From Knowing to Doing: Redesigning Business Education for AI

Monika Sońta[1], Lyubomyr Matsekh-Ukrayinskyy[2] and Maciej Mąkosa[3]

[1]Kozminski University, Warsaw, Poland, msonta@kozminski.edu.pl
[2]Reutlingen University, Reutlingen, Germany,
Lyubomyr.Matsekh-Ukrayinskyy@Reutlingen-University.de
[3]Kozminski University, Warsaw, Poland, 49844@kozminski.edu.pl

Abstract

As artificial intelligence transforms managerial practice, business schools face growing pressure to equip graduates with artificial intelligence literacy while keeping curricula accessible to non-technical learners. In this paper, artificial intelligence refers primarily to generative tools such as large language model assistants, the technology driving current classroom and workplace adoption; the broader term artificial intelligence is retained for consistency with the education-literacy literature. Despite emerging educational initiatives, limited evidence exists on effectively designing such courses within actionable pedagogical frameworks. This paper addresses this gap through two complementary pain-point analyses grounded in thematic inquiry: a corpus of 838 unique sources from academic, enterprise, and practitioner platforms, and a longitudinal dataset of 607 student evaluation records collected across five academic years from 1,236 enrolled management students. Findings reveal five systemic obstacles: entry-point paralysis, acute anxiety regarding self-efficacy, shallow enterprise adoption, workplace stigma, and institutional incoherence. Practical application, active tool integration, contemporary case studies, and collaborative pitch projects consistently outperformed traditional lecture-based instruction. Grounded in these empirical insights, this study proposes actionable guidelines for course redesign, alongside core pedagogical principles supporting agile, continuously evolving curricula for management education.

Keywords: *Artificial Intelligence in Education, Generative AI, Management Education, Curriculum Design, AI Literacy, Experiential Learning.*

1. Introduction

As artificial intelligence (AI) transforms managerial practice, business schools face growing pressure to prepare graduates with AI literacy while ensuring that curricula remain accessible to students without technical backgrounds. Throughout this paper, "AI" is used as the umbrella term established in the education-literacy literature, while "generative AI" is used specifically where findings concern large language model tools (e.g., ChatGPT, Copilot) — the dominant form of AI students and instructors encounter in practice today. This shift necessitates a departure from static pedagogical models toward dynamic frameworks that align AI literacy with evolving employment demands and institutional policy support [1]. The study proposes a structured taxonomy of pedagogical interventions designed to navigate the tension between rapid technological disruption and the foundational requirements of academic integrity [2]. By leveraging this taxonomy, educators can better reconcile student expectations for practical, future-oriented training with the institutional necessity for clear guidance on responsible and ethical AI adoption [3].

Although numerous AI education initiatives have emerged, limited evidence is available on how AI courses can be effectively designed for management students within a practical framework [4]. This framework identifies major pedagogical bottlenecks, including the misalignment between theoretical instruction and industry application, and advocates modular curricula [5] that develop core AI competencies while supporting institutional restructuring for long-term sustainability [4].

Integrating structured AI interactions also lets educators balance technological innovation with human-centric soft skills [6], so that students cultivate not only technical proficiency but also the critical evaluation and metacognitive engagement needed to navigate the AI-driven workplace [7]. Accordingly, this study offers a roadmap for transitioning from passive knowledge dissemination to active, andragogical models that mitigate overreliance while fostering professional autonomy [8], with AI literacy embedded across domain-specific management subjects rather than treated as a peripheral technical skill [9].

2. Theoretical Background

The rapid integration of generative AI into professional workflows has fundamentally transformed the skills expected of contemporary business graduates, shifting pedagogical priorities toward the critical evaluation and ethical application of these technologies [10]. Emerging scholarship grounded in social constructivism and connectivism seeks to make AI instruction more interdisciplinary by integrating technical competencies with ethical reasoning and informed AI systems management [11].

2.1 AI Literacy as a Conceptual Foundation

A first family of approaches centers on cultivating AI literacy: a consolidated set of competencies that equip nonexperts to understand, use, and critically evaluate AI without requiring programming skills. Laupichler et al. conclude that AI literacy research in higher and adult education is still in its infancy, with no settled definition of what content should be taught to non-expert audiences [12]. Ng et al. provide one of the most influential conceptual anchors by proposing four intertwined aspects of AI literacy — know and understand, use and apply, evaluate and create, and ethical issues — which reframe the goal of teaching from technical proficiency toward informed, responsible engagement with AI [13]. Institutions have operationalized this differently: the University of Florida's "AI Across the Curriculum" initiative infuses AI education into every discipline [14], while Locke and Rainer propose a dedicated three-course sequence moved out of computer science and into the mainstream business curriculum [15].

2.2 Experiential and Project-Based Learning with AI

A second family of approaches insists that literacy alone is insufficient and pairs conceptual grounding with handson, project-based experience. Wunderlich et al. demonstrate that machine learning is particularly amenable to experiential learning for business students: community-based tools and public datasets let non-programmers adapt open ML examples and interpret business implications without writing code from scratch [16]. An interdisciplinary project-based course combining creativity methods with AI prototype development across two editions with 32 students reports enhanced student confidence and a more nuanced grasp of AI technologies [17]. Survey evidence from business and economics students points the same way: students are aware of AI's impact and willing to learn, but their knowledge is limited by lack of training, and they benefit most from realistic use cases presented with the technology's real limitations rather than abstract theory [18]. These findings align with the recommendation that AI curricula for non-technical fields should embed case studies relevant to students' own disciplines, accompanied by explicit discussion of ethical implications such as algorithmic bias and data privacy [19]. This experiential turn addresses a documented failure mode: traditional coding education methods have consistently proven inadequate for non-technical learners, which is why low-code platforms and scaffolded, project-driven designs are increasingly positioned as the bridge between technological capability and practical professional application [20]. Adopting these modular, hands-on strategies lets educators demystify complex algorithms while grounding theory in the real-world scenarios essential for managerial decision-making [21].

2.3 Education as Sustainability

Beyond experiential and project-based designs, low-code and no-code development offers a complementary pathway for non-IT learners. Sońta and Przegalińska argue that students without programming backgrounds can co-create working IT solutions when educators articulate entry points into low-code learning and keep the technology "in the background" while students solve

authentic problems from their own experience [22]. Because traditional coding education has consistently proven inadequate for non-technical learners [23], low-code platforms lower the perceived access barrier and operate as a "building block approach" [20], conceptualized as "education as sustainability" [20]. This shift aligns with broader efforts to reimagine management education, where students leverage AI-powered tools not merely for technical proficiency but as a mechanism for addressing complex global challenges [24], [25]. Across these three frameworks, existing research has largely focused on single-course implementations and small cohorts, limiting generalizability across student populations, delivery formats, and institutional settings [17], [26]. Broader implementation also depends on instructor competence, infrastructure, and mechanisms for updating course content as AI capabilities evolve [27]. Against this background, the originality of the present study lies in its two-stage analytical design, combining a web-scraping analysis with a longitudinal student-evaluation dataset, establishing an open framework that educators can adapt to their own institutional contexts.

3. Methods

The study is structured around two complementary data sources that together capture AI pedagogy in business education from both a global and a classroom-level perspective. To structure the empirical inquiry, this study addresses three interrelated research questions: (1) What are the main challenges in teaching a general “AI in Business” course to management students without technical backgrounds? (2) Which elements of the learning process do students rate highest, and which lowest? (3) Which tools and pedagogical approaches are most effective?

We define short introductory ‘AI in Business’ courses as classes comprising between 12 and 24 teaching hours and typically not exceeding 3 ECTS credits, most often introduced by universities to rapidly enhance students’ digital competencies in response to labor-market demand [28]. To answer the research questions, we analyzed two study components separately — an analysis of online sources and an evaluative survey study — with the third question answered in the discussion section through data triangulation. Taking into account the possibility of systematic bias arising from the selection method and the nature of web-scraped data, we focused our recommendations primarily on solutions identified within corresponding thematic categories across both analyses, limiting potential discrepancies between theoretical discourse and practical educational needs.

3.1 Web-Scraping Analysis: Multi-Source Data Collection Framework

The first component is a web-scraping analysis: 838 unique raw sources collected from ten academic, enterprise, and informal community platforms — arXiv, OpenAlex, ERIC, Semantic Scholar, Exa web search, YouTube, Reddit, Forrester, and PwC — acquired through 15 targeted query clusters and 10 continuous data streams. Platforms were selected to deliberately triangulate three source types: peer-reviewed academic repositories (arXiv, OpenAlex, ERIC, Semantic Scholar), for methodological rigor and established pedagogical frameworks;

enterprise/industry research (Forrester, PwC), for workforce AI-skill demand and adoption-ROI data unavailable in academic literature; and informal community platforms (Reddit, YouTube, Exa web search), for unfiltered instructor and practitioner sentiment not captured by either of the above. This multi-source architecture balances rigorous peer-reviewed literature with real-time practitioner feedback, ensuring that the identified pain points reflect both published research and emerging classroom workarounds.

For YouTube specifically, the harvester used yt-dlp to collect public video title and description metadata together with the top viewer comments on each video — not the video or audio content itself — on the premise that comments on AI-education videos capture authentic learner reactions comparable in kind to Reddit discussion threads.

To capture high-signal qualitative insights while mitigating noise from unmoderated platforms, version 4 (v4) of the scraping pipeline scoped informal community extraction to high-relevance domain hubs (r/Professors, r/artificial, r/education).

Platform Category	Data Streams Included	Signal Density Rating	Methodological Contribution
Academic Repositories	arXiv, OpenAlex, ERIC, Semantic Scholar	High	Peerreviewed pedagogical frameworks, empirical interventions, and foundational theory.
Enterprise Insights	Forrester, PwC	High	Industry alignment metrics, workforce AI skill requirements, and institutional benchmarks.
Community & Web	Reddit, YouTube, Exa Web Search	Moderate–High	Unfiltered instructor sentiment, emerging classroom workarounds, and student feedback.

Table 1. The multi-source web-scraping data collection framework applied in this study (author's own elaboration).

Eight hundred thirty-eight unique raw sources were collected across nine working sources; the majority not cited above were off-topic false positives from generic queries (physics education, unrelated business-modeling papers, general tech news, etc.) — normal noise for keyword-based search, excluded rather than force-fit into the painpoint framing. ERIC drove most new findings in v2; Exa and YouTube drove v3; Reddit (once fixed) drove v4 and was the highest-signal single source for real, unprompted complaints.

Two limitations follow from this design. First, keyword-based retrieval and platform accessibility bias the corpus toward English-language, publicly indexed content; private communities (e.g., closed Slack/Discord groups) were unreachable and are under-represented. Second, community-sourced material (Reddit, YouTube comments) reflects self-selected, unverified posters rather than a representative sample, so these sources are treated as illustrative qualitative signal — not generalizable prevalence estimates — throughout.

3.2 Student Feedback Analysis

The second source comprises a longitudinal analysis of 607 student evaluation records collected over five academic years from the graduate course "Artificial Intelligence in Business." The course is offered within the Master in Management programme at Kozminski University in full-time, part-time, online, and English-track formats and has enrolled 1,236 students in total.

To evaluate instructional quality and learning outcomes, a standardized evaluation framework comprising two instruments was administered across academic years 2021/2022 through 2025/2026: a Course Quality Evaluation Survey and an Assessment Quality Evaluation Survey. Quantitative items were measured primarily using a 5-point Likert agreement scale (strongly disagree to strongly agree), discrete ordinal frequency scales for attendance and instruction mode (in-person, hybrid, remote), and a single-item overall course rating scale (1 = lowest to 5 = highest). Qualitative constructs gathered open-text responses on effective active-learning methods, elements requiring pedagogical improvement, and contextual feedback.

Across the five academic years from 2021/2022 through 2025/2026, the evaluation dataset comprised 607 survey responses from a total population of 1,236 enrolled students, yielding an overall mean course-satisfaction score of 4.71 out of 5.00. Annual mean evaluation scores remained consistently high, recorded at 4.88 in 2021/2022, 4.73 in 2022/2023, 4.83 in 2023/2024, 4.75 in 2024/2025, and 4.69 in 2025/2026. Mean instructor-evaluation scores were 4.91/5.00, 4.84/5.00, and 4.43/5.00 across the teaching staff. Regarding assessment and examination metrics, objective and fair exam administration received a mean score of 4.88/5.00 across 16 evaluated group instances. This matched the 4.88/5.00 rating assigned across 14 instances for the clarity of grading criteria presented during the first class.

For the thematic analysis, Saldaña's approach to thematic coding was employed [29], [47]. This methodological choice enabled a systematic transition from raw narrative data to recurring educational themes and facilitated the identification of latent patterns in student sentiment [30], [31]. AI tools were used to support the thematic analysis and the development of the coding map; the themes and concepts themselves were derived manually.

4. Results

Regarding the first research question — what are the main challenges involved in teaching a general "AI in Business" course to management students without technical backgrounds? — the findings revealed key structural obstacles.

4.1 Web-Scraping Analysis Pain Points

Table 2 highlights the key thematic obstacles identified across academic discourse and practitioner forums.

No.	Pain Point / Challenge	Evidence and Implications	Source / Research Confirmation
1	Knowing–doing gap	Learners express persistent uncertainty regarding enterprise use cases, starting points, and workflow alignment.	Lim et al. [32]
2	Broad but shallow application	High tool usage breadth (e.g., ChatGPT, DeepSeek) with minimal comprehension of mechanics, yielding dependency.	Vâlcea et al. [33]
3	Reduced struggle & cognitive atrophy	Unregulated GenAI bypasses problemsolving, risking critical thinking degradation and agency loss.	Klein & Klein [34]
4	Social punishment & concealed usage	Workers conceal AI use to avoid lowcompetence perception, destroying peerlearning networks.	Li et al. [35]
5	Faculty & infrastructure capacity gap	Acute shortages in faculty expertise, reskilling time, compute infrastructure, and curriculum updates.	Charow et al. [36]
6	Shallow Copilot tool adoption	Telemetry (5.5M sessions) shows enterprise use clusters on lowstakes writing tasks rather than complex analytics.	Dillon et al. [37]
7	Structural pretertiary equity gap	Uneven early computer science access presorts nontechnical students away from foundational AI concepts.	Bulathwela et al. [38]

Table 2. Key pain points and challenges identified in the web-scraping analysis (author's own elaboration).

Synthesizing these findings into student-centric dimensions reveals five core pain points: Overwhelming Entry Barrier (an “I don't know where to start” paralysis due to tool proliferation); AI Anxiety Suppressing Engagement (fear of job displacement and of appearing incompetent hinders adoption); Superficial Adoption vs. Unproven ROI (wide tool availability rarely yields deep implementation; industry estimates cited in the corpus put the share of enterprise GenAI projects with no measurable return at roughly 95% [39]); Social Stigma and Hidden Workflows (visible AI usage is socially penalized, so competent users hide it); and Corrosive Institutional Incoherence (institutions teach AI while building systems to detect and prevent its use).

4.2 Student Feedback Analysis Pain Points

The principal pain points identified in the student survey concerned course duration, delivery format, practical depth, and assessment transparency. Given the rapid evolution of AI, students described the course as compressed, expressing a strong need for additional contact hours and advanced follow-up modules. Students demonstrated stronger critical engagement when instructors moved beyond generic tool demonstrations toward critical validation of AI-generated analytical outputs [40]. From a delivery standpoint, students indicated the need for a sharper pivot away from theoretical lecturing toward hands-on technical exercises; general reflections on new technologies occasionally took an overly abstract, "philosophizing" form that limited time devoted to practical tool mechanics. Data also revealed friction concerning assessment clarity, showing misalignment between traditional lecture methods and practical management demands [41].

4.3 Web-Scraping Analysis Solutions

Students value curricula emphasizing discipline-specific applications, supporting autonomous skill development and problem-solving [42].

Core Pedagogical Enabler	Operational Mechanism & Practical Impact
Enabler A: NoCode Experiential Design	Replaces passive lecture delivery with active, nocode application building. Students test, iterate, and deploy functional prototypes directly within class workflows [43].
Enabler B: Metacognitive Regulation	Implements targeted interventions (e.g., 2hour workshops) focused on algorithmic questioning, hallucination auditing, and output critique to boost selfefficacy [44].
Enabler C: MultiSource Feedback (PAIRR)	Combines Peer review, AI evaluation, Integrated Reflection, and Revision. AI feedback complements human peer review to safeguard critical thinking [45].
Enabler D: Syntax Bridge Framework	Offloads syntactic and mechanical execution (e.g., code generation) to AI while requiring learners to focus strictly on business logic and interpretation.
Enabler E: AACSB Institutional Alignment	Moves institutional evaluation from isolated tool mastery toward crosscurricular output assessment, preventing siloed policies [46].

Table 3. Core Pedagogical Enablers (author's own elaboration).

4.4 Student Feedback Analysis Solutions

Satisfaction peaks when curricula prioritize scaffolded technical application over abstract conceptualization. Key teaching techniques include hands-on tool integration (direct in-class deployment, e.g., Chatfuel, ChatGPT, Moral Machine), no-code implementation, real-world case method, project pitching and practical assessment, and guest experts from industry. Students appreciated high content currency, clear concept translation, and professional delivery; recommendations for enhancement emphasized shifting the instructional ratio toward guided workshops, expanding contact hours, and communicating final grading rubrics earlier in the term.

4.5 Integrated Approach

To answer the third research question — which tools and pedagogical approaches are most effective? — we synthesized findings across both datasets; real-world case studies emerged as a primary interconnected theme [43].

Thematic Domain / Dimension	WebScraping Corpus Findings	Student Evaluation Survey Findings	Integrated Synthesis & CrossAnalysis	Targeted Pedagogical Enabler
1. Execution & Practical Application	Persistent knowing–doing disconnect; broad but shallow tool usage.	High satisfaction with handson tool testing; critique of abstract lecturing.	Passive conceptual instruction creates execution paralysis.	Enabler A & D: Nocode prototyping & Syntax Bridge Framework.
2. Cognitive Engagement & Learning	Unregulated GenAI risks cognitive atrophy and loss of agency.	Positive engagement with output verification exercises.	Tool overreliance is mitigated by output auditing.	Enabler B: Metacognitive Regulation Module (Week 1).
3. Assessment Design & Evaluation	Contradictory institutional mandates; traditional assignments obsolete.	Highly rated capstone pitches; pain point around late rubrics.	Traditional exam formats fail; pitch evaluations succeed with early rubrics.	Enabler C: PAIRR Framework & OutputAuditing Rubrics.
4. Social Dynamics & Culture	Stigma leads users to conceal usage, destroying peer networks.	High appreciation for guest speakers; need for clear boundaries.	Concealed usage damages collaborative learning.	Enabler E: AACSB Alignment & Disclosure Protocols.
5. Course Scope & Delivery	Faculty shortages, compute bottlenecks, update burdens.	High satisfaction with currency; friction over short contact hours.	Rapid AI evolution creates course compression strain.	RealWorld Case Method: Agile delivery & workshop focus.

Table 4. Master Integrated Thematic & Evaluation Matrix (author's own elaboration).

5. Discussion

The conclusions drawn from both thematic analyses reflect broader scholarly literature. Phenomena such as “cognitive atrophy,” the “credibility gap,” the “syntactic facade,” and AI stigma are increasingly recognized in academic and enterprise settings [48]. This convergence highlights three recurring problem categories: Adoption Dynamics (shift from generic text generation toward specialized no-code modeling and industry workflows — learning through empirical experience); Integrity & Perception (dissatisfaction with automated detection tools, driving demand for transparent usage rubrics — disclosing AI use); and Instructional Friction (balancing conceptual mastery with automated efficiency in assessment — assessing human work). Given the empirical dataset, connectivism in Seymour Papert's formulation serves as a compelling theoretical lens for understanding these dynamics [49].

5.1 Practical Implications for Educators

Grounded in these findings, we outline three practical guidelines for course redesign: (1) Integrate a Week 1 metacognitive regulation module — a mandatory two-hour intervention addressing AI anxiety, establishing cognitive boundaries, and equipping non-technical learners with strategies for questioning AI outputs. (2) Rebalance assessment criteria toward output auditing and the Peer + AI Review + Reflection (PAIRR) model [50], [51], emphasizing logical validation and hallucination detection over prompt syntax. (3) Establish transparent AI disclosure protocols to eliminate social stigma and normalize AI use as a peer-learning opportunity [52], supported by iterative design-thinking to deepen conceptual understanding [53]. Deep-dive real-world case studies further bridge theoretical frameworks and operational realities, providing empirical grounding and actionable benchmarks for curriculum design.

5.2 Study Limitations

The reliance on a single-institution cohort for student evaluation data limits the generalizability of these pedagogical findings across diverse sociocultural contexts. The web-scraping corpus, as noted in Section 3.1, is similarly bounded by platform accessibility and self-selection among posters. Future research should adopt multi-institutional quantitative designs paired with qualitative educator interviews to test robustness across varying higher-education settings.

6. Conclusion

The integration of generative AI into business education necessitates a transition from passive consumption to an "execution mindset," where students learn to contextualize and implement AI-derived insights to avoid abstract "philosophizing." Future iterations of management curricula must prioritize adaptive assessment models that evaluate analytical reasoning, critical auditing, and strategic synthesis over raw technical execution.

7. Acknowledgement

This research was funded by the 4InnoPipe2 – Strengthening Innovation Pipelines for Impactful Universities 2.0, EIT Cohort 4.

THE USE OF AI TOOLS

During the preparation of this manuscript, the authors used Gemini 2.0 Flash (Google DeepMind; accessed August 2026) for literature screening and supporting thematic coding visualizations. The authors independently evaluated all analytical outputs and take full responsibility for all final themes, conceptual models, and manuscript content.

References

[1] A. B. M. M. Rahman, J. Yang, Z. Zhan, M. K. Hossain, Y. Xu, and W. Feng, "Pedagogical Transformation Through Artificial Intelligence: Implementation Barriers and Adoption Strategies in Business Education," Journal of the Association for Information Systems, 2025.

[2] H. Rai, N. Malik, and A. Varma, "Generative AI and management education: a knowledge management perspective," Journal of Knowledge Management, pp. 1–28, 2026.

[3] M. Drummond and G. Dale, "Generating a Student-Informed Teaching and Learning Conceptual Framework for GenAI in Business Schools: A Case Study," Journal of University Teaching and Learning Practice, 2026.

[4] Q. Wu, L. Chen, M. Chen, and Y. Huang, "Exploring the impact of artificial intelligence on business talent development in higher education: A systematic literature review and research agenda," International Journal of Management Education, 2025.

[5] Y. Ma, S. Yufang, L. Ming-da, Y. Zhang, W. Chai, A. Huang, and X. Zhao, "Preparing Students for an AI-Driven World: Generative AI and Curriculum Reform in Higher Education," Frontiers of Digital Education, vol. 2, no. 4, 2025.

[6] L. C. Troy, "Enhancing Marketing Student Success with AI-Guided Experiential Learning: A Case Study," AMTP, 2025.

[7] M. Adamakis and T. Rachiotis, "Artificial Intelligence in Higher Education: A State-of-the-Art Overview of Pedagogical Integrity, Artificial Intelligence Literacy, and Policy Integration," Encyclopedia, vol. 5, no. 4, p. 180, 2025.

[8] S. J. Hyde, A. Busby, and R. L. Bonner, "Tools or Fools: Are We Educating Managers or Creating Tool-Dependent Robots?" Organizational Behavior Teaching Review, vol. 48, no. 4, pp. 708–734, 2024.

[9] J. Kim, S. Yu, R. Detrick, and N. Li, "Exploring students' perspectives on Generative AI-assisted academic writing," Education and Information Technologies, vol. 30, no. 1, pp. 1265–1300, 2024.

[10] C. K. Y. Chan, "A comprehensive AI policy education framework for university teaching and learning," International Journal of Educational Technology in Higher Education, vol. 20, no. 1, 2023.

[11] G. Eboh, "Educating for Responsible AI Governance - Building Interdisciplinary Frameworks for the Management of Artificial Intelligence," Digital Scholarship - Texas Southern University, 2026.

[12] M. C. Laupichler, A. Aster, J. Schirch, and T. Raupach, "Artificial intelligence literacy in higher and adult education: A scoping literature review," Computers and Education Artificial Intelligence, vol. 3, p. 100101, 2022.

[13] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and S. Qiao, "Conceptualizing AI literacy: An exploratory review," Computers and Education Artificial Intelligence, vol. 2, p. 100041, 2021.

[14] J. Southworth, K. W. Migliaccio, J. Glover, D. M. Reed, C. McCarty, J. H. Brendemuhl, and A. Thomas, "Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy," Computers and Education Artificial Intelligence, vol. 4, p. 100127, 2023.

[15] H. S. Wisniewski, "What is The Business with AI? Preparing Future Decision Makers and Leaders," Technology & Innovation, vol. 21, no. 4, pp. 337–350, 2020.

[16] L. Wunderlich, A. Higgins, and Y. Lichtenstein, "Machine Learning for Business Students," pp. 512–518, 2021.

[17] A. Azamnouri, D. Hörauf, B. Schönberge, J. Bogner, and S. Wagner, "Teaching AI competencies: Experiences from coaching interdisciplinary teams to develop AI prototypes," Computers and Education Artificial Intelligence, vol. 10, p. 100580, 2026.

[18] C. Almaraz-López, F. A. Menéndez, and C. López-Esteban, "Comparative Study of the Attitudes and Perceptions of University Students in Business Administration and Management and in Education toward Artificial Intelligence," Education Sciences, vol. 13, no. 6, p. 609, 2023.

[19] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," International Journal of Educational Technology in Higher Education, vol. 20, no. 1, 2023.

[20] M. Sońta and D. Kedziora, "Democratizing Software Development: Low-Code as an Educational Pathway towards Sustainable and Collaborative Organizations," 2023.

[21] K. Lucas and M. Elder, "Making the Cut: An Exercise in AI-Aided Decision Making," Management Teaching Review, 2025.

[22] M. Sońta and A. Przegalińska, "Say 'yes' to 'no-code' solutions: how to teach low-code and no-code competencies to non-IT students," in Edward Elgar Publishing eBooks, pp. 330–342, Edward Elgar Publishing, 2024.

[23] D. Sun, A. Boudouaia, C. Zhu, and Y. Li, "Would ChatGPT-facilitated programming mode impact college students' programming behaviors, performances, and perceptions? An empirical study," International Journal of Educational Technology in Higher Education, vol. 21, no. 1, 2024.

[24] S. M. Ghouse, "AI-Enhanced Curriculum for Sustainable Business," pp. 105–124, 2025.

[25] J. Roos, "The Next Management Education: Charting a New Path Forward," pp. 69–82, 2025.

[26] H. S. E. Samaty and N. Albadi, "From policy frameworks to AI mentoring practice: A structured approach to responsible innovation in architectural education," Alexandria Engineering Journal, 2026.

[27] T. I. Park, J.-M. Seo, H.-J. Yoon, and K. E. Lee, "Institutionalizing convergence education for medical artificial intelligence," Biomedical Engineering Letters, vol. 15, no. 6, pp. 1073–1083, 2025.

[28] M. Benmamoun, "Reinventing International Business Education: Integrating the Power of Generative AI," AIB Insights, vol. 24, no. 1, 2023.

[29] J. Saldaña, The Coding Manual for Qualitative Researchers, Hôpital Rivière-des-Prairies, 2025.

[30] N. Bunda, E. D. P. Jr., and G. Dizon, "Understanding student viewpoints: sentiment and thematic insights from course feedback," Journal of Education and Learning (EduLearn), vol. 20, no. 2, pp. 687–699, 2026.

[31] M. Hujala, A. Knutas, T. Hynninen, and H. Arminen, "Improving the quality of teaching by utilising written student feedback: A streamlined process," Computers & Education, vol. 157, p. 103965, 2020.

[32] W. M. Lim, A. Gunasekara, J. L. Pallant, J. Pallant, and E. Pechenkina, "Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators," The International Journal of Management Education, vol. 21, no. 2, p. 100790, 2023.

[33] S. Vâlcea, M. R. Hamdani, and S. Wang, "Exploring the Impact of ChatGPT on Business School Education: Prospects, Boundaries, and Paradoxes," Organizational Behavior Teaching Review, vol. 48, no. 5, pp. 915–947, 2024.

[34] C. R. Klein and R. Klein, "The extended hollowed mind: why foundational knowledge is indispensable in the age of AI," Frontiers in Artificial Intelligence, vol. 8, p. 1719019, 2025.

[35] P. Li, L. Ma, N. Dong, L. Xing, and S. Yuan, "When Hiding Hurts: How Stealth Use of Generative AI Resources Impairs Task Performance," Academy of Management Proceedings, vol. 2025, no. 1, 2025.

[36] R. Charow et al., "Artificial Intelligence Education Programs for Health Care Professionals: Scoping Review," JMIR Medical Education, vol. 7, no. 4, 2021.

[37] E. W. Dillon, S. Jaffe, S. Peng, and A. Cambon, "Early Impacts of M365 Copilot," arXiv preprint arXiv:2504.11443, 2025.

[38] S. Bulathwela, M. Pérez-Ortiz, C. Holloway, M. Cukurova, and J. Shawe-Taylor, "Artificial Intelligence Alone Will Not Democratise Education: On Educational Inequality, Techno-Solutionism and Inclusive Tools," Sustainability, vol. 16, no. 2, p. 781, 2024.

[39] J. Westover, "The GenAI Divide: Why 95% of Enterprise AI Investments Fail—and How the 5% Succeed," Human Capital Leadership, vol. 28, no. 3, 2025.

[40] S. McPhee and M. Jerowsky, "Beyond technical skills: a pedagogical perspective on fostering critical engagement with generative AI in university classrooms," Frontiers in Education, vol. 10, 2025.

[41] A. G. Ossai, M. B. Asabor, J. O. Oduma, and M. N. Oseji, "Reshaping management education for a globalized world," Frontiers in Education, vol. 10, 2025.

[42] X. Zhou, J. Zhang, and C. Chan, "Unveiling Students' Experiences and Perceptions of Artificial Intelligence Usage in Higher Education," Journal of University Teaching and Learning Practice, vol. 21, no. 6, 2024.

[43] S. Matook, Y. M. Wang, and M. Axelsen, "Experiential Learning for Citizen Developers," Business & Information Systems Engineering, vol. 67, no. 1, pp. 7–30, 2025.

[44] Y. Walter, "Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education," International Journal of Educational Technology in Higher Education, vol. 21, no. 1, 2024.

[45] M. MacArthur, S. Minnillo, L. Sperber, C. Whithaus, and N. Stillman, "GIFT-AI: teaching the game and leveling the field: Peer and AI Review + Reflection in a business writing course," Frontiers in Communication, vol. 10, 2025.

[46] A. A. S. Mohammad and S. Muhammad, "The Role of Artificial Intelligence Integration in Achieving AACSB Accreditation Standards," in Advances in computational intelligence and robotics, pp. 223–242, IGI Global, 2025.

[47] M. Lungu, "The Coding Manual for Qualitative Researchers," American Journal of Qualitative Research, vol. 6, no. 1, pp. 232–237, 2022.

[48] S. S. Ballal, "THE SYNTACTIC FACADE: A THEORETICAL PERSPECTIVE ON COGNITIVE ATROPHY IN AI-AUGMENTED LEARNING," Zenodo, 2026.

[49] R. Kop and A. R. Hill, "Connectivism: Learning theory of the future or vestige of the past?" The International Review of Research in Open and Distributed Learning, vol. 9, no. 3, 2008.

[50] T. Mzili, I. Mzili, A. Abatal, Z. Oughannou, A. K. Arya, and M. Kurdi, "AI Hallucinations in Retrieval- Augmented and Generative Systems: A Rigorous Review of Definitions, Failure Mechanisms, Evaluation, and Mitigation Strategies," EDRAAK, pp. 41–51, 2026.

[51] L. Sperber, M. MacArthur, S. Minnillo, N. Stillman, and C. Whithaus, "Peer and AI Review + Reflection (PAIRR): A human-centered approach to formative assessment," eScholarship, vol. 76, p. 102921, 2025.

[52] M. Peters, "Leveraging Generative Artificial Intelligence with Transparency: Enhancing Academic Integrity in Higher Education," Journal of Scholarly Publishing, vol. 56, no. 2, pp. 510–528, 2025.

[53] M. Sarıtepeci and H. Y. Durak, "Effectiveness of artificial intelligence integration in design-based learning on design thinking mindset, creative and reflective thinking skills: An experimental study," Education and Information Technologies, vol. 29, no. 18, pp. 25175–25209, 2024.