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Designing a Learning Matrix for Business Education within a Human–AI Learning Community: A Pedagogical Design Study

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Abstract

This study examines the redesign and implementation of a Management Accounting Practice course at a Chinese university during the autumn 2025 semester. Adopting a pedagogical design-study approach, the study draws on learner-context evidence, prior teaching records and reflection, professional digital demands, course-design documents, task and assessment materials, and selected student work. Three design problems were identified: insufficient integration of disciplinary content with digital and intelligent resources; fragmented teaching implementation that limited coherent progression from understanding to analytical application and integrative practice; and an assessment approach that did not adequately capture staged skill development and broader professional growth. In response, a learning matrix was developed around three progressive stages—exploratory understanding, analytical application and integrative practice—and three recurring dimensions of disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making. The matrix was enacted through foundation knowledge practice, project and case learning, integrative practice, differentiated support, and stage-specific use of digital and intelligent tools. Implementation records and an AI-Supported Cost–Volume–Profit (CVP) Decision Lab illustrate how disciplinary reasoning, digital tool use, verification and managerial judgement were connected in practice. The study contributes a problem-to-design framework for integrating digital and intelligent technologies into applied business education while retaining accountable human judgement.

Keywords: human–AI learning community, learning matrix, pedagogical design, digital and intelligent tools, applied business education

1. Introduction

Artificial intelligence (AI), data analytics and related digital technologies are reshaping business practice and the competencies expected of graduates. Beyond disciplinary knowledge, business graduates increasingly need to interpret complex information, work with intelligent technologies and exercise judgement in data-rich, uncertain settings (Holmes et al., 2019; Luckin, 2018). Yet integrating AI into disciplinary teaching is not straightforward: when AI is used mainly as a supplementary resource or efficiency tool, easier access to information does not necessarily translate into deeper learning, and students may obtain polished answers without learning to evaluate them critically, connect them to disciplinary knowledge or judge their suitability for a professional problem.

This challenge is especially relevant in applied business education, where students often enter through diverse educational pathways and differ in prior academic preparation, learning experience and digital literacy. A uniform model of AI-supported instruction is therefore unlikely to meet all learners' needs, while generative AI may also reduce opportunities for independent analysis and reflection when its use is not anchored in explicit pedagogical expectations (Holmes et al., 2019). Management accounting provides a useful setting in which to examine these tensions because contemporary practitioners must interpret financial information, analyse organisational data, support strategic decisions and work with emerging digital tools. Meeting these demands requires more than adding AI to existing activities; pedagogical design must keep disciplinary reasoning, verification and professional judgement visible.

Research on AI in education has mapped a wide range of learning and assessment applications while calling for stronger accounts of pedagogy and evidence (Chiu et al., 2023; Ouyang et al., 2022; Zawacki-Richter et al., 2019). Ouyang and Jiao (2021), for example, distinguish AI-directed, AI-supported and AI-empowered relationships to learner agency. In accounting education, Ballantine et al. (2024) emphasise the continuing importance of human judgement as AI enters teaching; Haugland Sundkvist and Kulset (2024) examine students' perceptions and use of ChatGPT; and Wiseman and Foster (2025) use error review to prompt students to interrogate AI-supported cost-accounting work. Building on this literature, the present study focuses on the design decisions and student work through which digital and AI support was embedded in a specific course, while keeping claims about learning outcomes proportionate to the available evidence.

In this article, a Human–AI Learning Community refers to a pedagogical arrangement that organises participation, support and responsibility around technology-supported learning tasks. It provides the relational logic of the design: students and peers interpret and challenge ideas; the instructor frames tasks, diagnoses difficulties, adjusts support and makes assessment decisions; and AI contributes explanations, analyses or alternative scenarios that remain subject to human checking (Wenger, 1998; Holstein & Aleven, 2022). The learning matrix translates this relational logic into a curricular architecture by organising what students do across three progressive stages—exploratory understanding, analytical application and integrative practice—and three recurring dimensions—disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making. In other words, the Human–AI Learning Community clarifies who participates and where accountability remains, whereas the learning matrix structures how learning tasks, tools and assessment progress. The study focuses on the autumn 2025 redesign, using a November 2024 teaching report and archived platform screenshots as the practice-oriented starting point rather than as a comparison cohort. The central design challenge is therefore how disciplinary content, digital and intelligent resources, learning activities and assessment can be coordinated within a coherent progression while students retain responsibility for checking evidence, interpreting outputs and making professional decisions.

Using design-based research as a methodological orientation (Brown, 1992; Design-Based Research Collective, 2003; McKenney & Reeves, 2019), this article asks: (RQ1) How can disciplinary content and digital and intelligent resources be integrated within a learning matrix to support progressive learning in business education? (RQ2) How can teaching implementation be systematically organised across exploratory understanding, analytical application and integrative practice? (RQ3) How can assessment be aligned with the learning matrix to capture differentiated skill development and broader professional growth?

Accordingly, the study adopts a pedagogical design focus. Learner-context indicators, prior teaching records and professional demands are used to diagnose the design problem; course documents, implementation records and selected artefacts are used to examine how the learning matrix was enacted. The contribution lies in the alignment among content, stage-specific digital and intelligent tools, learning activities and assessment, rather than in estimating a causal treatment effect.

2. Conceptual Framework

2.1 Human–AI Participation and Responsibility

Communities of practice locate learning in participation in shared activity (Wenger, 1998). In the present course, AI-generated material becomes an object for discussion, checking and revision rather than an accountable member of the learning community. The instructor designs tasks and judges when support is needed; students explain assumptions, compare outputs with accounting evidence and justify final choices; peers can question both the AI output and the student's interpretation. AI contributes rapid retrieval, alternative formulations and scenario generation, but its outputs remain open to error. This division of responsibility is the operational meaning of the Human–AI Learning Community used here (Luckin, 2018; Holstein & Aleven, 2022; Zawacki-Richter et al., 2019).

2.2 When AI Support Counts as Scaffolding

Scaffolding is support calibrated to a learner's current difficulty and directed toward more independent performance, rather than a permanent supply of answers (Wood et al., 1976; Vygotsky, 1978; Hmelo-Silver et al., 2007). Applied to digital tools, the concept requires caution: the availability of hints or software does not establish contingency, fading or transfer (Pea, 2004; Puntambekar & Hübscher, 2005). In this design, the instructor or learner first identifies a task difficulty, such as interpreting a variance or selecting a relevant decision criterion. AI may then provide a comparison or prompt, while later work requires the student to explain the reasoning with fewer prompts, critique a generated analysis or justify a conclusion in a new case. The unit of support is the task and the learner's demonstrated need.

Empirically, an activity is described as scaffolding only when the records show calibration or withdrawal of support; otherwise, it is treated as AI-assisted learning.

2.3 Learning Progression across Stages and Dimensions

The learning matrix combines three progressive stages—exploratory understanding, analytical application and integrative practice—with three dimensions that recur throughout: disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making. The stages represent increasingly integrative task demands rather than fixed levels of technology use. A student may return to conceptual explanation while completing a complex decision task, and the instructor may adjust support in response to performance. Digital and intelligent tools are therefore selected according to the learning task, while human verification and judgement remain visible across all three stages.

3. Research Design and Analysis

This study used a design-based research orientation to examine how a management accounting course was redesigned and enacted in its regular teaching setting (Brown, 1992; Design-Based Research Collective, 2003; McKenney & Reeves, 2019; Reeves, 2006). The unit of analysis was the course-level design and implementation in autumn 2025. The design problem was framed from three complementary sources: learner-context evidence from the 2025 cohort, prior teaching records and reflection, and changing professional demands. These sources were used to identify problems in content-resource integration, teaching implementation and assessment, and to trace the corresponding design response.

The setting was Management Accounting Practice, a compulsory third-year course for accounting majors at a university in Sichuan, China. The course carried two credits and 32 contact hours across a 16-week semester, including 16 theoretical and 16 practical hours. It was delivered in a blended format combining face-to-face teaching with online learning. The Chaoxing online learning platform was used to distribute instructional videos, preview materials and reference resources, collect student assignments, and organise selected case tasks and AI-supported practice activities. Course records report 1,279 students enrolled in autumn 2025, and 1,270 students completed the baseline questionnaire on 1 September 2025. Relevant questionnaire responses and platform-generated records used in this study were exported from the Chaoxing platform. Selected item-level frequencies are used descriptively to characterise learner preparation, patterns of generative-AI use and professional awareness at the start of the course. The selected baseline items asked students to rate their grasp of management-accounting concepts, their ability to select and explain a method in a business case, the frequency and primary purpose of generative-AI use, and their understanding of professional knowledge, digital skills and responsibilities. They serve as contextual and diagnostic evidence for course redesign rather than as outcome measures.

The evidence base comprised five sources: (1) the 2025 learner-context questionnaire; (2) prior teaching reports, platform records and teacher reflection; (3) course-design documents describing content, stage progression, digital and intelligent tools, learning activities and assessment; (4) 2025 task briefs, rubrics and implementation records; and (5) selected student work and associated feedback, reported without student identifiers. One product from the AI-Supported Cost–Volume–Profit (CVP) Decision Lab is analyzed as an illustrative Stage 2 artefact because it contains the full sequence from disciplinary calculation to tool construction, scenario comparison, verification and managerial recommendation. It illustrates enactment of the design rather than average cohort attainment.

For analysis, the evidence was organized around a problem-to-design chain: learner context and professional demand; teaching problem; design response; stage-specific implementation; assessment evidence; and documented adjustment. Questionnaire frequencies are reported descriptively where they clarify the teaching context and the denominator is identifiable, while course documents and selected artefact are examined for alignment among disciplinary content, digital and intelligent tools, learning activity and professional judgement. Because the analysis is document- and artefact-based rather than an independently double-coded thematic analysis, no inter-rater reliability statistic is reported. The analytical goal is to explain how the learning matrix was designed and enacted rather than to estimate population parameters or causal learning effects: learner-context evidence defines the starting conditions, prior teaching records diagnose instructional problems, professional demands orient target capabilities, and implementation records show how the response was enacted. Historical grades, competition awards and graduate feedback are treated as background to course development rather than outcome measures for the 2025 cohort.

4. Course Context and Design Problems

Management Accounting Practice is a compulsory third-year course covering strategic management accounting, planning and forecasting, operational decisions, cost management and performance evaluation through cases, projects and integrative practice. The autumn 2025 cohort included 1,279 students. The design diagnosis combined learner-context data with prior teaching records and changing professional demands so that the identified problems reflected both student starting points and the capabilities expected in increasingly digital management-accounting work. Among the 1,270 students who completed the baseline questionnaire, 57.9% described their grasp of basic management-accounting concepts as weak or relatively weak, 64.8% reported that they were unable or largely unable to select an appropriate method independently and explain the result in a business case, and 41.3% reported limited understanding of the knowledge, digital skills and professional responsibilities required in management-accounting work. Generative-AI use was already common: 54.4% reported using it often or in almost every learning task, yet 38.5% identified direct answer retrieval as their most common use, whereas only 2.8% most commonly used AI to compare alternatives with their own conclusions. These self-reported indicators are used as learner-context background for identifying design needs.

4.1 Design Problem 1: Insufficient Integration of Disciplinary Content and Digital Resources

The first problem concerned the separation between disciplinary learning and digital-resource use. Students entered with uneven preparation, while digital and AI-related activities had been added to the course without yet forming a coherent progression from concept learning to analytical use. The redesign therefore embedded disciplinary content and digital and intelligent resources within the learning matrix rather than treating technology as an additional technical component. In exploratory understanding, shared platform resources, guided inquiry and concept checks support foundational knowledge; in analytical application, Excel, Power BI and generative AI are linked to case and project analysis; and in integrative practice, Python, Power BI and other tools can be combined for modelling and complex problem solving. Across all three stages, tool choice follows the disciplinary task and does not itself define the stage.

4.2 Design Problem 2: Fragmented Teaching Implementation

The second problem was the lack of a systematic implementation path linking teaching activities to progressive capability development. Prior records and teacher reflection pointed to a need for clearer movement from data handling and basic application to modelling, verification and decision-making. The redesign therefore organised implementation around three learning forms: Stage 1 uses concept checks, introductory cases and basic data handling to establish a common disciplinary base; Stage 2 moves to project and case learning in which students apply accounting methods, visualize or model data and verify digitally supported outputs; and Stage 3 extends learning to competitions, enterprise or internship projects and student research, where multiple tools and professional constraints are combined. The AI-Supported CVP Decision Lab is a representative Stage 2 task: students calculate core cost–volume–profit relationships, construct a browser-based calculator with generative-AI assistance, vary price, cost and volume assumptions, check the results and explain the managerial implications. This stage-based organization is consistent with accounting-education research that stresses the continuing importance of human judgement and error checking when digital and AI-supported tools are introduced into disciplinary work (Ballantine et al., 2024; Wiseman & Foster, 2025). The emphasis is therefore on increasingly integrated professional tasks rather than on a hierarchy of software.

4.3 Design Problem 3: Assessment Not Aligned with Staged and Developmental Learning

The third problem concerned assessment. The earlier approach emphasised quantitative course results but did not fully represent differences in staged skill development or broader professional growth. The redesign therefore aligned assessment with the learning matrix by combining continuous and final assessment with task-level criteria for technical accuracy, analytical reasoning, verification, communication and professional judgement, while also retaining qualitative attention to self-directed learning, professional conduct, innovative thinking and breadth of perspective. Participation, case and project work, the final examination, task rubrics and qualitative indicators thus provide different forms of evidence across the learning progression. The purpose is not to create a single composite measure of growth, but to make different aspects of learning visible at the stage where they are developed. Table 1 maps the three teaching problems to their diagnostic basis and corresponding design responses in the learning matrix.

Table 1. Mapping Teaching Problems to Learning-Matrix Responses

Teaching problem	Diagnostic basis	Learning-matrix response
Insufficient integration of disciplinary content and digital resources	Learner-context questionnaire; prior course records; professional digital demands	Embed disciplinary content and digital/intelligent resources across all three stages; select tools according to the task.
Fragmented teaching implementation	Prior teaching records and teacher reflection; need for clearer progression from data handling to modelling and judgement	Organise implementation as foundation knowledge practice → project/case learning → integrative practice.
Assessment not aligned with staged and developmental learning	Review of existing course assessment and teaching goals	Align participation, cases, projects, task rubrics, final examination and qualitative indicators with the learning matrix.

5. Pedagogical Model and Implementation

5.1 Learning Matrix: Structure and Design Principles

The learning matrix is the core pedagogical design of the study. Its horizontal axis consists of exploratory understanding, analytical application and integrative practice, while its vertical axis consists of disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making. The horizontal progression increases task integration, whereas the vertical dimensions remain active across all three stages. The Human–AI Learning Community provides the governing relational principle for this structure: the instructor frames the disciplinary problem, selects or adjusts support and retains assessment responsibility; students interpret evidence, check calculations and technology-supported outputs, and justify final decisions; peers contribute through discussion and critique; and AI provides explanations, comparisons or alternative scenarios subject to human evaluation. The matrix therefore operationalises the community perspective by translating these differentiated responsibilities into a staged pattern of learning tasks, digital support and assessment rather than treating AI as an accountable member of the community.

Three design principles follow. First, disciplinary content and professional tasks precede tool selection. Second, digital and intelligent tool use should leave visible evidence of student checking, interpretation and decision-making. Third, learning activities and assessment should change with task demands while the three dimensions remain connected across stages. Table 2 summarises the learning matrix in textual form and Figure 1 provides the corresponding visual model. The stages are not rigid levels: students may return to an earlier conceptual or analytical task when later work exposes a gap in understanding, and instructors may adjust support according to student performance.

Table 2. Learning Matrix: Stages, Dimensions and Evidence

Dimension	Exploratory Understanding	Analytical Application	Integrative Practice
Disciplinary Knowledge	Core concepts and principles	Business methods and analysis	Complex enterprise problems
Digital and Analytical skills	Data collection, cleaning and platform use	Visualisation, modelling and problem analysis	Integrated modelling and multi-tool application
Professional Judgement and Decision-making	Check sources, accuracy and assumptions	Test assumptions and compare alternatives	Weigh constraints and justify decisions
Typical Learning Form	Foundation knowledge practice	Project and case learning	Integrative practice
Evidence Retained	Concept checks and corrected outputs	Case/project files, feedback and rationale	Integrated products and final justification

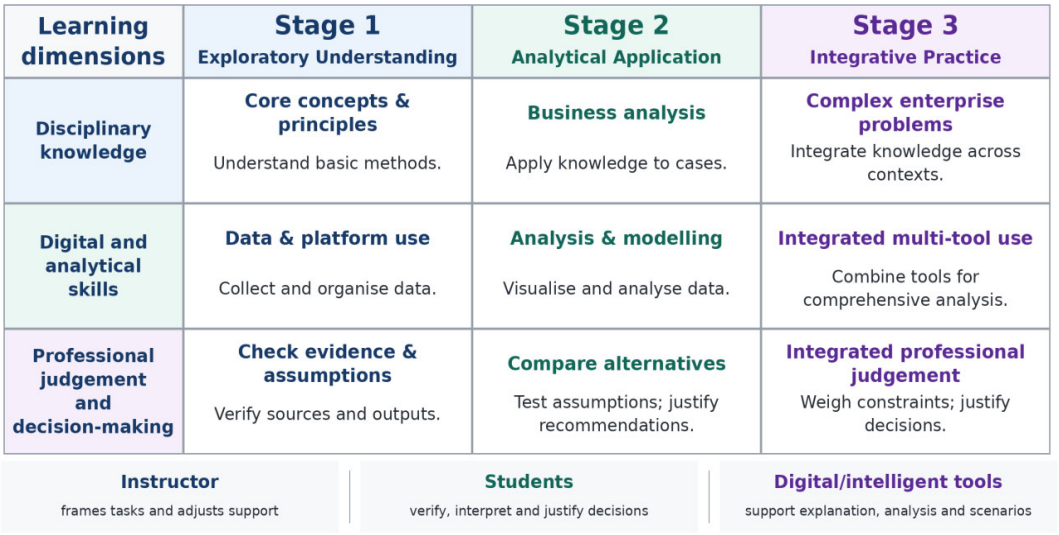


Figure 1. Learning Matrix within a Human–AI Learning Community

5.2 Stage-Specific Integration of Digital and Intelligent Tools and Learning Activities

Figure 2 shows how the learning matrix is enacted through stage-specific combinations of learning activity and digital and intelligent tools. The tools are not treated as AI tools collectively; the category includes learning platforms, digital resources, Excel, Power BI, Python and generative-AI services, selected according to the task.

Stage 1: Exploratory Understanding

Stage 1 takes the form of foundation knowledge practice. The Chaoxing platform provides access to instructional videos, preview materials and reference resources, while selected case exercises and AI-supported practice tasks are also distributed and submitted online. Shared digital resources and generative AI support inquiry, explanation and correction, while concept checks, introductory cases and basic data handling make students' understanding visible. The aim is to establish core concepts and principles before task complexity increases.

Stage 2: Analytical Application

Stage 2 takes the form of project and case learning. Excel and Power BI support calculation, data organisation and visualisation, while generative AI can support analysis or tool construction; students remain responsible for selecting accounting methods, checking outputs, comparing assumptions and explaining implications. The AI-Supported CVP Decision Lab illustrates this stage: students first complete the core calculation independently, then use generative AI to construct a browser-based calculator, vary price, cost and volume assumptions, and check the generated results against their own calculation. The task therefore moves from accounting logic to digitally supported analysis and a justified managerial recommendation.

Stage 3: Integrative Practice

Stage 3 extends learning to integrative professional practice. Python, Power BI and tools from earlier stages can be combined for programming, modelling, visualisation and scenario analysis, while competitions, enterprise or internship projects and student research provide settings in which students integrate disciplinary knowledge, digital skills and professional judgement under more open-ended constraints. Across the three stages, the progression is therefore from foundation knowledge practice to project and case learning and then to integrative practice; it concerns the growing integration of knowledge, skills and judgement rather than simply the increasing technical difficulty of software.

5.3 Layered and Developmental Assessment

Assessment is aligned with the learning matrix. The course uses a 100-point scale in which continuous assessment and the closed-book final examination each contribute 50%. Within continuous assessment, online participation and classroom participation each contribute 10 percentage points, while case work and project work each contribute 15; practice achievements may receive an additional bonus. This structure places evidence from participation, case analysis

and project work alongside the final examination rather than relying on a single outcome measure. Task-level rubrics then make stage-specific skill development visible: in the AI-Supported CVP Decision Lab, for example, criteria cover foundational calculation, digitally supported tool construction, accuracy and visualisation, scenario analysis and decision-making, and checking and reflection. Automated platform feedback is treated as formative information rather than a substitute for instructor oversight.

The assessment system also includes qualitative attention to self-directed learning, communication, professional conduct, innovative thinking and breadth of perspective, with feedback from teachers, peers, the platform and external participants. In this way, assessment is designed to capture both differentiated skill development and broader professional growth across the learning matrix.

5.4 Development and Documented Adjustment

The 2025 learning matrix developed from an existing practice-oriented course. Autumn 2024 materials documented an AI-practice "thinking-ladder" task and an accompanying teaching reflection; together, they provided a diagnostic starting point for redesign rather than an experimental comparison baseline. The 2025 redesign made the content–tool connection, stage progression and assessment alignment more systematic, with differentiated pacing and requirements according to student performance and stage-specific combinations of learning platforms, digital resources, analytical software and generative AI organised around increasingly integrated tasks. The AI-Supported CVP Decision Lab illustrates the Stage 2 transition from independent calculation to tool construction, verification, scenario testing and managerial recommendation. Taken together, these records support a design-based account in which learner context and prior classroom evidence informed the redesign of content, implementation and assessment; different cohorts are not treated as an experimental pre–post comparison.

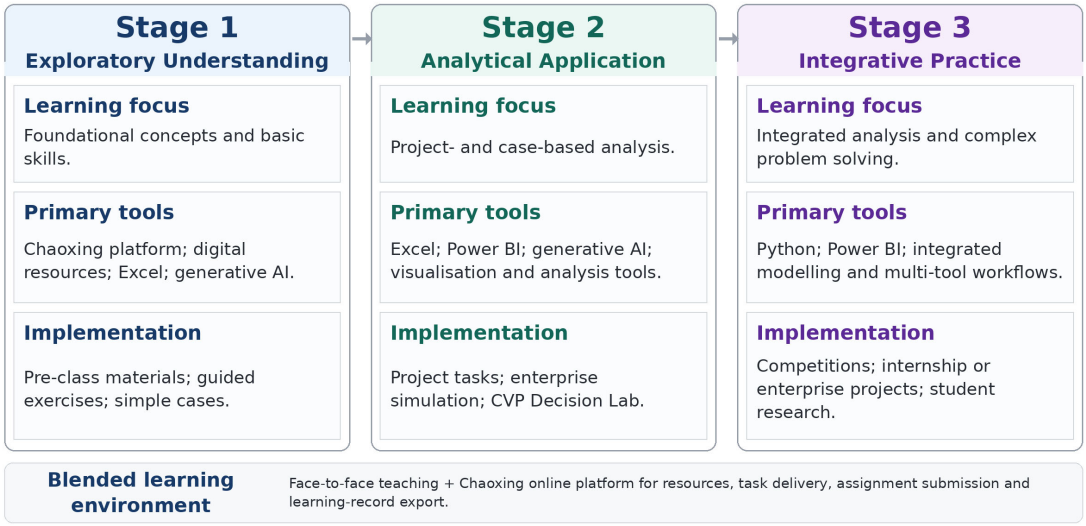


Figure 2. Stage-Specific Integration of Digital and Intelligent Tools and Learning Activities

6. Findings and Discussion

6.1 Implementation and Design Adjustment

The findings are organized around the three design problems and the corresponding learning-matrix responses. The 2025 learner-context questionnaire showed a combination of uneven conceptual preparation, limited independent case analysis and widespread but shallow generative-AI use, while prior teaching records pointed to the need for clearer progression from data handling to modelling and for more explicit checking of digitally supported outputs. Together with changing professional demands, these findings justified a redesign that linked course content, learning stages and assessment rather than simply adding more technology. The learning matrix translated these problems into a coherent structure by organizing learning through exploratory understanding, analytical application and integrative practice while keeping disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making

active across all stages. Implementation records also document differentiated expectations: students demonstrating stronger preparation could move toward more integrative tasks, while those needing additional support could focus first on foundation and project work.

A second finding concerns the role of technology. The redesign replaced a tool-centred logic with a task-centred one. Shared platforms and basic digital resources supported foundational work; Excel, Power BI and generative AI supported project and case analysis; and Python, Power BI and multi-tool combinations supported integrative practice. AI was therefore embedded within a broader digital and intelligent tool chain rather than treated as the organizing principle of the course.

6.2 Evidence from Course Implementation, Assessment and Student Work

Implementation records show that the redesign extended across course resources, learning activities and assessment. The 2025 teaching report describes two online learning platforms, seven resource repositories, more than 74 teaching videos and animations, 76 discussion resources, 86 case-practice resources, 56 project tasks and three practice-resource repositories. These counts do not demonstrate learning improvement, but they show that the learning matrix was supported by course-level resources rather than confined to one isolated activity. The assessment system was likewise aligned with the matrix: continuous assessment accounted for 50% of the course mark and included online participation, classroom participation, case work and project work, while the final examination accounted for the remaining 50%. Task-level rubrics and qualitative indicators added evidence of analytical reasoning, verification, communication and professional judgement, addressing the earlier limitation of relying predominantly on undifferentiated quantitative results.

A representative product from the AI-Supported CVP Decision Lab illustrates Stage 2 enactment. Students completed the accounting calculations, used generative AI to construct a simple interactive decision tool, tested alternative price, cost and volume assumptions, verified the results and provided a managerial recommendation. The artefact is included to make the analytical-application design visible rather than to represent average cohort performance or to estimate a learning effect. Table 3 aligns the three research questions with the design problem addressed, the evidence used and the design response supported by that evidence.

Table 3. Alignment of Research Questions, Evidence and Design Responses

Research Question	Design Problem Addressed	Evidence Used	Design Response Supported
RQ1	Content and digital/intelligent resources insufficiently integrated	2025 learner-context data; prior course records; professional-demand literature	Learning matrix integrates disciplinary content with stage-specific digital and intelligent resources.
RQ2	Teaching implementation lacked systematic progression	Teaching reports; task briefs; implementation records; selected Stage 2 artefact	Implementation progresses from foundation knowledge practice to project/case learning and integrative practice.
RQ3	Assessment did not fully capture staged skills and broader growth	Course assessment scheme; task rubrics; feedback arrangements	Layered and developmental assessment aligns participation, cases, projects, task criteria and qualitative indicators with the matrix.

6.3 Discussion and Design Implications

The study extends the Human–AI Learning Community idea from "using AI in class" to organising responsibility across a wider learning system. AI is one part of a digital and intelligent tool chain; students remain responsible for interpretation, verification and decision-making, and instructors coordinate content, tasks, support and assessment. This preserves Wenger's emphasis on human participation while using technological resources to expand inquiry and analysis (Wenger, 1998; Luckin, 2018; Holstein & Aleven, 2022).

The learning-matrix perspective also reframes scaffolding. Support is not defined by a particular software package or by permanent assignment to a stage. It is calibrated to the task and can be increased, redirected or reduced as students move among foundation knowledge practice, project and case learning, and integrative practice. This is consistent with scaffolding accounts that distinguish contingent support from simple tool availability (Pea, 2004; Puntambekar & Hübscher, 2005). The interpretation is also compatible with Vygotsky's account of assisted performance and with Holmes et al. (2019), who emphasise the continuing importance of human pedagogical agency when intelligent technologies enter learning environments.

For applied business education, the broader implication is a problem-to-design logic: diagnose where content, digital resources, implementation and assessment are misaligned; organise learning through progressively integrative tasks; select digital and intelligent tools according to those tasks; and make professional judgement visible in both learning products and assessment. The value of the matrix lies in coordinating these elements rather than in prescribing a fixed technology sequence.

6.4 Limitations

The study is based on one course at one institution and does not include a comparison group or a validated pre–post measure of analytical competence. The learner-context questionnaire is used descriptively to diagnose starting conditions, and historical grades, competition achievements and graduate feedback cannot estimate the effect of the 2025 redesign. Observed patterns may also reflect differences in prior preparation, task difficulty, instructor experience and students' access to external digital or AI tools. The findings therefore support the design rationale, documented implementation and selected examples of student work rather than a causal claim of improved competence.

7. Conclusion

This study examined the design and implementation of a learning matrix for an applied management accounting course within a Human–AI Learning Community. The matrix was developed in response to three linked teaching problems: insufficient integration of disciplinary content with digital and intelligent resources, fragmented teaching implementation, and assessment that did not fully capture staged skill development and broader professional growth. It combines exploratory understanding, analytical application and integrative practice with disciplinary knowledge, digital and analytical skills, and professional judgement and decision-making. Within this architecture, the Human–AI Learning Community defines how responsibility is distributed among instructors, students, peers and AI, while the matrix organises how those responsibilities are enacted through progressively more integrative tasks, stage-specific digital support and assessment. Implementation therefore progresses from foundation knowledge practice to project and case learning and then to integrative practice, with digital and intelligent tools selected according to the learning task rather than treated as ends in themselves.

Course documents, implementation records and the AI-Supported CVP Decision Lab show how the matrix can connect disciplinary reasoning, technology use, verification and managerial judgement in practice. These materials provide evidence of design enactment rather than a causal estimate of learning gains. The main contribution is therefore a practical problem-to-design framework for applied business education: diagnose misalignment among content, resources, implementation and assessment; organise learning through a matrix of progressive stages and recurring dimensions; distribute responsibility within a Human–AI Learning Community so that human verification and judgement remain accountable; integrate digital and intelligent tools according to task demands; and align assessment with differentiated skill development and professional judgement. Future research can test learning effects more directly through matched tasks, explicit rubrics and repeated or longitudinal measures.

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Investigation: Di Fan

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Consent for Publication

All authors have read and approved the published version of the manuscript.

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Declaration of Competing Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Informed Consent

Informed consent was obtained from all participants.

Ethics Approval

This study retrospectively analysed routine course-design documents, platform records, and coursework generated through normal teaching. The underlying teaching activities and assessed coursework formed part of ordinary instruction. For research use, participants were informed about the study and were able to choose freely whether or not to participate. Student-related material used for analysis and publication was de-identified; no student names or account identifiers are reproduced. Non-public information was treated as confidential, and the analysis was conducted with attention to participant welfare and honest, transparent reporting.

Data Availability Statement

The underlying student questionnaire responses, course-platform records and student work are not publicly available to protect participant privacy and confidentiality. The authors do not provide access to these underlying data.

Use of Artificial Intelligence

ChatGPT (OpenAI; GPT-4 in earlier language-editing work and GPT-5 during the September 2026 major-revision stage) was used for translation support, language editing, restructuring and drafting assistance. The authors reviewed and revised all AI-assisted text and independently verified references, factual claims, data, interpretations and final wording. No synthetic data generated by AI are reported as empirical findings in this article.

Supplementary Materials

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