

# What Can a Business School Do When Generative Artificial Intelligence Replaces Entry-Level Graduate Jobs?

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## Abstract

**Purpose:** To suggest how business schools can respond when generative AI automates routine, entry-level tasks and erodes early-career opportunities. The paper addresses a focused question: What can a business school do when graduates' entry-level jobs are replaced or reconfigured by AI?

**Approach:** This is a perspective article that synthesises recent empirical studies, labour-market evidence, and international policy guidance. Drawing on this integrative review, the paper develops a practical institutional blueprint for programme design, governance, and university-industry collaboration.

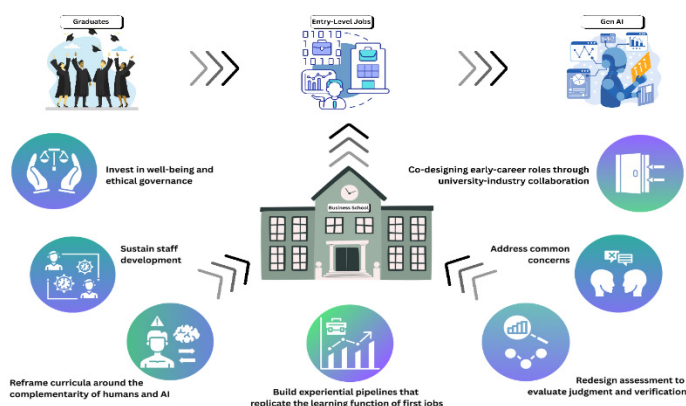
**Findings:** The existing literature indicates that traditional “first-rung” roles are thinning in AI-exposed occupations while expectations for day-one fluency with AI-augmented workflows rise. To bridge this capability gap, the paper proposes a coordinated blueprint: (1) reframe curricula around human-AI complementarity; (2) redesign assessment to evaluate judgment, verification, and communication; (3) build experiential pipelines that replicate the developmental function of first jobs; (4) co-design early-career roles through university-industry collaboration; (5) invest in student well-being and ethical governance; (6) sustain staff development; and (7) address common concerns (academic integrity, equity of access). Collectively, these actions enable business schools to restore apprenticeship-style learning within and immediately after degree programmes.

**Originality:** The paper links near-term labour-market disruption from generative AI to concrete, institution-level strategies in business education. It offers an actionable, literature-informed blueprint that moves schools beyond placement facilitation to co-creation of AI-era entry pathways, showing how higher education can rebuild the apprenticeship-like learning once provided by traditional entry-level jobs.

**Keywords:** AI-ready workforce, curriculum design, business curricula, and workplace

## Graphical Abstract

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## 1. Introduction

The rapid diffusion of generative artificial intelligence (AI) has sparked worldwide debate about its labour-market consequences. Leading technologies, such as Google's Gemini, OpenAI's ChatGPT, and DeepSeek, have equipped individuals and companies worldwide with unprecedented information-processing capabilities, including large-scale synthesis, drafting, and analysis (Bertomeu et al., 2025). Recent estimates suggest that current generative AI and related technologies could automate activities that account for roughly 60-70% of employees' time, accelerating the expected timeline for task automation (Bughin et al., 2018; McKinsey Global Institute, 2023). The potential impact spans most business functions, but four stand out when measured by their value relative to functional costs: customer operations, marketing and sales, software engineering, and research & development, together representing approximately 75% of the total value associated with generative-AI use cases (McKinsey Global Institute, 2023). Other functions, including supply chain and finance, are also highly exposed to AI. Complementing these projections, a 2024 global survey reports that 65% of organisations already use generative AI regularly, underscoring the high pace of adoption (McKinsey & Company, 2024). However, these headline figures can obscure important distributional dynamics, particularly where disruption is likely to appear first (Brynjolfsson et al., 2025).

In labour markets, the most visible effect of the AI era is not a uniform collapse in employment, but a selective erosion of early-career opportunities in occupations where AI can automate a substantial share of the routinised tasks (Del Río-Chanona et al., 2025). Employers describe a near-term shift in task composition and staffing, anticipating reductions where automation is feasible and viable alongside the creation of new jobs that combine human oversight with AI-enabled productivity (Leopold et al., 2025). Consistent with these expectations, recent evidence shows that employment has declined disproportionately among workers aged 22-25 in the most AI-exposed occupations (e.g., business management and finance), even as older workers in the same occupations have held steady or grown (Brynjolfsson et al., 2025). At the same time, nationally representative surveys document the rapid diffusion of generative AI across the workforce, with roughly two in five adults using such tools by late 2024 and a sizable minority using it for work every day (Bick et al., 2024). Taken together, these dynamics recast the challenge that business schools must address.

These converging trends fundamentally reframe the problem that university-based business schools must confront—preparing graduates for AI-reconfigured entry positions while preserving the developmental learning once provided by the traditional first rung of the career ladder (Del Río-Chanona et al., 2025). As AI automates or compresses the routine, low-risk tasks that historically scaffolded beginners' learning, early-career roles provide fewer opportunities for graduates to practise judgment under supervision and to acquire tacit norms “on the job.” At the same time, employers increasingly expect day-one fluency with AI-augmented workflows (Aleksieva et al., 2021; Gonzalez Ehlinger & Stephany, 2024; Portocarrero Ramos et al., 2025). Taken together, the loss of early, low-stakes practice and the rise of immediate performance expectations create a capability gap that cannot be bridged by conventional coursework alone. Accordingly, universities will need to assume a larger share of the on-the-job learning that previously unfolded during graduates' first one to two years of employment. The challenge, therefore, is not only technological but also pedagogical and organisational. Business schools must embed in their curricula the developmental experiences once gained through entry-level work.

The stakes are simultaneously educational and institutional. Management scholars caution that indiscriminate removal of entry-level roles erodes leadership pipelines, hinders the accumulation of tacit knowledge, and weakens organisational culture, effects that manifest over longer time horizons (Edmondson & Chamorro-Premuzic, 2025). Policy organisations likewise warn that the benefits and risks of AI will not be evenly distributed. Without intentional intervention, younger cohorts and those with limited access to high-quality training are likely to fall behind (OECD, 2024). In higher education specifically, many institutions are still drafting or refining their AI policies, implying that governance and pedagogy are only now trying to catch up with practice (Chen, 2022; UNESCO, 2025). Within this context, the central question of this paper is practical: What should a business school do when the entry-level jobs its graduates once stepped into are replaced or radically reconfigured by AI?

## 2. What Exactly Is Being Lost? The Learning Function of Entry-Level Roles

Entry-level positions in finance, marketing, operations, human resources, and consulting have historically served as sites of situated learning. Tasks such as compiling market scans, cleaning and merging spreadsheets, preparing first-draft memos, building simple dashboards, or resolving routine customer inquiries were not merely outputs to be delivered. Importantly, these were structured learning opportunities or pedagogical supports that helped beginners develop professional judgment. Contemporary AI systems can now perform many of these tasks at acceptable quality, shifting the human role toward oversight, exception handling, and client-facing sense-making (Del Río-Chanona et al.,

2025). Reflecting this shift, employers report reallocating effort away from routine drafting toward higher-value interaction and, in some cases, reducing headcount where automation appears sufficient (Leopold et al., 2025). From the student's perspective, the risk extends beyond a smaller number of job openings to the erosion of the tacit curriculum, that is, the countless micro-decisions (e.g., when to trust a number, how to handle ambiguity, and how to push back on a client request) that are difficult to teach in classrooms but are foundational for professional growth.

Recent labour-market evidence quantifies this qualitative loss. Brynjolfsson et al. (2025) document that employment among 22 to 25-year-olds in the most AI-exposed occupations began to fall relative to less-exposed occupations in late 2022, with declines continuing through mid-2025. Their results highlight that exposure to AI, rather than firm dynamics, is a primary driver of these outcomes. Meanwhile, many workers, including interns and graduate hires, are already expected to use generative AI as part of their daily workflow (Bick et al., 2024). The combined picture is clear: graduates will enter workplaces that presume AI fluency and expect human capabilities that complement the technology, while the structured, low-risk practice traditionally provided by entry-level tasks continues to recede.

The human consequences of this shift are not confined to skill formation. University students report elevated anxiety related to AI and unemployment (e.g., Li et al., 2025; McNamara & Thornton, 2025; Uçar et al., 2025). While anxiety should not impede innovation, it underscores higher education's responsibility to help students adapt to rapidly evolving expectations. If educational programs require students to master AI-augmented work, they must also equip them with ethical guardrails, verification strategies, and psychological supports that enable responsible and confident use (Knoth et al., 2024; Pinski & Benlian, 2024). Without these supports, disparities in access to tools and mentorship may widen, particularly for first-generation and international students who may have less social capital to buffer the transition (OECD, 2024).

### 3. Guiding Principles for Institutional Response

While institutional pathways will vary, several elements are foundational rather than optional: transparent permissioned use of AI within assessed tasks; grading of process evidence (problem framing, verification, governance) alongside product quality; and explicit ethics and well-being supports that make responsible use practicable. By contrast, the specific mix of experiential mechanisms (studio projects, micro-residencies), the granularity of micro-credentials, and the configuration of university-industry role co-design are context-dependent and should reflect local employer structure, regulatory constraints, and student demographics.

An effective response can begin with three principles that are consistently emphasised across employer reports, policy guidance, and scholarly work. First, business schools need to prioritise human-AI complementarity by cultivating capabilities such as problem framing, critical interrogation of data, reliability assessment, and empathic communication (Gupta & Jaiswal, 2024; Xu & Babaian, 2021). These capabilities are increasingly valuable when paired with AI rather than competing against it (OECD, 2024; Leopold et al., 2025). Second, schools need to adopt authentic assessment and practice. Because organisations expect responsible AI use, learning tasks should integrate AI under explicit rules rather than ban it altogether. Moreover, the evaluation should attend to both process and product by assessing elements such as prompting strategies, verification routines, and governance decisions (AACSB, 2024). Third, educational programs need to advance inclusion and well-being by pairing access to provisioned AI tools with clear policies, ethics education, and targeted support services that address AI-related anxiety (Uçar et al., 2025). Taken together, these principles offer a practical blueprint for reconfiguring curriculum and assessment, expanding experiential learning, strengthening labour-market intermediation, and enhancing student support.

### 4. Reframing the Curriculum Around Complementarity

Curriculum redesign needs to start by articulating explicit, programme-level learning outcomes for the AI era. The goal is not to transform business students into machine-learning engineers, but to cultivate translational leaders: e.g., graduates who can scope a business problem, design an AI-augmented workflow, select and evaluate appropriate tools, quantify value and risk, and communicate governance plans to non-technical stakeholders (Gupta & Jaiswal, 2024; Xu & Babaian, 2021). Consistent with this orientation, AACSB's (2024) recent guidance calls on schools to clarify what they will teach about AI (e.g., ethics, governance, data literacy), how they will teach it (e.g., AI-enhanced pedagogy, AI-based adaptive learning), and how they will operate as institutions in an AI-rich environment (Knoth et al., 2024).

In practice, we propose that business schools can pilot a required first-year module (e.g., "Managing with AI") that functions as a management laboratory rather than a coding course. Specifically, within this module, students can work in teams, practice scoping problems, construct and document auditable prompt chains and verification logs, evaluate AI model outputs against authoritative source data, and set an explicit error budget. Faculty could assess documented process artefacts (e.g., prompt chains, model-comparison notes, governance plans) alongside the managerial quality of the recommendation. This design treats AI as a transparently governed tool within assessment, consistent with sector guidance on responsible use and process-visible evaluation, and is intended to support academic integrity while cultivating employable capability (AACSB, 2024; UNESCO, 2025).

Embedding complementarity into the functional core areas of business is equally important (Gupta & Jaiswal, 2024). Thus, we propose discipline-specific micro-pilots that embed human-AI complementarity across the functional core while explicitly linking technical outputs to client-facing sense-making. For example, in marketing, students could build a market-intelligence workflow that triangulates AI-assisted synthesis with cited primary sources and then translate findings into tailored client narratives that frame options, trade-offs, and next steps for distinct stakeholder personas. Evaluation could weigh verification rigour alongside the clarity and persuasiveness of recommendations. In finance, learners could automate bounded elements of analysis and forecasting (or a three-statement model), document assumptions, verify reported figures, and deliver a concise “client read-out” that explains valuation drivers, defends scenario choices, and negotiates risk tolerances with non-technical executives. In operations, teams could generate AI-supported process maps, run sensitivity analyses to trace how errors propagate through the supply chain, and facilitate cross-functional discussions that convert diagnostics into actionable service-level agreements. Collectively, these small-scale trials surface where the technology performs well, where it fails, and why human oversight and communication remain indispensable, aligning with employer accounts that AI is reshaping task composition rather than eliminating the need for judgment and client interaction (Leopold et al., 2025).

Moreover, ethics and governance should be woven throughout courses rather than confined to a single elective (Pinski & Benlian, 2024). UNESCO’s (2025) guidance for AI in education emphasises transparency, human oversight, data protection, and equity. Business schools can translate these principles into case-based simulations that require students to weigh competing values, for example, speed versus privacy, creativity versus intellectual-property risk, and personalisation versus bias. These simulations prepare graduates to participate in or lead emerging governance structures (e.g., AI risk committees, model registers, incident-reporting processes) that many organisations are now building. By cultivating graduates who can both use and question AI, schools deliver to employers a capability scarcer than technical proficiency alone, that is, the ability to exercise sound judgment under uncertainty.

### **5. Redesigning Assessment to Reward Judgment, Not Just Output**

If graduates are expected to use AI in professional settings, assessments that prohibit AI may risk becoming artefacts of an outdated instructional model. Instead, educational programs need to design assignments that require AI use under transparent rules. As briefly mentioned above, students can submit prompts and prompt chains as appendices, document verification steps, and reflect on AI model errors, as well as the boundaries of acceptable reliance. Correspondingly, grading rubrics need to place substantial weight on problem framing, evidence vetting, ethical reasoning, and communication to non-technical audiences (Knoth et al., 2024; Pinski & Benlian, 2024). These criteria mirror the conditions under which employers extract value from AI while humans define problems, constrain and audit models, and take responsibility for decisions (Del Río-Chanona et al., 2025). In turn, this approach offers an academically sound response to integrity concerns by assessing the inquiry and judgment processes rather than the final product alone.

For example, programme-level projects can be particularly effective vehicles for authentic assessment. A project requirement could ask every student team to deliver a human-in-the-loop solution to a real stakeholder’s problem. Expected deliverables would include a functioning workflow, an error budget with test results, a governance plan addressing data provenance and bias-mitigation strategies, and an executive-level presentation. Given that many employers are still experimenting with AI adoption and governance, and often unevenly across different units (Bick et al., 2024), such projects that generate usable, auditable artefacts can create immediate value for partners while cultivating students’ ability to balance speed with responsibility. As graduates move into reconfigured entry-level jobs, these experiences can enable them to evidence not only tool familiarity but also fluency with the organisational conditions that make those tools productive.

### **6. Building Experiential Pipelines That Replace the Lost First Rung**

Suppose the core problem is the disappearance or thinning of entry-level jobs. In that case, business schools need to recreate the learning function through structured experiences that are closer to work than to coursework. One approach can be establishing an “AI Community of Learners”, that is, a centralised unit that sources a rolling pipeline of short projects from small and medium-sized enterprises, social enterprises, and public agencies. Teams of students, coached by faculty and industry mentors, tackle these projects in two- to four-week sprints using AI under explicit constraints. The pedagogical focus is on oversight, exception handling, stakeholder communication, and relationship management, the dynamic capabilities that remain hard to automate. In addition, these projects can be archived in a searchable portfolio system, allowing students to share verifiable artefacts with recruiters. By mimicking the rhythm and ambiguity of real work, the studio substitutes for the practice that has historically occurred in entry-level roles (Edmondson & Chamorro-Premuzic, 2025).

A complementary approach is the creation of micro-residencies, paid placements of three to six months, co-supervised by faculty and employers, that explicitly ask students to design and govern AI-augmented workflows rather than to

perform routine tasks. Such residencies provide employers with supervised talent and a low-risk mechanism for piloting workflow changes without committing to permanent headcount adjustments. At the same time, students earn both income and verifiable professional experience. As employer adoption remains heterogeneous even within sectors, micro-residencies also facilitate the diffusion of effective practices and accelerate organisational learning. Over time, a network of anchor employers can sustain a steady pace of placements, thereby effectively replacing the traditional first rung of the career ladder with a school-mediated pathway that preserves early-career development.

To ensure that experiential learning is legible in the labour market, business schools can issue micro-credentials, alongside the regular curriculum and diploma, that serve as substantive evidence rather than symbolic badges. Each credential could integrate multiple forms of verification, for example, documented artefacts of practice, supervisor evaluations, and outcome metrics (e.g., cycle-time reductions, error-rate improvements). Examples might include AI-Augmented Financial Analysis, Responsible Market Intelligence Prompting, or AI-Enabled Process Mapping. When graduates present these portable signals in applicant tracking systems, employers can more easily infer capability that has become harder to observe as traditional entry-level titles disappear. This approach is consistent with UNESCO's (2025) call for competency frameworks that make AI capability visible and with AACSB's (2024) emphasis on measurable learning outcomes.

There might be concerns that formalising school-mediated projects and micro-credentials could shift the burden of credentialing onto students. This represents a legitimate risk and should be considered in the programme design. To mitigate inequities, business schools need to ensure students' equitable access to AI tools, provide support for project work, and structure residencies as paid placements rather than unpaid volunteer roles. The marketplace should also be embedded within the curriculum so that students earn academic credit for verified practice (Gupta & Jaiswal, 2024). When these conditions are in place, the intermediary approach expands access by giving all students structured, credit-bearing ways to build and evidence competence, rather than adding extra hurdles for those with fewer resources. Employers benefit as well, that is, instead of hiring into ambiguous new roles with limited information, they encounter candidates presenting audited artefacts, a shared technical-managerial vocabulary, and evidence of sound judgment.

## **7. Co-Designing Early-Career Roles Through University-Industry Collaboration**

Business schools also need to move beyond an intermediary function to act as co-designers and collaborators in the AI transition, complementing existing internship pipelines and employer partnerships. First, schools can build curated talent marketplaces that match students to fractional, remote, AI-augmented projects sourced through alumni and partner networks. By commissioning clearly scoped deliverables, employers gain immediate value while students accrue verifiable experience. Second, business schools can co-create new entry-level career pathways with employers (e.g., by defining competency profiles, supervision expectations, and progression ladders) and help standardise job design and training pipelines as routine tasks are automated and new roles emerge (Leopold et al., 2025). Third, at the regional level, business schools can collaborate with public agencies and industry associations to align training funds with empirically observed AI exposure, ensuring recent graduates, not only mid-career workers, are eligible for reskilling support (OECD, 2024). Taken together, these initiatives reposition business schools from placement facilitators to market shapers and knowledge partners, creating structured, jointly governed pathways into reconfigured early-career roles.

Notably, to co-design early-career roles through university-industry collaboration, programme design choices should be adapted to both institutional capacity and regional constraints. Institutional type shapes what can be implemented, how quickly, and with what governance. Research-intensive universities may focus on stronger research infrastructure, advanced analytics support, and established ethics and data-governance offices to run secure "walled-garden" model instances and to negotiate partner-data agreements at scale. In contrast, professionally oriented institutions (e.g., universities of applied sciences) may prioritise faster-cycle, practice-embedded pilots integrated into existing work-based learning structures and long-standing local employer networks. Moreover, regional conditions then further determine delivery choices. In regions with strict data-protection rules, schools can rely on walled-garden model instances and synthetic or anonymised datasets during instruction, then transition to partner data under separate agreements. In regions dominated by small and medium-sized enterprises, shorter, fractional projects may be more feasible than long residencies; where employer associations are well coordinated, competency profiles and supervision norms can be standardised more quickly. To address variation in students' financial means, institutions could provide device-lending, provisioned licences, and supervised compute labs so that participation in AI-integrated learning does not depend on personal resources (OECD, 2024; UNESCO, 2025). Aligning programme design with the local regulatory, industrial, and equity landscape strengthens both feasibility and fairness. With this context-sensitive foundation in place, business schools can move beyond facilitation to co-design AI-era entry pathways in partnership with employers and public actors.

## 8. Well-Being and Responsible Use

The psychological and ethical dimensions of AI adoption are often treated as afterthoughts. However, in the context of disappearing entry-level roles, they are central. Students who fear that AI will foreclose early-career opportunities may either avoid experimentation or uncritically rely on tools, both of which undermine learning. Evidence links AI-related anxiety with broader employment concerns among university populations and suggests that attitudes toward AI and AI literacy shape job-seeking confidence (Li et al., 2025). Consequently, educational programmes need to pair technical literacy with care, for example, via structured workshops that demystify AI tools, explain reliability constraints, and teach verification strategies. In addition, it is necessary to provide counselling services that offer psychoeducation on uncertainty and career planning (Uçar et al., 2025). This dual emphasis aligns with international guidance calling for competency frameworks that help learners recognise both the opportunities and the risks of AI (UNESCO, 2025). AI use is already widespread and uneven across disciplines and demographics, so equitable access to tools and clear, supportive policies are necessary to prevent widening differences in students' academic performance (Freeman, 2025). In short, well-being and responsible use can reinforce one another. When students understand the limits of AI models and have access to supportive services, they are more likely to use AI in ways that build confidence, capability, and ethical awareness (Knoth et al., 2024; Xu & Babaian, 2021).

Faculty practice is the other pillar of a coherent strategy for well-being and responsible AI use. Evidence from higher education indicates rapid yet uneven uptake, with many educators experimenting cautiously and expressing uncertainty about appropriate applications (Chen, 2022; Shata & Hartley, 2025). Clear institutional guidelines can reduce this ambiguity and model the behaviours expected of students, thereby shifting AI governance from a narrow compliance exercise to a scholarly community of practice. When faculty engage directly in AI-augmented teaching and research, they are better positioned to mentor students through the “messy middle” between hype and harm, including how to document prompts, verify outputs, and articulate the limits of acceptable reliance (Petricini et al., 2024). Additionally, consistency between policy and practice also carries reputational weight—students are likely to push back if educators restrict AI for learners while using it themselves, underscoring the need for transparent norms. By embedding responsible-use standards in everyday pedagogy and investing in staff development to meet those standards, business schools can graduate professionals who not only use AI competently but also guide its implementation with ethical judgment and genuine care for human well-being (Pinski & Benlian, 2024).

## 9. Addressing Common Concerns

A frequent concern is that rapid advances in AI will soon automate even judgment-intensive tasks, rendering education for human-AI complementarity a short-lived solution. This argument underestimates the organisational frictions, governance demands, and change-management realities that accompany technological adoption. Current evidence points to uneven diffusion across firms and job families, with intensive use clustering among workers capable of redesigning workflows and assuming responsibility for outputs (Bick et al., 2024). Even in highly exposed occupations, the early employment effects are driven primarily by the automation of routine components rather than the wholesale displacement of human oversight (Brynjolfsson et al., 2025). Accordingly, education that strengthens problem framing, verification, and communication remains durable, even as tools evolve, because these are the levers through which organisations translate technical capability into dependable value.

A second common concern holds that permitting AI in assessment invites academic dishonesty. The more productive question is what, precisely, assessments are intended to measure. If grades rest solely on final outputs, authorship can indeed be obscured. However, when evaluation focuses on a documented process (e.g., how students structure problems, why they accept or reject AI suggestions, and how they mitigate bias), AI becomes both an object of inquiry and a medium for learning rather than a shortcut (Knoth et al., 2024). This reorientation aligns with accrediting guidance that encourages transparent and ethical AI use (AACSB, 2024) and with sector-level reports indicating that most institutions are now developing policies that embrace responsible practice (UNESCO, 2025).

A final common concern is about equity. AI-integrated models may advantage students with greater prior access to technology and social networks. This risk can be mitigated by standardising baseline access and embedding experience-building within required coursework. Schools should provide licences and virtual environments for core tools, maintain device-lending and on-campus compute labs, and adopt low- or no-cost, open-source alternatives where feasible. To reduce reliance on social capital, experience can be generated through structured, course-embedded projects that use shared datasets, standard brief templates, and rotating team roles, complemented by peer-mentoring clinics and educator office hours to provide just-in-time support. Assessment can emphasise the documented process and use an anonymised artefact review against rubrics, so that prior polish or networking does not unduly influence outcomes. Taken together, these design choices operationalise inclusive access to productivity-enhancing AI and help prevent pre-existing exposure differentials from hardening into unequal outcomes (OECD, 2024).

## 10. From Design to Delivery: A 0-36 Month Implementation Roadmap

To translate the preceding recommendations into practice, we organise them into a staged implementation roadmap that sequences decisions and investments over three academic cycles. This timeline recognises that governance, faculty capability, partner engagement, and evaluation capacity cannot be built all at once. Instead, early actions should establish responsible-use foundations and proof-of-concept teaching, with subsequent cycles focused on institutionalisation, scaling, and ecosystem alignment. The roadmap also provides checkpoints for measuring progress and refining design based on programme data and partner feedback, ensuring that changes remain feasible within typical resource and quality-assurance constraints.

In the first academic cycle (months 0-12), institutions can establish the foundations for governance and capability. Concretely, schools can publish responsible-use guidelines, resource faculty development in AI-integrated pedagogy, and adopt programme-level learning outcomes that make complementarity and verification explicit. A single required, practice-oriented module (e.g., “Managing with AI”, as mentioned above) can be launched with a limited number of vetted partner projects, ensuring quality control over data handling and assessment.

In the second cycle (months 12-24), the emphasis shifts to institutionalisation and scale. Each core business area can contain at least one assessed activity that requires AI, under transparent rules, and grades the process evidence. A small portfolio of micro-residencies, co-supervised with employers, can run continuously to replace lost early-career practice. Micro-credentials could be issued alongside common rubrics that combine artefacts, supervisor evaluations, and outcome metrics. At this stage, schools can convene employers to co-design entry-level role profiles, supervision expectations, and progression ladders that align with observed task reconfiguration.

By the third cycle (months 24-36), the priority is ecosystem alignment and evaluation. Schools could formalise regional collaborations (with public agencies and industry associations) to target training funds to high-exposure domains and to recognise micro-credentials in applicant tracking. A standing review process, drawing on programme data, partner feedback, and graduate outcomes, can help refine assessment rubrics, governance artefacts, and role profiles. The goal is not perpetual expansion but reliable, audited pathways that restore the learning function of first roles at scale.

## 11. Conclusion

Entry-level jobs once served as apprenticeships into a profession. However, as AI automates much of the routine work that previously underpinned those roles, the first rung of the career ladder is narrowing. Business schools cannot reverse this macrotrend, but they can redesign around it. By reframing curricula toward human-AI complementarity, assessing students on judgment and verification, building experiential pipelines that replicate the learning function of first jobs, co-designing early-career roles through university-industry collaboration, investing in well-being and ethical governance, sustaining staff development, and addressing common concerns, schools can restore early-career experience while improving the quality of graduates’ contributions. This is not a stopgap. It is a durable blueprint for educating professionals who can apply AI safely and productively-and for converting rapid technological advances in AI into measurable educational and organisational gains.

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## Authors contributions

Dr. Hugh J. Liu was responsible for the study design, connecting journals, manuscript writing, and revision. Ms. Junyu Wang was responsible for manuscript writing and revision. Ms. Froukje J. Wijma was responsible for manuscript writing and revision. All authors read and approved the final manuscript.

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