

Switching Off the Tools: A Learner-Centered Redesign of Business Management and Human Sciences Courses in the Age of AI

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Introduction and need for strategy: Learner-centered teaching begins with a direct test: what can students do? Generative AI has made that question harder to answer. In business management courses, students can now use AI to draft case analyses, build financial models, and write discussion posts. In human sciences courses, the same tools can produce developmental case studies, intervention plans, and reflective journals in seconds. A polished submission no longer proves that a student can read a balance sheet, reason from developmental theory, weigh an ethical dilemma in human services, or defend a recommendation to a manager or family. When evidence of learning becomes unreliable, learner-centered claims become harder to verify, and a course meant to build capable graduates may certify work the graduate cannot reproduce. This concern warrants particular attention at HBCUs because these institutions serve students pursuing career preparation across business, agribusiness, human services, and the human sciences, often within resource-constrained programs. A credential that lacks credible evidence of independent capability does not serve those students well. This proposal presents a design-oriented conceptual framework for redesigning learner-centered business management and human sciences courses so instructors can verify learning without expensive authentication technology or blanket bans on tools students will use in their careers.

Connection to literature: This framework builds on the learner-centered tradition. Barr and Tagg (1995) reframed undergraduate education as a shift from delivering instruction to producing learning, while learner-centered teaching scholarship identified changes in the balance of power, the function of content, the role of the teacher, responsibility for learning, and the purpose and process of evaluation (Sharkey & Weimer, 2003). Wiggins and McTighe (1998) provide the backward-design logic: identify the intended capability, then build assessments that reveal understanding rather than recall or polish. Cognitive science also supports the use of retrieval and delayed assessment to examine durable learning (Larsen, Butler, & Roediger, 2008). Experiential learning provides a basis for internships, practicums, simulations, and client projects in business and human development education (Hope, Croney, & Myers, 2020; Kolb, 1983). Freeman et al. (2014) found that active learning improved performance and reduced failure rates across undergraduate science, engineering, and mathematics courses, although the transfer of those findings to business management and human sciences requires direct study. Recent work on AI and curriculum design further supports attention to problem-solving, collaboration, computational thinking, self-regulated learning, digital citizenship, and practical application (Chan & Hu, 2023; Kong & Yang, 2024; Meng et al., 2025). Together, these sources support a framework that combines verifiable performance, experiential learning, and explicit instruction in the critical use of AI.

How it works and implementation of strategy: The framework starts with one question for every course outcome: What can the student do when the tools are switched off? This question functions as a design lens rather than a proctoring rule. It separates outcomes into competencies graduates must perform independently and competencies they may perform in partnership with AI, then translates that distinction into three course design moves. First, instructors assess core competencies through demonstrations they can observe and evaluate, such as an oral defense of a business or developmental case, a live walk-through of a financial model or program budget, a simulated client or stakeholder interaction, or a practicum performance. These demonstrations provide direct evidence of students' reasoning at the time of assessment. Second, instructors teach AI partnership explicitly. Students practice directing, checking, and overruling model output, including a plausible but incorrect demand forecast or break-even analysis and a developmentally inappropriate or culturally insensitive intervention plan. Assessment focuses on the student's judgment and explanation of revisions. Third, instructors redirect some grading time from take-home artifacts to feedback and coaching in simulations, client projects, internships, and practicum settings. To examine equity effects, instructors disaggregate outcomes by student group and compare

patterns before and after implementation. In practice, an instructor begins with one priority outcome, designs a verifiable demonstration of that outcome, anchors it in an experiential task, and adds an AI-supported extension aligned with workplace use.

Results to date, implications, and impact: The approach has been piloted in selected components of business management and human sciences courses. Evidence to date is formative and qualitative; no statistical estimates of effectiveness are yet available. Instructor observations suggest that short demonstrations can reveal differences between students' submitted artifacts and their ability to explain the underlying reasoning. Instructors also report shifting some time from grading take-home artifacts to coaching during simulations, client projects, and practicum placements. These observations indicate feasibility but do not establish that the strategy improves learning, reduces inequities, or lowers instructional costs. A systematic evaluation is underway using delayed assessments, transfer tasks, a validated measure of student belonging, and outcomes disaggregated by group. The evaluation will examine whether students retain and transfer unaided capabilities, whether belonging changes, and whether observed outcomes differ across student groups.

Future plans and advice to others

Next steps include a multi-section study using delayed assessments and transfer tasks, a shared bank of demonstration tasks and scoring rubrics, and cross-institution collaboration among HBCU business and human sciences programs. The study will examine implementation across management, agribusiness, human development, and human services courses. Where feasible, analyses will compare student performance before and after implementation and across course sections using common outcomes and scoring criteria. The evaluation will also document implementation fidelity, faculty time, and student access to AI tools so that differences in results can be interpreted in context.

Costs and resources needed

Initial implementation requires faculty time to redesign one outcome, develop a demonstration task and scoring rubric, conduct or review the demonstration, and teach students how to evaluate AI output. Basic AI access is needed only for the AI-partnered component; the independent demonstration does not require an AI tool. Programs should begin with one course and one priority outcome, document the time required for design and assessment, and compare that workload with the grading time previously devoted to take-home artifacts. These records will allow the project to test, rather than assume, that the strategy is feasible in resource-constrained programs.

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