Rethinking Practical Teaching in Human Resource Management: An AI-Embedded Curriculum Framework

Du Juan
Suzhou Vocational Institute of Industrial Technology, Suzhou, Jiangsu, China

Abstract: How AI tools should be incorporated into HRM practical teaching—not appended to the margins of an existing curriculum but woven into its structural core—is the driving question behind this paper. The study draws on a mixed-methods design combining framework development, model specification, and a single-institution pilot at Suzhou Institute of Industrial Technology. Central findings suggest that when AI competencies are distributed across all core HRM courses rather than quarantined in one elective, students demonstrate measurably stronger applied skills and show less hesitation when encountering novel HR technology tasks. The paper also elaborates a multi-stakeholder governance framework to handle the ethical dimensions that inevitably arise when real-seeming data and automated decision tools enter the classroom. Three governance levels—institutional, regulatory, and professional—are described, with the aim of giving faculty and administrators a usable reference for managing bias, privacy, and over-reliance risks.

Keywords: Artificial Intelligence; Human Resource Management; Practical Teaching; Teaching Model Innovation

1. Introduction

1.1 Research Background

Generative AI and predictive workforce analytics have moved from novelty to operational backbone in Chinese enterprise HR departments over roughly the past three years. What started as a handful of technology firms experimenting with automated resume screening has spread—unevenly but persistently—into performance review cycles, succession planning, and real-time employee sentiment monitoring. HR professionals working in these environments are routinely expected to interpret model outputs, challenge algorithmic recommendations, and explain data-driven decisions to line managers who have little technical background. The skill set has shifted, and it has shifted faster than university curricula can normally absorb.

The mismatch that results is not subtle. HRM programs at many institutions still organize their practical components around paper-based exercises and role-play scenarios that mirror how HR departments ran a decade ago. Students spend hours drafting job descriptions by hand and practicing performance appraisal conversations in pairs—both useful, but increasingly insufficient as standalone preparation. Employers hiring new HRM graduates have begun flagging this gap directly in feedback to career offices, noting that recruits often struggle with even introductory data tools that have become standard in HR workflows.

1.2 Research Questions and Contributions

This paper takes up three questions that the existing literature has treated only partially. The first is structural: how can AI literacy be built into the architecture of an HRM program rather than treated as an add-on? The second is pedagogical: what instructional methods and assessment designs actually develop that literacy rather than merely exposing students to it? The third is ethical: what governance mechanisms are realistic for institutions that lack dedicated AI ethics staff but still need to manage the risks that come with deploying AI tools in teaching?

Two contributions follow from this inquiry. The first is a fully integrated teaching model in which AI content is distributed across staffing, compensation, performance management, and training courses—not consolidated into a single dedicated module. The second is a governance framework built around four stakeholder groups whose responsibilities are differentiated but mutually reinforcing, offering a more practical starting point than generic ethical guidelines.

2. Theoretical Foundations and Research

Status

2.1 How AI Use in HRM Has Shifted

Early AI deployments in HR departments were, in retrospect, fairly limited in ambition: automate payroll, digitize personnel files, reduce the manual overhead of scheduling. These systems solved real problems, but they operated within narrow parameters and rarely required HR professionals to develop new analytical capabilities. The gains were operational, not strategic.

The picture changed when predictive modeling entered the mainstream. Rather than simply recording what employees had done, HR systems began forecasting what they were likely to do—who was at flight risk, which teams would miss performance targets in the next quarter, which candidates in the recruiting pipeline would likely accept offers. These applications require HR professionals to engage with probabilistic outputs and understand, at least roughly, how models generate their predictions. The professional responsibility involved is genuinely new: a manager acting on a flight-risk score needs to grasp both its limitations and its potential for discriminatory misuse.

Generative AI has introduced yet another layer. Tools that draft job postings, summarize performance review notes, or generate interview question sets from a job description are now accessible to HR departments of any size. For students, the pedagogical implication is that the boundary between 'knowing about' AI and 'working with' AI has moved—what used to require specialized training can now be accessed with a prompt. Curricula that were already behind on the previous wave are now further behind. The gap between field practice and university instruction is what these paper addresses, specifically in its most current form.

2.2 Where Practical Teaching Gets Stuck

A recurring structural problem in HRM practical teaching—one that shows up regardless of institutional context—is that simulation scenarios are kept simple. Role-play exercises and case discussions strip out the complexity of real data, often because faculty lack access to authentic HR datasets and because simplified scenarios are easier to assess. Students develop a reasonable feel for how HR decisions are made in principle, but they rarely encounter the messiness—data quality issues, conflicting signals from different tools, model outputs that contradict managerial intuition—that characterizes actual AI-assisted HR work.

Faculty capacity is a second constraint. Many HRM instructors built their careers before predictive analytics became central to HR practice, and the field-specific professional development infrastructure for getting up to speed has been thin. When instructors are uncertain about the tools themselves, they tend to either avoid AI content altogether or handle it at such a surface level that students gain little practical competence. This is not a criticism of individual faculty; it reflects a systemic lag.

Resource access compounds the problem. Maintaining a functional HR technology lab—licensing commercial tools, assembling datasets suitable for student use, keeping software current—requires financial commitment and technical support that many HRM programs have not secured. Cloud-based alternatives have reduced some of these barriers, but they have not eliminated them.

Assessment design is a third area where HRM practical teaching typically falls short. Written examinations can probe declarative knowledge about AI tools, but they do not reveal whether students can actually use them. A student who scores well on an HR analytics examination may never have run a genuine data analysis; she may have memorized how such analyses are described without being able to produce one. Until assessment includes performance-based tasks graded on demonstrated capability, the gap between knowing and doing will persist.

2.3 What the Literature Has and Has Not Done

Scholarship on AI in HRM education has grown noticeably in recent years, though from a small base. Work on intelligent tutoring systems that adapt to learning pace and studies exploring virtual reality environments for HR simulation have appeared with some regularity. Research on AI-powered feedback tools in HRM courses has also accumulated. Each of these contributions is valuable in isolation.

What the field mostly lacks, however, are whole-curriculum models—frameworks that describe how AI literacy is built and maintained across an entire HRM program rather than within a single course or a single experiment. Most published studies test one intervention, in one course, over one semester, with outcomes measured at course end. The question of how AI competencies developed in, say, a staffing course carry forward into a compensation course—or what happens when a graduate encounters an unfamiliar AI tool on the job three years later—remains largely unexamined. This paper is an attempt to address that larger-scale question, however partially.

3. The AI-Driven HRM Practical Teaching Model

3.1 Design Principles

Three principles shaped the model described in this paper. Each responds to a specific limitation in how HRM practical teaching currently operates.

The first principle is distributed integration: AI content is embedded into every core HRM course rather than isolated in a dedicated elective. This matters because learning to use AI tools in one course and then returning to AI-free instruction in all other courses does little for retention or transfer. When AI applications appear in staffing one week and are absent from compensation instruction the next, students understandably treat AI as a supplementary theme rather than a fundamental professional competency. Distributing AI content across the curriculum forces a different orientation.

The second principle treats ethical reasoning as an active skill rather than a topic to be covered. This distinction is not merely rhetorical. Students who read about algorithmic bias in a required textbook chapter and students who are asked to audit an AI recruitment tool for bias, document what they find, and defend their conclusions in a presentation are doing categorically different kinds of learning. The model embeds ethical reasoning tasks throughout the curriculum—students are not told what ethical issues look like; they are asked to find and analyze them using real or realistic tools.

The third principle is aligned assessment: if the graduate outcome is the ability to use AI tools effectively and responsibly, then assessments should require students to demonstrate that ability directly. The model replaces a significant portion of knowledge-recall assessment with performance tasks—data analysis exercises, AI-assisted report writing, bias audit projects—that are scored on the quality of what students actually produce.

3.2 Model Architecture

Three interdependent components constitute the model.

Instructional Methods are the most immediately visible change. Rather than lectures accompanied by slides, core sessions involve live demonstrations of AI tools, guided in-class practice, and structured debriefs in which students compare AI-generated outputs with their own judgments. This approach serves a dual purpose: it builds technical familiarity and, equally important, it develops the critical habit of interrogating AI outputs rather than deferring to them. Students who have watched an AI tool produce a flawed job description and been asked to identify the problems are less likely to accept AI outputs uncritically in a professional setting.

Curriculum Design is where distribution across courses becomes concrete. In the staffing module, students run resume screening simulations with AI tools and compare the results against their own evaluations, documenting discrepancies. In compensation, they use salary benchmarking software and learn to assess the reliability of its market data. In performance management, they work with AI-generated review drafts and practice revising them for tone, accuracy, and potential bias. In training, they design learning pathways using an adaptive learning platform and then review the platform's reasoning for its recommendations. Each course contributes to a cumulative AI competency profile rather than treating AI as its own self-contained topic.

Assessment Mechanisms use a layered approach. Some knowledge assessment remains appropriate—understanding what a particular algorithm does requires knowing some things—and written components handle this. The substantive emphasis, however, falls on practical assignments. These range from structured data analysis tasks with provided datasets to open-ended projects in which students identify a real or simulated HR problem, select appropriate AI tools, apply them, and write up a critical evaluation of both the process and the results. Final grades in each course include a portfolio element that accumulates evidence of AI competency development over the semester.

3.3 Implementation Requirements

Moving from model to practice requires

institutional commitment on several fronts, and this section is candid about the demands involved.

Curriculum revision is time-intensive. At Suzhou Institute of Industrial Technology, a cross-functional committee including HRM faculty, IT personnel, and industry representatives worked for approximately eight months to redesign course materials, identify appropriate AI tools for each module, and develop new assessment rubrics. Faculty who had not previously integrated AI content into their teaching required substantial support. The process surfaced disagreements about which AI tools were worth the learning curve for students and which were pedagogically questionable despite being technically impressive—disagreements that were ultimately productive but slow to resolve.

Faculty development is an ongoing commitment rather than a one-time event. Site visits to local companies that use AI HR systems, collaborative lesson design among colleagues with different AI competency levels, and access to curated professional development resources were all part of the implementation plan at Suzhou. Even with these supports in place, some faculty found the pace of tool change stressful. Building in time for instructor experimentation—specifically, time to try AI tools without the pressure of immediate classroom deployment—proved helpful.

Infrastructure requirements are more modest than institutions often assume. The Suzhou implementation relies primarily on cloud-based HR AI platforms, which eliminates the need for expensive on-premises licensing. A computer lab with reliable internet access and student accounts on two or three carefully chosen platforms covers most of the technical requirements. What the institution did invest in was curated anonymized datasets—produced in collaboration with industry partners—that students can work with without privacy complications.

Industry partnerships contribute more than internship placements. Partner organizations at Suzhou have provided anonymized HR datasets, hosted working visits for students at specific points in the curriculum, sent HR practitioners to class as discussants when AI-related decisions were the topic, and provided feedback on student project work. These partnerships require cultivation and maintenance, but they provide something coursework alone cannot: contact with AI tools used under real operational conditions, with all the messiness that implies.

4. Ethical Risks and Governance

4.1 Four Core Ethical Risk Areas

Embedding AI tools into HRM education creates a specific set of ethical risks that are distinct from, though related to, ethical risks in professional HR practice. They deserve attention on their own terms.

Algorithmic bias is the most documented risk in the literature, and the HRM educational context gives it a particular edge. AI recruitment and assessment tools trained on historical hiring records often encode the biases embedded in those records—biases that students need to be able to recognize and challenge, not inadvertently reinforce. An HRM program that uses AI screening tools in its simulation exercises without building in explicit bias analysis is implicitly teaching students that AI outputs are authoritative rather than contestable. Students who graduate with that assumption will bring it into their professional work.

Data privacy in educational settings takes a different form than in corporate settings, but it is no less serious. Practical HRM teaching requires students to work with employee-resembling data—realistic rather than obviously fake information about individuals' performance, compensation, and career history. The closer this data is to real data, both in structure and in content, the more effectively it supports learning. But realistic datasets create real privacy risks, especially when they involve identifiable individuals or when students use cloud-based AI tools that may store or analyze uploaded data. Establishing clear protocols for data handling—and explaining those protocols to students so they develop good habits—is necessary rather than optional.

Over-reliance on AI tools is a risk that is often underestimated in enthusiasm about what AI can do. A student who develops the habit of generating AI output first and editing it second is building a workflow that has significant professional limitations. When the AI tool is unavailable, performs poorly, or produces output that requires deep subject-matter expertise to evaluate, a student whose core skills have atrophied because AI handled that work is poorly positioned. The model described in this paper explicitly includes assignments in which AI tools are either unavailable or restricted precisely to build the foundational capabilities that AI reliance can erode.

Value displacement is the most diffuse of the four risks and, for that reason, the most difficult to address. HRM as a professional discipline has historically emphasized that employees are people, not inputs—that equitable treatment, dignity, and well-being are not soft concerns but core professional responsibilities. AI tools that reduce employees to data points, that optimize for efficiency metrics without capturing what those metrics miss, can gradually habituate students to a frame in which the human dimension of HR work is secondary. This is not an argument against using AI tools in HRM education; it is an argument for being deliberate about what values get reinforced alongside those tools.

4.2 Root Causes of Ethical Risks

Understanding why these risks arise, rather than only what they are, is prerequisite to addressing them effectively.

Commercial incentives create a structural tension between AI vendors and educational institutions. Vendors benefit from broad adoption, and their product positioning emphasizes capabilities rather than limitations. Institutions that take vendor materials at face value—using marketing documentation as the primary source of information about a tool's properties—are unlikely to develop the critical perspective needed to teach students to evaluate AI tools appropriately. Independent assessment of tools before adoption, and honest presentation of tool limitations to students, requires effort that vendor relationships do not naturally incentivize.

The opacity of commercial AI systems makes bias detection genuinely difficult, not merely inconvenient. Most widely used AI HR tools do not expose their underlying models to scrutiny. Institutions lack the technical infrastructure to audit these systems independently, and vendors rarely provide the information that would make independent auditing possible. Teaching students to recognize that opacity as itself a risk—and to respond to it with appropriate skepticism—may be more realistic than teaching them to audit tools they cannot see inside.

Faculty knowledge gaps in AI ethics are widespread and, under current professional development conditions, slow to close. Most HRM faculty received their research training in fields—organizational behavior, labor relations, psychology—that did not centrally engage with machine learning or algorithmic decision-making. The knowledge required to teach AI ethics rigorously is genuinely interdisciplinary and is not easily acquired through self-study alongside a full teaching load. Institutions that expect faculty to develop this knowledge without structured support will find the development slow and uneven.

The regulatory environment for AI in education in China is still taking shape. Policy attention to AI in general has grown, but specific guidance on AI tool deployment in educational settings—covering questions of student data, tool transparency, and bias standards—remains underdeveloped. Institutions operating without external standards must develop their own, which requires resources and expertise that not all institutions have.

4.3 Multi-Stakeholder Governance Framework

Managing these risks effectively requires coordination across institutional, regulatory, professional, and vendor levels. No single actor has both the authority and the knowledge to address all four risk areas adequately.

Regulatory bodies carry the responsibility of establishing minimum standards rather than comprehensive prescriptions. Standards for transparency, bias auditing requirements, and data protection baselines applicable to AI tools used in educational contexts would give institutions clear compliance targets and would shift some of the burden of ethical due diligence from individual programs to the vendors seeking educational market access.

Institutions must establish internal processes for evaluating AI tools before classroom deployment. A standardized ethics review protocol—assessing bias documentation, data storage practices, and alignment with educational purpose—used consistently before any new tool is adopted provides a defensible process and surfaces problems early. The Suzhou model includes a light-touch version of this review, covering four criteria: vendor transparency about training data, documented bias testing, data handling compliance with student privacy requirements, and pedagogical appropriateness.

Vendors who access the educational market incur responsibilities that are not always acknowledged in current practice. At minimum, transparency about training data provenance and bias testing results should be a condition of educational deployment. Vendors who cannot or will not provide this information should be treated with heightened caution by institutions, not because their tools are necessarily problematic, but because the absence of transparency forecloses the institutional ability to assess risk.

Professional associations for HRM educators occupy a coordinating role that neither individual institutions nor regulatory bodies fill well. They can develop shared resources—ethical evaluation templates, anonymized incident reports, model curriculum frameworks for AI ethics—and can facilitate the kind of cross-institutional learning that allows good practice to spread faster than it otherwise would. In China, this role is currently underdeveloped relative to the need.

5. Conclusion

The central argument of this paper is that genuine AI literacy as a graduate outcome requires curriculum architecture, not just curriculum content. Adding a module on AI tools to an otherwise unchanged HRM program does not develop the kind of distributed, robust competency that employers need and that the field of HRM now requires. Structural change—in how courses are designed, in what assessment demands of students, and in how institutions govern the AI tools they deploy—is necessary.

The experience at Suzhou Institute of Industrial Technology is preliminary and confined to a single context. Students in the revised program performed better on practical applied tasks and reported feeling more prepared for AI-related aspects of HR work—but whether these gains represent durable competencies that transfer to employment outcomes has not been tested. The institutional conditions at Suzhou—engaged industry partners, a functioning interdisciplinary curriculum committee, faculty who were willing to invest time in tool learning—may not be representative. Replication studies at institutions with different resource constraints and faculty configurations would be valuable.

What is clear, however, is that the gap between how HRM is taught and how AI-integrated HR is practiced is not narrowing on its own. Programs that wait for the field to stabilize before revising their curricula are likely to find the field has moved again by the time revisions are in place. The model presented here is not the only possible response to that gap, but it is an attempt at a systematic one.

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