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METHODOLOGY FOR DEVELOPING STUDENTS' PROFESSIONAL COMPETENCIES THROUGH ARTIFICIAL INTELLIGENCE-BASED ADAPTIVE LEARNING TOOLS

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Abstract

Artificial intelligence-based adaptive learning tools are increasingly used to diagnose learners' prior knowledge, recommend resources, adjust task difficulty, generate feedback, and analyse learning traces. However, the availability of such functions does not automatically produce professional competence, because competence is demonstrated through integrated performance in authentic situations rather than through isolated test scores. This article develops a methodology for using artificial intelligence-based adaptive learning tools to support the development of university students' professional competencies. The study is theoretical and design-oriented. It combines conceptual analysis, competence mapping, pedagogical modelling, and synthesis of research on adaptive learning, intelligent tutoring systems, learning analytics, formative feedback, self-regulated learning, and human-centred artificial intelligence. The results are presented as an eight-stage adaptive cycle: competency profiling, multisource diagnosis, construction of an explainable learner model, design of an individual pathway, performance of authentic professional tasks, AI-supported feedback, reflection in an electronic portfolio, and competency assessment with subsequent recalibration. Six components of professional competence are operationalised: motivational-value, cognitive-professional, operational-digital, communicative-collaborative, reflective-analytical, and innovative-ethical. The scientific novelty lies in connecting adaptive recommendations with professional tasks, triangulated evidence, teacher orchestration, explainability, data minimisation, and ethical safeguards. The proposed methodology can guide the design of LMS courses, simulations, intelligent tutoring systems, and generative

AI assistants, while future studies should validate its effectiveness through discipline-specific pedagogical experiments.

Keywords: Artificial intelligence; adaptive learning; professional competence; higher education; learning analytics; intelligent tutoring system; formative feedback; human-centred AI

Introduction

The digital transformation of professional activity changes not only the instruments used in the workplace but also the structure of professional decision-making. Graduates are expected to identify problems, work with data, select appropriate digital tools, collaborate in distributed teams, evaluate risks, justify decisions, and continue learning in situations that cannot be fully predicted by a curriculum. Therefore, professional competence should be interpreted as an integrated ability to mobilise knowledge, practical skills, values, communication, digital resources, and reflection in a concrete professional context. This understanding shifts attention from the amount of information acquired to the quality, autonomy, transferability, and ethical responsibility of student performance.

Higher education groups are heterogeneous. Students enter a course with different prior knowledge, learning strategies, professional experience, language resources, motivation, and access to technology. A fixed sequence of identical content and assignments can be too difficult for some learners and insufficiently challenging for others. It also limits the teacher's capacity to detect hidden misconceptions, provide timely feedback, and organise individual support at scale. Adaptive learning responds to this problem by modifying content, pace, task complexity, representation, scaffolding, or feedback according to a continuously updated learner model [4].

Artificial intelligence expands the possibilities of adaptive learning. Intelligent tutoring systems can compare a student's actions with domain models, generate hints, and select the next task; learning analytics can identify patterns of engagement and risk; recommender systems can propose resources or activities; natural-language systems can support dialogue, explanation, simulation, and formative feedback. Evidence from research on computer tutoring indicates that

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well-designed intelligent systems can improve learning outcomes, particularly when feedback is immediate, task-specific, and connected with active problem solving [5, 6]. Nevertheless, these effects depend on instructional design and should not be interpreted as proof that any AI tool is pedagogically effective.

The central methodological problem is that many digital systems optimise what is easy to measure: number of clicks, completion time, test accuracy, or frequency of access. These indicators may be useful, but they are not equivalent to professional competence. A student may answer factual questions correctly and still be unable to solve an ill-structured professional case, coordinate with others, explain the evidence behind a decision, or recognise an ethical risk. Consequently, AI-based adaptation must be organised around authentic professional actions and observable evidence of performance rather than around platform activity alone.

AI-supported education also raises questions of learner agency, explainability, privacy, bias, accessibility, academic integrity, and overdependence on automated assistance. Generative systems may produce plausible but inaccurate responses; prediction models may reproduce bias in historical data; recommendations may become opaque to students and teachers. Human-centred guidance therefore emphasises that AI should augment, rather than replace, pedagogical judgment and that users should understand the purposes, limitations, and consequences of automated recommendations [13-17].

The purpose of this article is to develop a methodology for using artificial intelligence-based adaptive learning tools to support the development of students' professional competencies. The study addresses three questions: which components and indicators of professional competence should be represented in an adaptive system; how should diagnostic data be transformed into an individual learning pathway and authentic professional tasks; and what pedagogical and ethical conditions are necessary for reliable implementation? The article follows the IMRAD logic and presents a theoretical, design-oriented result rather than data from a completed pedagogical experiment.

Literature Review

Competence-oriented higher education requires alignment between expected outcomes, learning activity, and assessment. Constructive alignment emphasises that students develop complex capabilities when they perform tasks that require the intended form of understanding and when assessment examines the same performance [1]. Shulman's distinction between content knowledge, pedagogical knowledge, and knowledge for transforming content into teachable forms also shows that professional competence cannot be reduced to factual knowledge [2]. In technology-rich learning, the TPACK framework adds the requirement to coordinate technological, pedagogical, and subject-specific decisions [3]. These approaches provide a basis for designing adaptive learning around professional activity rather than around content delivery.

Adaptive educational systems traditionally use a domain model, a learner model, and an adaptation model. The domain model represents concepts, skills, tasks, and prerequisite relations. The learner model contains estimates of knowledge, misconceptions, preferences, progress, or support needs. The adaptation model applies rules to select content, sequence tasks, change difficulty, or provide guidance [4]. Intelligent tutoring systems add interactive problem solving, feedback, and coaching. Reviews comparing tutoring conditions and meta-analyses of controlled evaluations generally show positive effects, but they also demonstrate that results vary by subject, task structure, duration, and the quality of feedback [5, 6].

Research on artificial intelligence in higher education has commonly grouped applications into profiling and prediction, assessment and evaluation, adaptive systems and personalisation, and intelligent tutoring [7]. Ouyang and Jiao describe a progression from AI-directed learning, where the learner mainly receives system decisions, to AI-supported collaboration and AI-empowered learning, where the learner retains agency and uses AI as a partner [8]. For professional competence development, the third orientation is preferable because students must learn to make and justify decisions rather than merely follow recommendations.

Molenaar's concept of hybrid human-AI learning technologies further explains why control should move dynamically among the learner, teacher, and system [9]. AI can detect patterns, estimate risk, and provide scalable support; teachers can interpret context, recognise emotional and ethical factors, design authentic activity, and make high-stakes judgments; students can set goals, monitor progress, request assistance, and evaluate the quality of AI output. This orchestration is especially important in professional education because successful

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performance often depends on contextual knowledge and responsibility that cannot be fully represented by an algorithm.

Formative feedback and self-regulated learning are essential mechanisms of adaptation. Effective feedback should be timely, specific, usable, and directed toward improving the next action rather than merely reporting a score [10]. Self-regulated learners plan, monitor, seek help, evaluate outcomes, and modify strategies [11]. AI can support these processes by visualising progress, providing prompts, generating alternative examples, or signalling a need for intervention. However, excessive automation may weaken metacognitive effort if students accept recommendations without analysing them. Therefore, every adaptive cycle should include explanation, student choice, and reflection.

Competence frameworks provide additional design criteria. DigCompEdu describes educators' use of digital resources, teaching and learning, assessment, learner empowerment, and the facilitation of learners' digital competence [12]. The European Commission's ethical guidelines call for attention to human agency, fairness, transparency, privacy, safety, and accountability when AI and data are used in teaching [13]. UNESCO's guidance for generative AI proposes a human-centred approach and stresses the need for institutional rules, capacity building, validation of outputs, and protection of personal data [14]. The UNESCO AI Competency Framework for Teachers organises competence around a human-centred mindset, ethics, AI foundations and applications, AI pedagogy, and professional learning [15].

Recent literature on large language models highlights opportunities for explanation, dialogue, content generation, feedback, and creativity, together with risks related to inaccuracy, bias, dependency, assessment validity, and academic integrity [16]. Explainable AI research argues that educational recommendations should be interpretable and actionable for students and teachers [17]. A meta-systematic review of AI in higher education similarly calls for stronger ethical analysis, interdisciplinary collaboration, and methodological rigour [18]. The literature therefore reveals a gap between the technical capability to personalise learning and the pedagogical methodology required to develop transferable professional competence.

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Methodology and research design

Research design: The article is a theoretical and design-oriented study. Its outcome is a pedagogical methodology that can be adapted to different university disciplines. No completed experiment or fabricated performance data are reported. The methodology was developed through analysis and synthesis of competence-based education, adaptive learning, artificial intelligence in education, formative assessment, self-regulated learning, and ethical governance frameworks.

Analytical procedure: The design process consisted of five steps. First, professional competence was decomposed into components that can be observed through student activity. Second, AI and adaptive-learning functions were classified according to the pedagogical decisions they can support. Third, each function was connected with an authentic professional task and a source of evidence. Fourth, the elements were organised into a cyclical process that includes diagnosis, adaptation, activity, feedback, reflection, assessment, and recalibration. Fifth, safeguards were added to preserve teacher responsibility, learner agency, explainability, accessibility, privacy, and academic integrity.

Competence structure: Six components were selected. The motivational-value component includes professional responsibility, persistence, and willingness to improve. The cognitive-professional component covers concepts, procedures, standards, and the ability to connect theory with a professional problem. The operational-digital component concerns the appropriate use of digital tools, data, and AI in performing tasks. The communicative-collaborative component includes explanation, negotiation, teamwork, and peer feedback. The reflective-analytical component involves self-assessment, interpretation of evidence, and strategy correction. The innovative-ethical component combines creativity, risk recognition, academic integrity, fairness, and responsible innovation.

Diagnostic data: The learner model should be based on triangulation rather than on a single test. Recommended sources include criterion-referenced diagnostic tasks, self-assessment, teacher observation, peer assessment, prior products, electronic portfolio evidence, simulation performance, and relevant LMS traces. Sensitive or weakly interpretable indicators should not be used merely because they are technically available. Data collection must be proportionate to the educational purpose, and students should be informed about what is collected,

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why it is used, how long it is retained, and how a recommendation can be questioned.

Adaptation parameters: The methodology allows adaptation of content depth, task complexity, sequence, pace, representation, level of scaffolding, type of feedback, collaboration format, and assessment opportunity. Adaptation is not intended to create permanently separate tracks. Its function is to provide the support or challenge required for all students to reach shared competency outcomes. The teacher defines the boundaries of adaptation, approves professional tasks, validates AI-generated materials, and intervenes when the system's recommendation conflicts with contextual evidence.

Assessment logic: Competence is evaluated through performance evidence and analytic rubrics. A proposed composite result may be expressed as $C = \sum(w_i \times s_i)$, where s_i represents the rubric score for a competence component and w_i represents its programme-specific weight, with $\sum w_i = 1$. The numerical result is secondary to the profile: a high total score should not hide a critical weakness in ethics, safety, communication, or professional responsibility. Institutions should establish thresholds only after pilot testing, expert review, and analysis of reliability and validity.

Research Results

The first result is an eight-stage methodological cycle that connects AI-based adaptation with authentic professional activity. The cycle begins with a competency profile rather than with a list of digital resources. Each expected outcome is described through observable indicators, performance conditions, quality criteria, and acceptable evidence. This profile guides diagnosis and prevents the adaptive system from optimising irrelevant platform metrics.

Multisource diagnosis produces an initial learner model that describes strengths, misconceptions, support needs, preferred forms of representation, and readiness for complex professional tasks. The model must be explainable: the student and teacher should be able to see which evidence influenced a recommendation. The system then proposes an individual pathway by varying content, pace, examples, scaffolds, practice density, and task complexity. The teacher may accept, modify, or reject the proposal.

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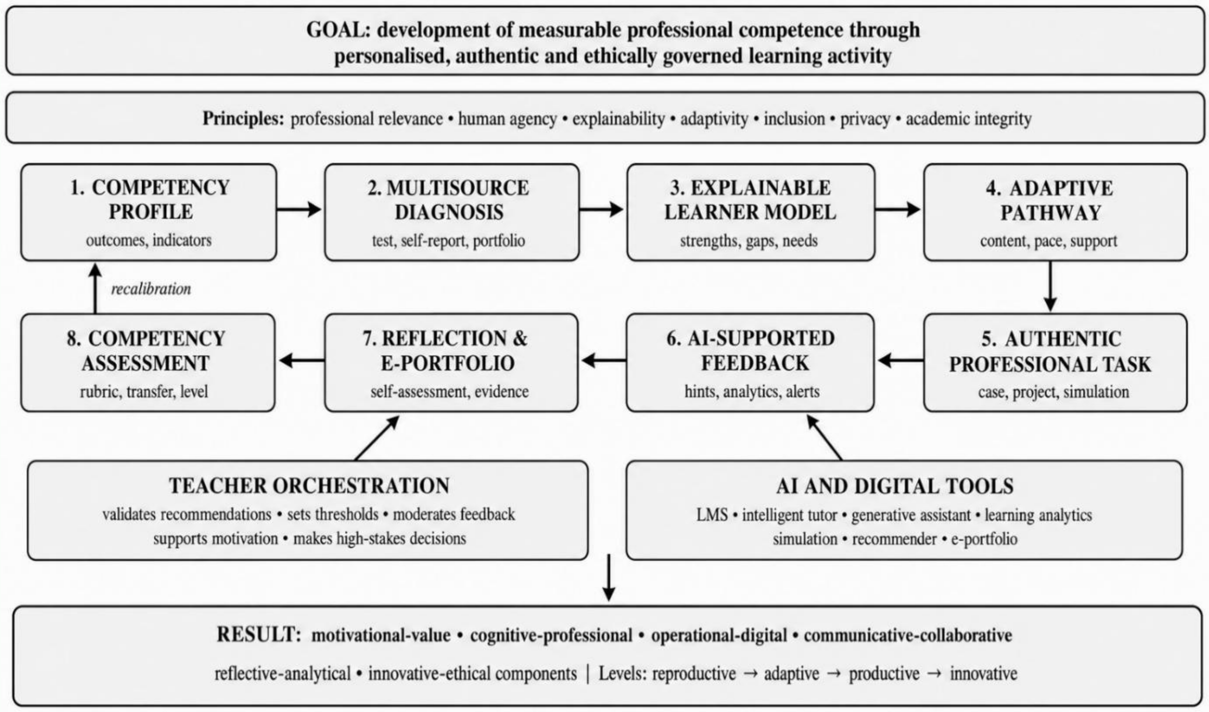

Figure 1. AI-based adaptive methodology cycle for developing students' professional competencies.

The central stage is the performance of an authentic professional task. Depending on the discipline, this may be a case analysis, design brief, clinical scenario, lesson plan, laboratory investigation, engineering simulation, business decision, legal argument, or social project. AI can supply differentiated resources, simulated roles, hints, counterexamples, and feedback, but it should not complete the core reasoning on behalf of the student. The final product, decision process, explanation, and reflection become evidence in an electronic portfolio.

The next stage combines AI-supported formative feedback with teacher and peer feedback. Automated feedback is most useful for recurrent patterns, prerequisite gaps, procedural errors, and rapid practice. Teacher feedback is essential when performance involves context, values, originality, interpersonal judgment, safety, or an ambiguous standard. Students are required to interpret feedback, decide which recommendation to use, explain rejected advice, and document the resulting revision. This turns feedback into a professional learning action rather than a passive message.

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Table 1 Integration of competence components, adaptive AI functions, professional activity, and evidence.

Competence component	Adaptive AI function	Authentic professional activity	Evidence of development
Motivational-value	Goal prompts, progress visualisation, risk alerts	Planning a personally meaningful professional challenge	Goal sheet, persistence record, justified learning choices
Cognitive-professional	Knowledge tracing, prerequisite diagnosis, adaptive explanation	Solving a discipline-specific case with standards and evidence	Concept map, case solution, oral or written justification
Operational-digital	Tool recommendation, simulation, scaffolded workflow	Producing a professional product with digital and AI tools	Product quality, process log, tool-selection rationale
Communicative-collaborative	Role allocation, dialogue prompts, peer-feedback support	Team project, consultation, negotiation, presentation	Communication rubric, peer evidence, joint decision record
Reflective-analytical	Learning analytics dashboard, error pattern summary	Analysing performance and revising a strategy	Reflective note, revision trace, updated action plan
Innovative-ethical	Alternative generation, bias and integrity prompts	Designing an original solution and evaluating consequences	Innovation product, ethical risk analysis, disclosure of AI use

The second result is a set of adaptive decision rules. When diagnostic evidence shows a prerequisite gap, the system should provide a short foundational module, a worked example, guided practice, and a new diagnostic opportunity. When conceptual accuracy is acceptable but transfer is weak, the next task should change context and reduce scaffolding. When students can perform a routine task but cannot justify a decision, adaptation should increase explanation, comparison of alternatives, and evidence use. When performance is high and stable, the system should offer an open-ended project, interdisciplinary constraint, or innovation challenge rather than additional repetitive exercises.

Adaptation should also respond to collaboration and reflection. A student who contributes little to group reasoning may receive a defined professional role, a preparation prompt, and a requirement to present evidence. A student whose reflective entries are descriptive rather than analytical may receive prompts that ask what changed, why it changed, which evidence supports the judgment, and what will be done differently. These rules demonstrate that the object of

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adaptation is not only content difficulty; it is the entire structure of professional learning activity.

The third result is a four-level developmental scale. The reproductive level is characterised by performance with a model, explicit instructions, and substantial support. At the adaptive level, the student selects and adjusts known methods in a changed but familiar situation. At the productive level, the student independently integrates knowledge, tools, communication, and evidence to solve an ill-structured professional task. At the innovative level, the student creates and evaluates an original solution, anticipates consequences, explains AI use, and transfers learning to a new context. Progression is determined by autonomy, quality, transfer, collaboration, reflection, and ethical responsibility, not by speed or test accuracy alone.

Table 2 Proposed levels of professional competence development in an AI-adaptive learning environment.

Development level	Performance profile	Typical adaptation	Required evidence
Reproductive	Acts by model and needs explicit support	Worked example, micro-task, frequent hints	Correct routine action with explanation
Adaptive	Adjusts known methods to a modified situation	Reduced scaffolding, varied context, targeted feedback	Appropriate method selection and revision
Productive	Independently solves an ill-structured professional task	Complex case, collaboration, delayed hints	Integrated product, evidence-based decision, transfer
Innovative	Creates and evaluates an original responsible solution	Open project, multiple constraints, AI as co-creative tool	Novel product, ethical analysis, transparent AI-use statement

The methodology requires six pedagogical conditions. First, the curriculum must contain explicit competence indicators and authentic tasks. Second, the adaptive system must use valid and proportionate data. Third, teachers need competence in instructional design, AI literacy, feedback, and data interpretation. Fourth, students need orientation in prompt use, source verification, privacy, academic integrity, and critical evaluation of AI output. Fifth, digital infrastructure must

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support accessibility, secure authentication, portfolio evidence, and integration among the LMS, analytics, simulation, and communication tools. Sixth, institutions need a governance procedure for approving tools, documenting data flows, responding to errors, and reviewing bias or unequal impact.

Implementation can begin with a limited module rather than an institution-wide platform. A teacher may define two or three professional outcomes, prepare a diagnostic task, create three levels of support, connect each level with an authentic assignment, and use a rubric and portfolio for evidence. AI may assist with generating alternative examples, analysing recurrent errors, or drafting feedback, while the teacher verifies every consequential output. After a pilot, the team can compare diagnostic and final profiles, examine student revisions, collect perceptions of agency and fairness, and refine adaptation rules before scaling.

Discussion

The proposed methodology differs from a technology-centred approach in three ways. First, it begins with professional competence and evidence, not with the functions of a platform. Second, it treats adaptation as a pedagogical decision about the next productive activity rather than as automatic content recommendation. Third, it places teacher orchestration, learner choice, and ethical governance inside the model rather than presenting them as external precautions. In this respect, the methodology moves from AI-directed learning toward AI-supported and AI-empowered learning [8].

The model is consistent with research showing that intelligent tutoring is effective when it supports active problem solving and provides appropriate feedback [5, 6]. It also extends this logic beyond well-structured tasks. Professional competence includes communication, collaboration, creativity, ethical judgment, and transfer, which cannot be inferred reliably from closed questions alone. The use of portfolios, simulations, authentic products, peer evidence, and reflection therefore broadens the evidence base and reduces the risk that the system confuses platform success with professional readiness.

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Hybrid human-AI regulation is a necessary condition of implementation [9]. AI is strong at processing repeated patterns, maintaining a detailed history, and generating rapid provisional support. Teachers are stronger at interpreting context, recognising exceptions, establishing trust, and making judgments that involve values or safety. Students need opportunities to accept, reject, and critique recommendations. A methodology that removes these human decisions may increase efficiency but weaken responsibility and self-regulation.

Explainability has both technical and pedagogical meanings. Technically, users should know which evidence influenced an alert or recommendation. Pedagogically, the recommendation should be expressed in a form that helps the learner decide what to do next. A message such as 'risk level: high' is less useful than an explanation that identifies the missing prerequisite, shows the supporting evidence, and offers several possible actions. Explainability also allows teachers to detect inappropriate inferences and students to develop data and AI literacy [17].

The main risks are inaccurate generated content, hidden bias, excessive data collection, unequal access, automation of high-stakes decisions, dependency on hints, and unacknowledged AI contribution. These risks cannot be solved by a general statement about responsible use. They require specific procedures: source verification, minimal data collection, role-based access, audit logs, alternative non-AI pathways, accessibility checks, disclosure of AI assistance, and teacher review of consequential recommendations. The ethical guidelines of the European Commission and UNESCO provide an important basis for such procedures [13-15].

The present study has limitations. It develops a design framework and does not establish causal effectiveness. The components, weights, and adaptation rules must be contextualised for particular professions and validated with students, teachers, and employers. A future pedagogical experiment should compare an adaptive methodology with a non-adaptive but otherwise equivalent course, use pre- and post-performance tasks, analyse rubric reliability, examine transfer to a new professional situation, and collect qualitative evidence about agency, trust, workload, and fairness.

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Conclusion

Artificial intelligence-based adaptive learning tools can contribute to the development of professional competence only when their technical functions are embedded in a coherent pedagogical methodology. The proposed methodology links competency outcomes, multisource diagnosis, an explainable learner model, an individual pathway, authentic professional tasks, AI-supported formative feedback, reflection, electronic portfolio evidence, and competency assessment in a continuous cycle.

Its key methodological principle is that adaptation should change the conditions of productive professional activity, not merely the order of information. Content, pace, scaffolding, task complexity, collaboration, feedback, and reflection are adjusted so that students can progress from reproductive performance to adaptive, productive, and innovative action. Teacher orchestration and learner agency remain central, while AI provides scalable diagnosis, recommendation, simulation, and feedback.

For practical implementation, universities should begin with explicit competence indicators and a limited pilot module, validate data and rubrics, train teachers and students in AI literacy, and establish rules for explainability, privacy, academic integrity, accessibility, and human review. Subsequent research should test the methodology in discipline-specific settings and determine which forms of adaptation produce reliable improvement in professional performance and transfer.

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