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Enhancing experiential learning in data analytics through university–industry collaboration: a pilot study

Daniel D. Wu, *Georgia College & State University, daniel.wu@gcsu.edu*
Jenq-Foung Yao, *Georgia College & State University, jf.yao@gcsu.edu*

Abstract

This study presents a structured university–industry collaboration designed to advance experiential learning in data analytics education. Seven undergraduate students partnered with MineralCom, a leader in the industrial minerals sector, to analyze a decade of de-identified maintenance records (~3 million observations) within a secure Virtual Desktop environment governed by individual non-disclosure agreements. Through the deliberate application of Kolb's experiential learning cycle, students progressed from cleaning "messy" real-world data to delivering predictive maintenance models. Quantitative pre- and post-course surveys revealed significant perceived competency gains across all domains, with the most substantial growth observed in Data Wrangling (d = 5.65) and Exploratory Data Analysis (d = 4.55). Qualitative reflections underscored a shift in professional identity, as students transitioned from classroom learners to "adaptive experts" capable of navigating domain-specific jargon and ethical data governance. While limited by sample size, this pilot offers a replicable, secure, and resource-efficient framework for bridging the gap between theoretical instruction and authentic industry practice in the AI era.

Keywords: experiential learning, data analytics education, university–industry collaboration, project-based learning, predictive maintenance, pilot study

Introduction

The rapid integration of data analytics and machine learning across industries has redefined how organizations operate and innovate. As automation and predictive modeling reshape organizational decision-making, industry demand is shifting toward graduates capable of synthesizing technical mastery with strategic insight (Davenport & Patil, 2012; Dorschel, 2021). However, despite the proliferation of analytics programs, industry reports continue to highlight a skills gap where graduates often struggle to work with unstructured data, communicate findings to non-technical stakeholders, and uphold ethical data governance standards (Howard et al., 2025; Saltz et al., 2017). These deficiencies reveal a fundamental disconnect between traditional academic instruction and the realities of data-centric workplaces.

As higher education confronts this gap, the data-driven AI age demands new pedagogical models emphasizing adaptability, applied problem-solving, and ethical awareness (Matook et al., 2025; Esangbedo et al., 2024). Scholars and professional associations alike have called for experiential ecosystems that foster these capacities, moving beyond static, textbook-based instruction toward authentic engagements with complex data (Leidig & Salmela, 2022; Taş, 2024). This shift is further reinforced by emerging experiential and challenge-based learning frameworks that explicitly integrate industry collaboration into curriculum

design, demonstrating measurable gains in student engagement and applied problem-solving (Cardador et al., 2024; Garcia, 2024). Experiential Learning Theory (Kolb, 1984; Kolb & Kolb, 2017) provides a robust framework for such reform, positioning learning as a continuous cycle of experience, reflection, conceptualization, and experimentation. Prior conceptual and applied work has also emphasized the role of experiential learning in information systems (IS) education as a mechanism for aligning theoretical instruction with evolving industry needs (Badro & Adelakun, 2024; McCarthy, 2016). When applied in data analytics education, this model equips students to connect theoretical constructs with practical application while developing professional confidence and ethical judgment.

Recent research across IS education confirms the power of experiential approaches in producing career-ready graduates. Empirical studies show that live industry projects enhance students' technical proficiency, communication skills, and self-efficacy far more than simulated coursework (Kang et al., 2022), while also improving career readiness and professional confidence across business disciplines (Spanjaard et al., 2018; Speier-Pero & Schoenherr, 2020). For instance, Burris and Regis (2024) demonstrated that experiential learning in cybersecurity governance improved critical thinking and policy reasoning, while Ritter et al. (2025) found that engagement with real datasets heightened statistical reasoning and confidence in dealing with ambiguity. These findings converge on the notion that authentic, high-stakes learning environments cultivate the data analytics readiness that modern employers demand. Recent open-case and applied curriculum initiatives further demonstrate that exposure to real-world datasets enhances statistical reasoning and interdisciplinary thinking in analytics education (Wright et al., 2024; Zhang et al., 2024).

Within this pedagogical landscape, university–industry collaborations have proven particularly effective in operationalizing experiential learning (Taş, 2024; Esangbedo et al., 2024). Such partnerships expose students to genuine data complexity, organizational context, and ethical constraints while delivering actionable insights to corporate partners. Yet, successful implementation requires navigating logistical challenges such as data confidentiality, resource management, and alignment of academic and business objectives (Silva & Nicolau De França, 2023). Despite growing interest, few detailed case studies describe how these collaborations can be sustainably integrated into undergraduate curricula, especially within the emerging domain of contemporary data analytics.

This pilot study contributes to that dialogue by documenting a semester-long university–industry collaboration between a regional U.S. university and an industry partner, a leading producer in the industrial minerals sector. Seven undergraduate students analyzed over 3 million maintenance work orders (2013–2022) to develop predictive models for equipment failure. Operating under individual non-disclosure agreements within a secure Virtual Desktop environment, participants engaged in every stage of the analytics process, from data wrangling and exploratory analysis to model interpretation and business translation. The design explicitly embedded Kolb's experiential learning cycle, combining technical rigor with ethical and professional learning objectives.

By aligning experiential pedagogy with the technical and ethical imperatives of the AI era, this study highlights how structured, small-scale collaborations can yield significant educational and operational value. It contributes to the broader IS discourse by offering a replicable model for integrating authentic industry data into analytics education, one that prepares students not only to apply analytics tools but to think critically and responsibly within data-centric organizations.

Theoretical Framework and Methodology

This study was grounded in Experiential Learning Theory (ELT), which conceptualizes learning as a cyclical process of transforming experience into knowledge through four interdependent stages: Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation (Kolb, 1984). Subsequent extensions of the model (Kolb & Kolb, 2017) emphasize deliberate practice within authentic contexts, a critical dimension for preparing students to operate in the data-driven workplace. Systematic reviews across engineering and computing education similarly confirm that experiential learning environments promote deeper conceptual understanding and long-term retention when embedded within authentic problem contexts (Tembrevilla et al., 2023). In IS and analytics education, ELT provides a conceptual bridge between technical skill development and professional formation (Saltz et al., 2017). These findings align with broader calls for integrating project-based and industry-linked learning frameworks to enhance student readiness for complex, real-world environments (Naseer et al., 2025).

In designing the present collaboration, each stage of Kolb's cycle was operationalized through structured project milestones (Table 1). Students engaged in Concrete Experience by analyzing a decade of real industrial maintenance data characterized by unstructured text, missing values, and domain-specific terminology. Reflective Observation occurred through weekly debriefings, faculty-mentor discussions, and guided journals encouraging metacognitive awareness of challenges encountered. Abstract Conceptualization was supported by linking observations to scholarly literature on predictive maintenance, model interpretability, and ethical data management. Finally, Active Experimentation involved iterative model building, testing, and presentation of insights to company engineers. This intentional mapping ensured that learning was both technically rigorous and theoretically grounded.

Participants and Context

The pilot involved seven upper-level undergraduates, including four Data Science majors and three Computer Science majors, enrolled in Data Mining and Big Data Analysis courses during Fall 2025 at a regional U.S. university. Participation was voluntary and approved under Institutional Review Board exemption as a course-improvement activity (Protocol #2024-178E). Students were selected based on foundational knowledge of Python, SQL, and machine learning.

Industry Data and Secure Infrastructure

The industry partner, hereafter referred to by the pseudonym "MineralCom" to maintain confidentiality, provided a de-identified dataset of maintenance work orders spanning 2013–2022, with over three million records and over 100 features. Variables included equipment identifiers, failure modes, downtime hours, labor costs, and unstructured technician notes. Given the sensitivity of industrial data, students accessed the dataset through a university-managed Virtual Desktop environment with comprehensive audit logging and no external download permissions. Each participant signed an individual Non-Disclosure Agreement (NDA), a practice that enhanced professionalism and simplified compliance administration. This secure architecture mirrors best practices recommended for scalable university–industry collaborations (Taş, 2024; Esangbedo et al., 2024) and is consistent with prior case studies highlighting the importance of structured data governance and collaboration protocols in academic–industry partnerships (Silva & Nicolau De França, 2023; Cardador et al., 2024).

Pedagogical Design and Implementation

The 15-week project followed an incremental design aligned with Kolb's learning cycle:

- Weeks 1–3: Data familiarization, cleaning, and exploratory data analysis.
- Weeks 4–8: Feature engineering and baseline model development (logistic regression, random forest, XGBoost).

- Weeks 9–12: Model validation, interpretability, and communication of business implications.
- Weeks 13–15: Final report preparation and live presentation to MineralCom stakeholders.

One faculty member and industry mentors, including CFO, Director of IT, and several staff members from IT and functional areas, jointly supervised the teams, ensuring that both academic learning outcomes and business relevance were achieved. Students dedicated approximately 1 to 2 hours per week to the project outside of scheduled class time. Reflective prompts throughout the course encouraged students to link experiential challenges to theoretical constructs, reinforcing the ELT cycle.

Data Collection and Analysis

Three data sources informed the study's evaluation:

- Pre- and post-course self-assessment surveys (11 items, 5-point Likert scale) measuring perceived proficiency across key competencies such as SQL, data wrangling, machine learning, and visualization. The full survey instrument, including specific response anchors and validation details, is available upon request from the corresponding author.
- Reflective essays (1,000–1,500 words) analyzed using inductive thematic coding to identify recurring learning patterns and professional insights.
- Project artefacts (Jupyter notebooks, Tableau dashboards, and presentation slides) used as triangulating evidence for performance and engagement.

Quantitative data were analyzed using paired t-tests to measure changes in perceived competence. Qualitative reflections underwent thematic analysis with inter-rater reliability verification ($\kappa = 0.89$). This mixed-methods approach ensured both statistical robustness and interpretive depth, aligning with recent IS education research advocating for integrated evaluative frameworks (Ritter et al., 2025).

Integration of Theory and Design

By embedding each element of the ELT cycle into a real-world analytics project, the study exemplifies how AI-era experiential learning can be deliberately engineered. The secure digital infrastructure, reflective scaffolding, and cross-sector mentorship collectively created a cognitive apprenticeship environment (Morris, 2020), enabling students to apply AI and analytics techniques within authentic industrial constraints. The methodological rigor of this design supports replication across institutions seeking to align IS curricula with the evolving technological and ethical demands of the modern data economy.

Table 1. Experiential Learning Framework.

Kolb Stage	Project Implementation
Concrete Experience	Access to real decade maintenance dataset; unstructured fields, missing values, domain jargon
Reflective Observation	Weekly guided reflection prompts and team debriefs
Abstract Conceptualization	Faculty- and industry-mentor feedback sessions; literature on predictive maintenance
Active Experimentation	Iterative model building and presentation to company engineers

Results

The results of the pilot are presented in two parts: (1) quantitative analyses of perceived competency gains and (2) qualitative themes derived from reflective essays. Together, these findings illustrate how experiential engagement with authentic industry data, structured according to Kolb's learning cycle, enhanced both technical proficiency and professional identity formation among participants.

Quantitative Perceived Skill Gains

Across all measured domains, the pre–post comparisons indicate substantial gains in students' self-reported familiarity, with effect sizes consistently in the large to extremely large range (Table 2 and Figure 1). In particular, Exploratory Data Analysis (d = 4.55), Data Visualization (d = 4.14), and Data Wrangling (d = 5.65) exhibit exceptionally large effects, suggesting improvements in foundational data competencies. Substantial effects are also observed in Machine Learning (d = 2.41), indicating strong gains in more analytically intensive areas. Although comparatively smaller, the effects for Python Programming (d = 1.47) and SQL (d = 1.73) remain well above conventional thresholds for large effects, reflecting meaningful improvement in technical skill acquisition. Taken together, the magnitude and consistency of Cohen's d across domains provide compelling evidence of the effectiveness, particularly in strengthening core data analytical skills while also yielding significant, albeit relatively more moderate, gains in programming-oriented competencies.

Table 2. Perceived Skill Improvement (n=7, score between 1 and 5).

Competency	Pre Mean	Post Mean	Cohen's d	t-stat	p-value
Exploratory Data Analysis	1.43	4.57	4.55	12.1	<0.0001
Machine Learning	1.29	3.57	2.41	6.36	0.0007
Data Visualization (Tableau/Power BI)	1.43	4.29	4.14	10.95	<0.0001
Data Wrangling/Cleaning	1.14	3.86	5.65	15.1	<0.00001
Python (pandas, scikit-learn)	2.14	3.57	1.47	3.86	0.008
SQL	1.86	2.86	1.73	4.59	0.0036

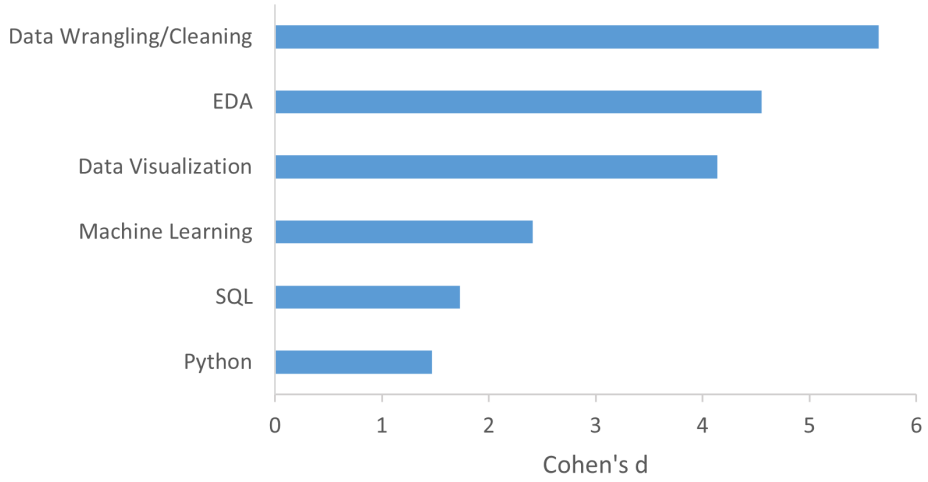


Figure 1. Average learning gains across key data analytics competencies (n=7).

These improvements appear consistent with the stages of Kolb's experiential learning sequence. Concrete experience by working with unstructured, real-world maintenance data challenged students to adapt theoretical knowledge to complex situations. Through reflective observation, guided weekly debriefs, and mentor feedback prompted metacognitive awareness of both technical and interpersonal growth. Abstract conceptualization occurred as students connected their practice to predictive maintenance literature and ethical data management frameworks. Finally, active experimentation through model iteration and stakeholder presentations demonstrated transfer of learning to professional contexts.

Although constrained by a small sample size, the magnitude of these gains mirrors or exceeds outcomes reported in larger experiential learning studies (Saltz et al., 2017; Ritter et al., 2025). These preliminary results are consistent with the possibility that small, high-intensity collaborations may be an effective approach for developing workforce-ready data analytics competencies.

Qualitative Findings: Reflective Themes of Learning and Identity

Thematic analysis of reflective essays (n = 7) identified five dominant learning themes, summarized below. Inter-rater reliability for coding (conducted by a single coder) achieved $\kappa = 0.89$, indicating strong agreement.

Authentic Data Complexity as a Catalyst for Deep Learning

All participants emphasized that engagement with "messy" industrial data enhanced their understanding of real-world analytics, validating Kolb's emphasis on concrete experience. Students described grappling with missing values, ambiguous terminology, and domain-specific jargon as transformative for their confidence and problem-solving skills. This observation is consistent with prior experiential learning studies, which find that exposure to unstructured, real-world data significantly enhances problem-solving ability and learner adaptability (Wright et al., 2024; Garcia, 2024).

Bridging Technical and Business Communication

Every student reported significant growth in translating analytic results for non-technical audiences. This skill development reflects the abstract conceptualization and experimentation phases, where students linked data findings to business relevance and articulated actionable insights for MineralCom engineers.

Ethical and Legal Awareness

The NDA requirement and restricted-access environment heightened sensitivity to data governance, bias, and responsible AI practices. Students demonstrated emerging ethical maturity, frequently referencing the social implications of predictive modeling.

Collaborative Problem-Solving Under Constraint

Six participants noted improvements in teamwork, conflict resolution, and time management—dimensions of experiential learning that extend beyond technical proficiency. The project's time-bound, high-stakes context simulated authentic workplace pressure.

Career Self-Efficacy and Professional Identity

All students linked the experience to enhanced employability and confidence, perceiving themselves as future data professionals rather than students. Several reported updating resumes and LinkedIn profiles to reflect their applied project work.

A representative reflection (Student #5) captures this transformation:
"Textbook datasets are clean and tiny. This was (one) of missing values, misspellings, and slang only a technician would understand. I learned more in one semester than in my last three classes combined."

Synthesis of Quantitative and Qualitative Insights

Together, the data show that embedding Kolb's experiential stages within a real industry collaboration produced not only measurable skill development but also significant professional socialization. Students transitioned from passive recipients of knowledge to active analysts, communicators, and ethical decision-makers. In the context of the AI age, where technical fluency must be paired with judgment, communication, and adaptability, these outcomes affirm experiential learning as a scalable model for preparing IS graduates for data-centric careers.

Discussion and Implications

The findings of this pilot affirm that a deliberately structured university–industry collaboration, grounded in Kolb's Experiential Learning Theory, can produce rapid and meaningful development of data analytics competencies within a short academic term. Quantitative analyses provided statistically significant, albeit preliminary, gains across all measured technical domains, while qualitative reflections revealed deeper learning outcomes related to communication, ethics, and professional identity. Together, these results reinforce the value of experiential learning as a pedagogical response to the challenges of data analytics education.

Integrating Experiential Learning in the Contemporary Data Analytics
In an environment where analytics systems increasingly automate technical processes, the distinguishing human capabilities are interpretation, contextualization, and ethical reasoning. The outcomes of this study illustrate that experiential frameworks allow students to cultivate these higher-order capacities by engaging with authentic, ambiguous data and real organizational constraints (Matook et al., 2025; Esangbedo et al., 2024). Similar outcomes have been observed in interdisciplinary and engineering education contexts, where experiential learning fosters integrative thinking and the ability to navigate uncertainty (Tembrevilla et al., 2023; Naseer et al., 2025). Students did not simply learn to execute code. Rather, they learned to translate insights, question assumptions, and manage uncertainty. This process aligns closely with what Kolb and Kolb (2017) describe as the iterative "learning spiral," in which concrete experience and reflection coevolve into adaptive expertise.

A particularly noteworthy result was the disproportionate improvement in Exploratory Data Analysis (EDA) and Machine Learning (ML) relative to foundational skills such as Python and SQL. Theoretically, this pattern can be understood through the lens of the latter half of Kolb's cycle, i.e., Abstract Conceptualization and Active Experimentation, which correspond most directly to creative problem solving and hypothesis testing. EDA and ML demand flexible reasoning, pattern recognition, and decision-making under uncertainty, all of which are amplified by exposure to messy, unstructured, and context-rich industrial data. In contrast, Python and SQL represent more procedural competencies anchored in the Concrete Experience phase, skills that students often acquire through prior coursework or structured exercises. Consequently, the authentic ambiguity of the MineralCom dataset acted as a catalyst for deeper cognitive engagement in EDA and ML, where students could iteratively explore, model, and validate hypotheses with immediate practical relevance. This finding supports prior evidence that authentic, ill-structured problems foster more durable learning in higher-order analytical tasks (Ritter et al., 2025).

The outcome of this study suggests that the skills gap is not merely a lack of technical tool proficiency, but a deficit in "adaptive expertise". By applying Kolb's stages of Abstract Conceptualization and Active Experimentation, students were forced to bridge the gap between executing code and generating business value. The significant gains in Exploratory Data Analysis demonstrate that when students are removed from the "clean" environments of typical coursework, they develop the critical interpretation and communication skills necessary to succeed in a data-centric workplace. This model shifts the focus from procedural knowledge (Python/SQL) to higher-order reasoning, directly targeting the deficiencies highlighted by modern employers.

Moreover, the project's use of a secure virtual desktop infrastructure and individualized NDAs exemplifies how universities can scale experiential learning responsibly without compromising data integrity. As corporations increasingly guard proprietary datasets, this configuration provides a sustainable model for embedding live projects into academic curricula (Taş, 2024). These design features position the model as both innovative and feasible, aligning with emerging digital apprenticeship paradigms in IS education.

Theoretical Implications
The study contributes to the theoretical refinement of Experiential Learning Theory in IS education by demonstrating how its four stages can be operationalized within a modern analytics curriculum. The integration of industry mentorship and ethical protocols extends ELT beyond classroom simulation, offering evidence that authenticity amplifies learning depth. The results support Morris (2020) who argue that experiential learning is most effective when embedded in contexts that require iterative problem-solving under uncertainty, a condition inherent to real-world data analytics environments.

Furthermore, this research adds to the growing literature on data literacy and professional formation. While prior work has focused primarily on tool proficiency, this pilot illustrates that experiential engagement nurtures the cognitive and ethical dispositions that underpin responsible analytics practice. By linking theory, application, and reflection, the study advances an integrative model of data-driven learning that combines technical mastery with social and ethical awareness.

Pedagogical and Institutional Implications
From an instructional standpoint, this study offers a replicable and cost-effective model for embedding experiential learning into analytics curricula. The secure cloud-based infrastructure, modest resource requirements, and flexible project design make the framework attainable for small and mid-sized institutions. Faculty reported that individual NDAs reduced administrative complexity and increased student ownership of the work, an approach other programs could easily adopt.

At an institutional level, the collaboration demonstrates how universities can engage regional industries to produce mutual benefit: students gain real experience while organizations receive actionable insights. Such partnerships enhance community engagement, align curricula with workforce needs, and strengthen the integration of scholar–practitioner models within IS education (Speier-Pero & Schoenherr, 2020; Spanjaard et al., 2018), and contribute to the accreditation emphasis on applied learning articulated by the AIS and ACM IS 2020 Competency Model (Leidig & Salmela, 2022). For business and IS programs navigating the AI transition, this structure offers a practical blueprint for sustainable experiential integration.

Limitations and Future Directions
As a pilot with seven participants, generalizability is limited. Future research should replicate the model across multiple institutions and incorporate objective performance metrics such as rubric-based deliverables or coding challenge assessments. Longitudinal studies tracking post-graduation employment outcomes would also clarify the lasting career impact of such experiences. Expanding partnerships to include data-driven sectors, e.g. logistics, healthcare, and finance, would test the framework's adaptability and further validate its relevance to the evolving data economy.

While the quantitative gains observed are substantial, the study's reliance on self-reported data introduces the potential for social desirability bias, particularly given the high-intensity, small-group nature of the pilot. Students may have overestimated their proficiency to align with faculty expectations or the perceived importance of the industry partnership. To mitigate this, the researchers triangulated survey data with objective project artifacts, including Jupyter notebooks and final stakeholder presentations, which confirmed that the perceived growth was reflected in the technical quality and professional delivery of the deliverables.

In summary, this study suggests that experiential learning remains a powerful, adaptable paradigm for preparing IS and analytics graduates for a data-driven world. By combining theoretical grounding, ethical rigor, and practical engagement, the pilot provides a scalable framework that directly addresses the skills

gap between academia and industry while advancing the pedagogical conversation within the IS community.

Conclusion

This pilot study provides preliminary evidence that experiential learning, when deliberately integrated with authentic industry collaboration, can accelerate both technical and professional development in data analytics education. Grounded in Kolb's Experiential Learning Theory and implemented through a secure university–industry partnership, the project enabled students to navigate the full data analytics lifecycle using a decade of real maintenance data. Quantitative results revealed significant self-reported skill gains across all major competencies, while qualitative evidence highlighted growth in communication, ethical awareness, and teamwork, which are skills essential for success in the data-driven workplace.

The findings reaffirm that experiential learning remains a powerful pedagogical approach for cultivating adaptive expertise, reflective judgment, and data ethics in IS education. By aligning technical instruction with authentic industry contexts and embedding structured reflection, this model prepares students not only to use analytics technologies but also to reason critically and responsibly within them. The framework's low cost, secure infrastructure, and clear replicability make it particularly valuable for institutions seeking to operationalize analytics readiness without extensive resources.

Beyond the immediate educational outcomes, this collaboration offers a blueprint for sustainable engagement between academia and industry. As the digital economy continues to evolve, such partnerships will be central to bridging the persistent gap between theoretical instruction and practical application, ensuring that IS graduates emerge as competent, ethical, and data-literate professionals ready to add value from day one.

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References

Badro, D., & Adelakun, O. (2024). The need for information systems in experiential learning. *AMCIS 2024 TREOs*. 113. https://aisel.aisnet.org/treos_amcis2024/113

Burris, J.W., & Regis, P. (2024). Bridging theory and practice: Preparing future IT service leaders through experiential learning in cybersecurity policy and governance. In *Proceedings of the 2024 8th International Conference on Information System and Data Mining (ICISDM '24)*, 39–43. https://doi.org/10.1145/3686397.3686404

Cardador, D., Teixeira, B., Pereira, M., Rodrigues, L., Gama, C., Ladeira, R., Robichez, G., & Nasser, R. (2024). Bridging the gap: an extended challenge-based learning framework for university-industry collaboration. In: Gonçalves, J.A.d.C., Lima, J.L.S.d.M., Coelho, J.P., García-Peñalvo, F.J., García-Holgado, A. (eds) *Proceedings of TEEM 2023. TEEM 2023. Lecture Notes in Educational Technology*. Springer, Singapore. https://doi.org/10.1007/978-981-97-1814-6_84

Davenport, T.H., & Patil, D.J. (2012). Data scientist: the sexiest job of the 21st century. *Harvard Business Review*, 90(10), 70–76.

Dorschel, R. (2021). Discovering needs for digital capitalism: the hybrid profession of data science. *Big Data & Society*, 8(2). https://doi.org/10.1177/20539517211040760

Esangbedo, C.O., Zhang, J., Esangbedo, M.O., Kone, S.D., & Xu, L. (2024). The role of industry-academia collaboration in enhancing educational opportunities and outcomes under the digital driven Industry 4.0. *Journal of Infrastructure, Policy and Development*. 8(1), 2569. https://doi.org/10.24294/jipd.v8i1.2569

Garcia, R. (2024). A business analytics experiential learning narrative. *MWAIS 2024 Proceedings*. 17. https://aisel.aisnet.org/mwais2024/17

Howard, H., Phillips, M., & Wang, J. (2025). From classroom to boardroom: employer perspectives of business graduates' information literacy skills. *Ticker: The Academic Business Librarianship Review*, 10(1). https://doi.org/10.3998/ticker.6913

Kang, J., Roestel, N.M.E., & Girouard, A. (2022). Experiential learning to teach user experience in higher education in past 20 years: a scoping review. *Frontiers in Computer Science,* 4(812907). https://doi.org/10.3389/fcomp.2022.812907

Kolb, D.A. (1984). *Experiential learning: experience as the source of learning and development*. Prentice Hall.

Kolb, A.Y., & Kolb, D.A. (2017). Experiential learning theory as a guide for experiential educators in higher education. *Experiential Learning and Teaching in Higher Education*, 1(1), 38. https://doi.org/10.46787/elthe.v1i1.3362

Leidig, P.M., & Salmela, H. (2022). The ACM/AIS IS2020 competency model for undergraduate programs in information systems: a joint ACM/AIS task force report. *Communications of the Association for Information Systems*, 50, 470-480. https://doi.org/10.17705/1CAIS.05021

Matook, S., Wang, Y.M., & Axelsen, M. (2025). Experiential Learning for Citizen Developers. *Business & Information Systems Engineering*, 67, 7–30. https://doi.org/10.1007/s12599-024-00921-3

McCarthy, M. (2016). Experiential learning theory: from theory to practice. *Journal of Business & Economics Research*,14(3), 91–100. https://doi.org/10.19030/jber.v8i5.725

Morris, T.H. (2020). Experiential learning – a systematic review and revision of Kolb's model. *Interactive Learning Environments*, 28(8), 1064–1077. https://doi.org/10.1080/10494820.2019.1570279

Naseer, F., Tariq, R., Alshahrani, H.M., Alruwais, N., & Al-Wesabi, F.N. (2025). Project-based learning framework integrating industry collaboration to enhance student future readiness in higher education. *Scientific Reports*, 15, 24985. https://doi.org/10.1038/s41598-025-10385-4

Ritter, C., Jones-Farmer, L.A., & Faltin, F.W. (2025). Expensive but worth it: live projects in statistics, data science, and analytics courses. *Journal of Statistics and Data Science Education*, 33(2), 236–246. https://doi.org/10.1080/26939169.2024.2374565

Saltz, J., Shamshurin, I., & Crowston, K. (2017). Comparing data science project management methodologies via a controlled experiment. In *Proceedings of the Annual Hawaii International Conference on System Sciences,* 1013-1022. https://doi.org/10.24251/hicss.2017.120

Silva, S., & Nicolau De França, B.B. (2023). A case study on data science processes in an academia-industry collaboration. In *Proceedings of the XXII Brazilian Symposium on Software Quality (SBQS '23)* (1–10). https://doi.org/10.1145/3629479.3629514

Spanjaard, D., Hall, T., & Stegemann, N. (2018). Experiential learning: helping students to become 'career-ready'. *Australasian Marketing Journal*, 26(2), 163-171. https://doi.org/10.1016/j.ausmj.2018.04.003

Speier-Pero, C., & Schoenherr, T. (2020). Creating impactful student learning in a business analytics program through leveraging scholar-practitioner engagement. *Decision Sciences Journal of Innovative Education*, 18(1), 59-89. https://doi.org/10.1111/dsji.12198

Taş, E. (2024). Data literacy education through university-industry collaboration. *Information and Learning Sciences*, 125(5-6), 389–405. https://doi.org/10.1108/ILS-06-2023-0077

Tembrevilla, G., Phillion, A., & Zeadin, M.G. (2023). Experiential learning in engineering education: A systematic literature review. *Journal of Engineering Education*, 113, 195-218. https://doi.org/10.1002/jee.20575

Wright, C., Meng, Q., Breshock, M.R., Atta, L., Taub, M.A., Jager, L.R., Muschelli, J., & Hicks, S.C. (2024). Open case studies: statistics and data science education through real-world applications. *Journal of Statistics and Data Science Education*, 32(4), 331–344. https://doi.org/10.1080/26939169.2024.2394541

Zhang, Y.G., Dang, M.Y., & Albritton, M.D. (2024). Delivering a business analytics course focused on data mining for both technical and non-technical students. *Journal of Information Systems Education*, 35(1), 86-98. https://doi.org/10.62273/MWCG1518