects students' cognitive processes and emotional experiences and poses ethical challenges in educational contexts. While traditional studies have primarily focused on task efficiency and learning outcomes, new research examines how GenAI affects students' mental health, their academic self-beliefs, and their views on fairness (Williamson & Eynon, 2020; Clark et al., 2016). However, real-world, classroom-based evidence remains limited. A systematic review by Zawacki-Richter et al. (2019) confirms that while AI research in education is growing, most studies are conceptual or simulation-based, with a scarcity of empirical, classroom-based interventions.

Recent scholarship on GenAI in higher education has emphasized academic integrity, assessment redesign, and institutional policy responses (Bittle & El-Gayar, 2025; Francis et al., 2025). Those conversations are important, but they are limited in terms of explaining how students experience GenAI while completing authentic course assignments in live classroom settings. Also, there remains limited empirical evidence on whether course-embedded GenAI support affects students' stress, anxiety, mental well-being, perceived understanding, perceived output quality, and fairness-related perceptions during assignment completion.

This study addresses that gap by examining GenAI through the lens of Amplified Intelligence, which treats AI as a *tool* for human cognitive enhancement rather than as a *replacement* (Brynjolfsson & McAfee, 2014; Shrestha et al., 2019). Guided by this perspective, this study investigates whether GenAI-supported assignment workflows are associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions in an undergraduate classroom context. This focus is important because institutions are now making decisions about whether, when, and how to integrate GenAI into teaching. Evidence from authentic classroom settings can help instructors and administrators move beyond abstract debate and toward more informed decisions about course design, student support, and responsible implementation. Accordingly, this study addresses the following research question:

- *What are the influences of GenAI support during authentic course assignments on students' psychological well-being, learning-related perceptions, and fairness-related perceptions, in a face-to-face university classroom setting?*

2. Literature Review

Before the rise of GenAI, research on artificial intelligence in higher education had already established AI as an important educational technology topic, although much of that earlier literature focused on broader AI applications rather than generative tools specifically (Zawacki-Richter et al., 2019). Since the public release of ChatGPT, GenAI has intensified scholarly attention around teaching, learning, assessment, and institutional adaptation, leading to a rapid expansion of higher education research in this area (Qian, 2025).

A growing line of research suggests that students often perceive GenAI as useful for brainstorming, writing support, feedback, and learning assistance (Chan & Hu, 2023). At the same time, those perceived benefits are accompanied by concerns about accuracy, overreliance, and the quality of student thinking (Kasneci et al., 2023). This tension underscores the importance of examining GenAI not only as a productivity tool but also as a classroom support mechanism that may affect how students experience assignment completion. Although AI is increasingly embedded in higher education, its impact on student well-being remains underexplored (Klimova & Pikhart, 2025). Recent review work suggests that AI may support students through personalization and efficiency, but it may also introduce digital fatigue, technostress, anxiety, and new forms of dependency (Klimova & Pikhart, 2025). As a result, psychological outcomes such as stress, anxiety, and mental well-being deserve more direct empirical attention in classroom-based GenAI studies.

GenAI in higher education also raises questions about fairness, equity, and access. Recent reviews and surveys highlight concerns about bias, the digital divide, and uneven readiness or comfort across student groups. Taken together, the literature suggests a clear need for empirical classroom studies that examine psychological well-being, learning-related perceptions, and fairness-related perceptions together during authentic academic work rather than in hypothetical or policy-only discussions (Francis et al., 2025; Maxwell et al., 2025).

3. Theoretical Background

By combining Amplified Intelligence, the Technology Acceptance Model (TAM), and Extended Cognition theories, this research explains how GenAI systems affect students' psychological well-being, learning outcomes, and perceptions of fairness. The study design relies on these frameworks to interpret the effects observed during GenAI-supported assignments.

Amplified Intelligence frames AI as a tool that augments human cognition rather than replaces human judgment (Brynjolfsson & McAfee, 2014; Shrestha et al., 2019). In educational settings, this perspective is useful because it positions GenAI as a scaffold that can help students manage complexity, reduce ambiguity, and improve clarity while preserving student agency. Under this view, GenAI support may influence psychological outcomes by reducing cognitive strain during demanding assignments, and it may influence learning-related outcomes by helping students better understand what they are trying to do and how to do it. The Technology Acceptance Model (TAM) helps explain why students are more likely to use technology when they perceive it as useful and easy to use (Venkatesh & Davis, 2000). In a classroom setting, these perceptions matter because they shape whether students experience GenAI as supportive, frustrating, trustworthy, or intrusive. TAM helps explain why GenAI support may affect not only students' willingness to use the tool but also their perceptions of learning quality, confidence, and classroom support. Extended Cognition suggests that tools can become part of a person's cognitive process when they are integrated into ongoing problem-solving (Clark & Chalmers, 1998). In the context of coursework, GenAI may serve as a cognitive extension, helping students externalize part of the planning, drafting, or clarification process. If students experience GenAI as part of their work problem-solving environment, the tool may affect not only task performance but also emotional experiences, such as stress reduction and perceived support during difficult academic work.

Taken together, these three theoretical perspectives support an integrative view of GenAI in classroom settings. Amplified Intelligence explains why GenAI may reduce cognitive burden and improve perceived clarity. TAM explains why perceived usefulness and ease of use may shape students' responses to the tool. Extended Cognition explains why GenAI may become part of students' active problem-solving process during assignment completion. Accordingly, this study organizes its outcome variables into three families: psychological well-being, learning-related perceptions, and fairness-related perceptions. Figure 1 presents this theory-informed integrative model. Importantly, the model is presented as a conceptual framework for interpreting the study's findings rather than as a formally tested structural, mediation, or moderation model.

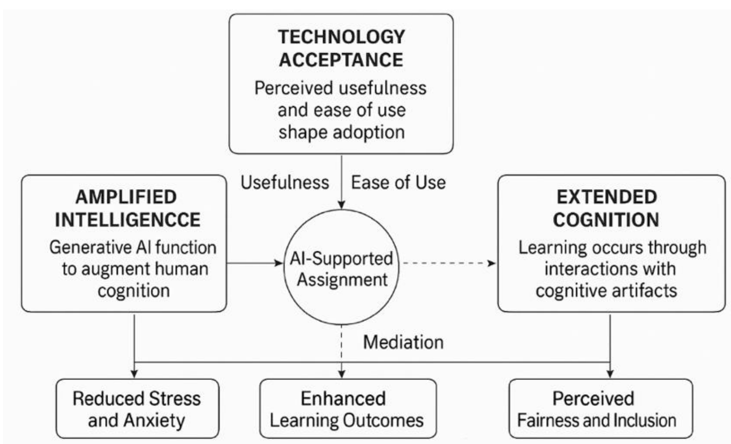

Figure 1: Research Framework

4. Methodology

4.1 Research Setting and Design

This study was conducted in an undergraduate Information Systems class using a quasi-experimental 2×2 factorial design. This study examines the impact of GenAI-assisted assignment tools on students' psychological well-being, learning-related perceptions, and fairness-related perceptions. The study implemented a dual-phase analytical approach (Shadish et al., 2002). Phase 1 used a strictly verified subset of observations to prioritize internal validity. Phase 2 used a larger set of inferred assignment-level observations to examine whether the Phase 1 pattern persisted in a broader classroom dataset.

4.2 Experimental Setting and Assignment Conditions

The course included multiple assignment opportunities completed under two instructional conditions: (1) GenAI-supported assignments, in which students had access to a course-provided ChatGPT-enabled interface through Canvas, and (2) non-GenAI assignments, in which students completed the work without course-provided GenAI support. Assignments varied in format, including structured form-based tasks and open-ended narrative tasks. Because the assignment type was not modeled as a focal independent variable in the analyses reported in this paper, it is described here as part of the instructional context rather than as a tested factor in the final statistical results.

The primary unit of analysis was the student in Phase 1 and the assignment observation in Phase 2, with Phase 2 observations contributed by students across multiple assignments.

4.3 Phase 1: Exploratory Analysis

Phase 1 prioritized internal validity by restricting the analysis to a subset of observations for which exposure status could be clearly verified. This phase included 35 verified cases. Exposure status was confirmed using three sources: (1) Canvas access logs for GenAI tool usage, (2) section rosters and assignment time stamps, and (3) manual matching of student identifiers to assignment conditions. Only cases with clear and consistent evidence across these sources were retained in the Phase 1 dataset.

The verified control group in Phase 1 was small ($n = 6$). This limitation reduces statistical power and constrains generalizability, so Phase 1 should be interpreted as a conservative exploratory analysis rather than as definitive evidence.

4.4 Phase 2: Repeated-measures Analysis

Phase 2 expanded the analysis to 346 assignment observations drawn from the broader classroom dataset. Because direct verification was not feasible for all observations, exposure status was inferred using a conservative heuristic classification process. An assignment was classified as GenAI-supported when two or more of the following conditions were met: (1) the assignment was submitted from a Canvas environment with GenAI features, (2) system logs indicated GenAI tool use within a 30-minute window surrounding submission, and (3) the student reported GenAI use in the post-assignment survey.

An assignment was classified as non-GenAI-supported when one or more of the following conditions were met: (1) the assignment was submitted in a course section that was not assigned GenAI access, (2) neither system logs nor the post-assignment survey indicated GenAI use, or (3) the assignment was submitted outside designated GenAI access windows. Observations with ambiguous evidence were excluded from Phase 2 to preserve a more conservative classification process. Importantly, non-GenAI-supported in Phase 2 should be interpreted as non-course-supported rather than as proof of zero outside AI use, because students may have had access to personal GenAI tools beyond the course environment.

4.5 Survey Measures

Post-assignment surveys measured three families of outcomes: psychological well-being, learning-related perceptions, and fairness-related perceptions. Psychological well-being was measured using items related to stress, anxiety, and mental well-being. Learning-related perceptions were measured using items related to understanding, output quality, and goal clarity. Fairness-related perceptions were measured using items assessing support for fairness and peer equality.

All measures used a 7-point Likert scale, with higher values indicating more favorable outcomes. To create the Psychological Well-Being Index, stress and anxiety items were reverse-coded so that higher index values reflected lower psychological strain. Table 1 presents the construct definitions, variable mapping, and reliability estimates.

Construct	Item Code(s)	Example Item	Cronbach's α
Psychological Well-Being Index	Stress anxiety mental well-being	"Using GenAI improved my mental well-being compared to not using GenAI."	0.81
Learning-Related Perceptions Index	understanding output quality goal clarity	"I understood the course material better with GenAI."	0.79
Fairness-Related Perceptions Index	support fairness peer equality	"Using GenAI made the learning environment fairer and more inclusive."	0.75

Table 1. Survey Items and Construct Mapping

Note. Higher values indicate more favorable outcomes. Stress and anxiety items were reverse-coded before the Psychological Well-Being Index was computed.

4.6 Missing Data and Processing

During data preparation, surveys and assignment records were matched using Stata-assisted identifier reconciliation. Minor variations in student identifiers (e.g., abbreviated versus full names) were resolved where possible. Observations that could not be confidently matched were excluded from the dataset, representing less than 5% of the records.

5. Results

5.1 Phase 1: Exploratory Analysis

The effect of GenAI-supported assignments was assessed using data from students who completed all required assignments. Independent-samples t-tests were used to evaluate differences across outcome variables. Descriptive statistics are presented in Table 2, and the corresponding inferential results are presented in Table 3.

Outcome Variable	GenAI Mean (SD)	Control Mean (SD)
Stress	3.19 (1.12)	3.98 (1.21)
Anxiety	2.91 (1.03)	3.75 (1.16)
Mental Well-being	5.52 (0.91)	4.83 (1.02)
Comprehension	5.87 (0.83)	5.06 (0.96)
Output Quality	5.66 (0.88)	4.88 (1.05)
Goal Achievement	5.74 (0.85)	4.94 (1.12)
Fairness/Support	5.42 (0.92)	4.61 (1.09)
Peer Equality	5.31 (0.88)	4.62 (1.01)

Table 2: Descriptive Statistics

Students in the GenAI-supported condition reported lower stress and anxiety and higher mental well-being than students in the non-GenAI condition. These differences were statistically significant for stress ($p = 0.030$), anxiety ($p = 0.015$), and mental well-being ($p = 0.048$). Taken together, these findings suggest that course-embedded GenAI support may reduce psychological strain during assignment completion. Students in the GenAI-supported condition also reported higher understanding, higher perceived output quality, and greater goal clarity than students in the non-GenAI condition.

All three differences were statistically significant (all p < 0.001), suggesting that GenAI support was associated with more favorable learning-related perceptions in Phase 1.

No statistically significant differences emerged for support of fairness or peer equality in Phase 1. Although the descriptive statistics favored the GenAI-supported condition, the verified control group was small (n = 6), so these null findings should be interpreted cautiously. Accordingly, Phase 1 should be read as a conservative exploratory analysis that provides directional evidence rather than definitive conclusions.

Outcome Category	Variable	GenAI Group Mean	Control Group Mean	*p*-value	Significance
Psychological	Stress	3.12	4.39	0.030	*
	Anxiety	2.95	4.11	0.015	**
	Mental Well-being	5.36	4.42	0.048	*
Learning	Comprehension	5.77	4.91	< 0.001	***
	Output Quality	5.66	4.88	< 0.001	***
	Goal Clarity	5.71	4.94	< 0.001	***
Inclusivity	Fairness	5.11	4.75	0.312	n. s.
	Peer Equality	5.17	4.80	0.281	n. s.

Table 3: Results from Strict Matching Analysis (N = 35)

5.2 Phase 2: Repeated-Measures Analysis

Phase 2 expanded the analysis to 346 assignment observations contributed across multiple assignments. A repeated-measures ANOVA was used to examine whether GenAI support was associated with differences in aggregated outcome indices. The Psychological Well-Being Index was significant (F = 84.98, p < 0.001), indicating that GenAI-supported assignments were associated with lower psychological strain and stronger reported well-being across repeated observations. This pattern was consistent with the Phase 1 findings and strengthens the interpretation that GenAI support may ease assignment-related stress and anxiety. The Learning-Related Perceptions Index was also significant (F = 27.11, p < 0.001), indicating that students reported stronger understanding, stronger perceived output quality, and greater goal clarity in the GenAI-supported condition. This pattern again mirrored the Phase 1 results.

Fairness-related outcomes were significant in Phase 2. The support fairness index (F = 19.02, p < 0.001) and the peer equality index (F = 16.74, p < 0.001) both favored the GenAI-supported condition. Unlike Phase 1, the larger sample suggests that students may perceive course-provided GenAI support as improving fairness-related conditions in the classroom, although these findings should be interpreted cautiously because exposure status in Phase 2 was inferred rather than directly randomized. See Table 4 for Repeated Measures Results.

Outcome Index	F-value	df	*p*-value	Effect Summary
Psychological Index	84.98	1, 84	< 0.001	GenAI reduced stress/anxiety, increased well-being
Learning Index	27.11	1, 84	< 0.001	GenAI improved comprehension, output, and clarity
Fairness Index	19.02	1, 84	< 0.001	GenAI increased perceived fairness and inclusion
Peer Equality Index	16.74	1, 84	< 0.001	GenAI improved perceptions of equity

Table 4: Repeated Measures Results - Exploratory Analysis (N = 346)

The psychological advantages of GenAI support become evident through visual comparisons. Figure 2 and Figure 3 illustrate distinct differences in stress and mental well-being scores between GenAI-supported and control assignments, with more pronounced trends evident in the exploratory sample. Findings show that GenAI-based tools provide both cognitive and emotional support within academic environments.

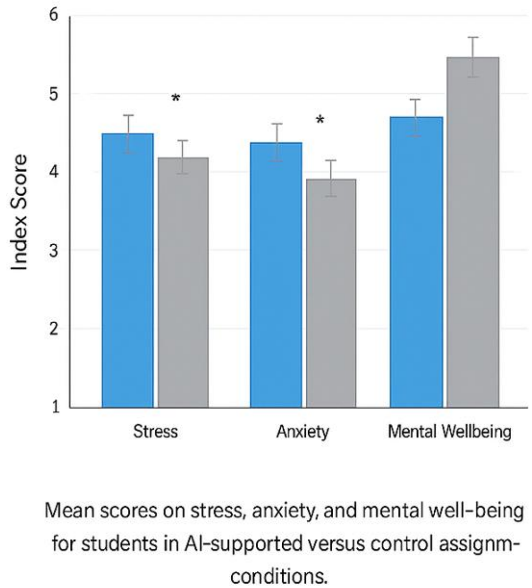

Figure 2: Psychological Index (N = 35)

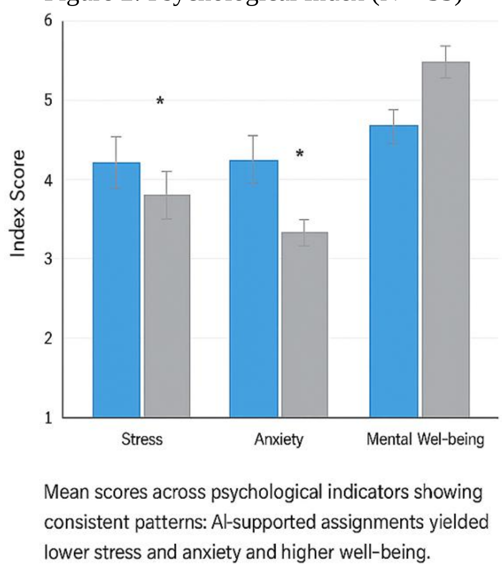

Figure 3: Psychological Index (N = 346)

6. Discussion

This exploratory study examined whether course-embedded GenAI support during authentic assignments was associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions. Across both analytical phases, the most consistent finding was psychological: students in GenAI-supported conditions reported lower stress and anxiety and stronger mental well-being. Learning-related outcomes also favored the GenAI-supported condition in both phases. Taken together, these findings suggest that GenAI support may serve as a cognitive scaffold, helping students navigate difficult assignments with less strain and greater perceived clarity.

The fairness-related findings were more mixed. Phase 1 did not reveal any statistically significant differences for support of fairness or peer equality, whereas Phase 2 did reveal them. One plausible explanation is statistical power, given the very small, verified control group in Phase 1. Another possibility is that fairness perceptions are especially sensitive to how GenAI access is structured, communicated, and experienced within a course. Students may perceive course-provided GenAI support as fairer when access is visible and integrated, but those perceptions may weaken when access is limited, uneven, or uncertain.

The findings offer preliminary support for the study's integrative theoretical framing. Amplified Intelligence helps explain why students may experience GenAI as cognitive augmentation rather than simple automation. TAM helps explain why perceived usefulness and ease of use may contribute to more favorable learning-related perceptions. Extended Cognition helps explain why students may experience GenAI as part of the problem-solving process itself. However, these findings should be interpreted as being consistent with existing theory, rather than as a definitive confirmation of the full conceptual model.

The practical implications of this study are meaningful and applicable to academic institutions. If institutions choose to embed GenAI tools in coursework, they are expected to pair such access with clear expectations, transparent communication, and instruction in responsible prompt use (Francis et al., 2025; García-López & Trujillo-Liñán, 2025). Faculty development should therefore address not only the technical use of GenAI, but also assignment design, ethical boundaries, and ways to preserve student agency while using AI-supported workflows.

7. Limitations and Future Work

This study has several important limitations. First, Phase 1 included a very small, verified control group, limiting power and generalizability. Second, Phase 2 relied on inferred exposure classification rather than direct random assignment. Third, non-GenAI-supported observations in Phase 2 should be interpreted as non-course-supported rather than as proof that students did not use personal GenAI tools outside the course environment. Fourth, the study was conducted in a single undergraduate course, limiting external validity. For these reasons, the results should be interpreted as preliminary and exploratory rather than as causal or conclusive.

Future research should test these relationships in larger, multi-course designs with clearer randomization or stronger embedded controls. Future studies should also analyze assignment type directly if structured versus open-ended tasks are expected to shape outcomes. In addition, future work should examine longer-term effects, including whether GenAI support influences learning transfer, self-efficacy, overreliance, and changes in perceptions of fairness as institutional norms around AI become more established (Zhai et al., 2024).

8. Conclusion

This study examined whether course-embedded GenAI support was associated with differences in students' psychological well-being, learning-related perceptions, and fairness-related perceptions during authentic assignment work. Across both analytical phases, the clearest and most consistent pattern was that GenAI-supported assignments were associated with lower reported stress and anxiety and with more favorable learning-related perceptions. Fairness-related outcomes were more mixed across phases, suggesting that this domain may depend more heavily on the implementation of conditions and measurement context. Overall, the study offers preliminary evidence that GenAI can function as amplified intelligence in classroom settings, while underscoring the need for more rigorous, multi-course research before strong causal claims are made.

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About the Authors

	**Dr. Steven A. Schilhabel** is an Assistant Professor in the Information Systems Department at the University of Wisconsin Oshkosh. His research explores the intersections of blockchain, generative AI, and instructional technology. He holds a DBA from the University of Wisconsin–Whitewater and serves as the Academic Director of the MSITM program at UW Oshkosh.
	**Dr. John M. Muraski** is a technologist, researcher, and educator dedicated to helping organizations thrive in a rapidly changing landscape. He is a Teaching Assistant Professor of Information Systems at UW Oshkosh, where he also leads the Small Business AI Clinic and the Center for Entrepreneurship and Economic Development. His research centers on technology education pathways, AI in instruction, and socio-technical integration in organizations. With 20 years of industry experience before joining academia, and a mission to engage, educate, and enable, he specializes in empowering others to harness technology as a practical tool for solving complex problems.
	**Dr. Meena Subedi** is an Assistant Professor of Accounting at Carroll University. She holds a DBA in Accounting, a Ph.D. in Public Administration, and an MSA in Accounting. Her research spans financial reporting quality, audit risk, AI applications in accounting, and nonprofit governance. She has published in peer-reviewed journals and presented widely at conferences, including the American Accounting Association.
	**Dr. Balaji Sankaranarayanan** is a Professor in the Department of Information Technology and Supply Chain Management at the University of Wisconsin–Whitewater. His research focuses on IT strategy, outsourcing, healthcare informatics, and AI in business. He has published extensively in journals such as *Information Systems Research*, *MIS Quarterly Executive*, *Journal of Medical Internet Research*, *International Journal of Medical Informatics*, and *Telemedicine and e-Health*.

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Integrating Generative AI in Business Education: A Structured Review for Developing a Strategic Framework and Addressing Research Gaps

Katryna Johnson
Metropolitan State University, Katryna.johnson@metrostate.edu

Abstract

This paper examines the evolving role of generative artificial intelligence (GAI) in business education through a structured narrative review of recent scholarship and practice-oriented reports. The review synthesizes research across information systems, education, and management to develop a three-dimensional framework comprising pedagogical transformation, ethical integration, and career preparedness. For each dimension, the analysis identifies both emerging applications and critical gaps that warrant additional investigation. The pedagogical dimension highlights how GAI supports adaptive learning, redesigned assessments, simulations, and multimodal instructional practices. The ethical dimension addresses challenges related to academic integrity, data governance, transparency, bias, privacy, and equitable access. The career preparedness dimension identifies the technical capabilities and human-centered competencies—such as AI literacy, judgment, creativity, and adaptability—that graduates must demonstrate in AI-augmented workplaces. Together, these dimensions provide a coherent framework for guiding the responsible adoption of GAI, helping business schools align pedagogical innovation with ethical expectations and evolving labor-market demands.

Keywords: *Generative AI, AI ethics, pedagogy, career readiness*

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1. Introduction

Generative artificial intelligence (GAI) is increasingly shaping business education by influencing course design, assessment practices, and expectations for student learning (Huo & Siau, 2024; Jiang & Nakatani, 2025; Leckrone, 2025; Mao et al., 2024; Moorhouse et al., 2023; Van Slyke et al., 2023). As GAI becomes a routine instructional resource, business schools must integrate it responsibly while preparing students for AI-mediated organizational environments. Research across information systems and education identifies both benefits—adaptive learning systems, simulations, automated feedback, and scalable content generation (Brynjolfsson et al., 2023; Diaz, 2024; Hamilton, 2025; Kasneci et al., 2023) — and risks tied to academic integrity, data governance, algorithmic bias, and inequitable access (Cotton, 2024; Fleckenstein et al., 2024; Moorhouse et al., 2023; OECD, 2023a; Wagman et al., 2025).

GAI is now a central element in ongoing digital innovation within higher education, extending previous transitions to online learning and multimedia technologies (McKinsey & Company, 2023; Strohl et al., 2024; World Economic Forum, 2024). Although students and instructors must adapt to new workflows, GAI's opportunities — including rapid content production and multimodal communication — are increasingly embedded in curriculum design (Mayer et al., 2025). These developments underscore the need for institutional strategies that strike a balance between innovation and academic rigor, governance, and accountability.

This paper presents a three-dimensional framework for integrating GAI in business education: pedagogical transformation, ethical integration, and career readiness. Pedagogically, GAI supports adaptive learning, simulations, and assessment redesign (Brynjolfsson et al., 2023; Diaz, 2024; Hamilton, 2025; Hwang & Lee, 2025). Ethically, concerns persist around integrity, bias, privacy, and transparency (Cotton, 2024; Hagendorff, 2020; Lim et al., 2023; OECD, 2023a; Pitts et al., 2025). For career readiness, GAI cultivates essential competencies such as AI literacy, adaptability, creativity, and judgment (AACSB, 2024; Barger et al., 2025; Beninger, 2025; Kasneci et al., 2023; Ratten & Jones, 2023; Slimi, 2023; Wang, 2022).

1.1 Contribution to the Literature

This study contributes by (1) consolidating research across IS, education, and management into a coherent synthesis, (2) proposing an integrated framework that links pedagogical, ethical, and workforce considerations, and (3) offering guidance for institutions seeking responsible, future-oriented GAI adoption.

2. Methodology

This study employed a structured narrative review to synthesize perspectives on generative AI within the context of education, information systems, and management. A narrative approach was selected due to the rapid evolution of generative AI research, which requires flexibility to incorporate emerging themes and high-quality gray literature while maintaining conceptual depth. The review process followed an iterative, three-stage design: (1) preliminary thematic mapping to identify key topics, (2) targeted literature discovery using academic databases and authoritative sources, and (3) conceptual synthesis to organize and interpret findings.

2.1 Data Sources and Selection Criteria

Peer-reviewed articles and authoritative reports from major educational and policy organizations (AACSB, EDUCAUSE, NACE, OECD, UNESCO, and the U.S. Department of Education) were included. The search also incorporated gray literature and specialized industry reports from recognized sources such as Forbes, McKinsey & Company, the MIT Sloan Management Review, the Federal Reserve Bank, the RAND Corporation, and the World Economic Forum. Searches were conducted in EBSCOhost, JSTOR, Academic Search Premier, and Google Scholar using terms such as *generative AI, business education, AI ethics, AI pedagogy, assessment redesign, curriculum redesign, and career readiness.* Snowball sampling of reference lists identified additional relevant studies.

2.2 Inclusion criteria:

1. Published between 2020 and 2025
2. Focused on generative AI or AI-enabled learning in higher education or business programs
3. Addressed pedagogy, ethics, assessment, digital transformation, or workforce competencies
4. Originated from peer-reviewed journals or reputable policy bodies

5. Snowball sampling of reference lists identified additional relevant studies

2.3 Exclusion criteria:

1. Technical machine-learning papers without educational relevance
2. Duplicate or superseded reports

2.4 Research Process

All studies were manually coded to identify recurring patterns across pedagogy, ethics, and workforce preparation. The author then conducted an interpretive synthesis by comparing insights across peer-reviewed articles, policy reports, and gray literature. AI tools were additionally employed to surface relevant articles not retrieved through traditional database searches, enhancing efficiency and reducing search bias (Bendig & Bräunche, 2024; Bolaños et al., 2024; Chen et al., 2024; Cheng et al., 2025; Goyanes et al., 2025, Resnick & Hoseeini, 2025; Wu et al., 2025). After manual coding was complete, ChatGPT-4.1 was used as a secondary analytical tool to support theme verification and refinement for the *Systematic Integration of Generative AI in Business Education* framework. Final interpretation and theme selection were conducted solely by the author.

2.5 AI-Assisted Literature Discovery

To support comprehensive source gathering, AI tools (ChatGPT-4.1 and ChatGPT-5.0) were used strictly to assist in locating additional literature. They were **not** used to evaluate evidence, interpret findings, or generate conceptual arguments. Specifically:

- Author-designed, complex queries were used to surface possible sources.
- AI-identified items were treated only as preliminary leads and were verified directly against peer-reviewed materials.
- No AI-generated summaries, interpretations, or claims were accepted without full human review.

This process reflects a pragmatic abductive orientation, allowing iterative movement between emerging patterns in the literature and potential additional sources while maintaining conceptual and methodological rigor. This is justified by the approach's pragmatic view that the AI-assisted identification of new sources leads to added utility and value to the review's scope, even though the final conceptual themes were developed solely by the author.

2.6 Cross-Checking and Reliability

All AI-assisted outputs were reviewed for:

- **Accuracy**: Verification of citations, publication details, and factual claims
- **Fidelity:** Confirmation that the source material's meaning or intent was preserved, ensuring the content was not taken out of context.
- **Bias:** Identification of omissions, overgeneralizations, or distortions
- **Misclassification:** Validation that the source aligned with the thematic scope and met all defined inclusion criteria (e.g., confirming the source was not a technical machine-learning paper).

2.7 AI Disclosure

AI tools (ChatGPT-4.1, ChatGPT-5.0, Copilot, Gemini, and Grammarly) were used to improve clarity, reduce redundancy, and generate the final draft of Figure 1. All literature analysis, coding, interpretation, and final synthesis were conducted solely by the author.

3. An Integrated Framework for Generative AI in Business Programs

Although existing research often examines instructional design, academic integrity, or employability as separate issues, few studies integrate these threads into a comprehensive model. This paper addresses that gap by proposing a unified framework that links pedagogical transformation, ethical integration, and career preparedness as mutually reinforcing dimensions of responsible AI adoption. Drawing from recent literature on generative AI, digital transformation, instructional design, and business education, three themes consistently emerge across domains:

1. **AI is accelerating changes in teaching and learning**, enabling adaptive, interactive, and data-informed instructional practices.

2. **Ethical concerns—including transparency, privacy, bias, and fairness—are intensifying** as AI becomes embedded in everyday academic work.
3. **Employers increasingly expect graduates to demonstrate AI literacy alongside human-centered capabilities** such as creativity, judgment, and collaboration.

Despite these intersecting trends, most existing models treat each domain independently. A unified framework is needed to reflect how pedagogical, ethical, and workforce considerations interact in AI-enabled learning environments. The following constructs define the components of the proposed model and establish the foundation for Figure 1.

3.1 Definition of the Three Constructs

Pedagogical Transformation

Refers to the redesign of curricula, learning activities, and assessment systems to incorporate AI-enhanced simulations, analytics, multimodal feedback, and adaptive tools (Brynjolfsson et al., 2023; Hamilton, 2025). This dimension captures how AI alters instructional strategies, learning processes, and faculty workload.

Ethical Integration

Encompasses the policies, norms, and safeguards necessary to ensure AI is used transparently, equitably, and responsibly (Cotton, 2023; Hagendorff, 2020; OECD, 2023a). It includes academic integrity, data governance, privacy protections, bias mitigation, and global variations in AI expectations.

Career Preparedness

Reflects the growing need for students to cultivate both technical abilities (e.g., AI-assisted analysis, prompt construction) and enduring human competencies such as judgment, adaptability, creativity, and collaboration (Barger et al., 2025; Ratten & Jones, 2023). AI proficiency is positioned as one component of a broader professional skill set.

3.2 Relationships Among the Three Dimensions

The three constructs are interdependent rather than hierarchical. Pedagogical transformation shapes how students engage with AI; ethical integration provides the guardrails for responsible use; and career preparedness represents the outcomes institutions expect graduates to demonstrate. Effective adoption requires alignment across all three:

- Without ethical integration, pedagogical innovations may reinforce inequities or misconduct.
- Without pedagogical transformation, students lack the experiential grounding needed to build AI-related competencies.
- Without career preparedness, AI adoption risks becoming technologically novel but educationally superficial.

3.3 Scope and Boundary Conditions

This framework is designed for undergraduate and graduate business programs but may be adaptable to other professional fields. It provides a conceptual structure rather than prescribing specific tools or platforms and assumes baseline digital infrastructure for implementation. Institutions with limited technological access may require alternative adaptations.

Figure 1 illustrates how the effective adoption of GAI requires consideration of three key constructs: pedagogical change, ethical Integration, and career preparedness.

3.4 Application of the Framework

To translate the framework into practice, each construct informs specific strategies for teaching, policy, and workforce development. The following applications illustrate how institutions can operationalize the three dimensions in cohesive, research-aligned ways.

Figure 1. A Framework for the Systematic Integration of Generative AI in Business Education

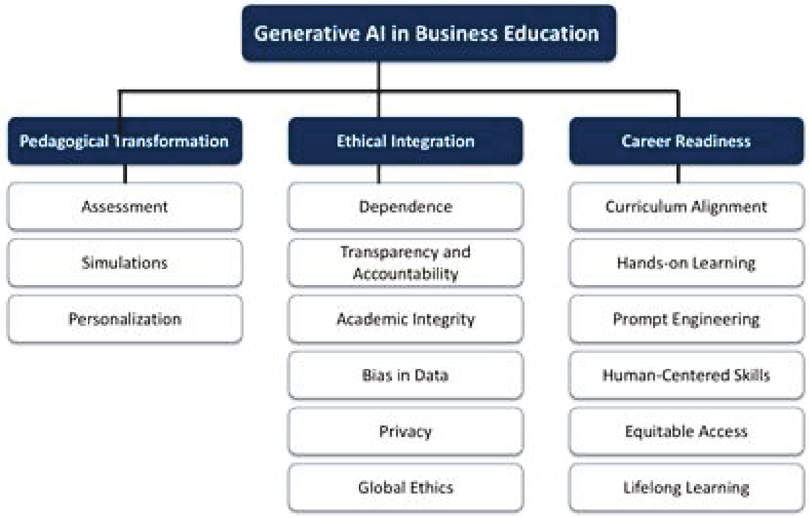

Figure 1 was created in conjunction with ChatGPT (OpenAI, 2025).

1. Pedagogical Transformation

Integrating AI into course design enables adaptive, interactive, and context-responsive learning experiences. Faculty may implement AI-supported simulations, generative case studies, and personalized learning activities that enhance engagement and conceptual understanding (Brynjolfsson et al., 2023; Gupta et al., 2024). Assignment redesign and transparent guidelines further support responsible instructional use.

2. Ethical Integration

Operationalizing this dimension requires institutional and course-level safeguards that address transparency, privacy, academic integrity, algorithmic bias, and global contexts (Moorhouse et al., 2023; OECD, 2023a). Policies must account for unequal technological access and ensure consistent expectations across programs.

3. Career Preparedness

GAI can strengthen students' professional readiness by supporting résumé refinement, interview practice, scenario analysis, and content development—tools that complement human judgment, adaptability, and creativity (Kasneci et al., 2023; Mayer et al., 2025). These skills align with evolving employer expectations in AI-enabled workplaces.

Together, these applications demonstrate how the three dimensions operate in practice, offering a coherent structure that is pedagogically meaningful, ethically grounded, and responsive to evolving workforce demands.

4. Literature Review

4.1 Pedagogical Transformation in Business Education

As Figure 1 illustrates, business schools are undergoing a substantive shift in how curricula are designed and delivered, particularly within the pedagogical dimension. Faculty across accounting, finance, management, management information systems, and marketing are increasingly integrating AI to create dynamic business cases, simulate market environments, and build customized quizzes. These tools allow instructors to design learning experiences that mirror real-world decision-making, providing students with richer opportunities to apply theory to practice.

Generative AI is transforming instructional design in higher education, yet critical evidence gaps persist. Existing studies primarily emphasize short-term perceptions and adoption rather than longitudinal impacts on cognitive development or skill retention (Abbas et al., 2024; Weng et al., 2024). Systematic reviews confirm that research focuses on pedagogy and faculty attitudes rather than rigorous, outcome-based evaluations across diverse contexts (Amofa et al., 2025; Luo, 2025; Qian, 2025). Although emerging work addresses personalization, longitudinal studies are largely absent (Ansari & Qamari, 2025).

4.1.1 Assessment

Assessment practices are shifting as students increasingly use GAI to complete traditional assignments. To maintain academic integrity, faculty are adopting alternative formats—applied problem-solving tasks, presentations, live case analyses, and reflective journals—that reduce AI misuse and deepen engagement (Cot et al., 2023; Fenton, 2025; Foley et al., 2024; Mao et al., 2024; Moorhouse et al., 2023; Van Slyke et al., 2023). Assignments that integrate AI with students' critical thinking help build employer-valued competencies, fostering authentic learning and higher-order skills such as adaptability, collaboration, and judgment (Akbar, 2025; Lim et al., 2023; Newell, 2023).

4.1.1.1 Gaps in Assessment Research

Significant gaps remain in assessment research. Few studies examine whether AI can support longitudinal assessment or track student growth across semesters. More evidence is needed to validate the fairness, reliability, and pedagogical soundness of AI-assisted scoring, particularly regarding algorithmic bias across student groups (Mpolomoka, 2025). Research on hybrid human–AI assessment models is limited, particularly regarding best practices for integrating AI-generated formative feedback (Banihashem et al., 2025). Guidance is also sparse on how to ensure AI-enabled assessments meet accessibility and universal design principles.

4.1.2 Simulations

AI-powered simulations offer significant benefits by enabling students to interact with realistic environments that mirror actual business conditions (Burger et al., 2023; Dwivedi et al., 2022; Hamilton, 2025). In operations management, AI-embedded tools enable learners to explore "what-if" supply chain scenarios, while in finance and accounting, AI supports balance sheet analysis and real-time revenue forecasting (Brynjolfsson et al., 2023; Gupta et al., 2023). MIS research further highlights how AI-driven digital twins—virtual replicas of real-world systems—standardize training, support decision-making, and strengthen predictive analytics across complex organizational processes (Ahmad, 2025; Liu & David, 2025).

4.1.2.1 Gaps in Simulation Research

Despite these benefits, several gaps remain. Few studies compare learning outcomes across business disciplines, leaving open the question of whether simulations support students in accounting, marketing, and MIS differently (Dai & Ke, 2022). Cost–benefit and scalability analyses are also limited, particularly for resource-constrained institutions. Although cognitive load has been studied in specific simulation contexts (Tremblay et al., 2023), broader patterns across disciplines, complexity levels, and simulation types remain unclear, as do ethical risks embedded in predictive or scenario-based models (García-López & Trujillo-Liñán, 2025).

4.1.3 Personalized and Career-Aligned Learning

GAI increasingly functions as a personalized mentor, guiding students through real-world, career-relevant assignments such as developing marketing campaigns or designing ERP implementations (Donner & Hummel, 2025; Kasneci et al., 2023; Slimi, 2023). It provides adaptive feedback that builds confidence, strengthens professional readiness, and supports individualized learning. By tailoring guidance to each student's goals, AI helps create more meaningful, relevant, and higher-quality learning experiences (Mehrabi et al., 2025). This market-responsive approach also aligns business education with evolving labor market demands, supplying employers with graduates who possess up-to-date skill sets (Kasneci et al., 2023).

4.1.3.1 Gaps in Personalized Learning Research

Despite these benefits, significant research gaps remain. It is unclear whether AI-generated recommendations serve all student groups equitably or unintentionally reinforce existing inequities (Baker & Hawn, 2022). Limited evidence assesses the accuracy and stability of AI-personalized learning pathways or identifies effective strategies for integrating AI-generated feedback into instruction (Mah et al., 2024). Additionally, few studies examine how students understand the data that drives AI recommendations, raising concerns about privacy and ethical implications in AI-mediated learning

(Chan & Hu, 2023; Zhai & Wibowo, 2024).

4.2 Ethical Integration

Institutions and educators must ensure that AI is used ethically in the classroom. Faculty play a central role in teaching students to recognize potential bias embedded in AI datasets, to be transparent about their use of AI—such as through proper citation—and to verify the accuracy and legitimacy of AI-generated content (Bender et al., 2021; Evangelista, 2025; López-Solís et al., 2025; Mehrabi et al., 2021). Business schools also need coherent, clearly articulated policies that distinguish between appropriate AI use and academic misconduct. At the same time, educators must help students avoid becoming overly dependent on AI by reinforcing the importance of critical thinking, originality, and creativity.

Although ethics instruction is widely recommended, few empirical studies identify which ethical frameworks effectively support student decision-making (Yan & Liu, 2025). Cross-cultural differences in AI acceptance and use remain insufficiently examined, despite their relevance in global business education (Ma et al., 2024a). Additionally, little research investigates unreported or covert AI use—a growing concern in higher education (Doss et al., 2025; Fleckenstein et al., 2024). These gaps underscore the need for research that clarifies institutional strategies for proactive ethics instruction while balancing student autonomy and accountability.

4.2.1 Risks of Dependence

Over-reliance on GAI is a growing concern among faculty, who worry that students may lean too heavily on AI for ideation, writing, and problem-solving, ultimately weakening their own cognitive engagement (Delello et al., 2025; Hazari, 2025; Jeyaraj & Sethi, 2025). Students must be trained to critically evaluate AI outputs, as underlying datasets may reflect biases and perpetuate inequities (Jun et al., 2023; Kasneci et al., 2023). As a result, business programs must integrate digital literacy and AI ethics throughout the curriculum to ensure responsible, reflective, and informed use of AI.

4.2.1.1 Gaps in Risks of Dependence Research

Although concerns about over-reliance are widespread, key gaps remain. Few studies measure actual dependence, relying instead on faculty perceptions (Zhang et al., 2024). Little is known about which students are most vulnerable, such as those with low confidence or limited prior knowledge (Al-Emran et al., 2025). Cognitive mechanisms—whether AI reduces cognitive effort or metacognitive monitoring—are understudied (Jose et al., 2025). The effects of different AI task types and the effectiveness of interventions, such as scaffolding or reflective practice, also remain unclear.

4.2.2. Transparency and Accountability / Academic Integrity

Before formal institutional adoption, students were already using tools like ChatGPT to generate content. As GAI becomes more common, educators must emphasize transparency, proper citation, and verification of information. Clear course policies should outline appropriate use and reinforce expectations for academic integrity (Baker & Hawn, 2021). Educators must also recognize that AI detectors are unreliable, often producing false positives, particularly for advanced or highly polished writing (Freeman et al., 2025; Jung et al., 2025; OpenAI, 2023; Saha & Feizi, 2025; Turnitin, 2025; Webb, 2025; Weber-Wulff et al., 2023). These tools may misclassify sophisticated human writing as AI-generated due to linguistic patterning (Liang et al., 2023; Májovský et al., 2024).

4.2.2.1 Gaps in Transparency and Integrity Research

Significant gaps persist in understanding effective reporting practices and student compliance with citation expectations (Gonsalves, 2025). Research is also limited on the implementation of institution-wide policies and their impact on student behavior across departments (Gonsalves, 2025). Furthermore, due to the unreliability of AI detectors, scholars have yet to establish valid alternatives for verifying authorship (Perkins et al., 2024).

4.2.3 Bias in Data / Privacy and Student Rights / Global Ethics

Educators and students must recognize that AI systems are trained on datasets that contain historical and structural biases, which can perpetuate inequities if not critically examined (Hazari, 2025; Kasneci et al., 2023). Research indicates that AI language models perpetuate gendered and racialized stereotypes, influencing classroom interactions and potentially compromising learning environments (Blodgett et al., 2020; Hazari, 2025; Mehrabi et al., 2021; Wei et al., 2025). Institutions, therefore, need digital literacy training to help users identify and mitigate biased outputs.

AI adoption also raises concerns about student data privacy and institutional responsibility. Because AI relies on sensitive personal and academic information, data practices must be transparent, accountable, and aligned with global ethical frameworks, such as those established by UNESCO, OECD, and the U.S. Department of Education (Slimi & Villarejo, 2023; OECD, 2023a; UNESCO, 2023; World Economic Forum, 2025). These efforts establish a shared foundation for the responsible integration of AI in higher education.

4.2.3.1 Gaps in Bias, Privacy, and Global Ethics Research

Despite growing attention, substantial gaps persist. Although algorithmic bias is well documented, most studies focus on detecting disparities rather than designing classroom interventions that help students identify and correct biased outputs. Bias can harm marginalized groups and emerge at multiple stages of data generation and model design (Baker & Hawn, 2022; Bird et al., 2025; Idowu et al., 2024). Little is known about effective bias-literacy strategies or how students' intersectional identities shape their interpretations of AI decisions. Privacy research similarly reveals gaps between conceptual safeguards and actual practice, with students often unaware of how their data is collected or protected (Francis et al., 2023; Liu & Khalil, 2023). Institutional policies remain fragmented and risk-oriented (Archambault, 2025; Luo, 2024). Cross-national studies reveal a wide variation in ethical and accountability standards (Li et al., 2025; OECD, 2023a; UNESCO IESALC, 2025).

4.3 Career Readiness

Companies are rapidly integrating generative AI (GAI) into workplace processes, making it essential for students to gain meaningful experience with these tools before graduation (Lee et al., 2024; López-Solís et al., 2025; Mayer et al., 2025; Walravens, 2025). To meet industry expectations, faculty must design curricula that incorporate experiential learning and foster advanced problem-solving skills. Institutions also need to ensure equitable access to AI learning opportunities while creating pathways that support lifelong learning for working professionals. Collectively, these efforts position higher education as a catalyst for career readiness, innovation, and inclusive economic participation in an AI-driven workforce.

Despite strong industry interest, research on AI-related education and workforce outcomes remains limited. Few longitudinal studies track how AI-prepared graduates perform over time in the workplace (Portocarrero Ramos et al., 2025; Walsh, 2024). Evidence is also sparse on micro credentials in AI and how employers interpret their value (Alenezi et al., 2024; Lumina Foundation, 2025). Additionally, limited research examines socioeconomic or demographic differences in AI readiness or how career services can support equitable skill development (Capraro et al., 2024; Tomas & Felix, 2025). More empirical work is also needed to measure employer expectations for AI competencies, which are often described anecdotally rather than systematically (Galeano et al., 2025; Rasdi et al., 2024).

4.3.1 Curriculum Alignment with Industry Expectations

Business schools must update their curricula to align with the realities of an AI-powered job market and prepare graduates for the rapidly evolving career demands (Mayer et al., 2025; Wang, 2025). Integrating GAI tools into core business courses and applied learning experiences strengthens student learning and builds industry-relevant competencies (Wang, 2025). AACSB (2024) reports that AI is shifting from an elective topic to a required and embedded component of business programs. This trend is reflected in American University's Kogod School of Business, where leaders integrated AI across the entire curriculum in just six months, demonstrating both the urgency and feasibility of aligning academic programs with industry expectations (McNaughton, 2024). Ultimately, the effectiveness of business schools will be measured by their ability to equip graduates with AI-enabled skills, critical thinking, and adaptive mindsets for long-term career readiness in a transforming economy.

4.3.1.1 Gaps in Curriculum Alignment with Industry Expectations

Although scholars emphasize the need to pair AI-related technical skills with human competencies such as critical thinking, ethical judgment, and reflective decision-making, systematic evidence on how these capacities develop together remains limited (Melisa et al., 2025; Nguyen, 2025). Concerns about overreliance persist, yet few studies examine how human and technical skills co-develop in AI-rich learning environments. Evidence on effective instructional models is also scarce despite calls for stronger pedagogical frameworks (Wittig McPhee, & Jerowsky, 2025). Little is known about the relative effectiveness of case-based learning, simulations, and problem-based learning or how cultural contexts shape expectations for human–AI skill integration.

4.3.2 Hands-On Learning

When educators integrate AI-based assignments into the curriculum, students strengthen both their digital literacy and workplace-relevant skills. For example, college students who used GAI in a content-creation contest demonstrated enhanced creativity and critical evaluation abilities (Hwang & Lee, 2025). AI-focused hackathons similarly allowed students to solve real-world problems under authentic constraints, showcasing adaptability and innovation (Sajja et al., 2024). In cybersecurity courses, students applied technical knowledge while demonstrating professionalism and ethical reasoning when evaluating AI policies and legislation (Elkhodr & Gide, 2025). Together, these examples demonstrate how hands-on AI learning fosters practical competencies and ethical awareness, which are essential for workplace readiness.

4.3.2.1 Gaps in Hands-On Learning Research

Despite enthusiasm for AI-focused hackathons, simulations, and competitions, significant gaps remain. Although studies highlight benefits, little empirical evidence examines the long-term impact of experiential AI activities on learning or professional identity (Sajja et al., 2024). Few studies compare the effectiveness of formats such as hackathons, simulations, or client-based projects in developing computational thinking, AI fluency, or higher-order skills (Hsu & Chen, 2025). Research is also limited on scalability for resource-constrained institutions (Govea et al., 2023) and on how experiential AI learning affects diverse student groups.

4.3.3 Prompt Engineering

Prompt engineering has become an essential competency for knowledge workers, requiring the ability to design complex, context-specific prompts that generate reliable and meaningful AI outputs (Lo, 2023; Park & Choo, 2024). Recent research shows that this skill is now regarded as a core qualification across a wide range of professional roles (Dwivedi et al., 2023; Firth & Triche, 2024; Hwang & Lee, 2025; Mok, 2025; Strohl et al., 2024). In fields such as marketing and consulting, for example, professionals increasingly rely on prompt engineering to refine AI-generated insights, develop targeted campaigns, and accelerate client deliverables. By integrating prompt engineering into the curriculum, business programs can ensure that graduates are equipped to apply AI responsibly and effectively, aligning with industry expectations.

4.3.3.1 Gaps in Prompt Engineering Research

Although prompt engineering is increasingly recognized as a key professional competency, research on its educational integration remains limited. Systematic reviews reveal a lack of empirical evidence on the most effective instructional strategies for developing prompt engineering skills, particularly in business and professional fields (Lee & Palmer, 2025). Few studies have examined the cognitive processes students use when refining prompts or how proficiency varies across diverse groups, raising concerns about equity (Hu & Lee, 2025). Evidence is also limited on workplace transferability and on the development of validated, discipline-sensitive rubrics for assessing prompt engineering performance.

4.3.4 Balancing Human and Technical Skills

To be career-ready in the contemporary workplace, students must possess both technical and human skills, such as critical thinking and decision-making (Hatami, 2025; Higher Ed Dive, 2024; Miao & Holmes, 2023; OECD, 2023b; Pitts et al., 2025; Slimi, 2023). For instance, humans need to be able to demonstrate the ability to think quickly and decisively with an understanding of context and culture, a skill AI finds difficult to imitate (Eachempati et al., 2025; Foley et al., 2024; Slimi, 2023).

Workers must become increasingly agile as GAI continues to develop rapidly, where adaptability, collaborative capacity, and ethical judgment are key (Lo, 2023; Park & Choo, 2024; Ratten & Jones, 2023; World Economic Forum, 2025). Embedding these competencies ensures business schools lead in shaping ethical, future-ready leaders for the AI era.

4.3.4.1 Gaps in Human and Technical Skill Research

Despite recognition that students need both technical and human skills for an AI-driven workplace, systematic research on integrating these competencies remains limited. Although scholars emphasize the development of critical thinking and ethical judgment alongside technical proficiency, few empirical studies have evaluated effective pedagogical models (Calma & Davies, 2020; Wittig, McPhee, & Jerowsky, 2025). Emerging AI literacy frameworks often overlook the role of instructional strategies in fostering adaptability, collaboration, and decision-making (UNESCO, 2025). Little evidence also examines the scalability of such approaches across diverse contexts or their equity implications.

4.3.5 Equity, Access, and Global Competitiveness

Equity remains a concern in AI-supported career readiness. Underserved schools and students without access to developed AI technologies may be marginalized in an AI-driven economy (Higher Ed Dive, 2024; Kasneci et al., 2023). UNESCO (2023) maintains that access to AI literacy and training should be high-quality and a priority on higher education's agenda. Moreover, the international competitiveness of AI industries is reliant on diverse talent pipelines, including women, international students, and historically underrepresented populations.

4.3.5.1 Gaps in Equity, Access, and Global Competitiveness Research

Although equity concerns are widely noted, the research base remains limited. Few studies examine how unequal access to AI affects learning outcomes or career readiness across demographic groups (Varsik & Vosberg, 2024). Evidence is also scarce on institutional strategies that reduce AI-related inequities, particularly in under-resourced settings. Little is known about cross-national differences in AI readiness or how unequal access shapes global talent pipelines (UNESCO, 2025). Existing work rarely employs an intersectional lens, despite evidence suggesting that overlapping identities impact AI literacy (UNESCO, 2023).

4.3.6 Lifelong Learning and Professional Adaptability

In today's workforce, continuous learning is a necessity. Workers must perpetually reskill to stay ahead of AI developments, building adaptability, judgment, and the ability to manage human–machine workforces (Brynjolfsson et al., 2023; Mayer et al., 2025; World Economic Forum, 2025). By embedding AI fluency, ethical judgment, and experiential learning into their curricula, business schools ensure that graduates remain adaptable and career-ready in an AI-driven workforce (Hamilton, 2025).

4.3.6.1 Gaps in Lifelong Learning and Professional Adaptability Research

Despite widespread agreement that lifelong learning is essential in an AI-driven economy, significant gaps persist. Little research evaluates which reskilling models—such as micro credentials, executive boot camps, or online AI academies—most effectively support adaptation to technological change. Limited evidence also examines how workers maintain AI literacy over time or the institutional supports required (OECD, 2023a). Employer roles in shaping lifelong learning ecosystems remain understudied (World Economic Forum, 2023). Additionally, the motivational and cultural factors influencing adults' participation in AI learning, as well as its effects on career mobility and job stability, are not well understood (OECD, 2023a).

5. Discussion

A central insight from this structured review is that GAI’s benefits and risks are deeply interdependent: advances in adaptive learning, assessment redesign, and experiential activities cannot be fully realized without parallel attention to governance, data practices, and equitable access.

The literature reveals that pedagogical gains depend on protecting human judgment, ensuring students develop critical evaluation skills, and preventing overreliance on AI-generated outputs. Ethical concerns—such as bias, transparency, privacy, and institutional accountability—cut across all uses of GAI and require coherent governance aligned with international guidelines. Career readiness expectations highlight the need for integrated pathways that develop both AI literacy and human-centered competencies; however, empirical evidence linking educational preparation to workplace outcomes remains limited.

Overall, responsible GAI adoption requires institution-wide strategies that integrate pedagogy, ethics, and workforce preparation, rather than treating them as isolated domains.

6. Conclusion

The literature indicates that integrating GAI requires more than technical adoption—it demands coordinated pedagogical, ethical, and workforce-oriented strategies. Business schools that establish transparent governance, align curricula with evolving industry needs, and ensure equitable access to AI learning opportunities will be best prepared to support student success in AI-intensive environments. Thoughtful, responsible integration can enhance educational relevance while safeguarding human agency, ethical reasoning, and long-term professional adaptability.

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Author's Biography

Katryna Johnson is a Professor of Marketing at Metropolitan State University in Minneapolis. She earned her Ph.D. from the Carlson School of Management at the University of Minnesota. Her research examines the pedagogical integration of generative AI and agentic AI in business education, with particular attention to student career readiness and workforce skill development. She is currently conducting research on risk-balanced governance of lecture capture in higher education, with particular attention to accessibility, identity protection, and synthetic media risk.

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Connections between Vibe Coding and Knowledge Creation: Examination of Organizational Implications of AI-Mediated Software Utilization

Todd A. Little
Simpson College, todd.little@simpson.edu

Abstract

The continued development of vibe coding indicates a paradigm shift in how AI-assisted software brings an evolving and significant challenge to established organizational processes, along with knowledge creation practices. Utilizing the established SECI framework associated with organizational knowledge management and creation processes, this paper provides a conceptual examination of the utilization of natural-language-driven and large language model (LLM) content generation influencing knowledge conversion processes in the context of organizational learning practices. Drawing on extant literature, this paper provides an argument that vibe coding indicates the transitional shift in how organizational personnel externalize, combine, and internalize knowledge to advance a foundational perspective of vibe coding and future research considerations.

Keywords: Vibe Coding, Knowledge Creation, Generative AI, SECI Model, Organizational Learning

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1. Introduction

The knowledge management model (SECI) involving four modes of knowledge creation (socialization, externalization, combination, and internalization) is often referenced as the common approach to understanding knowledge (Nonaka, 1991, 1994; I. Nonaka & H Takeuchi, 1995). It is also recognized that the model provides a framework for understanding organizational approaches to knowledge within the given environment of the organization, as each organization can apply varied approaches based on its own context of knowledge management. As such, the model provides an opportunity for the organization to reflect on its own specific processes and seek new methods to engage with new techniques that might be applied to knowledge creation processes. The SECI model provides the perspective of knowledge creation through continuous connections between both tacit and explicit knowledge. The four modes of SECI demonstrates how socialization creates tacit knowledge through a series of either formal or informal interactions designed to share insight and experiences with others; externalization converting tacit to explicit knowledge through codified instructions and procedures, rules, and other means to assist individuals in the understanding of the tacit knowledge; combination allows for explicit knowledge to be converted to additional explicit knowledge in the form of more complex structures; and internalization explores how explicit knowledge can then be converted back to tacit knowledge through appropriate application of that knowledge (Nonaka, 1994). As additional technologies are obtained for task completion and to support multiple organization infrastructures, it is essential to examine how one aspect of AI-assisted content generation impacts the overall SECI process and general knowledge management processes.

As noted by Philipson and Kjellström (2020), dynamic changes in environmental variables often result in new knowledge creation, which then impacts organizational innovation and learning opportunities. Organizations need to continue their learning aspects and expand their knowledge to assist in their adaptation to emerging technologies. By establishing a knowledge-based culture, the organization is committing itself to the KM overall vision of providing both formal and informal means, allowing workers to engage with each other to support the SECI model aspects. Further, learning becomes a key component within the SECI model; however, it is not guaranteed that knowledge is gained and relevant to the organization process (Bratianu & Orzea, 2010). Although multiple influences can impact the knowledge processes, technologies are acknowledged as being one of these major influential items. It should also be noted that technologies serve to support KM processes and assist knowledge workers; technologies do not necessarily serve as a motivator for engaging with knowledge processes (Chang & Lin, 2015). Therefore, it becomes important for organizations to examine new technologies and their impact on KM processes.

The emergence of vibe coding over the past couple of years has initiated a potential shift in the use of AI within the area of software development and content creation, but has also shown a more unexplored influence on knowledge management itself. The term "vibe coding" was initially introduced by Andrej Karpathy (AI researcher and founding member of OpenAI) in 2025 in a social media post and further defined as a concept of "using AI without the understanding…" and further recognized as an evolutionary shift from more traditional development foundations toward more conversational-based interactions dictating intuitive expressions over more detailed specifications (Quiroz-Gutierrez, 2025). Within the context of this paper, vibe coding is not specifically viewed as a means to support software development but rather suggests vibe coding is a means to support multiple areas of content and document generation and is a term which can lend itself as a tool for human users to gain access to explicit knowledge. The generated content can then be applied and utilized within current organizational practice and task processes. Essentially, vibe coding provides the opportunity to develop content simply through the process of "ask something; get something," but also potentially occurs without prior knowledge of the subject content. The further challenge is then associated with how explicit knowledge is converted either to support higher level explicit knowledge or converted to tacit knowledge for appropriate utilization on behalf of the human user.

Vibe coding is viewed as a subset of AI-assisted content development; however, the perspective of vibe coding shifts toward developing content based on the user's end-goal intent through clear high-level prompts. Therefore, it is perceived that vibe coding reduces the need for demonstrated expertise in the content and potentially lowers the requirement for specific training in business tasks. Whereas more traditional AI-applications may require the user to guide how to do a task, vibe coding allows the AI to provide content without expertise guidance from the user. Further, this also reduces the need for specific knowledge on proper validation and critical evaluation of the AI response without the expectation of user understanding. Meske et al. (2025) provided an additional perspective on defining vibe coding where "artifacts" are created through engaged interchange with AI-based systems, essentially providing an alternative path for how knowledge can be envisioned and obtained. Essentially, this type of engagement seeks to provide more effortless interactions and more "seamless idea generation" (Gaggioli et al., 2020) between the human user and the AI application. As such, vibe coding provides the means toward an evolving aspect of the knowledge management SECI process.

As shown in Figure 1, the four modes of the SECI process provide opportunities for a shared experience between individuals, articulating the concepts, synthesizing artifacts, and building on the understanding of those artifacts. However, there can be a perception of challenges within the SECI process associated with vibe coding. Whereas the externalization quadrant allows the user to build on a conversation with the AI application to develop content further, the socialization quadrant can be limited unless further actions are provided. Socialization is an aspect where one individual is expected to have shared experiences with another, and in this case, it is expected that the shared experience can provide tacit knowledge on appropriate prompt development to interact with the AI application. Without this type of shared experience for tacit-to-tacit knowledge transfer, an individual may risk being unable to develop and build on appropriate vibe-coding prompts to generate explicit knowledge through the AI application. Combination is demonstrated as the AI application utilizes the vibe coding prompts from the individual and then generates content through its own connections to other explicit forms of knowledge. However, another aspect of the SECI model that can prove to be problematic is the internalization component, where it is expected that the individual will appropriately apply the new explicit knowledge and develop new tacit knowledge. As suggested through the SECI model, the knowledge creation emphasizes the need to have the knowledge support ongoing development (Alavi et al., 2005; Cerchione et al., 2024; Chang & Lin, 2015).

Figure 1. Four modes of SECI connecting to vibe coding and AI utilization

SOCIALIZATION Shared Experiences – Tacit to Tacit An individual requires the transfer of knowledge from another to develop appropriate prompt understanding.	**EXTERNALIZATION** Articulating Concepts – Tacit to Explicit A conversation with AI through vibe coding provides an opportunity for idea formation.
INTERNALIZATION Developing Understanding – Explicit to Tacit An individual develops tacit knowledge through the codified explicit knowledge from the AI	**COMBINATION** Synthesizing Artifacts – Explicit to Explicit AI provides codified knowledge through its existing connections to other explicit knowledge.

Further, a new era of knowledge development through vibe coding begins to emerge as the AI-based application provides the knowledge, and the human user selectively engages with the application through prompts requesting guidance and possible solutions. As stated by Weber et al. (2024), when good-quality prompts are utilized, AI-based applications can potentially provide higher levels of content explanations and documentation. These interactions reshape the SECI process by now including a collaborative effort between the human user and the AI system, influencing skill development and knowledge quality (Dellermann et al., 2019). The emergence of vibe coding potentially introduces challenges and a shift in knowledge management processes, ranging from requirements of expertise in content areas to overall knowledge gaps, which can lead to the reduction of requirements to complete tasks. Although these types of challenges can already exist, vibe coding requires another level of organizational awareness to establish oversight and guidance. Therefore, vibe coding is viewed as providing users with a means of content generation, but does not necessarily require a critical understanding of the findings themselves. Although the practice of using artificial intelligence generative language models within content creation has seen an increase in utilization, it is argued that the implications for knowledge creation theories also need to be addressed. This paper seeks to bridge the gap between these two topic areas and identify key themes connecting the concept of “vibe coding” and knowledge management.

The methodology for this paper included a review of academic journal articles, conference proceedings, and other peer-reviewed studies. The nature of the review included identifying artifacts relying, but not limited to, keywords such as artificial intelligence, vibe coding, and knowledge management. Although knowledge management research on the SECI model provides a wide spectrum of extant studies, limitations to this paper are related to the more recent nature of the term “vibe coding,” therefore reducing the historical aspect of its impact on organizational policies. Artificial intelligence is also a subject across the past several years, but has gained more attention as the utilization of AI has continued to become more embedded into organizational structures and processes. The review of articles was focused on topic areas such as information systems, computer science, business management, and ethical foundations. The structure of the paper is designed to provide a conceptual foundation for future research studies based on the recognition of how more accessible

AI-based applications have become within organizational structures. The sections that follow provide a literature review of KM, knowledge creation, and the SECI model connections toward vibe coding while also exploring its connections to technology acceptance, organizational learning, and technology fit models. The paper continues with an examination of vibe coding within the context of knowledge creation, which leads toward an illustrative perspective of vibe coding as part of the SECI model. Finally, suggestions for practitioner governance of vibe coding within the KM process and suggestions for future research agendas are provided.

2. Literature Review

Knowledge management and processes have also been extensively researched across several decades with a baseline framework model such as SECI being provided initially and in revised versions (Nonaka, 1991, 1994; I. Nonaka & H Takeuchi, 1995; Nonaka et al., 2006). In addition, the concept of knowledge itself has also been widely accepted and viewed as part of the KM processes (Marjanovic, 2010). It is also accepted that tacit and explicit knowledge are two types of knowledge (Alavi & Leidner, 2001; Nonaka, 1994). Whereas explicit knowledge is more formally stated through a specific codified context or written form (Nonaka, 1991; I. Nonaka & H. Takeuchi, 1995; Polanyi, 1961), it is tacit knowledge that poses more challenges, given its subjective and individualistic behavior as tacit knowledge learned through experience. As modeled by Nonaka and Takeuchi (1995), SECI provides guidance on the process with which to develop knowledge and illustrates the continuous conversion process between tacit and explicit knowledge. Further, the model seeks to provide an understanding of these interconnections and the overall dynamic nature of knowledge creation. It is this conversion process through which individuals, and therefore organizations, will be able to gain new knowledge to be applied to established practices or solicit potential alternative tasks.

Within the framework of knowledge creation, it is recognized that knowledge-intensive processes (KIPs) and tasks also exist within organizational structures. As such, organizations need to recognize the areas requiring more knowledge-based experience and training, which can include, but are not limited to, areas such as software development and engineering, within the context of this paper. Organizations across multiple industries can all include various knowledge-intensive processes that require a higher level of knowledge to complete certain tasks (Little & Deokar, 2016). Additionally, it has been established that KIP often requires a higher level of innovative learning tasks along with extended time periods to grasp task requirements and expectations (Berniak-Wozny & Szelagowski, 2022; Unger et al., 2015). As suggested through a research study by Weber et al. (2024), which examined the use of AI-based applications in software development, differences in how AI support tools were used depended on the complexity of task requirements and indicated that individuals with lower technical skills tended to use shorter AI prompts while more experienced employees utilized more elaborate prompts. As such, prior experience and deeper knowledge of the content can assist in more robust collaborative efforts between the human user and the AI application. Therefore, the AI-assisted knowledge generation can potentially demonstrate solutions beyond the user's current experience (Meske et al., 2025), which influences an individual's expertise in knowledge-intensive processes.

Another aspect of knowledge management studies has focused on the cultural influences and barriers within organizational structures. These perspectives are often cited as a continuing challenge for organizations to grasp as technologies evolve to support knowledge-intensive processes and tasks (Alavi et al., 2005). Further, previous studies have shown the essential aspect of having organizations work to develop multiple aspects of KM processes, such as where knowledge is obtained, the mediums through which knowledge is shared, and to whom the knowledge is directed (Miranda & Saunders, 2003; Sussman & Siegal, 2003). Additional studies (Meyerson & Martin, 1987) provided the perspective suggesting organizations have more than one embedded culture influencing KM processes, which does provide an argument where functional areas of organizational structures establish their own influential components. Although it might be beneficial for an organization to develop a more unified approach to its knowledge culture, it does seem plausible for each functional area or silo of the organization to develop different influences based on leadership, experiences, task dependencies, and events through the virtual medium (Ardichvili et al., 2006; De Long & Fahey, 2000; Magnier-Watanabe & Senoo, 2010). Additional studies have explored the relationship between how leadership handles knowledge tasks through more flexible or rigid governing policies. Knowledge sharing behavior amongst individuals was found to be negatively impacted when policies attempted to control the process more rigidly (Chang & Lin, 2015), suggesting organizations seek to provide more flexibility in knowledge sharing experiences.

Extant literature has explored the concepts of the acceptance of technologies within organizational structures extensively. One such perspective examined involved the development of the technology acceptance model (TAM) initially introduced by Davis (1985, 1989), which modeled the overall end-user acceptance toward technologies. This was further studied through a revised model of TAM, indicating user-defined perceived usefulness (Venkatesh & Davis, 2000). Although these models do provide a framework for how organizations implement and utilize technologies and infrastructures, the continuing development of artificial intelligence-based applications for various knowledge-intensive processes may also present challenges in both implementation and understanding (Hasija & Esper, 2022). This will further emphasize whether or not the use of such AI-based technologies will be vital to the overall task being performed (Nysveen & Pedersen, 2016; Yoo et al., 2012). Further, as noted by Hadidi and Power (2020), new and innovative technologies continue to demonstrate usefulness to the point where they can be deemed beneficial to both individuals and organizations. Similar to the TAM structure, Goodhue and Thompson (1995) proposed the theory of task-technology fit to explore the connections between tasks and technologies. Within the theory, it is recognized that the individual needs to understand the task characteristics, which can be supported by the technology characteristics. To have a higher impact on task performance, the overall task-technology fit needs to be established. As such, there needs to be a direct practical aspect to the use of the technology, which fits the need. One aspect of this theory indicates that individual characteristics also influence the context of the perceived fit. The task-technology fit theory is associated with how technology meets the needs of the individual, or perhaps the organization as a whole, toward the given task (Pal & Patra, 2020). Within TAM, vibe coding may not be seen as being accepted; however, the task-technology fit theory indicates the opportunity where vibe coding may be the technology that is a good fit for particular tasks. Whereas TAM leans toward individual perceptions of technology acceptance and fit, two other theories can provide a wider perspective for an organization.

Additional literature and research have examined the broader perspective of organizational learning where individuals have the ability to “create the results they truly desire,” and the organization benefits from the continual learning across the organization (Senge, 1990). Within this framework of the organizational learning theory, it is the ability of the organization to be adaptive and flexible that allows the organization to continually learn to be beneficial. However, as stated within this theory, individuals may not have the resources or guidance to help them understand the content. The theory can also be perceived across two main concepts referred to single-loop and double-loop learning. The differences between these two concepts are connected to the overall scope of the learning process. Whereas single-loop learning allows for adjustments to influence performance without altering policies, double-loop learning initiates more in-depth evaluation and modifications across the organization (Edmonson & Moingeon, 1998). As vibe coding suggests, prior knowledge of the content desired is not required, which also reduces the ability to understand the AI-provided response. As such, vibe coding can be perceived as limiting the double-loop learning ability, as the deeper understanding of how to apply the provided knowledge may not be hindered.

Another perspective explored is associated with the affordances theory, which was expanded by Gibson (1979), in which a human user can perceive what an object can offer and not the properties of the object directly. In this case, if vibe coding is viewed through the affordances concept, humans can view vibe coding and the use of AI applications as a direct opportunity to gain potential new knowledge. If vibe coding is to be viewed as an affordance, Gibson’s theory suggests three foundations: an affordance does not necessarily exist for another person; an affordance exists independently of the user’s ability to perceive it; and an affordance does not change despite changes in the goals of the person. If vibe coding is perceived as an affordance, vibe coding is viewed as providing the opportunity to gain solutions or insights based on the request of the user. Additionally, vibe coding exists and is available whether it is being utilized or not by an individual, and it continues to provide content despite changes in the user’s goals and objectives. However, as Gibson further noted, the ability to understand the affordance can depend on additional factors such as experiences and other cultural influences (Volkoff & Strong, 2017); however, these can be enhanced through training, education, and ongoing experiences (Faraj & Azad, 2012).

3. Vibe Coding within the Context of Knowledge Creation

Across more recent years, the development of artificial intelligence (Bencsik & Szalai) has also led to the establishment of large language models (LLMs), which have influenced various industries and applications. As such, it is clear the use of LLMs, such as ChatGPT, Claude, GitHub Copilot, Google Gemini, and others, has also started to influence organizational processes such as knowledge management. These are designed to be able to anticipate user intent, suggest potential corrections, and propose relevant knowledge within the context of the process function through which the AI is being referenced (Sergeyuk et al., 2025; Ulfsnes et al., 2024). With KM defining organizational frameworks as to how knowledge can be obtained, stored, created, and distributed, AI and LLMs provide processes for automating tasks, summarizing data and information, and text generation, and as such, can be viewed as contributing to the KM processes (Chiarello et al., 2024). These AI-generative tools can then be argued as an evolving influence toward KM tasks ranging from generalized automated decision-making processes to more complex strategic initiatives. Although a more recent study (Nguyen, 2025) has explored this influential technology within a higher education environment, similar concepts can also be viewed outside the realm of education.

Overall, generative AI tools have already begun providing organizations with a different medium through which KM can be assessed. As Nonaka et al. (1991, 1994; 1995; 2006) have examined KM development and others have reviewed cultural influences on KM (Alavi et al., 2005), the role of generative AI concepts should also become a part of research studies. It should also be acknowledged that technological advancements have influenced organizational processes for many decades, and as these technologies evolve, they have been embedded into organizational tasks (Fousiani et al., 2024; Wright & Schultz, 2018) and potentially impact adoption strategies (Yu et al., 2023). Within the larger scope of LLMs, the concept of "vibe coding" has emerged, defining how "natural language descriptions" can be converted into content (Cabot, 2025) and even described as a means for "an iterative, conversational workflow" (Meske et al., 2025). Although vibe coding is more often associated with programming and system development, it should be acknowledged that these aspects require a higher level of knowledge to work toward completion. Therefore, as a knowledge-intensive process, vibe coding will also be a direct influence on the broader perspective of KM and knowledge conversion experiences.

As noted previously, although the SECI process for knowledge creation does provide a model for the conversion aspects between tacit and explicit knowledge, the use of vibe coding can present some underlying challenges requiring organizational oversight. As shown in Figure 1, the aspect of socialization requires individuals to know appropriate prompt the AI application to begin the conversation with the AI application. Socialization provides the opportunity for individuals to share their experiences through an exchange of tacit knowledge (Han & Zhao, 2026). It is through these socialization aspects that one individual can learn how to appropriately prompt the AI for content generation. As vibe coding is often perceived as not requiring a higher level of experience, individuals may not have the opportunity to interact through socialization activities. Therefore, the vibe coding experience of the individual may be reduced due to the lack of appropriate tacit knowledge to engage the AI in a meaningful manner. This can lead to a decrease in the ability to convert new explicit knowledge into new tacit knowledge as part of the internalization process. Without proper guidance, the expected ascending spiral of the SECI model (Nonaka, 1994; I. Nonaka & H Takeuchi, 1995) most likely will not be effective but rather becomes more cyclical in nature, where we see vibe prompting leading to output and back to an additional vibe prompt. The aspect for consideration is how internalization can be enhanced to form stronger vibe prompts.

3.1 Externalization without Internalization

As suggested within the SECI framework (Nonaka, 1994; I. Nonaka & H. Takeuchi, 1995), KM utilizes two processes identified as externalization and internalization. Extant studies have defined externalization as the means to convert tacit knowledge into explicit forms, whereas internalization is the conversion of explicit knowledge into tacit knowledge, which corresponds to the overarching process of learning. With knowledge-intensive processes, often perceived as requiring higher levels of intuition, judgment, critical thinking, and extensive knowledge of context for the process action, it is generally obtained through ongoing intentional experiences and interactions (Casillas et al., 2009; Tsai & Lee, 2006). Further, as noted by Cohen and Levinthal (1990), it becomes an important part of the process to have individuals dedicate more effort toward learning knowledge to enhance the use of knowledge for later purposes.

Through these ongoing experiences to obtain knowledge, the conversion of internalization becomes part of an individual's tacit knowledge dedicated toward specific work contexts associated with knowledge-intensive processes and even more generalized task association. Vibe coding, as described in the previous sections, then leans toward reducing the effort of an individual to work through a particular task, and therefore potentially reducing the level of internalization undertaken. Tacit knowledge required by the individual is not necessarily required as the AI application itself becomes the source of tacit knowledge. Although it is noted that the use of these tools associated with vibe coding can reduce the need for a higher level of knowledge, it should be further acknowledged that this reduced knowledge requirement also limits the ability to further enhance knowledge, as mastery of task understanding is not necessarily required for implementation (Meske et al., 2025). Vibe coding is implemented through user-provided prompts to initialize the generative AI process, with these prompts ranging from vague to perhaps more specialized high-level directives. Although this process can be perceived as a form of externalization through natural language, the result provides additional explicit forms of knowledge in AI-generated formats (Tsai & Lee, 2006).

Nonaka (1994) indicated that the spiral nature of learning knowledge required the ability to scaffold knowledge obtained across multiple experiences over a period of time. Otherwise, obtaining knowledge without the foundational perspective of why or how knowledge should be used can potentially have a negative influence on applying knowledge effectively when required. The organization will need to be aware of the potential risks involved with the use of vibe coding as its continued use and evolving nature may produce potential knowledge gaps due to loss of knowledge quality and innovation (Meske et al., 2025). Without intentional guidance from the organization in the use of these tools, knowledge workers potentially may develop a sense of disconnect between the use of knowledge and fundamental understanding, leading to the development of deskilling and disinformation (Wagman et al., 2025). This requires organizations to dedicate attention toward knowledge creation within the context of knowledge-intensive processes, provide guidance for workers in the use of generative AI, and support knowledge scaffolding involving explicit knowledge obtained through generative AI methods (Wagman et al., 2025). It is then argued that vibe coding and the use of generative AI-based technologies interrupt the internalization process within KM, as the generative AI tool retains the knowledge, but the user is not fully internalizing the findings.

3.2 Expertise Redistribution

As the use of AI-enabled processes such as vibe coding continues to be deployed within organizational processes, it will be essential for knowledge workers to be adaptive to new upskilling experiences that focus on training experiences. Expertise redistribution is expected due to the continued development of vibe coding, requiring organizations to integrate the process into their existing tasks, practices, and procedures (Hasija & Esper, 2022). Vibe coding can create opportunities for novice users to engage with previously unexperienced tasks. As such, vibe coding is not perceived as eliminating the need for tacit knowledge. Vibe coding does not reduce the need for more knowledge workers across the organization, but does require workers to develop the need to redistribute knowledge expertise to include the appropriate handling of these tools. Utilization of vibe coding prompts for generative AI tools will continue to evolve, and therefore, new tacit knowledge will need to be developed to engage with these tools through effective prompting and evaluation. It will be essential to understand the explicit form provided through vibe coding, which requires critical thinking perspectives (Xiao et al., 2022).

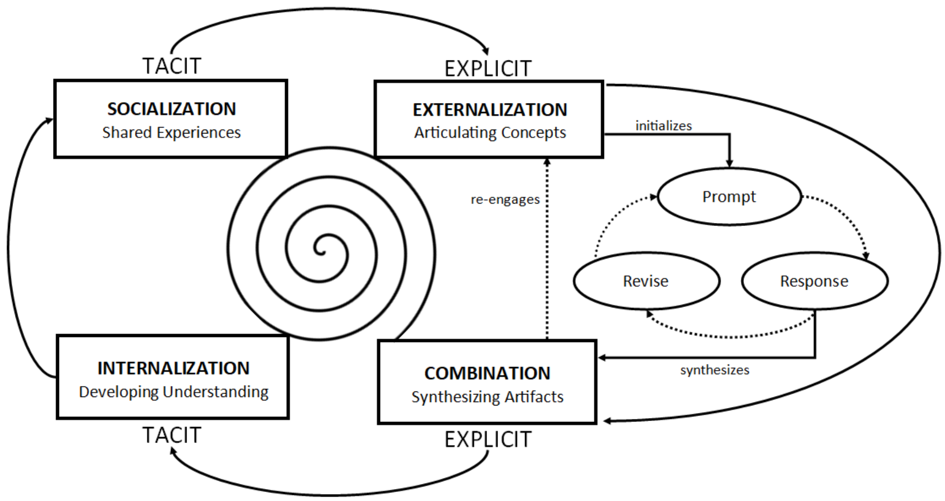
Aligning with the SECI model aspect of recombination, vibe coding can lead to more cross-disciplinary knowledge opportunities, combining prior knowledge with new sources of content (Moaniba et al., 2018). As knowledge recombination has been noted as providing positive correlations with organizational innovation (Zhong et al., 2024) when it is used effectively for knowledge creation. Further, expanding the foundation of knowledge workers through training interventions can enhance innovative behavior by connecting the vibe coding techniques into a more capable learning experience for the worker (Han & Zhao, 2026). This further suggests that organizations provide a foundation for the use of vibe coding to understand how it can connect to knowledge creation. As such, providing structured activities for workers to share their understanding of vibe coding findings directly links back to the SECI model and provides opportunities to enhance current knowledge sources and repositories (Cerchione et al., 2024). This would argue that vibe coding processes can be an enabler of the knowledge creation but requires active participation to expand worker experiences. When the rationale behind the use of generative AI-based tools cannot be articulated, documented, or internalized through organizational structures, knowledge governance, and techniques, the process will present flaws in the process.

4. Envisioning the SECI and Vibe Coding Model

As noted extensively throughout knowledge management literature, the SECI model (Nonaka, 1991, 1994; I. Nonaka & H Takeuchi, 1995) is perceived as a continual spiral connecting socialization, externalization, combination, and internalization for the transformation of knowledge as discussed in the previous sections. As suggested, the SECI spiral is not a reflection of a continual loop but rather resembles an ascending spiral that allows individuals and organizations to build on their knowledge and organizational understanding. However, with vibe coding, the overall process resembles the SECI model by also suggesting the perspective of a spiral, but the concept perhaps removes the internalization step to further build knowledge. Therefore, the vibe coding aspect forms a micro spiral within the SECI process. This micro spiral includes the initial vibe prompt, which generates output for consideration and utilization. Additional prompts can then be included to either enhance previous prompts or engage the AI application in a new conversation. Therefore, the research can suggest a micro-spiral of vibe coding within the larger SECI spiral of knowledge creation. Although this type of model suggests vibe coding supporting the externalization and combination segments of the SECI model, it does provide the argument for organizations to understand the need for additional opportunities to connect to socialization and internalization areas.

As shown in Figure 2, the traditional SECI model is viewed as a continual spiral allowing for knowledge growth, building upon previously obtained knowledge through socialization, externalization, combination, and internalization. The vibe coding circular process is viewed as a connection point between Externalization and Combination, where the user has the opportunity to input the vibe prompt to allow the AI to provide its response. Then, the user can either continue to revise the prompt to engage the AI further or utilize the provided response to synthesize artifacts. Moving forward in the SECI spiral, it is expected the Internalization aspect can proceed as the user can utilize the synthesized artifacts toward organizational tasks and processes where needed. However, when appropriate methods are not available or avoided moving from Combination to Internalization, the risk exists for Combination to shift back to Externalization, essentially bypassing the internalization and socialization aspects.

Figure 2. SECI and Vibe Coding Model



It is argued that vibe coding should not be considered as only a part of organizational workflow but as part of the knowledge creation process, building on the SECI model. Socialization can therefore occur as users provide knowledge transfer of prior experiences of AI application use and appropriate vibe prompting. Externalization is where users initiate conversations with the AI and obtain explicit dialogue. The user can refine the vibe prompts to gain further explicit conversations. The AI application has a distinct advantage as it can synthesize explicit knowledge from multiple sources based on the intentional vibe prompt. As each SECI spiral occurs, the internalization is where those explicit artifacts generated through the AI can be reviewed, reflected upon, and applied to appropriate organizational processes, allowing for the knowledge to be carried forward.

5. Implications for Knowledge Management Governance

A critical aspect within knowledge management is the opportunity to maintain explicit documentation supporting knowledge content management; however, within vibe coding, practitioners tend to emphasize speed over knowledge content strategies, leading to inconsistencies in generating findings (Mitchell & Shaaban, 2025). Thus, the use of generative AI can pose challenges to multiple governance issues, including, but not limited to, reliable knowledge sources, quality assurance, and lack of modification opportunities, all impacting organizational knowledge overall (Elgendy et al., 2026). As noted previously, without clear governance policies to guide the use of vibe coding techniques, the organization can potentially lose its ability to develop a clear understanding of why such technologies were used and what new knowledge may be gained. This type of challenge can be referred to as organizational amnesia, which impacts the ability of organizations to maintain or limit their ability to "communicate lessons" across the organizational structure as needed (Sadat & Lin, 2018; Stein, 1995).

As mentioned in previous studies and across multiple extant studies, an organization should work toward supporting the conversion of explicit and tacit knowledge as defined through the SECI model. Vibe coding adoption rates will most likely continue to see growth in the coming years. As such, organizations need to be prepared and adapt to avoid potential erosion of tacit knowledge across their knowledge-intensive work areas. It is important to work toward maintaining knowledge workers as practitioners of knowledge instead of workers relying on generative-AI tools potentially initiating a decline in overall knowledge, skills, and competencies. This aspect would negatively impact the SECI model, where tacit knowledge would traditionally be part of a socialization perspective (I. Nonaka & H. Takeuchi, 1995).

The main themes identified do not necessarily result in an organization completely transitioning its current KM strategies; however, by failing to acknowledge potential pitfalls of generative AI usage within their knowledge-intensive process, an organization risks not being able to adapt to the use of vibe coding as a new knowledge source. Rather, the organization can examine its current practices to intentionally engage with new technologies that influence KM processes.

Therefore, it would be argued that to avoid competency gaps in knowledge, an organization needs to provide more deliberate practices of knowledge sharing through mentorships, review processes, and other opportunities for experienced workers to partner with others new to the organization. As shown in Table 1, various themes can be identified to help provide some guidance for organizations.

Theme	Description	Key Sources	SECI Model Connection(s)	Practitioner Guidance	Organizational Segments
Knowledge Conversion	Translation between personal and codified knowledge	(Bratianu & Orzea, 2010; Nonaka, 1994; I. Nonaka & H Takeuchi, 1995; Nonaka et al., 2006)	Socialization Internalization	• Enhancing interpretation through group learning; • Evaluating current process for learning to avoid rigid or legacy traditions; • Validation techniques of knowledge learning	Team and organization segments benefit from sustained group learning and sharing.
Expertise Redistribution	Shifts tacit knowledge toward context management and when to override AI outputs; knowledge recombination	(Hasija & Esper, 2022; Moaniba et al., 2018; Xiao et al., 2022)	Externalization Combination	• Developing new tacit skills toward AI prompt creation, AI evaluation, critical thinking; • Institutionalizing knowledge into tasks processes to remove dependency on original source • Documenting reflection on findings against prior knowledge	Individual, team, and organization supported by embedding knowledge into processes and policies.
Tacit Knowledge Atrophy	Sustained use of AI-based tools eroding foundational competencies; decline in knowledge effectiveness	(Berniak-Wozny & Szelagowski, 2022; Han & Zhao, 2026; Levallet & Chan, 2019)	Socialization Combination Internalization	• Supporting use of mentorships, direct interactions between co-workers; • Enhancing socialization methods; • Integrating shared understanding	Team and organization segments enhanced through intentional integration.
Organizational Memory Loss	AI-generated responses retained without rationale being understood; poor documentation; knowledge applied but forgotten	(Erben & Dogantemur, 2019; Kransdorff, 1998; Unger et al., 2015)	Internalization	• Formally capturing AI-generated findings; • Diffused to functional areas where needed; • Interpreting findings through individual and group learning; • Routine audits of documentation	Organization develops governance on retaining artifacts for application.

Table 1. Main themes toward organizational guidance

As provided in Table 1, the four main themes can also be associated with the four main quadrants of the SECI model. Socialization is required to obtain appropriate knowledge transfer; externalization is impacted through expertise redistribution; combination is affected if the organization identifies tacit knowledge atrophy; and internalization is negatively impacted when organization memory loss is experienced. The practitioner guidance can provide opportunities for the organization to ensure a negative impact on the SECI model is reduced. Although this guidance may suggest renovations toward individual preparedness and allowance for developing tacit knowledge, the guidance provides perspectives toward benefiting both the group (or teams) and overall organization structures. For the team and organization structure, establishing a common "intentionality" (Philipson & Kjellström, 2020) presents a shared understanding within business tasks. Whereas individuals may develop personal preferences toward the use of their own tacit knowledge and can support team activities, the team itself needs to establish its common objective. As such, teams can then provide opportunities to expand the organization's externalized knowledge.

Further, with enhancements of organizational policies and guidance, opportunities exist to continue the development of user trust and perception of legitimacy of vibe coding within AI applications. This provides the means to reduce any ambiguity that may arise, along with reducing potential auditability gaps. However, this also requires organizations to undertake AI literacy standards designed to develop skills. Reducing auditability gaps indicates the need for more governance of audit trail mandates and vibe coding tracking to ensure documentation is provided and available to individuals as needed for task completion. With organizational dynamics shifting toward vibe coding and AI-based applications, AI-use policies and frameworks should also be designed to provide appropriate oversight. It should also be recognized that differences in organizational structures, such as organizational age, size, and complexity of tasks, will also serve as moderators for these guidance areas. Regardless of the organizational differences, providing opportunities for feedback can help revise governance of these initiatives from a linear perspective to a more reflective and adaptive environment for organizational change.

6. Conclusions

The main objective of this paper is to provide a conceptual foundation for further studies into the connections between vibe coding (or generative AI-based) tools and the overarching perspective of knowledge management. The limitation of this paper is the lack of direct case study research; however, findings of the extant articles and resources provide empirical evidence to support the need for organizations to understand how these new technological tools are being implemented within their knowledge-intensive tasks and processes. It is acknowledged that future studies would be required to assess the impact generative AI has had on KM processes. Future research recommendations would include three main categories. First, specifically understanding how the organization includes these tools within their current work processes through provided support, or whether individuals are utilizing the tools without organizational guidance or training. Second, understanding how the organization or individuals incorporate the AI-provided content directly into existing organizational documentation or determine the nature of the intent behind its utilization, if not to enhance organizational tasks and processes. Third, do individuals discuss the AI-provided content with others to share experiences and knowledge with the intent of improving additional utilization, or if not, explore the perception of why individuals are not sharing? These main areas for consideration would then relate to the SECI areas to explore justification for individuals initiating vibe coding (externalization to combination), applying obtained content to organizational tasks (combination to internalization), and sharing of obtained content with others (socialization).

With vibe coding seemingly influencing the externalization step of KM, additional studies are recommended to continue exploring these gaps on how to progress the externalized knowledge toward internalization growth. The findings also indicate the need for an organization to develop policies and governance methods to support continuing development in knowledge creation. Although the use of vibe coding methods does not generally require extensive knowledge, it can disrupt the knowledge conversion process between externalization and internalization, thus limiting the ability of knowledge workers to appropriately develop and apply new knowledge.

The more immediate practical implication suggests organizations develop structured experiences to support peer-sharing, problem-solving, and overall reflection on explicit knowledge obtained through vibe coding. Vibe coding can be viewed as another source of knowledge and therefore can add itself into an already diverse pool of external sources. However, workers will need support and a foundation of knowledge in the context area to fully comprehend and interpret the findings provided through vibe coding. As vibe coding continues to evolve, organizations will also need to adjust their learning activities and evaluations to allow workers to ideally strengthen their current knowledge base and role in task completion.

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Author Biography

Todd A. Little is an Associate Professor of Management Information Systems in the Department of Computer Science and Mathematics at Simpson College. He received his Sc.D. in Information Systems from Dakota State University in 2013 and teaches courses in Information Systems, Project Management, Systems Analysis & Design, and E-Commerce. His research interests include knowledge creation, organizational learning and strategies, and project management, and his co-authored research has been published in the *Journal of Knowledge Management*. He recently earned the Distinguished Teaching Award and has previously earned the Excellence in Adult Education Award at Simpson College.