AI Digital Competency Coverage in Intelligent Accounting Course Systems: A Reproducible Analytical Method for Curriculum Enhancement

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Abstract. Accounting practice now runs on artificial intelligence, analytics and networked information systems, and accounting education has been slow to adjust. Curricula are expected to keep pace with shifting competency demands while still teaching technical knowledge and professional judgement as one thing rather than two, and that expectation has become the central problem in intelligent accounting education reform. This paper develops a framework for measuring how far a curriculum actually covers digital competency, and does so in a form that other programmes can rerun on their own data. Digital competency is treated as three connected layers: explicit AI capability, foundational digital capability, and the application of both to accounting tasks. Text analysis in Python is applied to 8,276 finance job advertisements from Zhaopin, and the competency signals found there are set against six accounting curriculum schedules from two undergraduate programme levels and three cohorts. Advertisements emphasise foundational capabilities (data processing and analytics, enterprise information systems, forecasting and decision support) far more than they name AI technologies, positions described in explicit AI terms are rare. Demand also varies across job groups, which argues against a single uniform digital module. The curriculum analysis shows AI content becoming more visible in formal course structures, but the three layers remain weakly connected to one another. The theoretical contribution is the three-layer framework for digital competency in intelligent accounting. The methodological contribution is a reproducible way of linking labour-market evidence to curriculum review without collapsing the two into one weighted score. Together they give programmes a basis for moving past the accumulation of technology courses toward competency development that holds digital foundations, intelligent applications and professional judgement together.

Keywords: Intelligent Accounting; Digital Competency; Curriculum Design; Reproducible Analysis.

1. Introduction

Artificial intelligence (AI), automation, predictive analytics and intelligent information systems have changed how accounting information is produced, processed, interpreted and used in organisational decisions. Transaction processing, financial analysis, reporting, risk identification and management support now involve these technologies to some degree, and accounting education has to respond. Graduates are expected to work with digital systems and analyse data, but also to judge what an AI system produces, recognise where an automated recommendation breaks down, and take responsibility for the professional judgement that follows [1,3,10]. The usual response has been to add software-oriented or AI-related courses. Course titles, however, are a poor guide to whether a curriculum offers a coherent path to digital competency. A programme can list AI courses while leaving data processing, programming, database management and systems integration thinly covered. In the other direction, courses in data analytics, accounting information systems and process automation may already carry much of what intelligent accounting requires, without any AI label. Curriculum review therefore has to separate explicit AI content from the enabling foundations and the accounting-task applications that make intelligent technologies usable.

Research on this question runs along two lines: what employers ask for, and what programmes teach. Suarta et al. [1] and Elo et al. [7] read accounting job advertisements for evidence of changing employer expectations, and Tiron-Tudor et al. [8] connect future-oriented digital skills to labour-market demand and to what students themselves expect. On the curriculum side, Birt et al. [2] analyse

how information technology and data analytics have been folded into accounting degrees, Dzuranin et al. [4] set out a framework for building analytics into a programme, Vysotskaya and Prokofieva [9] look at technology acceptance in management accounting and analytics teaching, and Busulwa et al. [3] frame the design dilemma of balancing present against future competency requirements. Generative AI has widened the field further. Ballantine et al. [10] weigh the opportunities against the risks for accounting education, Tharapos et al. [11] examine what ChatGPT does to assessment and skill development, and Blondeel et al. [12] report the effects of GenAI in an accounting data analytics course. Read together, these studies point in one direction: technological knowledge has to be taught alongside accounting capability, analytical reasoning and professional judgement, not in place of them. What is still missing is methodological. As labour-market demand and curricula both keep moving, how can the fit between them be examined systematically, transparently, and in a way others can repeat? The distinction that matters is between explicit AI capability, the enabling digital foundations beneath it, and the competencies required by particular accounting tasks. Without that distinction, review tends to count AI-related courses and overlook the wider foundation on which intelligent accounting practice rests. This study builds such a method. External evidence from job advertisements is combined with internal evidence from curriculum schedules, and the two are kept analytically separate: advertisements show which digital competencies employers name, schedules show how those competencies appear in formal course structures. Keyword frequency is not treated as a measure of educational importance, and a course title is not treated as proof that students have acquired the corresponding competency. The setting is two programme pathways at one institution, regular and top-up undergraduate accounting; six curriculum schedules for the 2023, 2024 and 2025 cohorts are compared against 8,276 finance-related advertisements from Zhaopin, using Python-based text analysis and course-level curriculum mapping.

The paper makes three contributions. It proposes a three-layer framework of digital competency coverage: explicit AI capability, enabling digital foundations, and accounting-task applications. It sets out a dual-evidence method that links job-advertisement analysis to formal curriculum mapping without aggregating unlike evidence into a weighted composite score that could not be defended. And it provides a reproducible workflow in Python and Jupyter Notebook, with coding procedures documented, so that coverage can be compared across pathways and cohorts and re-run as schedules change. The purpose behind all three is to help intelligent accounting education move past the simple addition of technology courses.

2. Three-Layer Framework of AI-Related Digital Competency

AI digital competency is not treated here as a synonym for familiarity with AI software. It is a layered capability structure: explicit AI knowledge rests on data, computational and system foundations, and becomes professionally meaningful only when applied inside accounting tasks. The first layer is direct engagement with AI and intelligent applications. It covers understanding AI-enabled accounting applications, using intelligent decision-support tools, and interpreting what AI systems produce. In the evidence used here, the layer is identified through job-advertisement terms such as artificial intelligence, machine learning, deep learning, large language models, intelligent agents and generative AI, and through course titles such as Artificial Intelligence Fundamentals and Applications and Intelligent Financial Decision-Making. The layer is deliberately narrow: it captures visible references to AI rather than every digital capability that may support AI use. The second layer is the foundation for acquiring, structuring, processing, analysing and communicating data. It includes spreadsheets, databases and SQL, Python and programming, business intelligence and visualisation, ERP and accounting information systems, data processing and analytics, and process automation. None of this is necessarily labelled AI, in a schedule or in an advertisement, yet it supplies the data pipelines, system connections and repeatable workflows on which AI deployment in accounting depends. The third layer is application to accounting tasks: forecasting, variance analysis, financial decision support, audit and risk work, and the interpretation and review of outputs. A technically

correct model output is not an accounting conclusion. Students have to place evidence in its accounting context, identify exceptions, explain the implications, and recognise when a matter needs human review. The three-layer structure and its relationship to accounting practice are summarised in Figure 1.

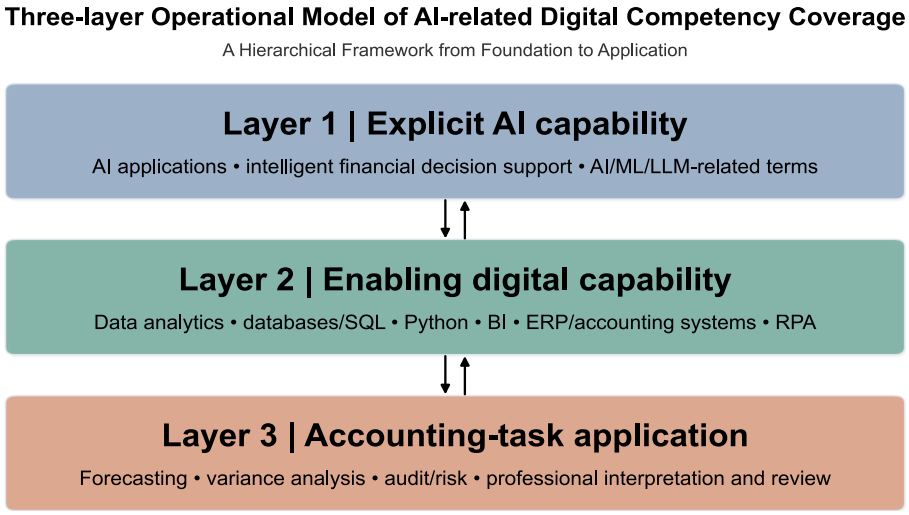


Figure 1. Three-Layer Framework of AI-Related Digital Competency Coverage.

The three layers complement one another rather than forming a sequence of course prerequisites. A single course can contribute to more than one layer, and one competency can be built across several courses. The study therefore reports course presence, listed credits, practical hours and AI-interdisciplinary markers as separate measures. It does not combine them into a single coverage score, because the weights for such a score could not be justified from the evidence available.

3. Research Design and Data

3.1. Research Design and Data Sources

The design is descriptive and comparative, and oriented toward curriculum design. External evidence comes from a local backup of 9,853 Zhaopin job-detail records; the fetchedAt field places retrieval between 29 and 31 August 2026, which dates the collection rather than any individual advertisement. Internal evidence comes from six official accounting curriculum schedules: regular undergraduate (2023, 2024 and 2025) and top-up undergraduate (2023, 2024 and 2025). These documents record course titles, credits, teaching hours, practical hours, course nature, semester and a course-feature marker. The regular undergraduate programme carries 160 credits over four years; the top-up programme carries 76 over two. Because the two differ in duration and in graduation-credit structure, they are examined separately. Credits listed for mapped course clusters are inventory measures only: they are not the share of a degree devoted to a competency, and should not be read as such.

3.2. Job-Advertisement Data Cleaning

Records were filtered to keep successful downloads (status = success), non-empty job descriptions (jdText) and records whose jobType field identified the finance category, which left 8,500. Duplicate keys were built from company name, detailed position title and full job text after Unicode NFKC normalisation, lowercasing and whitespace removal; removing 224 duplicates left 8,276 advertisements. The unit of analysis is the deduplicated advertisement, not a unique employer, a vacancy or an employee. Coding was applied to the responsibility and requirement fields rather than to company profiles, so that general corporate description is not mistaken for employee competency. Job titles were grouped by explicit regular-expression rules; the resulting role groups are analytical categories, not a validated occupational taxonomy.

3.3. Occupational Competency Identification

A dictionary-based coding procedure identified nine competency families, covering AI and enabling digital capability alike: AI and intelligent applications; data processing and analytics; ERP and accounting systems; forecasting and decision support; spreadsheet and office tools; BI and visualisation; databases and SQL; Python and programming; and automation/RPA. An advertisement scored 1 for a family if at least one matching expression appeared in its responsibility or requirement text, and 0 otherwise. The dictionary and the cleaned data are kept in the reproducibility package. The method is interpretable by design and suited to a first-stage scan. It does not establish semantic equivalence, proficiency, or whether an advertised capability is mandatory; it will miss synonyms and implicit requirements; and it counts a term even when that term appears in a hedged or marginal statement. Prevalence is therefore read as textual visibility in the sampled advertisements, not as a ranking of occupational importance.

3.4. Curriculum Mapping and Coverage Coding

Course-level records were extracted from the six schedules with Python and openpyxl, covering pathway, cohort, course code, title, credits, total hours, theory hours, practice hours, semester, course nature, and the AI-interdisciplinary marker (○) where present. Titles were mapped through an explicit codebook to seven clusters: AI applications and decision support; programming and computational thinking; data analytics and statistics; accounting and enterprise systems; process automation; financial analysis and decision-making; and audit, risk and compliance. Three kinds of evidence were retained. Course-title visibility records whether a cluster appears explicitly in a schedule. Listed credits and practice hours describe the formal scale of the listed course inventory. The AI-interdisciplinary marker identifies courses that the schedule itself flags as AI-cross-disciplinary. That marker is not proof that a marked course teaches AI content in depth, and an unmarked course may still contain relevant digital content.

3.5. Demand–Coverage Assessment

For advertisement j and competency family k, the lexical indicator J(j,k) equals 1 when the dictionary detects at least one matching expression in the responsibility or requirement text, and 0 otherwise. Observed job-advertisement prevalence is $P(k) = [\Sigma j\ J(j,k) / N] \times 100$, with $N = 8,276$. For curriculum cohort c and competency cluster k, course visibility C(c,k) equals 1 when at least one course title in cohort c maps to cluster k, and 0 otherwise. Listed credits and practice hours are reported next to C(c,k); they carry no weight in a composite index. Keeping the two apart is necessary. Job-advertisement prevalence and curriculum credits are different units of measurement, and dividing one by the other would yield a coverage ratio with no meaning. The analysis instead builds a demand–coverage diagnostic matrix, setting the visibility of occupational signals beside the visibility and formal position of related courses, and uses it to identify where syllabus-level review is warranted.

4. Results

4.1. Occupational Signals of AI-Related Digital Competencies

The most frequently detected signal was data processing and analytics, appearing in 3,367 advertisements (40.68%). ERP and accounting systems appeared in 2,450 advertisements (29.60%), followed by forecasting and decision support in 1,720 advertisements (20.78%) and spreadsheet/office tools in 1,588 advertisements (19.19%). By contrast, explicit AI and intelligent-application terms appeared in 107 advertisements (1.29%). BI and visualisation appeared in 2.80%, database/SQL in 1.05%, Python/programming in 0.47%, and automation/RPA in 0.42%. Figure 2 presents the relative visibility of these competency signals across the sampled advertisements.

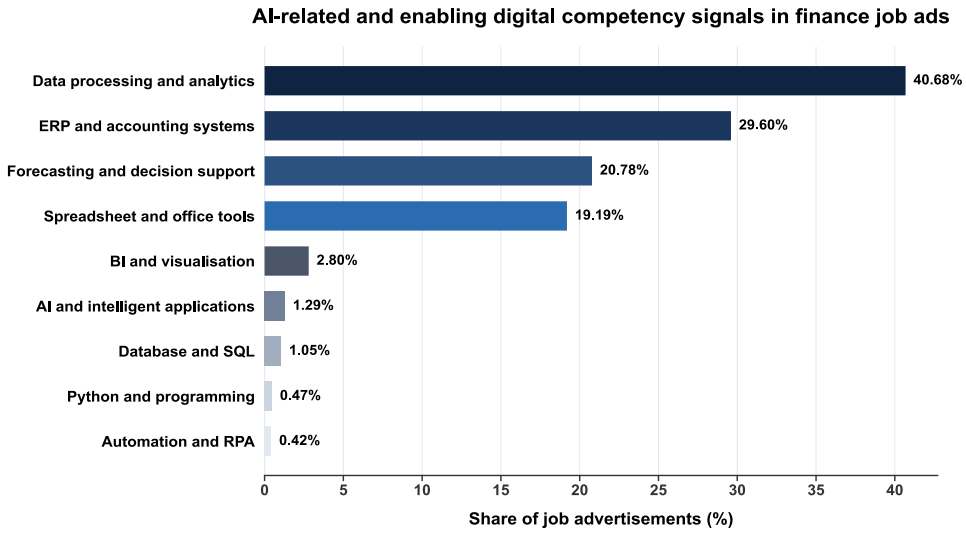


Figure 2. Occupational Visibility of Explicit AI and Enabling Digital Competency Signals.

Employers evidently describe broad data, system and decision-support tasks more often than they name AI technologies. That does not make AI unimportant. AI may sit inside a software product, or be described through the task it performs rather than by name. What the distribution does show is that an AI-oriented curriculum cannot be reduced to a single AI course: data processing, systems operation, analytics and decision support make up much of the visible digital capability environment in which graduates will work.

4.2. Competency Variation Across Job Groups

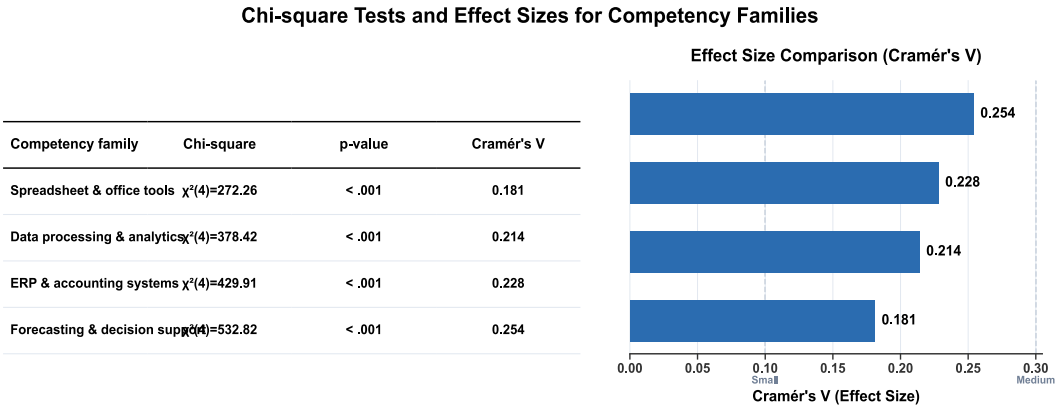


Figure 3. Competency Variation Across Five Job Groups.

As shown in Figure 3, four competency categories differ significantly across the five job groups: data processing and analytics, ERP and accounting systems, forecasting and decision support, and spreadsheet and office tools. Forecasting and decision support shows the strongest association with job group (Cramér's V = 0.254), followed by ERP and accounting systems (V = 0.228), data processing and analytics (V = 0.214) and spreadsheet and office tools (V = 0.181); all four are significant at $p < .001$. Digital competency requirements thus vary by accounting role, most of all in analytical and decision-support work. A single uniform digital skills module is unlikely to serve that variation, and competency development has to be differentiated by professional task. The tests cover only these four common enabling competencies. Less frequent terms, including explicit AI, Python, SQL and robotic process automation (RPA), are described but not tested.

4.3. AI-Related Course Coverage Across Programme Cohorts

The course-title analysis shows a clear increase in the formal visibility of AI-related content in the 2025 schedules. Neither the 2023 nor the 2024 regular undergraduate cohort includes a course

mapped to the direct AI application and decision-support category. In 2025 two courses appear, Artificial Intelligence Fundamentals and Applications B and Intelligent Financial Decision-Making, together worth four listed credits. The top-up programmes follow the same pattern: Intelligent Financial Decision-Making (2 credits) is first listed in the 2025 schedule. Beyond course titles, AI-related content also spreads across disciplinary courses. No course carries the AI-interdisciplinary marker in the 2023 and 2024 schedules; in 2025 the marker appears on eight regular undergraduate courses and four top-up courses, in areas such as accounting information systems, financial big data analysis, ERP, financial robotics and financial shared services. The shift is toward embedding AI content in existing accounting and digital technology courses rather than relying on standalone AI courses. Formal visibility, though, is not teaching depth. The marker is an official curriculum designation, not evidence of what happens in the classroom or of what students learn. One data discrepancy also needs checking: the eight marked regular undergraduate courses account for 18 listed credits, while the supplied programme summary reports 16. The approved master curriculum should be consulted before these figures go into formal programme reporting. The four marked top-up courses account for 10 listed credits.

4.4. Coverage of Enabling Digital Competencies

Enabling digital capabilities appear in all six cohorts, though coverage varies by pathway. The regular undergraduate programmes offer a relatively broad foundation in programming, data analytics, databases, statistical analysis, accounting information systems, enterprise systems and financial automation. The top-up programmes cover accounting information systems, financial big data analysis, statistical analysis and financial shared services, among other areas. One change stands out: Python Data Analysis Fundamentals (2 credits) appears in the 2023 schedule and in neither of the later ones. The credit-distribution heatmap shows the wider range of mapped digital competency courses in the regular undergraduate programmes, particularly in accounting and enterprise systems. That difference reflects programme duration and credit structure rather than educational quality. Nor does the absence of a standalone Python course in the later top-up schedules mean that Python content has dropped out of teaching. Only syllabus-level analysis can establish how far competency coverage actually extends. The listed-credit distribution across all seven competency clusters and six programme cohorts is shown in Figure 4.

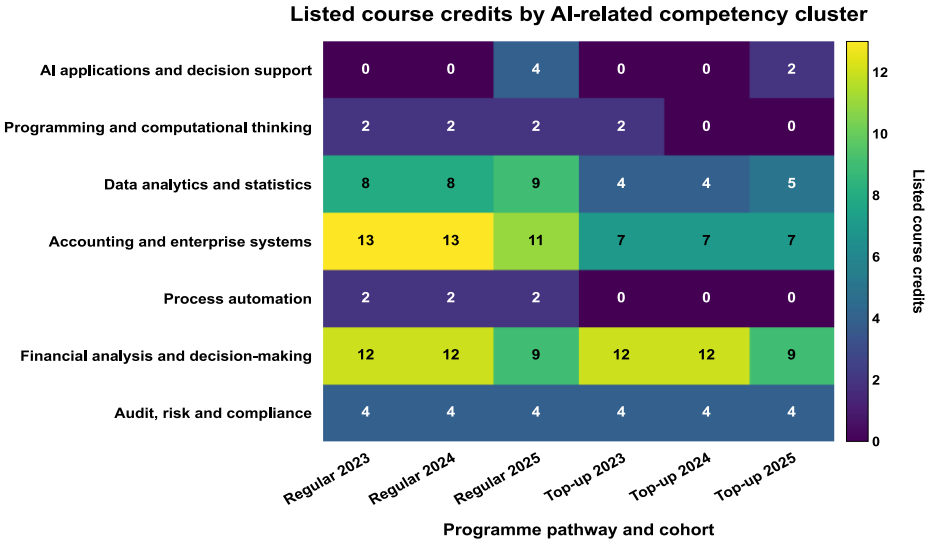


Figure 4. Listed Credits by Competency Cluster and Programme Cohort.

4.5. Integrated Demand–Coverage Diagnosis

Taken together, the occupational and curriculum evidence supports three observations. AI-related content becomes formally more visible in the 2025 schedules, while explicit AI references stay rare in the advertisements sampled. Occupational demand concentrates on enabling digital capabilities,

especially data analytics, enterprise systems, forecasting and spreadsheet applications, rather than on technologies labelled AI. And although existing curricula do provide a foundation in those enabling capabilities, course titles and curriculum markers cannot show whether students develop AI-ready data workflows, model evaluation, output verification or responsible technology use. Presence of courses is therefore a weak proxy. What matters is how those courses connect to professional accounting tasks and to stated learning outcomes.

5. Curriculum Enhancement Implications

5.1. From AI Course Counts to Integrated Competency Pathways

AI readiness cannot be assessed by counting courses with 'AI' in the title. Explicit AI courses and AI-interdisciplinary markers are one part of the picture; the more useful question is whether students can access, prepare, analyse and interpret data, work with accounting and enterprise systems, understand automation, use intelligent decision-support applications, and judge the outputs in an accounting context. The three-layer model makes those elements visible without assuming that any single course delivers the whole capability. The occupational evidence puts data processing and analytics, ERP and accounting systems, and forecasting ahead of explicit AI terminology, so AI-related courses need to be tied to foundational data and system capabilities. Assignments can require students to extract accounting data, document data quality, construct analytical features, use an AI-enabled tool on a defined task, compare its output against source evidence, and explain what follows. Justified that way, Python and SQL become part of a workflow rather than syntax to be memorised.

Python Programming Fundamentals has run continuously, and the 2025 addition of explicit AI-related courses gives the programme a visible foundation on which to build. The next priority is vertical integration: connect Python, databases, financial big-data analysis, ERP and accounting systems, financial robotics and intelligent decision-making through shared datasets and progressive assignments. The 2025 marker discrepancy should be reconciled with the approved programme record. For the top-up programme, Intelligent Financial Decision-Making and the four AI-marked courses point to a stronger formal AI orientation. Given the two-year structure, enhancement should concentrate on integration rather than on adding several new standalone courses. The disappearance of the Python Data Analysis Fundamentals title after 2023 warrants a syllabus audit of statistics, financial big-data analysis and accounting information systems; where practical data scripting is not already embedded, a compact applied Python/SQL component could be built into existing courses.

5.2. Embedding AI Verification and Professional Judgement

The schedules make AI and intelligent decision support more visible, but course titles cannot show whether students learn to question AI outputs. Curriculum enhancement should therefore specify learning outcomes and assessment tasks for output verification, source tracing, exception handling, data privacy, bias awareness, explainability and escalation to human review. These are recommendations drawn from the nature of AI-enabled accounting work, not findings that current courses lack such content; syllabi, assignments and assessments would be needed to establish actual coverage.

5.3. Reproducible Workflow for Continuous Curriculum Review

The workflow is built for continuous review, since recruitment data and curriculum schedules both change. Its procedures repeat by updating the competency codebook, recoding job descriptions, extracting course information and regenerating the coverage matrices. Jupyter Notebook supports this by keeping executable code, explanatory documentation and analytical outputs in one environment [5,6]. Reproducibility still depends on version-controlled input data, documented software dependencies, consistent cleaning procedures and a specified execution environment [6]. Because processing can be repeated and mapping is systematic, the approach works as a standing instrument for curriculum evaluation and quality assurance, not only as a one-off analysis.

6. Conclusion

This study develops a reproducible method for examining digital competency coverage in intelligent accounting education, drawing on two bodies of evidence: occupational requirements and curriculum structures. Its three-layer framework (explicit AI capability, enabling digital foundations, accounting-task applications) keeps AI technologies, the digital capabilities beneath them and accounting practice in the same view, which gives intelligent accounting education an analytical handle on how digital competency actually develops. Analysis of 8,276 finance job advertisements and six curriculum schedules shows occupational practice weighted toward foundational digital capability, particularly data processing and analytics, enterprise information systems, forecasting and decision support, and spreadsheet applications; explicit references to AI technologies are comparatively limited. The curriculum analysis finds greater formal visibility of AI-related content in the 2025 regular undergraduate and top-up programmes, alongside existing provision in data analytics, information systems, programming and process automation. Intelligent accounting curricula, on this evidence, should extend past the introduction of AI-labelled courses toward integration of digital foundations, intelligent applications and professional accounting tasks. The practical implication is a shift from adding technology-oriented courses one at a time to developing integrated digital competencies in a coordinated way: strengthening the links among data processing, analytical tools and enterprise information systems, and embedding AI applications in financial analysis, auditing, risk identification and decision support. Output verification, professional judgement and responsible technology use belong in learning objectives and assessment as well.

Acknowledgments

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