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Preparing Information Systems and Information Technology Graduates for AI-Augmented Work: A Task-to-Curriculum Framework for Reweighting

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Abstract

Recent evidence suggests that artificial intelligence (AI) and generative AI (GenAI) are changing the task composition of knowledge work more visibly than they are eliminating entire occupations. For information systems and information technology (IS/IT) education, the resulting challenge is not simply to add AI tools to existing courses, but to reconsider when and how students develop the capabilities needed to frame problems, coordinate work, and validate AI-supported outputs. This paper develops a task-to-curriculum framework through an integrative conceptual synthesis of labor-market research, IS/IT curriculum standards, curriculum and employability scholarship, AI-literacy research, and studies of GenAI in computing education. The framework identifies three curricular priorities: business context and problem framing, professional communication and coordination, and human–AI interaction and oversight. This paper does not claim that these competencies are new. Rather, it contributes by explaining why AI-driven task reconfiguration makes their earlier introduction, repeated practice, integration with technical work, and direct assessment more consequential. Four design propositions and an implementation matrix specify how programs can reweight existing curricula without abandoning technical foundations. Together, these propositions provide a theoretically grounded agenda for curriculum redesign and future empirical validation.

Keywords: Generative AI; IS/IT education; curriculum design; AI literacy; human-AI interaction; graduate employability.

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Preparing Information Systems and Information Technology Graduates for AI-Augmented Work: A Task-to-Competency Framework for Reweighting.

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1. INTRODUCTION

The rapid diffusion of artificial intelligence (AI) and generative AI (GenAI) has intensified concerns about occupations centered on coding, analysis, documentation, and other knowledge-intensive activities. Recent evidence, however, suggests that AI's near-term effects are better understood as the automation or augmentation of specific tasks within occupations rather than the immediate replacement of entire occupations. Hampole et al. (2025) find that tasks with greater AI exposure subsequently experience reduced labor demand, although overall employment effects are moderated by task reallocation and productivity-driven firm growth. Complementary evidence at the economy-wide level comes from Gimbel et al. (2025), who identify no discernible disruption in the occupational mix attributable to GenAI since ChatGPT's release, while cautioning that broader labor-market transformations may take years to become visible.

Aggregate stability does not imply that effects are evenly distributed. The Iceberg Index identifies substantial technical exposure in computing and technology occupations but explicitly distinguishes capability exposure from realized adoption or displacement (Chopra et al., 2026). Brynjolfsson et al. (2025) further report relative employment declines among workers aged 22–25 in highly AI-exposed occupations while employment among more experienced workers in the same occupations remains comparatively stable. Although this evidence is still developing and is primarily U.S.-based, it raises a specific educational question: what happens when tasks that historically provided entry-level practice are increasingly assisted or partially automated?

Technical knowledge remains necessary because students cannot evaluate generated code, queries, analyses, or recommendations without disciplinary knowledge. The more important question is whether programs that assess student readiness mainly through routine artifact production adequately prepare graduates for work in which they may be expected earlier in their careers to define problems, interpret requirements, validate outputs, communicate uncertainty, and remain accountable for AI-supported work.

Existing IS/IT curriculum standards already recognize business context, communication, professional responsibility, and competency development (ACM/AIS IS2020 Task Force, 2020; ACM/IEEE-CS Task Group on Information Technology Curricula, 2017). Consequently, the contribution of this paper is not the discovery that these competencies matter, but a task-to-curriculum translation framework that explains why AI changes their timing, weighting, integration, and assessment within existing programs. The paper addresses the following question: How should undergraduate IS/IT curricula be reweighted when GenAI changes the task composition of early-career work?

In response to this question, the framework identifies three connected priorities: (1) business context and problem framing through authentic and reflective learning; (2) professional communication and coordination as assessed components of technical practice; and (3) systematic human-AI interaction focused on evaluation, validation, escalation, and accountability. It does not propose a new degree or the removal of technical foundations. Instead, it specifies how some repetitive execution-only activities can be replaced, once students have achieved foundational mastery, with integrated activities that make students' judgment and supervisory competence visible.

2. CONCEPTUAL DEVELOPMENT APPROACH

This paper uses an integrative conceptual synthesis rather than a systematic evidence review. The purpose is to connect bodies of scholarship that are usually discussed separately: task-based technological change, IS/IT curriculum standards, higher-education curriculum and employability

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research, AI literacy, human-AI interaction, and emerging research on GenAI in computing education. Sources were included when they supplied one of four elements needed for framework development: evidence about changing task structures, an established competency baseline for IS/IT programs, a mechanism for curriculum or learning design, or evidence about the educational use and risks of GenAI.

Framework development proceeded in four stages. First, labor-market and technology research was used to identify how AI may substitute for, complement, or reorganize tasks. Second, IS2020 and IT2017 were treated as curriculum baselines to identify competencies already expected in IS/IT programs. Third, curriculum, reflective-learning, employability, and AI-literacy scholarship was used to specify how these competencies can be developed and assessed. Fourth, the task changes and curriculum baseline were compared to derive design propositions concerning sequencing, practice, assessment, and curriculum reweighting. Although the synthesis is not exhaustive, its purpose is to establish a coherent explanatory link between anticipated task changes and curricular design choices.

To support this synthesis, a structured but non-systematic literature search was conducted. Initial searches were performed between January and March 2025 and updated through November 2025 using Google Scholar and academic databases including Scopus, Web of Science, and the ACM Digital Library. Key search terms included combinations of "artificial intelligence," "task-based technological change," "information systems education," "IT curriculum," "AI literacy," "human–AI interaction," and "graduate employability." Additional sources were identified through backward and forward citation tracking of highly cited articles and key reports. References were selected based on their relevance to AI's impact on work tasks, curriculum design, and competency development in IS and IT education, with priority given to peer-reviewed journal articles, major curriculum frameworks, and widely cited theoretical contributions. Sources were retained when they informed task change, IS/IT competency baselines, curriculum and learning mechanisms, or AI-use risks and practices. Sources were excluded when they were duplicative, primarily tool-specific, or did not contribute to framework development. The three priorities were derived by comparing recurring curriculum implications across these source groups and mapping them to existing IS/IT outcomes.

3. LITERATURE SYNTHESIS AND CURRICULUM GAP

3.1 AI, Task Substitution, and Labor Demand

Task-based theories view occupations as bundles of activities that can be affected differently by technology. Autor et al. (2003) showed that computerization substitutes most readily for routine tasks governed by explicit rules while complementing nonroutine analytical and interpersonal work. Historical reviews similarly show that automation can both displace tasks and complement labor (Autor, 2015; Bessen, 2015), while firm-level research links information-technology adoption to organizational redesign and increased demand for skilled labor (Bresnahan et al., 2002). Acemoglu and Restrepo (2019, 2022) extend this reasoning through displacement and reinstatement mechanisms: automation can reduce labor demand in existing tasks, while new tasks and complementary activities can restore demand for human work. This perspective explains how AI can reduce demand for selected components of IS/IT work without eliminating the occupation itself.

Recent evidence is consistent with this interpretation. Hampole et al. (2025) construct task-level measures of AI exposure and find that highly exposed tasks experience reduced labor demand, while within-job reallocation and firm growth moderate aggregate losses. The Budget Lab likewise finds no clear economy-wide labor-market disruption attributable to GenAI to date (Gimbel et al., 2025). These findings should not be interpreted as proof that education need not change. They instead suggest that task structures may change before occupation-level effects become visible.

3.2 Computing Exposure and Career-Stage Asymmetry

Computing and technology occupations are prominent sites of technical AI exposure. The Iceberg Index estimates that visible exposure in computing and technology represents approximately 2.2% of national wage value, or about $211 billion across 1.9 million workers, while emphasizing that exposure is not equivalent to displacement (Chopra et al., 2026). For curriculum purposes, the important implication is that standardized coding, documentation, testing, and analysis may become easier to delegate, whereas architecture, integration, exception handling, governance, and stakeholder coordination remain dependent on contextual and organizational knowledge.

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Career-stage asymmetry is especially relevant. Entry-level roles have often provided supervised opportunities to learn through relatively bounded production tasks. If some of these tasks are automated or completed more quickly with AI, graduates may be expected to exercise integrative judgment earlier, while simultaneously receiving fewer low-risk opportunities to develop that judgment. Brynjolfsson et al. (2025) provide early evidence consistent with this concern, but the causal role and durability of the pattern remain unsettled. The framework therefore treats entry-level disruption as a theoretically grounded risk and design problem, not as an established prediction.

Organizational adoption of AI is unlikely to be uniform across industries, occupations, and employers. Graduates may therefore enter workplaces ranging from extensive AI integration to limited adoption. This heterogeneity reinforces the need for curricula to prepare students both for AI-supported workflows and for settings in which independent disciplinary performance remains essential.

3.3 Existing IS/IT Curriculum Baselines

A curriculum framework should begin with the competencies that existing programs are already expected to develop. IS2020 organizes undergraduate IS education around competencies that integrate knowledge, skills, and dispositions in organizational contexts, while IT2017 similarly emphasizes competencies connecting technical knowledge with professional performance (ACM/AIS IS2020 Task Force, 2020; ACM/IEEE-CS Task Group on Information Technology Curricula, 2017). These standards already include communication, organizational understanding, teamwork, ethics, and professional practice. The gap is therefore not the complete absence of such outcomes.

The unresolved issue is whether those outcomes are introduced early enough, practiced often enough, integrated sufficiently with technical work, and assessed in forms that remain valid when AI can generate plausible artifacts. Curriculum mapping is useful here because it makes visible how program outcomes are communicated, progressively developed, and assessed across courses (Veltri et al., 2011). The proposed framework therefore treats existing standards as a baseline and identifies the incremental changes required for AI-augmented work. Table 1 summarizes the existing IS/IT curriculum baseline and the proposed AI-related reweighting across key curriculum elements.

Curriculum element	Existing baseline	AI-related reweighting
Business and organizational context	Already recognized in IS/IT standards	Introduce earlier; require students to define goals, constraints, stakeholders, and evaluation criteria before using AI.
Communication and teamwork	Already recognized as a professional competency	Assess explanation of AI-supported decisions, uncertainty, trade-offs, and escalation as part of technical performance.
Technical foundations	Core and indispensable	Retain foundations; use AI-generated artifacts as objects of diagnosis only after or alongside manual conceptual practice.
Professional judgment and responsibility	Present in ethics and professional-practice outcomes	Make validation, auditability, exception handling, accountability, and responsible human-AI task allocation explicit.
Experiential/project learning	Common but unevenly implemented	Add structured reflection comparing assumptions, generated outputs, verification evidence, revisions, and transfer to new problems.
AI literacy	Emerging and often isolated	Distribute critical use, evaluation, and responsible interaction across technical courses rather than confining them to one elective.

Table 1. Existing Curriculum Baseline and AI-Related Reweighting

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3.4 AI Literacy and GenAI in Computing Education

AI literacy extends beyond operational tool use. Long and Magerko (2020) define competencies that enable people to understand, interact with, and critically evaluate AI, while Ng et al. (2021) organize AI literacy around knowing, using, evaluating, and ethical engagement. UNESCO's student competency framework similarly emphasizes a human-centered mindset, ethics, AI techniques and applications, and AI-system design (UNESCO, 2024). For IS/IT graduates, these dimensions should be integrated with disciplinary knowledge and accountability for AI-supported work in organizational contexts.

Research in computing and higher education shows both opportunity and risk. Denny et al. (2024) argue that code-generating systems challenge established programming pedagogy and assessment while creating opportunities for explanation, feedback, and higher-level work. Interviews with students and instructors identify enthusiasm alongside concerns about overreliance, learning goals, integrity, and appropriate integration (Zastudil et al., 2023). Higher-education guidance and stakeholder studies similarly emphasize the need to align GenAI use with learning goals, ethical expectations, and institutional policy (Gimpel et al., 2025; Sah et al., 2025). A systematic review of higher-education cases likewise identifies a diverse but still limited body of empirical implementation research, with longer-term outcomes remaining underexamined (Belkina et al., 2025). These findings support deliberate and staged curriculum integration, but not the replacement of foundational learning with unrestricted AI use.

3.5 The Conceptual Gap

Existing scholarship provides substantial guidance on labor-market exposure, curriculum competencies, employability, experiential learning, and AI literacy. What remains underdeveloped is a mechanism that translates changes in occupational task composition into specific decisions about curriculum sequencing, practice, and assessment in IS/IT programs. The proposed framework addresses this narrower gap. It explains why established competencies become more time-critical as routine execution is increasingly shared with AI and identifies the implications for curriculum sequencing, practice, and assessment. Accordingly, the framework complements rather than replaces existing IS/IT curriculum standards and AI-literacy models by focusing on how AI-driven task changes alter the timing, emphasis, integration, and assessment of established competencies.

4. INTEGRATED TASK-TO-CURRICULUM FRAMEWORK

4.1 Core Constructs and Mechanism

The framework distinguishes four linked constructs. AI-driven task reconfiguration refers to changes in who or what performs components of work and how those components are combined. Competency value shift refers to changes in the relative importance and timing of different graduate contributions. Curriculum reweighting refers to redistributing instructional time, practice opportunities, and assessment weight across existing outcomes without simply expanding program requirements. Supervisory competence refers to the ability to select, question, verify, document, escalate, and accept responsibility for AI-supported outputs.

The central mechanism is as follows: when AI lowers the cost of selected execution tasks, organizations may reallocate human effort toward problem definition, interpretation, coordination, exception handling, and accountability. Because entry-level workers may be expected to perform these activities earlier, curricula should introduce the corresponding competencies earlier and reinforce and assess them repeatedly across the program. The curriculum recommendation therefore follows from a specific translation logic: as routine execution becomes less central to early-career contribution, curricula should preserve the technical knowledge needed for evaluation while increasing opportunities to practice complementary activities requiring contextual judgment, validation, coordination, and accountability. This translation is moderated by occupational subfield, degree of AI adoption, regulatory context, learner expertise, institutional resources, and whether AI is used primarily for automation or augmentation. This framework differs from existing curriculum and AI-literacy frameworks primarily in purpose rather than competency content. Whereas existing frameworks identify competencies graduates should develop, the present framework provides a task-based mechanism for determining when established competencies should be introduced, how strongly they should be weighted, and how they should be integrated and assessed.

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4.2 Integrated Theoretical Mechanism

Task-based technological-change theory provides the starting mechanism. When AI can perform or accelerate codifiable components of work, the human contribution may shift away from direct execution and toward complementary activities (Acemoglu & Restrepo, 2019, 2022; Autor et al., 2003). However, labor-market effect depends on how tasks are reallocated, how organizations redesign work, and whether workers can move into less automatable or more complementary tasks (Bresnahan et al., 2002).

Coordination theory explains why faster execution does not necessarily remove organizational complexity. Coordination involves managing dependencies among activities (Malone & Crowston, 1994). In AI-supported work, increases in the volume and speed of generated outputs may intensify the need to manage dependencies among people, systems, decisions, and stakeholders. Communication and coordination therefore become integral to technical practice rather than optional interpersonal additions.

Experiential and reflective learning explain how students may develop contextual judgment before entering professional work. Authentic tasks expose students to uncertainty, while reflection helps them convert experience into transferable understanding (Boud et al., 1985; Kolb, 1984; Schön, 1983).

Human-AI interaction, automation, and AI-literacy perspectives explain the importance of critical evaluation, monitoring, validation, intervention, and responsible use (Amershi et al., 2014; Long & Magerko, 2020; Parasuraman et al., 2000; UNESCO, 2024). These capabilities depend on disciplinary knowledge because students cannot reliably evaluate outputs in domains they do not understand.

Together, these perspectives motivate the following mechanism:
AI capabilities and organizational adoption change the distribution of tasks within entry-level work. These changes alter the relative value and timing of contextual, coordinative, and supervisory competencies. Curricula should therefore be reweighted so that students develop these competencies earlier, reinforce them across the program, and apply them in direct connection with technical practice.

4.3 Design Propositions

- Proposition 1: As AI assumes a greater share of routine execution, IS/IT curricula should reallocate assessment weight from artifact production alone toward problem framing, validation, explanation, and accountability, while retaining sufficient manual practice to establish disciplinary understanding.
- Proposition 2: Contextual judgment should be developed through authentic activities that are introduced progressively and include structured reflection on assumptions, AI outputs, verification evidence, revisions, and transfer to new contexts.
- Proposition 3: Communication and coordination should be embedded and assessed within technical courses because the management of dependencies and uncertainty is part of competent technical work in AI-augmented environments.
- Proposition 4: Human-AI oversight should be introduced and reinforced throughout the curriculum and sequenced in relation to learner expertise; students should not be expected to supervise outputs in domains they have not learned well enough to evaluate.

5. THREE CURRICULUM PRIORITIES

Figure 1 summarizes the translation from AI-driven task reconfiguration to curriculum priorities: changes in the composition of early-career tasks alter which competencies graduates may need to exercise earlier, thereby motivating changes in curriculum sequencing, practice, and assessment.

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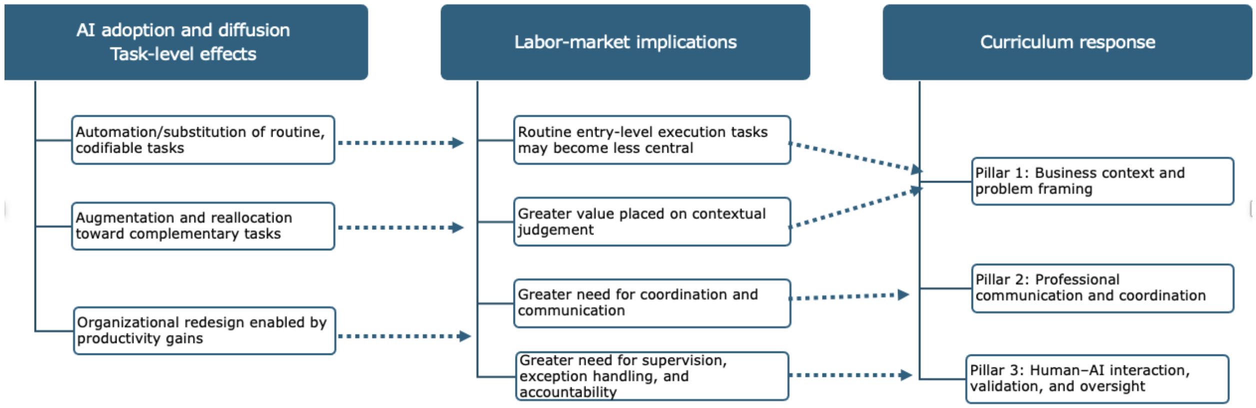

Figure 1. From AI-Driven Task Reconfiguration to Curriculum Priorities in IS/IT Education
Note. The figure integrates task-based technological change, organizational complementarity, experiential and reflective learning, coordination theory, and human–AI interaction to illustrate the proposed relationship between AI-driven task reconfiguration and curriculum priorities in IS/IT education.

5.1 Business Context and Problem Framing

As AI systems take on a larger share of standardized coding and analytical work, human contribution may become relatively more concentrated in defining goals, constraints, stakeholders, trade-offs, and evaluation criteria. Programs should therefore embed organizational context throughout the curriculum, beginning well before capstone. Database, systems analysis, networking, cybersecurity, and software courses can require students to define the problem and success criteria before producing a technical solution.

The distinguishing feature is not the use of a case study, which is already common, but the reflective task sequence. Students first state their assumptions and proposed criteria; they then examine AI-generated alternatives; next, they test those alternatives against business rules, evidence, edge cases, and stakeholder needs; finally, they explain what changed in their reasoning and how the lesson transfers to another context. This process makes contextual judgment visible and assessable.

Programs can strengthen this priority through client-based projects, business-process analysis, cases, internships, simulations, and cross-disciplinary assignments. However, these activities should incorporate structured reflection that requires students to examine their assumptions, justify revisions, and transfer their learning to new contexts (Boud et al., 1985; Schön, 1983).

5.2 Professional Communication and Coordination

As AI lowers the cost of producing drafts, analyses, and code suggestions, a greater share of human effort may shift from execution to alignment. Professionals must translate requirements, interpret outputs, reconcile stakeholder interests, justify decisions, communicate uncertainty, and coordinate responsibility across workflow. Communication should therefore be treated as part of technically competent performance rather than as a peripheral soft skill. Students should repeatedly practice writing design rationales, documenting AI-assisted workflows, explaining technical trade-offs to nontechnical audiences, and participating in collaborative decisions. In AI-supported work, communication also serves a governance function: explaining where AI was used, what evidence was checked, why outputs were accepted or rejected, which uncertainties remain, and when an issue should be escalated.

5.3 Human-AI Interaction and Oversight

AI should not be treated merely as an optional convenience tool or as a separate topic confined to a single elective. It should be understood as a workflow component requiring systematic evaluation, validation, and human oversight.

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Students should encounter AI across the curriculum in ways that emphasize evaluation, comparison, verification, auditability, and responsible use. In a database course, students might compare AI-generated queries with manually constructed alternatives. In software development, they might analyze generated code for correctness, maintainability, security, and hidden assumptions. In systems analysis, they might evaluate whether recommendations align with business rules, stakeholder priorities, and compliance requirements. Students should also be required to preserve evidence how they evaluated and supervised AI-supported work. Relevant artifacts include prompt and revision histories, test cases, error logs, source checks, rejected outputs, decision rationales, and escalation records.

5.4 Curriculum Mapping

Decisions about what to reduce should be made through curriculum mapping rather than isolated course changes. Program teams can map where each technical and professional outcome is introduced, reinforced, and assessed; identify unnecessary repetition; and then create space for reflective, coordinative, and supervisory activities (Veltri et al., 2011).

6. IMPLICATIONS FOR CURRICULUM DESIGN

The framework translates curriculum reweighting into decisions about what to retain, redesign, and assess. Table 2 illustrates these decisions across representative IS/IT course contexts.

Course context	Priority	Illustrative activity	Assessment evidence	Potential Curriculum Space Created
Introductory database	Context and framing	Define stakeholders, business rules, constraints, and success criteria before schema or query work; compare a generated solution with a manual solution (ACM/AIS IS2020 Task Force, 2020; Long & Magerko, 2020).	Requirements brief; rule-to-query traceability; error analysis; reflection.	A portion of repeated syntax-only exercises after mastery.
Systems analysis and design	Coordination and communication	Use AI to draft requirements or process models; identify omissions; negotiate conflicts; present a recommendation to a nontechnical audience (ACM/AIS IS2020 Task Force, 2020; Malone & Crowston, 1994).	Revised model; decision log; stakeholder presentation; oral defense.	A stand-alone presentation replaced by communication integrated with technical project.
Programming /software engineering	Human-AI oversight	Audit generated code for correctness, maintainability, security, provenance, and hidden assumptions (Denny et al., 2024; Parasuraman et al., 2000)	Test suite; code review; log of accepted and rejected outputs rationale.	A portion of repetitive near-identical coding exercises after foundational competence.
Cybersecurity/systems administration	Human-AI interaction and oversight	Evaluate AI recommendations under ambiguous, adversarial, or incomplete conditions and determine when escalation is required (ACM/IEEE-CS Task Group on Information Technology Curricula, 2017; Parasuraman et al., 2000).	Threat analysis; validation protocol; escalation memo; postmortem.	Tool demonstration that assesses only procedural completion.

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Capstone or work-integrated learning	Integrated competence	Manage an end-to-end AI-supported project with authentic stakeholders and structured reflection (Boud et al., 1985; Kolb, 1984; Schön, 1983).	Process portfolio; client feedback; audit trail; individual reflection; team defense.	Duplicate stand-alone professional-skills tasks already demonstrated in context.

Table 2. Illustrative Implementation and Assessment Matrix

Note. The activities are illustrative applications of the proposed framework. The cited literature supports the underlying curricular, learning, and human–AI interaction principles rather than providing empirical validation of the specific activities.

6.1 What Should Be Retained

Curriculum reweighting retains programming, data, systems, security, and analytical foundations. Students require disciplinary knowledge to evaluate AI-generated work. Manual reasoning and technical construction remain especially important at introductory levels and when students are learning concepts that AI-generated outputs may conceal.

6.2 What May Be Reduced or Redesigned

Once foundational competence has been demonstrated, programs may reduce repeated execution exercises that add little conceptual difficulty; syntax-focused tasks that do not require explanation or validation; generic communication assignments disconnected from technical decisions; short-lived instruction tied to a particular AI product or prompting formula; and duplicated coverage across courses without progressive development. The resulting curriculum space can be used for activities requiring students to inspect, test, explain, revise, and defend technical work completed with AI assistance.

6.3 Assessment of Judgment and Oversight

Assessment of technical work often focuses on whether students produce a correct technical artifact. In AI-augmented settings, a correct artifact may be produced without understanding, while an initially incorrect artifact may demonstrate substantial learning if the student detects and corrects the problem.

Constructive alignment requires assessment evidence to correspond with intended outcomes related to judgment, communication, and oversight (Biggs, 1996). Assessment should therefore include observable evidence of the quality of problem framing, identification of assumptions and constraints, choice of verification strategy, detection and explanation of errors, use of authoritative evidence, recognition of uncertainty and limitations, and appropriateness of escalation decisions. It should also assess students' justification for accepting or rejecting AI outputs, accountability for the final result, and ability to reflect on and transfer learning to a new task.

These elements can be evaluated through analytic rubrics, oral defenses, process portfolios, audit logs, demonstrations, and structured reflections. Structured reflection is particularly important because it enables students to examine how experience changed their understanding and to consider how that understanding might inform future situations (Boud et al., 1985; Schön, 1983).

6.4 Progression Across the Curriculum

The competencies should develop progressively rather than appear at the same level in every course. This approach is consistent with competency-oriented curriculum models that emphasize the integration and progressive development of knowledge, skills, and dispositions (ACM/AIS IS2020 Task Force, 2020; ACM/IEEE-CS Task Group on Information Technology Curricula, 2017; Association for Computing Machinery & IEEE Computer Society, 2020).

At the introductory level, students may identify obvious AI errors, compare generated outputs with worked examples, and explain basic verification. At the intermediate level, students may evaluate competing solutions, design tests, interpret stakeholder requirements, and justify revisions. At the advanced level, students may manage ambiguous projects, balance technical and organizational

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constraints, communicate risk, defend escalation choices, and remain accountable for an end-to-end AI-supported workflow. Curriculum mapping should identify where each competency is introduced, reinforced, advanced and assessed (Veltri et al., 2021). The learning activities and assessments at each stage should be constructively aligned with the intended level of student performance (Biggs, 1996).

6.5 Implementation Challenges

Implementation requires more than revising assignment instructions. Programs should anticipate needs related to faculty development, assessment design, responsible-use policies, institutional governance, and access to approved tools (Gimpel et al., 2025; Robert et al., 2025; Sah et al., 2025). Authentic and process-based assessments may also increase demands on instructional time and consistency. Programs can address these demands through shared rubrics, calibration using samples of student work, assessment moderation, and staged pilots before program-wide implementation.

Equity must also be considered. Students may differ in access to paid AI systems, computing resources, workplace experience, and professional networks. Institutions should provide equitable access to approved tools and avoid assessments that primarily reward access to more capable commercial systems.

7. DISCUSSION

The framework addresses a central tension in emerging research on AI and labor markets. Available evidence does not yet show immediate economy-wide employment disruption (Gimbel et al., 2025), but aggregate stability should not be interpreted as evidence that task structures and entry-level pathways are unchanged (Brynjolfsson et al., 2025; Hampole et al., 2025). AI may alter how work is divided even when occupational employment remains relatively stable.

The framework does not replace IS2020, IT2017, or related AI-literacy models. Its contribution is a translation mechanism linking changes in occupational task composition to decisions about when and how established competencies should be developed and assessed. Curriculum reweighting therefore concerns the treatment of existing outcomes rather than the creation of a separate set of AI competencies.

The framework adopts a broad conception of employability rather than equating it with immediate employer requirements. Employability includes adaptability, reflection, identity, understanding, and the capacity to perform effectively in changing contexts (Dacre Pool & Sewell, 2007; Tomlinson, 2017; Yorke, 2006). Its emphasis on AI oversight also aligns with contemporary AI-literacy frameworks, which treat critical evaluation, ethical awareness, human agency, and effective human–AI interaction as core competencies (Long & Magerko, 2020; UNESCO, 2024).

The framework also raises several tensions.

7.1 Foundational Competence Versus AI-Supported Performance

Students cannot reliably evaluate generated code, queries, analyses, or security recommendations without disciplinary knowledge. Curriculum redesign should therefore sequence AI-supported performance in relation to foundational learning. The complexity of AI-supported tasks should reflect the learner’s level of expertise.

7.2 Automation Versus Augmentation

Organizational responses to AI are likely to vary. Some organizations may augment junior employees, enabling them to perform more advanced work. Others may reduce routine positions. Educational programs should therefore prepare students to work effectively across different organizational models.

7.3 Employability Versus the Broader Purposes Of Education

Labor-market readiness is important, but it is not the only purpose of higher education. Curriculum should also support ethical judgment, intellectual independence, critical inquiry, civic responsibility, and durable disciplinary knowledge. These capabilities may also strengthen employability, but their value should not depend solely on immediate employer demand.

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7.4 Efficiency Versus Accountability

AI can increase production speed, but speed may conceal weak reasoning, unsupported claims, security risks, or unexamined bias. Curriculum should resist equating faster output with higher competence. Students should learn that the use of AI does not remove human and organizational accountability for the final product (Gimpel et al., 2025; UNESCO, 2024).

8. LIMITATIONS AND FUTURE RESEARCH

First, this paper is conceptual rather than empirical. It does not test a curriculum intervention, analyze student outcomes, or provide direct causal evidence that the proposed framework improves graduate readiness or employment outcomes. Accordingly, the framework should be interpreted as a theoretically grounded design framework requiring empirical validation rather than as evidence of the effectiveness of the proposed curriculum changes. Its claims should therefore be read as design-oriented propositions derived from an integrative interpretation of emerging evidence. Second, labor-market evidence on AI remains early and incomplete, so claims concerning entry-level work remain theoretically grounded inferences rather than settled facts.

Third, the literature search was structured but non-systematic. Although sources were drawn from multiple research domains and identified through database searches and citation tracking, the synthesis may not capture all relevant evidence and remains subject to interpretive selection. Fourth, the framework was developed specifically for undergraduate IS and IT programs. Although its principles may be relevant to related computing disciplines, including computer science, cybersecurity, data science, and software engineering, disciplinary differences in learning outcomes, professional roles, and technical emphasis should be considered before broader application. Fifth, much of the motivating labor-market evidence is drawn from the United States. The framework should therefore be examined in relation to national qualification systems, institutional structures, and regional employment conditions. Lastly, implementation depends on resources, faculty expertise, class size, industry relationships, governance, and equitable access to AI systems. Variation in organizational AI adoption also limits the extent to which any single pattern of task reconfiguration can be assumed across graduate employment contexts. Because AI capabilities, organizational practices, and workplace expectations continue to evolve, the proposed curriculum recommendations should be viewed as adaptive rather than permanent and may require refinement as evidence and patterns of adoption develop.

Future research should empirically test the four design propositions. Proposition 1 could be examined by comparing artifact-only and process-based assessments using measures of error detection, verification quality, and justification. Proposition 2 could be tested through changes in problem-framing quality, recognition of constraints, reflective reasoning, and transfer to new cases following authentic learning activities. Proposition 3 could be examined using rubric-based and stakeholder assessments of requirement clarification, explanation of technical trade-offs, communication of uncertainty, and coordination decisions. Proposition 4 could be tested by measuring AI-error detection, verification choices, acceptance or rejection of generated outputs, escalation decisions, and accountability across different levels of disciplinary expertise. Employer interviews, job-posting analyses, curriculum mapping, Delphi studies, classroom experiments, and longitudinal studies could provide complementary evidence concerning the framework’s relevance, feasibility, and effects on student and early-career performance.

9. CONCLUSION

The educational significance of AI lies not only in what the technology can produce, but also in how it changes the human contribution to technical work. When AI performs parts of coding, analysis, documentation, and solution generation, professional value may shift toward defining the problem, interpreting context, coordinating dependencies, validating outputs, and taking responsibility for their use.

The task-to-curriculum framework developed here connects this change in work composition to curriculum design. It identifies three priorities for undergraduate IS/IT education: business context and problem framing, professional communication and coordination, and human–AI interaction and oversight. The framework does not treat these as separate additions to an already crowded curriculum. Instead, it positions them as dimensions of technically competent performance that should be developed progressively and assessed within disciplinary work.

Curriculum mapping provides a practical means of making this shift. By identifying where outcomes are introduced, reinforced, and assessed, programs can preserve foundational learning while creating space for authentic and reflective AI-supported practice. The central question for IS/IT education is therefore not simply whether students can use AI, but whether they can exercise informed judgment over work produced with it.

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