

## Article

# Sustainable and AI-Based Support in the Module of Educational Support Systems

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## Abstract

Artificial intelligence (AI)-based support systems are transforming the educational landscape by enhancing teaching efficiency, personalized learning, and accessibility. Despite rapid technological progress, educational institutions face persistent challenges such as unequal access to quality learning resources, limited teacher support, and the need for individualized student engagement. These issues hinder effective learning outcomes and inclusivity in modern classrooms. This study presents a comprehensive literature review and a methodology grounded in constructivist learning theory to develop an AI-based educational support framework. The study is situated within the context of a higher education course integrating AI-supported learning. The proposed framework is developed by synthesizing theoretical and empirical evidence and is subsequently evaluated by experts in educational technology and artificial intelligence. Data are collected through structured expert questionnaires and qualitative feedback. Quantitative data are analyzed using descriptive statistics, while qualitative responses are examined through thematic analysis to inform framework refinement. The study adheres to established ethical principles, including informed consent, voluntary participation, confidentiality, anonymity, and secure data management. Moreover, the paper explores the design and implementation of sustainable and AI-based educational support systems that address these challenges through intelligent tutoring, adaptive learning analytics, and automated feedback mechanisms. By integrating natural language processing, machine learning, and predictive modelling, the proposed framework provides real-time assistance to educators and learners, fostering data-driven decision-making and inclusive pedagogy. Qualitative expert evaluation suggests that an AI-based educational support framework has the potential to improve teaching support, learner engagement, and personalized learning while providing a scalable and equitable approach for higher education.



Academic Editor: Fernando Moreira

Received: 12 June 2026

Revised: 10 July 2026

Accepted: 15 July 2026

Published: 17 July 2026

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**Keywords:** artificial intelligence; support; module; educational systems

## 1. Introduction

The rapid advancement of artificial intelligence is increasingly shaping the educational domain, heralding profound changes in how teaching and learning are conceived and delivered. Traditional instruction—often based on uniform pacing and content delivery—struggles to accommodate diverse student needs, varying learning styles, and the demand

for inclusive and equitable learning environments [1]. In response, AI-based support systems have emerged as promising solutions to personalise learning trajectories, optimise teacher support, and enhance educational outcomes. Studies in the field of AI in education (AIEd) reveal several key trends. For instance, research indicates that adaptive learning platforms powered by AI can tailor content, pace, and feedback to individual learners, thereby improving engagement and achievement [1]. Moreover, systematic reviews highlight that intelligent tutoring systems (ITSs) and other AI-driven tools show positive effects on students' performance, though the impact varies across contexts and designs [2]. According to Wang et al. [3], AI-powered systems within learning management frameworks are supporting teaching and learning in ways previously not feasible.

Despite these advances, persistent challenges remain. Educational inequalities, limited teacher capacity, and rigid one-size-fits-all models continue to hinder the effectiveness of conventional approaches [4]. Additionally, the integration of AI in education raises questions of data privacy, algorithmic bias, alignment with pedagogical goals, and the role of the teacher in AI-based settings [2,4]. These concerns underscore the need for frameworks that not only deliver adaptive, intelligent support but also align with inclusive, ethical, and evidence-based educational practices.

The integration of artificial intelligence in educational settings has become increasingly pertinent as schools and higher-education institutions face mounting pressures to accommodate diverse learner needs, improve equity, and harness digital transformation [5]. AI's relevance stems from its capacity to personalise learning trajectories, automate routine tasks, and provide analytic insights that were previously difficult or impossible to realise at scale [6]. For instance, systematic reviews show that the volume of research in AI in education has surged in recent years, especially in higher-education contexts. One review found that publications in 2021–2022 more than doubled compared to earlier years [7].

Beyond mere volume, the types of AI applications are expanding from adaptive learning systems and intelligent tutoring systems to learning analytics, predictive modelling, and generative AI. These systems promise to enhance instructional quality, support individualized feedback, and improve learning outcomes [8].

Furthermore, in the context of inclusive education, ensuring that all learners, including those with disabilities or from disadvantaged backgrounds, receive equitable opportunities, AI can potentially offer tailored support, scaffolded interaction, and real-time analytics that help educators differentiate instruction more feasibly than ever before. This aligns directly with contemporary priorities in education policy around accessibility and personalised pedagogy. In short, the relevance of AI in education is underpinned by both technological advances and systemic educational needs: the need for scalable personalization, teacher support, inclusive pedagogy, and efficient analytics in increasingly complex educational environments.

Despite the growing body of research on AI in education, existing studies tend to focus on isolated solutions, such as intelligent tutoring systems, adaptive learning platforms, or learning analytics tools. Limited attention has been paid to integrated frameworks that simultaneously support students, teachers, and educational administrators in a unified educational support environment. Furthermore, empirical evidence on the implementation of such frameworks in higher education remains limited. This gap motivates the development of the framework proposed in this study.

In this paper, we propose a comprehensive framework for AI-based support systems in education that addresses these gaps by combining adaptive analytics, real-time feedback, and teacher-centred design. The goal is to equip both educators and learners with tools that foster personalised engagement, data-driven decision-making, and scalable support, while maintaining a commitment to inclusivity, transparency and pedagogical alignment.

Through this work, we aim to contribute to the evolving discourse on how AI can meaningfully transform education in equitable and effective ways. Therefore, the aim of this study is to develop and evaluate an AI-based educational support framework for higher education. The main contributions of this research are: (1) the development of an integrated AI-based educational support framework that combines Adaptive Learning Pathways, AI-supported feedback, learner analytics, and teacher-decision support tools; and (2) the evaluation of the proposed framework through expert evaluation in the master's level module Educational Support Systems. Accordingly, the study addresses the following research question:

RQ1: How pedagogically suitable and effective is the proposed AI-based educational support framework for enhancing teaching and learning processes?

The novelty of this study lies in integrating established AI functionalities within a unified, constructivist, theory-based educational support framework. Unlike existing models that address isolated AI applications, the proposed framework combines pedagogical, technological, and inclusive learning principles into a coherent model for sustainable higher education.

The proposed framework addresses the need for continuous educational support by integrating adaptive learning, intelligent feedback, and learning analytics in a unified educational environment. Moreover, the authors investigate how effective the pedagogical suitability of the proposed AI-based support framework is in enhancing teaching and learning processes. Specifically, it examines whether the integration of adaptive learning mechanisms, intelligent feedback systems, and learning analytics can meaningfully support diverse learners within a unified educational environment. The question focuses on the extent to which the framework aligns with established pedagogical principles such as learner-centered instruction, differentiation, continuous assessment, and formative feedback. It also explores how well the system responds to individual learner needs by adapting content difficulty, pacing, and instructional strategies in real time. The originality of this study does not lie in introducing new AI components individually, as adaptive learning, learning analytics, automated feedback, and instructor dashboards are well established in the literature. Rather, its contribution is the design of a unified, constructivist, theory-based educational support framework that systematically integrates these components into a coherent pedagogical model. Furthermore, the framework is validated through expert evaluation within a higher education context, providing evidence of its pedagogical suitability and practical applicability. In addition, RQ1 evaluates the quality and educational value of AI-generated feedback, particularly whether it is timely, understandable, and actionable for improving student performance. Another important aspect is the use of learning analytics to support teachers in monitoring progress, identifying learning gaps, and making informed instructional decisions; however, the research question aims to determine whether the proposed AI framework not only functions technically but also provides pedagogical benefits that enhance engagement, learning outcomes, and teaching efficiency in modern educational settings.

Adaptive analytics, real-time feedback, and teacher-centred design form a complementary triad for effective higher-education course support systems. Adaptive analytics combine learner models, interaction traces, and item/sequence modelling to generate individualized learning pathways that respond to evolving student proficiency [9,10]. Empirical reviews indicate adaptive analytics can increase engagement and improve targeted learning gains when systems use fine-grained diagnostics and continuous profile updating [9,11]. Importantly, adaptive pipelines must surface understandable recommendations (not opaque scores) so instructors and learners can act on them; human-interpretable indicators increase trust and adoption [12].

Real-time feedback extends adaptive analytics by delivering immediate, formative guidance at the moment of learning: on quizzes, discussion posts, and draft submissions [13,14]. Studies report that timeliness strongly moderates feedback effects—feedback delivered within days (ideally minutes to hours in active learning tasks) better supports revision cycles and motivation than delayed responses [13,15]. Automated feedback engines leveraging NLP and rubric mapping can provide consistent, rapid comments on structure and concept coverage and suggest next steps or resources; however, they are most effective when paired with teacher review loops so that nuance and disciplinary judgement are preserved [16,17].

Teacher-centred design is the linchpin that makes analytics and automated feedback pedagogically useful. Research on teacher-facing dashboards and tools emphasises co-design, iterative prototyping, and situating indicators in teachers' workflows [18–20]. Teacher involvement aligns analytics outputs with curriculum goals, reduces data fatigue, and ensures interventions are contextually appropriate [20,21]. Dashboards that combine at-a-glance alerts (risk flags) with interactive drilldowns and recommended pedagogical actions (e.g., grouping suggestions, targeted prompts) improve teacher decision-making and increase uptake compared to static visualizations [16,22].

Integrative designs that connect adaptive analytics, real-time feedback, and teacher dashboards follow three practical patterns. First, a learner model layer fuses pretest diagnostics, time-on-task, and assignment performance to maintain an evolving competency vector for each student; this vector drives resource recommendation and difficulty adaptation [23,24]. Second, a feedback orchestration layer generates immediate formative messages and suggests corrective tasks; messages are versioned so teachers can audit and refine automated feedback templates [13,16]. Third, a teacher interface surfaces cohorts and individuals needing intervention, explains why a student was flagged (feature-level explanations), and offers concrete interventions aligned to learning objectives [17,25].

Evidence from higher-education pilots suggests measurable benefits but also important caveats. Adaptive pathways and timely feedback improve assignment revision rates, self-regulated learning behaviours, and short-term assessment scores when systems are transparent and integrated into course activities [11,26]. However, gains vary by discipline, prior attainment, and students' digital literacies; subgroup analyses are essential to detect differential effects and to prevent widening achievement gaps [27,28]. Studies also show that teacher training and workload redesign (time to interpret dashboards and to act on recommendations) are critical mediators of success [20,29].

Design recommendations emerging from the literature converge on four principles. (1) Transparency: Make data sources, indicators, and algorithmic logic intelligible to teachers and students. (2) Actionability: Pair analytics with recommended, low-cost pedagogical actions (e.g., targeted formative tasks, adaptive grouping). (3) Timeliness: Optimize the latency of feedback to match pedagogical cycles (instant for low-stakes practice; short delays for drafted assessments). (4) Teacher agency: Enable teachers to edit thresholds, tune recommendations, and author feedback templates so systems augment—not replace—pedagogical judgement [12,14,17].

Artificial intelligence-based support systems in higher education are commonly conceptualized through integrated frameworks that combine learning analytics, adaptive technologies, and human-centred pedagogical design. Several studies emphasize that effective AI support systems must be grounded in learning analytics architectures that collect, process, and interpret learner data to inform instructional decision-making [10,30]. Within these frameworks, learner modelling and adaptive mechanisms are used to personalize content, pace, and feedback based on students' evolving needs and interaction patterns [6].

Teacher-centred frameworks highlight the importance of instructor-facing components, such as dashboards and recommendation systems, which translate complex analytics

into actionable pedagogical insights. Research demonstrates that teacher-facing learning analytics dashboards support instructors' awareness of student engagement, learning progress, and collaboration dynamics, enabling timely and targeted interventions [17,21]. These frameworks stress that AI systems should augment, rather than replace, teachers' professional judgement by providing interpretable indicators and flexible control over instructional actions [12].

Implementation challenges are nontrivial. Data quality and interoperability across LMS, assessment platforms, and external tools limit robust learner modelling [31]. Privacy, consent, and ethical use of constraints require anonymisation, minimal data retention, and transparent governance [10]. Algorithmic bias and differential impacts demand ongoing monitoring and subgroup evaluation. Finally, teachers need professional development that blends dashboard literacy with pedagogical strategies for adaptive and feedback-rich instruction [19,31].

The literature highlights that adaptive analytics, real-time feedback, and teacher-centered design are key components of effective AI-based educational support systems. Together, these elements provide a theoretical foundation for the development of integrated educational support frameworks that enhance personalization, instructional decision-making, and support for learners in higher education.

## 2. Materials and Methods

This methodology describes the adaptation and implementation of the Educational Support Systems module for fully distance online delivery within a master's degree programme. The module was redesigned to support 22 graduate students through AI-based educational support tool based on Chatbase, ensuring flexibility, personalization, and active engagement in a fully virtual learning environment.

To ensure methodological transparency, the expert evaluation followed a structured interview protocol consisting of open-ended questions aligned with the study objectives and evaluation criteria. Six experts in educational technology and artificial intelligence were purposively selected based on their academic qualifications, research experience, and expertise in AI-supported learning. All interviews were audio-recorded, transcribed verbatim, and analyzed using thematic analysis. The coding process involved an initial round of open coding, followed by the grouping of related codes into broader categories and themes reflecting key aspects of the proposed framework. To enhance the credibility of the qualitative analysis, two researchers independently coded the transcripts, compared their coding decisions, and resolved discrepancies through discussion until consensus was achieved. The identified themes were then used to refine the framework. The presentation of the results follows the same sequence as the methodological steps, ensuring clear alignment between data collection, analysis, and the interpretation of findings.

### 2.1. Research Design

The study employed a qualitative expert evaluation approach to assess the pedagogical suitability and effectiveness of the proposed AI-based educational support framework implemented in the Educational Support Systems module. The module involved 22 master's-level students. All students had prior experience with online learning platforms. The course was delivered entirely online over eight weeks using a learning management system (LMS) and synchronous video conferencing.

### 2.2. Study Context

The module was structured around weekly thematic units combining asynchronous and synchronous activities. AI-based support systems included: (1) an Adaptive Learning

Pathway that recommended readings, case studies, and practical tasks based on prior knowledge and interaction patterns; (2) an AI-Supported Feedback Engine that generated formative feedback on assignments and discussion contributions; (3) a Learner Analytics Component that monitored engagement, progress, and collaboration patterns; and (4) an instructor dashboard providing real-time insights into student performance and suggested pedagogical interventions. The design emphasized self-regulated learning, peer interaction, and reflective practice, aligned with master's level learning outcomes.

Chatbase was integrated into the module Educational Support Systems as an AI-supported feedback tool to enhance formative assessment and student learning. A course-specific chatbot was developed using module materials, enabling students to ask questions, receive immediate explanations, and obtain personalized feedback on assignments and learning tasks. The system provided continuous support beyond classroom sessions, encouraged self-regulated learning, clarified complex concepts, and helped students identify areas for improvement while complementing instructor feedback.

Students completed an online diagnostic assessment at the start of the course to initialize learner profiles. Weekly activities included guided readings, interactive simulations, collaborative forums, and project-based tasks. Synchronous sessions focused on discussion, problem-solving, and reflection, supported by AI-generated summaries and prompts. The instructor used dashboard insights to adjust pacing, provide targeted support, and facilitate group work.

### 2.3. Participants and Expert Evaluation

During the expert evaluation, experts analysed the design and implementation of the proposed AI-based educational support framework and evaluated its suitability for supporting learners in higher education. The aim of this evaluation process is to validate the developed model.

Experts were selected based on the following criteria: at least five years of experience in the field of online course development, experience in the field of online course delivery, experience in working in a virtual learning environment, and experience related to e-learning research or practice (see Table 1).

**Table 1.** Characteristics of the expert group.

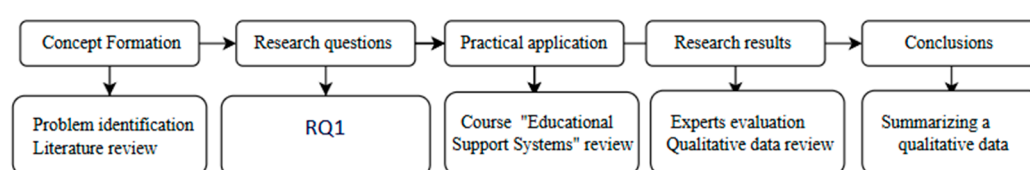
| Expert | Field of Expertise      | Years of Experience | Relevant Experience           |
|--------|-------------------------|---------------------|-------------------------------|
| E1     | E-learning              | 15                  | Educational technologies      |
| E2     | E-learning              | 8                   | Virtual Learning Environments |
| E3     | E-learning              | 9                   | Technologies and applications |
| E4     | Artificial intelligence | 10                  | Big data, security            |
| E5     | Artificial intelligence | 8                   | GenAI, big data               |
| E6     | Artificial intelligence | 3                   | GenAI                         |

The expert group consisted of six experts working in different areas of e-learning, information technology, computer engineering, teaching technology, and systems engineering. Experts reviewed the proposed framework and provided evaluations regarding its strengths, limitations, and potential areas for improvement. Since the study employed qualitative expert evaluation and thematic analysis, the emphasis was placed on the rele-

vance and diversity of expertise rather than on large sample sizes. Previous methodological research suggests that meaningful thematic patterns can be identified within relatively small samples, particularly when participants possess specialised domain expertise and are selected according to clearly defined criteria [32].

The main criteria for evaluation of the multifunctional model are: (1) accessibility and usability; (2) efficiency; (3) effectiveness; and (4) functionality and importance of functions.

Figure 1 presents the qualitative research process used to investigate AI-based support in the module Educational Support Systems. The process begins with concept formation, where the research problem is identified and supported by a review of the relevant literature on AI in education. This stage establishes the theoretical background and defines the focus of the study. The second stage introduces the research question that guides the investigation into how AI can support teaching, learning, and accessibility within Educational Support Systems (see Figure 1).



**Figure 1.** Research design and expert evaluation process.

The third stage focuses on the practical application of the study through the course Educational Support Systems review. At this stage, AI-based tools and strategies are explored and applied in the educational context. The fourth stage involves research results, where experts conduct evaluations and qualitative data are reviewed to identify themes, perceptions, and the effectiveness of AI support. Finally, the findings are synthesized to identify the benefits, challenges, and future potential of AI-based educational support systems.

#### 2.4. Data Collection and Analysis

Data were collected through semi-structured expert interviews. Six experts evaluated the AI-based educational support framework and the course implementation. The interview protocol consisted of seven open-ended questions addressing teaching tools, assessment methods, support mechanisms, quality of feedback, communication, learner engagement, and potential challenges.

Qualitative data obtained from expert interviews were analyzed using thematic analysis. The analysis involved reviewing the experts' responses, identifying recurring patterns, grouping them into broader themes, and interpreting similarities and differences in the experts' opinions. The identified themes were used to assess the strengths, weaknesses, and opportunities for improvement of the proposed AI-based educational support framework.

The study employed purposive sampling to recruit six experts with recognized expertise in AI, educational technology, and higher education. A structured interview protocol guided data collection. Interview transcripts were analyzed using thematic analysis through open coding, category development, and theme generation. Two researchers independently coded the data, discussed discrepancies, and reached consensus to strengthen the credibility and trustworthiness of the qualitative findings. The researchers updated the framework regarding the findings and implemented it into an educational platform.

#### 2.5. Ethical Considerations

All experts participated voluntarily and were informed about the purpose of the study. The evaluation data were anonymized to ensure confidentiality and used only for research purposes. The study was conducted in accordance with the ethical principles of informed

consent, data protection, and responsible use of information, and taking into account the recommendation of the Research Ethics Commission of the University, as well as indicating that ethics approval is not required for this type of study.

### 3. Results

#### 3.1. Proposed AI-Based Educational Support Framework

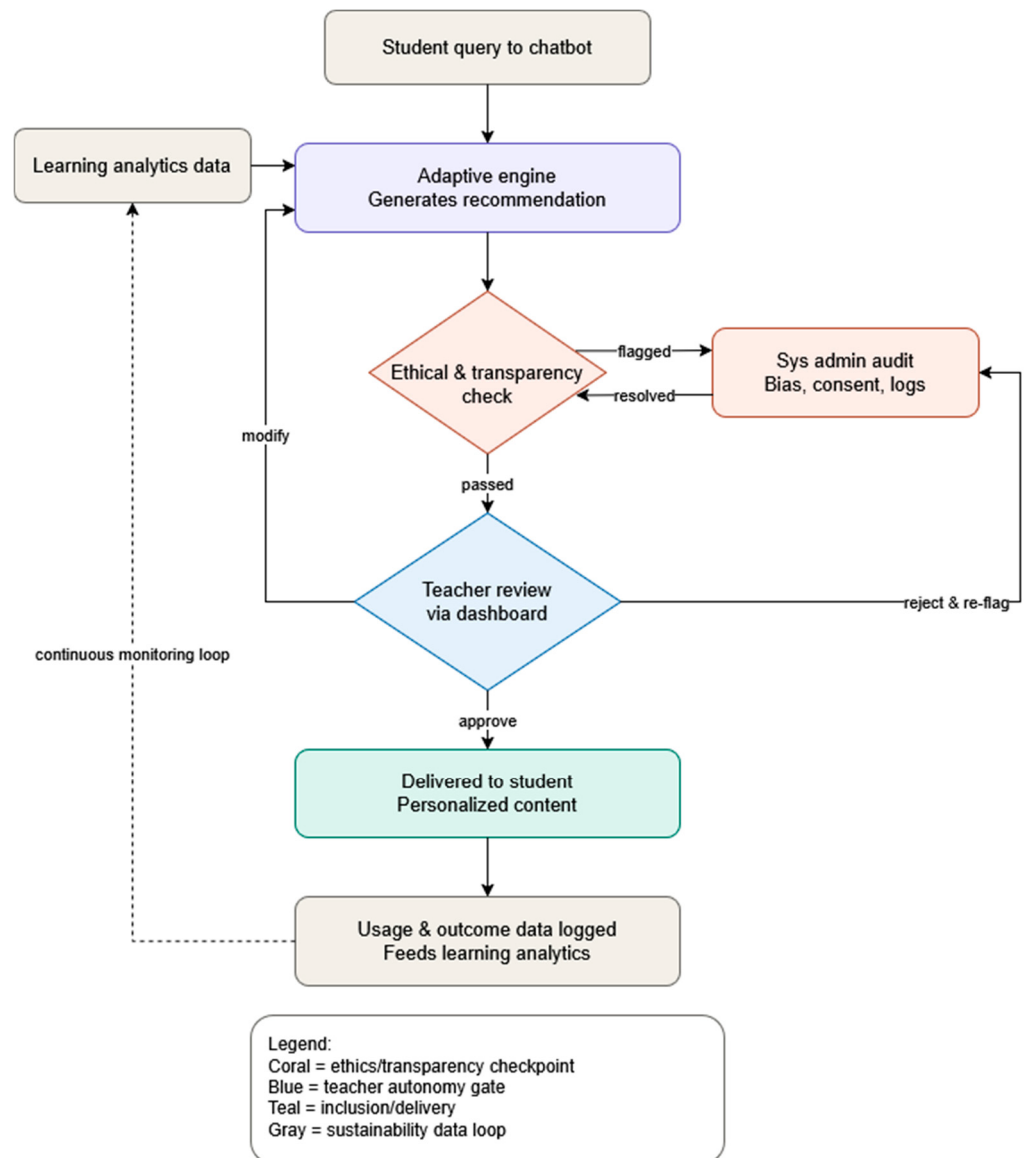
The proposed framework for AI-based support systems in education addresses these challenges through a multi-layered, inclusive, teacher-centred, and data-driven design. The qualitative research focused on expert evaluation to assess the pedagogical suitability, coherence, and feasibility of the proposed AI-based educational support framework from teachers' perspectives.

This section presents the proposed conceptual framework and its pedagogical design. The findings of the qualitative expert evaluation are presented separately in Section 3.2.

Compared with existing AI-supported learning models, this study proposes a systemic, constructivist theory-based framework that integrates adaptive learning, learning analytics, intelligent feedback, accessibility, instructor support, and inclusive online learning into a unified educational ecosystem. While these components are adapted from established research, their conceptual integration and alignment with sustainable higher education principles constitute the primary contribution. The framework further distinguishes itself by emphasizing the complementary roles of AI and educators in supporting personalized, accessible, and learner-centered teaching and learning.

The proposed AI-based Support System framework involves three main actors: Teacher, Student, and System Administrator. The system is designed to improve personalized learning, monitoring, and ethical management through artificial intelligence technologies. Teachers interact with the system to monitor student learning progress, view analytics dashboards, customize adaptive learning rules, co-design personalized learning experiences, review chatbot interactions, and ensure ethical data usage. Students mainly use the platform to interact with the AI chatbot and access learning materials that support their educational needs. The System Administrator is responsible for maintaining the technical and ethical aspects of the system, including managing user roles and permissions, maintaining system data integrity, auditing ethical and transparent AI layers, and monitoring overall system performance. The framework (see Figure 2) demonstrates collaboration between educational stakeholders and AI tools to create an adaptive, transparent, and efficient learning environment. The proposed framework also recognizes the importance of responsible AI implementation in higher education. During the implementation of AI-supported educational systems, particular attention should be given to informed consent, responsible management of learner data, explainability of AI-generated recommendations, potential algorithmic bias, hallucination risks associated with generative AI, human oversight, and clear accountability for AI-supported decisions. These considerations support the transparent, ethical, and trustworthy use of AI in educational environments.

The proposed framework incorporates an Adaptive Learning Pathway designed to personalize learning content, activities, and pacing according to individual learner needs (see Figure 3). The Adaptive Learning Pathway is essential because students enter courses with varying prior knowledge, learning speeds, and goals; adaptive pathways personalize content, tasks, and pacing, ensuring that each learner receives appropriate challenge and support rather than a one-size-fits-all curriculum.



**Figure 2.** AI-based support system framework.

Figure 4 presents the internal structure of the proposed AI-Based Educational Support System, consisting of four interconnected components: Adaptive Learning Pathway, AI-Supported Feedback Engine, Learner Analytics Component, and Instructor Dashboard. Each module contributes to improving teaching effectiveness and student learning outcomes through artificial intelligence technologies.

The AI-based educational support framework will ensure clear use of the support system in education and ensure the (1) Adaptive Learning Pathway implementation, (2) use of AI-Supported Feedback Engine, (3) Learner Analytics Component helping teachers to analyse real-time students' data, and (4) use of the instructor dashboard.

The proposed framework represents a conceptual model rather than a fully implemented AI system. Its purpose is to define the pedagogical architecture and functional interactions of AI-supported learning within a constructivist theory-based course. The framework specifies the intended roles of adaptive learning, automated feedback, learning analytics, and instructor dashboards, but these components were not implemented or tested using specific AI tools or learner data. Instead, the framework was evaluated through

expert review to assess its pedagogical suitability, feasibility, and coherence, providing a foundation for future technical implementation and empirical validation.

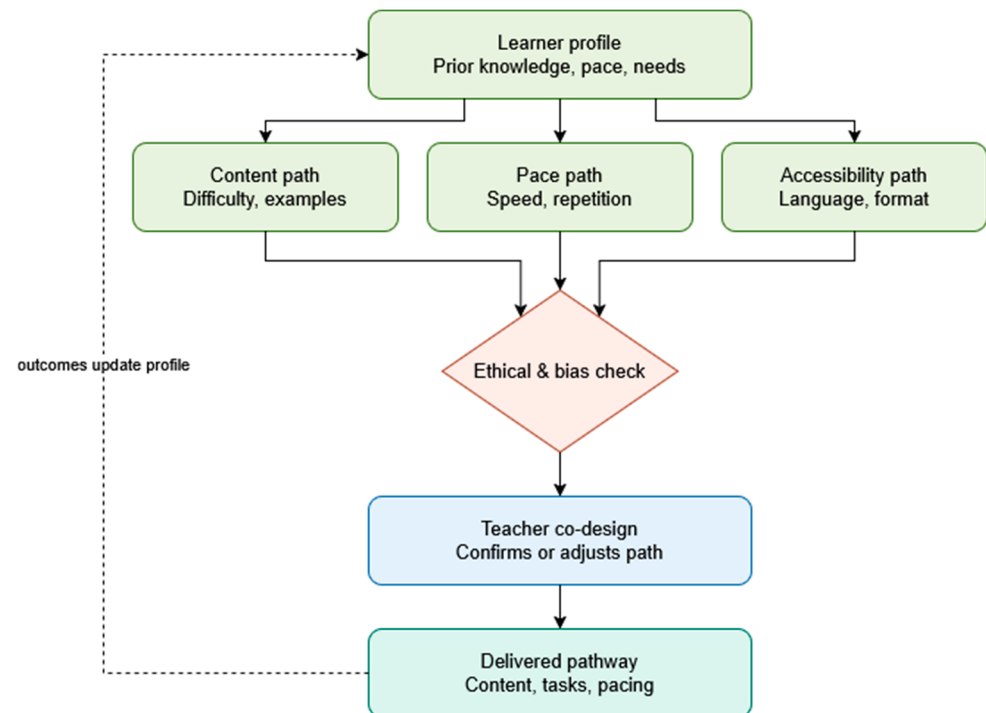


Figure 3. Personalized AI-based support.

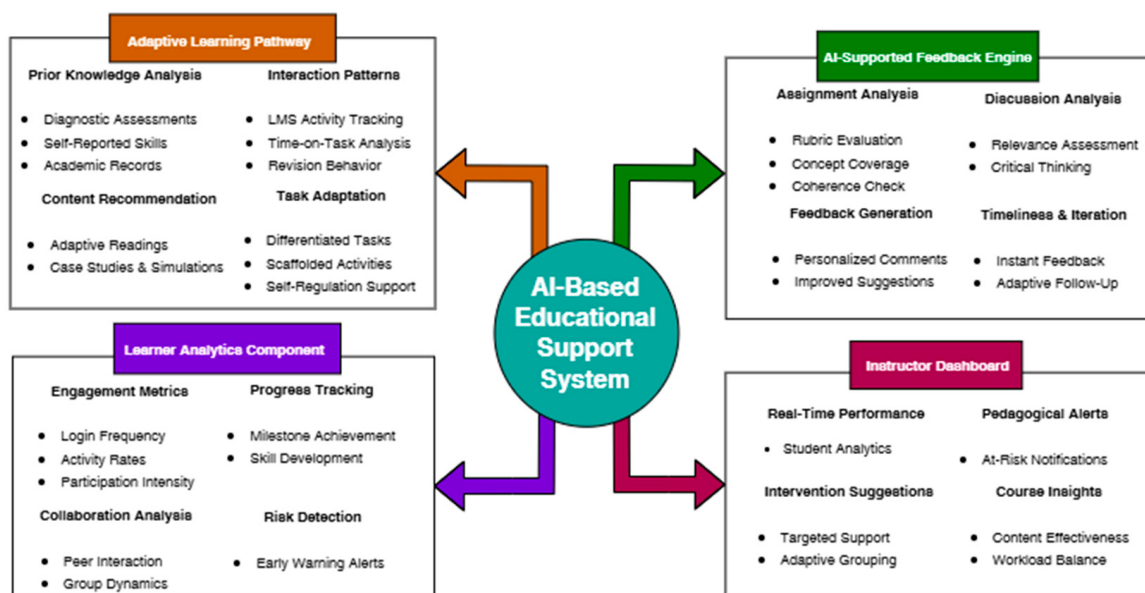


Figure 4. AI-based educational support framework diagram.

The paper proposes an AI-based (using the Chatbase platform) educational support framework for a master's-level online module that integrates Adaptive Learning Pathways, AI-driven formative feedback, learner analytics, and an instructor dashboard. The framework is underpinned by transformer-based large language models (LLMs) for conversational tutoring and feedback generation, combined with rule-based adaptive sequencing algorithms that adjust learning content based on learner performance thresholds and mastery levels. Learner data are derived from learning management system (LMS) logs, including clickstream data, time-on-task, quiz scores, assignment submissions, and discus-

sion forum activity. The AI chatbot component follows a retrieval-augmented generation (RAG) architecture, where domain-specific course materials are indexed and retrieved to ground model responses in curriculum-aligned content. Prompt engineering strategies are guided by structured instructional prompts and rubric-based evaluation templates to ensure consistency in feedback quality. Adaptive rules are defined using performance-based decision logic, where learners are redirected to remedial or advanced content based on predefined mastery criteria. The framework is validated through qualitative expert evaluation involving six specialists in educational technology and AI, confirming its pedagogical relevance and practical feasibility.

**Adaptive Learning Pathway.** The Adaptive Learning Pathway is responsible for personalizing the learning experience for each master's-level student in the fully online course. It begins with prior knowledge analysis, which uses an initial diagnostic assessment, self-reported competencies, and previous academic experience to establish a baseline learner profile. This profile is continuously updated through interaction pattern analysis, including frequency of LMS access, navigation paths, time spent on learning materials, revision behaviour, and completion of activities. Based on these data, the content recommendation engine dynamically suggests relevant readings, research articles, multimedia resources, and case studies aligned with the module's learning outcomes. Practical tasks are adapted in complexity and scope, offering scaffolded activities for students needing support and advanced challenges for high-performing learners. The pathway also integrates self-regulation support by proposing weekly goals, pacing recommendations, and reflective prompts, enabling students to manage their learning autonomously while maintaining alignment with course objectives.

**AI-Supported Feedback Engine.** The AI-Supported Feedback Engine provides timely, formative, and pedagogically grounded feedback to support deep learning. It analyses written assignments using predefined rubrics, assessing conceptual understanding, argument coherence, methodological rigor, and alignment with academic standards. In discussion forums, the engine evaluates contributions based on relevance, critical thinking indicators, and engagement with peers' ideas. Using natural language processing, the system generates personalized feedback comments that highlight strengths, identify gaps, and suggest concrete improvements. Feedback is delivered shortly after submission to maximize its formative value and may include references to exemplary responses or additional learning resources. The engine supports iterative learning by adapting subsequent feedback based on prior revisions, encouraging reflection and continuous improvement. This component reduces instructor workload while maintaining consistent, transparent, and learner-centred feedback practices.

**Learner Analytics Component.** The Learner Analytics Component continuously monitors and interprets student learning behaviours within the online environment. Engagement metrics include login frequency, duration of learning sessions, activity completion rates, and participation intensity in collaborative tasks. Progress tracking focuses on the achievement of learning milestones, the development of targeted competencies, and performance trends across assessments. The component also analyses collaboration patterns by examining peer interactions, discussion networks, and the balance of contributions in group work. Using these indicators, the system identifies early warning signs of disengagement, overload, or underperformance. Analytics outputs are designed to be interpretable rather than predictive alone, emphasizing transparency and educational relevance. By transforming raw interaction data into meaningful insights, this component supports both students' self-awareness of learning behaviours and informed instructional decision-making by the course instructor.

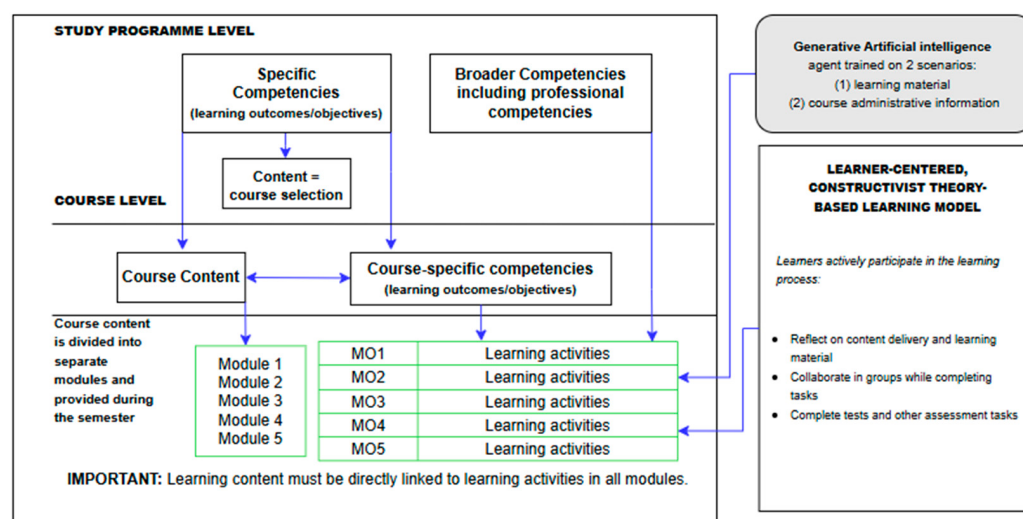
**Instructor Dashboard.** The Instructor Dashboard serves as the central interface for pedagogical decision support in the fully online master's course. It provides real-time visualizations of individual and cohort-level performance, engagement trends, and progress toward learning outcomes. Pedagogical alerts notify the instructor of at-risk students, sudden drops in participation, or persistent misconceptions. Based on learner analytics and feedback data, the dashboard offers evidence-informed intervention suggestions, such as targeted feedback, adaptive grouping for collaborative tasks, or adjustments to workload and pacing. Course-level insights highlight content effectiveness, assessment difficulty, and alignment between learning activities and outcomes. The dashboard is designed to support reflective teaching practice, enabling instructors to fine-tune instructional strategies while maintaining academic rigor and personalized support in a distance learning context.

To ensure pedagogical alignment, the proposed AI-based educational support framework was integrated into a constructivist course design model. Constructivist learning emphasizes interaction, collaboration, reflection, and problem-solving, enabling learners to actively construct knowledge rather than passively receive information.

An integrated support system strengthens this learning model by providing continuous guidance, resources, and feedback throughout the learning process. The support system may include generative artificial intelligence, digital learning platforms, assessment tools, and collaborative environments that help students engage more effectively with course content. AI-based support can deliver personalized learning materials, answer questions, assist with administrative tasks, and adapt learning activities to individual needs. This increases accessibility, flexibility, and learner motivation.

The model also ensures strong alignment between programme competencies, course objectives, module outcomes, and learning activities. Each module is directly connected to measurable learning outcomes, helping students clearly understand what they are expected to achieve. At the same time, teachers can monitor progress more efficiently and provide targeted support when needed.

Moreover, the integrated constructivist approach promotes active participation through group work, reflection, discussion, and assessment activities. Students become responsible participants in their own learning process rather than passive listeners. This creates a more engaging, inclusive, and student-centered educational environment that supports deeper understanding, lifelong learning, and professional competence development. The integration of these pedagogical principles within the proposed framework is illustrated in Figure 5.



**Figure 5.** A constructivist theory-based course concept with an integrated support system.

Figure 5 presents a learner-centered, constructivist learning model integrated with generative artificial intelligence in higher education. At the study programme level, broader professional competencies and specific learning outcomes guide course design and content selection. At the course level, the selected content is linked to course-specific competencies, ensuring that learning objectives are clearly aligned with teaching activities. The course content is divided into modules delivered throughout the semester, with each module connected to measurable learning outcomes (MO1–MO5) and related learning activities. The model emphasizes that all learning content must directly support learning activities in every module. Generative AI functions as an educational agent by providing learning materials and course administrative support. Learners actively participate by reflecting on content, collaborating in group tasks, and completing assessments.

The proposed conceptual framework was subsequently evaluated by experts to assess its pedagogical suitability, coherence, and practical feasibility. The results of this qualitative evaluation are presented in the following section.

### 3.2. Expert Evaluation Findings

This section presents the findings of the qualitative expert evaluation of the proposed conceptual framework. The main characteristics of the course are first described to provide the context for the expert evaluation. The course is a fully online, constructivist-oriented learning experience designed to empower students to actively construct understanding of complex information technologies through engagement, collaboration, and real-world problem solving. The course leverages Massive Open Online Course (MOOC) principles, such as flexibility, open access, and self-paced learning, while embedding pedagogical features that promote deep learning, reflection, and social interaction rather than passive content consumption. In constructivist terms, learners are not recipients of information but co-creators of knowledge: they interpret and integrate new concepts through exploration, discussion, and authentic challenge activities. Constructivist strategies such as problem-based tasks, mini-challenge teamwork, and interactive forums support meaning-making and critical thinking.

The course content is organized into modular units that introduce foundational concepts (e.g., data processing data analytics, time-series analysis, and low-code visualization frameworks) alongside practical applications and collaborative challenges. Learners engage with video lectures and reading materials, reflect on key ideas, engage in technology-mediated discussion spaces, and participate in team-based mini-projects that tackle real data problems—allowing learners to connect theory with practice. Weekly assessments and team interactions create opportunities for reflection, peer learning, and continuous self-assessment, all aligned with constructivist learning theory, which emphasizes active engagement, multiple perspectives, and situated cognition. MOOC methodology enhances this constructivist design by facilitating global learner access, flexible pacing, and community interaction across diverse contexts. Learners can revisit materials, contribute to discussion forums, and receive peer and instructor support asynchronously, fostering a distributed community of practice that mirrors social constructivism (knowledge built through interaction and shared meaning). Through these mechanisms, the course supports not only the acquisition of technical skills in big data analytics but also the development of learner autonomy, collaborative competencies, and reflective judgment, core objectives of constructivist learning in online environments. To assess the effectiveness of the AI-based support system, which was implemented in the master's-level course module Educational Support Systems, a qualitative evaluation of the module's online course was conducted. The evaluation focused primarily on ease of use, perceived usefulness, and the quality of learning support. The evaluation methodology involved inductive thematic analysis

of evaluation data, conducted by reviewing experts' responses to the questions posed, identifying recurring themes (codes), determining similarities and differences, and formulating recommendations.

In this study, data were collected exclusively through expert evaluation, as the primary aim was to assess the pedagogical suitability and conceptual coherence of the proposed framework rather than to measure student-level outcomes. Therefore, student surveys, LMS interaction logs, learning performance indicators, feedback quality metrics, dropout or retention data, and faculty workload measures were not included. The evaluation focused on qualitative expert interviews, enabling in-depth assessment of the framework's design, feasibility, and alignment with constructivist principles. This approach was selected to validate the conceptual model prior to future empirical implementation with learners.

Qualitative evaluation data were collected through semi-structured online interviews with 6 educators and experts in distance learning and support systems (E1–E6). The qualitative findings are organized according to the seven themes identified through thematic analysis, corresponding to the seven interview questions used during the expert evaluation. These themes represent experts' perceptions of the pedagogical suitability, feasibility, and practical applicability of the proposed framework rather than direct evidence of educational effectiveness. The seven interview questions used during the expert evaluation:

1. Have appropriate teaching tools been selected for the course?
2. Are appropriate teaching and assessment methods being used in the course?
3. Does the course include appropriate support mechanisms?
4. Is there adequate feedback in the course?
5. What makes the collaborative learning process and its participants in the course unique?
6. How is communication conducted in the course, what measures are used to encourage participant engagement and learning, and how is support provided?
7. What problems and threats are identified in the course, how could they be addressed, and what steps could be taken to improve the course?

A review of the experts' (E1–E6) responses to the first interview question "Were appropriate teaching tools selected for the course?" revealed recurring positive themes such as an overall positive assessment of the tools' suitability, the use of multimodal content, the use of tools relevant to NM principles, and the use of additional AI-based support tools. The following gaps and risks were also identified: an excessive abundance of tools that could hinder learning and minor inconsistencies in terminology.

### 3.2.1. Teaching Tools for Support

The experts' evaluations indicate that the teaching tools used in the course generally align with the principles of distance and technology-based learning and facilitate consistent theoretical and practical progress among students. Experts highlight the structured theoretical content (slides, notes, and the supplementary literature) and the multimodal nature of the content: audio and video lectures, independent study of materials, and the completion of practical activities using Colab notebooks and mini-project assignments. According to the experts, this combination of tools facilitates differentiated and self-directed learning, as students can individually adjust their learning pace, revisit more complex topics, apply knowledge in practical situations, and assess their progress through tests. In addition, some experts find it useful to integrate additional AI tools, such as audio summaries or content generated by Perplexity.ai, to provide further clarification of information and a theoretical foundation.

Experts identify several challenges that may limit the effectiveness of the tools used. Some experts note that the abundance of teaching materials in the Moodle environment can lead to information overload. Attention is also drawn to the varying levels of IT

proficiency among learners, which may make practical tasks too complex for some students. To address this issue, it is recommended to include an introduction to the IT tools used in the course. Nevertheless, the experts' overall assessment indicates that the teaching tools used in the course are appropriately selected, systematically linked to the course objectives, and aligned with contemporary distance learning practices in higher education, thereby facilitating effective content mastery and the development of practical competencies.

A review of the experts' responses to the second interview question "Are appropriate teaching and assessment methods used in the course?" revealed recurring positive themes such as blended methodology, an emphasis on self-directed learning, and the assessment framework. Gaps and risks were also identified, such as a lack of reflection of real-world skills in practical tasks, a lack of feedback and objectivity in assessment, and the complexity of assessing teamwork.

### 3.2.2. Teaching and Assessment Methods

The expert evaluation revealed that the teaching and assessment methods used in the course are appropriate and consistently integrate theoretical and practical components. A blended learning approach was identified, where learning is combined with structured lectures and notes, while the practical component is based on assignments and team projects. Assessment includes knowledge assessment using automated tests designed for self-assessment and practical skills assessment through teamwork, which involves both internal and external evaluation of assignments. This combination accommodates different learning styles and supports self-paced learning within the context of an open online course.

To improve the quality of the course, experts identified several areas for improvement. First, they described that it is imperative to strengthen practical assessment to ensure that knowledge assessment through tests is balanced with real-world tasks.

Additionally, clearer assessment criteria and instructor moderation would help ensure the objectivity of peer assessment, while regular, qualitative feedback would increase the perceived fairness of assessment and the visibility of learning progress. Furthermore, it is recommended to facilitate the coordination of teamwork by defining clear roles and interim checkpoints. Although teamwork is viewed as an element of significant added value, its logistics sometimes pose challenges.

### 3.2.3. Assistance and Support Mechanisms

A review of the experts' responses to the third interview question "Does the course provide appropriate assistance and support mechanisms?" revealed recurring positive themes, such as the availability of support channels and the strengths of asynchronous support. Gaps and risks were also identified, such as the need for synchronous support and varying experiences regarding participation in discussion forums.

The experts' assessments indicate that the help and support mechanisms provided in the course generally function well and are appropriate for the context of distance learning. The main support channels mentioned include: the Chatbot AI tool, the instructor's general information posts in the "Teacher's announcements" section, the Notes discussion tool, Chat, as well as peer support fostered through group work, which enables students to quickly receive answers to content-related questions and share experiences while solving practical tasks. Some experts also highlight the benefits of the forum and Perplexity.ai integration for self-directed learning.

Identified areas for improvement: there is a lack of direct (synchronous) consultations for more complex technical inquiries; the purpose of support channels and response times is not clearly defined, especially in the case of Chat and Notes; student experiences

regarding forum usage vary. It is recommended to create a map of support channels with estimated response times, introduce regular Q&A sessions at scheduled times, and standardize guidelines for AI use to establish boundaries between automated and instructor-provided support.

Upon reviewing the experts' responses to the fourth interview question, "Is there adequate feedback in the course?", the following positive recurring themes emerge: an ecosystem of feedback mechanisms, timely self-assessment, and the benefits of collaborative learning. Gaps and risks were also identified, such as a lack of personalization and inconsistent intensity, transparency, and access.

#### 3.2.4. Feedback in the System

Expert evaluations indicate that feedback in the course is organized through several mechanisms that allow students to assess their progress and adjust their learning strategies. First, after tests, students immediately receive automated feedback showing correct and incorrect answers. Following practical assignments, internal and external peer assessment is applied, helping teams understand the strengths and weaknesses of their solutions. Additionally, channels such as Notes, Chat, an AI-powered Chatbot, and a forum are utilized to provide targeted assistance on specific content sections.

However, gaps in the quality and availability of feedback have been identified. Experts highlight the lack of personalized instructor comments and inconsistent frequency—often, students receive only a grade or a general conclusion, without clear guidance on what to improve. Furthermore, experts evaluating the course in "guest" mode were unable to experience the test feedback firsthand, so the transparency of its format and criteria remains limited. It is recommended to establish minimum standards for providing feedback, use brief, personalized comments based on criteria, and calibrate peer evaluation with clear rubrics and instructor moderation. It is also recommended to increase structural transparency (examples, screenshots) and optimize the use of communication channels.

After reviewing the experts' responses to the 5th interview question, "What makes the NM process organized in the course and its participants unique?", the following recurring themes emerged: clear, structured, and logical course organization; an emphasis on independence and individual pace; the instructor's role as a consultant; the promotion of practical application of knowledge and real-world problem-solving; and communication as a natural part of the course. Gaps and risks were also identified, such as a lack of face-to-face consultations, varying levels of student preparation, and the fact that tasks may be too difficult or too easy for some students.

#### 3.2.5. Collaborative Learning Process

An analysis of the expert evaluations revealed that the learning process organized within the course is clearly structured, logical, and focused on independent and practical learning. The course begins with basic concepts and gradually moves on to more complex topics, both theoretical and practical. The material is presented in clearly defined topics and subtopics. The sequence of lectures allows students to orient themselves and plan their learning. Meanwhile, practical assignments, team projects, and real-world data analysis cases enable students to directly apply their knowledge and develop problem-solving competencies. This demonstrates that the course is organized in a methodical, pedagogically sound manner and is well-suited for independent learning, focusing not on passive information reception but on active engagement. Course participants have varying skill levels, but this creates opportunities for collaboration and learning from one another. The instructor's role is more consultative, and teaching is based on solving real-world

problems. This fosters student engagement, problem-solving, and the development of self-directed learning skills.

To improve the learning process so that it is even more engaging and supportive, aspects such as balancing different competencies, ensuring the availability of consultations, and fostering emotional engagement could be strengthened. These insights indicate that the learning process is effective but could be strengthened through synchronous activities and individualized support. According to the experts, the lack of face-to-face consultations weakens the connection with the instructor and may lead to a sense of isolation.

Reviewing the responses of experts to the 6th interview question, “How is communication conducted in the course, what measures are used to encourage participant activity/learning, and how is support provided?”, the following positive recurring themes were identified: the organization of asynchronous communication, collaboration and teamwork as a key pillar of the course, measures to encourage participant engagement, and the support mechanisms in place. Gaps and risks were also identified, such as a lack of live communication and consultations, a lack of interactive elements that encourage active discussions, in some cases a weak connection with the instructor, and an insufficiently transparent communication structure.

### 3.2.6. Communication Models

An analysis of expert evaluations revealed that the communication model used in the course is primarily asynchronous and based on the interaction of several virtual channels. The main communication takes place via Notes, Chat, AI-based support agents, and official instructor announcements. The discussion forum and team activities provide opportunities for student interaction and knowledge sharing. This course model facilitates flexible, self-directed learning but limits the ability to address more complex issues in real time.

Participant engagement in the course is fostered through challenge-based learning, teamwork, practical tasks, and self-assessment tests, which help track progress and maintain motivation. Although these measures are considered effective, several experts note a lack of interactivity and recommend incorporating more live discussions and dynamic activities that can reduce the sense of isolation caused by distance learning.

The support system in the course is evaluated as functional but varies in intensity. Students most often rely on peer support and structured materials, while access to the instructor’s consultations is limited. In the experts’ opinion, a greater availability of synchronous consultations and a clearer definition of the purpose of communication channels would enhance the accessibility of support and the overall learning experience.

### 3.2.7. Problems and Threats

A review of the experts’ responses to the 7th interview question, “What problems and threats are identified in the course, how could they be addressed, and what actions could be taken to improve the course?”, revealed the following problems and threats were identified: high dropout rates and lack of motivation, uneven student preparedness, unreliable communication and limited availability of in-person consultations, limitations in communication structures, technical difficulties, constraints on independent problem-solving, ambiguities in the assessment process, and limited feedback. Solutions such as structured deadlines, introductory modules for weaker students, more synchronous communication, an active discussion space/forum, a technical support procedure, a clearer assessment structure, and feedback are also proposed.

An analysis of expert evaluations revealed several key problems and risks related to the organization of the course and the learning experience. First and foremost, the high dropout rate and the varying levels of IT proficiency among participants were highlighted.

This results in varying learning paces among students and poses the risk that beginners may fall behind. Also highlighted are the limited availability of face-to-face interaction with instructors and an insufficiently clear communication structure, which complicates the resolution of more complex issues and weakens the sense of community. Additionally, technical issues, insufficient feedback, and a lack of transparency in the assessment process are highlighted. Automated tests provide only basic information, and peer assessment is not always considered objective. This limits the ability to accurately understand progress and improve in a targeted manner.

#### 4. Discussion

Regarding the research question, we discussed how effective the pedagogical suitability of the AI-based support framework is in the learning process, as in today's education, artificial intelligence (AI) has emerged as one of the most influential technologies in the development of modern educational support systems, offering innovative solutions that improve both teaching and learning processes. AI-based support modules enable personalized learning experiences by adapting educational content, assessment methods, and learning pathways to the individual needs and abilities of students. AI in personalized learning facilitates adaptive content delivery, enabling students to learn at their own pace and according to their individual strengths and weaknesses. Intelligent tutoring systems, for instance, offer customized feedback, explanations, and recommendations based on real-time student interactions, fostering deeper comprehension and engagement. Moreover, AI-powered recommendation engines provide personalized learning resources and materials that align with students' interests, preferences, and skill levels, creating a more tailored and immersive learning experience [33]. Through machine learning algorithms and learning analytics, these systems can continuously monitor learner performance [34], identify knowledge gaps, and provide timely recommendations for improvement. Such adaptive functionality contributes to higher learning effectiveness and increased student engagement. Another significant advantage of AI integration is the automation of repetitive educational tasks, including grading assignments, generating feedback, and managing administrative activities. This allows educators to dedicate more time to instructional planning, mentoring, and individualized student support. AI-powered intelligent tutoring systems can also provide immediate assistance outside classroom hours, promoting self-directed learning and continuous knowledge acquisition [35].

AI-based educational support systems play an important role in fostering inclusive education [36] by offering accessible learning materials, speech and text recognition, automatic translation, and assistive technologies for learners with disabilities or diverse educational needs. These capabilities contribute to reducing educational inequalities and creating more equitable learning environments. In addition, predictive analytics can identify students at risk of poor academic performance or dropout, enabling early interventions that improve retention and academic success.

Despite these considerable benefits, successful AI implementation requires careful consideration of ethical issues, data privacy, algorithm transparency, and the evolving role of educators. Human supervision remains essential to ensure fairness, accountability, and pedagogical quality in AI-assisted learning environments. Overall, AI-based educational support systems enhance learning efficiency, accessibility, personalization, and institutional effectiveness, representing a key technological advancement that supports the transition toward more adaptive, inclusive, and student-centered education in the digital era. Moreover, the experts identified several key aspects of AI-based support in the module (Table 2).

Table 2. Key aspects identified.

| Key Criteria                                                 | Advantages of AI-Based Support                                                                                                                                                                                                                                                                                                                                                   | Challenges of AI-Based Support                                                                                                                                                                                                                                                                                                            |
|--------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Strengthen synchronous communication and consultations       | <ul style="list-style-type: none"> <li>AI chatbots and virtual assistants provide 24/7 support.</li> <li>Automated scheduling and reminders improve consultation management.</li> <li>Real-time translation and speech-to-text tools enhance accessibility for students with disabilities.</li> <li>AI can personalize responses based on student needs.</li> </ul>              | <ul style="list-style-type: none"> <li>Lack of human empathy and emotional understanding.</li> <li>AI may provide inaccurate or overly generic answers.</li> <li>Technical issues can disrupt live communication.</li> <li>Students may become overly dependent on automated support.</li> </ul>                                          |
| Create an active discussion forum                            | <ul style="list-style-type: none"> <li>AI moderation tools can encourage respectful and organized discussions.</li> <li>Recommendation systems can suggest relevant topics and resources.</li> <li>Automated summarization helps students review discussions efficiently.</li> <li>AI can stimulate participation through prompts and engagement analytics.</li> </ul>           | <ul style="list-style-type: none"> <li>Discussions may become less authentic if overly AI-driven.</li> <li>Risk of misinformation generated by AI tools.</li> <li>Privacy concerns regarding student interactions and data collection.</li> <li>Some students may feel uncomfortable interacting in AI-monitored environments.</li> </ul> |
| Develop introductory modules for students with special needs | <ul style="list-style-type: none"> <li>AI enables adaptive learning tailored to individual abilities and learning speeds.</li> <li>Assistive technologies (text-to-speech, speech-to-text, sign language avatars) improve accessibility.</li> <li>Personalized pathways reduce barriers to learning.</li> <li>AI analytics help identify learning difficulties early.</li> </ul> | <ul style="list-style-type: none"> <li>High development and implementation costs.</li> <li>AI systems may not fully understand complex or diverse special needs.</li> <li>Accessibility tools may vary in quality and language support.</li> <li>Ethical concerns related to student profiling and data use.</li> </ul>                   |
| Simplify the structure of the course material                | <ul style="list-style-type: none"> <li>AI can automatically summarize complex content into simpler formats.</li> <li>Intelligent tutoring systems can recommend step-by-step learning paths.</li> <li>Content can be personalized according to learner performance.</li> <li>Visual and interactive AI tools improve comprehension.</li> </ul>                                   | <ul style="list-style-type: none"> <li>Oversimplification may reduce academic depth.</li> <li>AI-generated summaries may omit critical concepts.</li> <li>Students may rely too heavily on simplified materials instead of developing critical thinking.</li> <li>Requires continuous monitoring by instructors for accuracy.</li> </ul>  |

Table 2. *Cont.*

| Key Criteria                                                          | Advantages of AI-Based Support                                                                                                                                                                                                                                                                                                                                | Challenges of AI-Based Support                                                                                                                                                                                                                                                                                                                |
|-----------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Include more practical and laboratory activities                      | <ul style="list-style-type: none"> <li>• AI-powered simulations and virtual labs allow safe and flexible experimentation.</li> <li>• Virtual reality and intelligent simulations support remote learning.</li> <li>• Students can practice repeatedly without material limitations.</li> <li>• AI can provide instant feedback during experiments.</li> </ul> | <ul style="list-style-type: none"> <li>• Virtual labs cannot fully replace hands-on physical experiences.</li> <li>• Advanced simulation technologies can be expensive.</li> <li>• Technical limitations may affect realism and engagement.</li> <li>• Unequal access to devices and internet connectivity can create disparities.</li> </ul> |
| Improve the quality of feedback and transparency of assessment        | <ul style="list-style-type: none"> <li>• AI provides immediate feedback and automated grading.</li> <li>• Learning analytics helps identify strengths and weaknesses quickly.</li> <li>• Transparent rubrics and performance tracking improve fairness.</li> <li>• Personalized feedback can support student improvement.</li> </ul>                          | <ul style="list-style-type: none"> <li>• Automated grading may misinterpret creative or complex answers.</li> <li>• Bias in AI algorithms can affect assessment fairness.</li> <li>• Students may question the reliability of machine-generated evaluations.</li> <li>• Reduced human interaction in feedback processes.</li> </ul>           |
| Regularly update the course in line with current technological trends | <ul style="list-style-type: none"> <li>• AI can monitor emerging trends and recommend updated content.</li> <li>• Automated content curation reduces instructor workload.</li> <li>• Courses remain aligned with industry and technological developments.</li> <li>• Faster integration of new learning resources and tools.</li> </ul>                       | <ul style="list-style-type: none"> <li>• Constant updates may overwhelm students and instructors.</li> <li>• Dependence on AI recommendations may reduce academic autonomy.</li> <li>• Risk of prioritizing trends over pedagogical quality.</li> <li>• Requires continuous technical maintenance and staff training.</li> </ul>              |

Improvement measures proposed by experts include strengthening the course's pace, introducing weekly deadlines, and organizing synchronous consultations to increase external accountability and reduce the risk of dropout. It is also recommended to create introductory modules to help standardize student readiness, as well as active discussion forums to foster a sense of community and knowledge sharing. Improved feedback, clearer assessment rubrics, and technical support tools would be important steps toward higher course quality and a better learning experience.

The findings of the present study should be interpreted as expert evaluations of the proposed conceptual framework rather than empirical evidence of its educational effectiveness. Although the experts considered the framework pedagogically appropriate and practically feasible, its effectiveness in improving learning outcomes, learner engagement, or instructor performance remains to be validated through empirical studies involving students. Furthermore, the applicability of the framework across different disciplines, learner populations, and institutional contexts requires further empirical investigation.

## 5. Conclusions

The expert evaluation demonstrated that the proposed AI-based educational support framework is pedagogically sound, theoretically grounded, and suitable for implementation in higher education courses designed according to constructivist learning principles. Overall, the experts agreed that the framework effectively integrates artificial intelligence

with learner-centered pedagogical approaches, providing adaptive, personalized, and data-informed support for both students and instructors.

Authors focused on personalized learning pathways, delivering timely AI-supported feedback, monitoring learner progress through learning analytics, and assisting instructors in identifying students who require additional academic support. These findings suggest that the framework aligns well with current developments in artificial intelligence in education and addresses many of the challenges associated with digital and blended learning environments.

The qualitative feedback also provided valuable recommendations for strengthening the proposed framework. Experts emphasized the importance of expanding opportunities for synchronous communication between learners, instructors, and AI-supported systems to complement automated feedback with meaningful human interaction.

Experts recommended refining assessment procedures by providing clearer criteria for formative and summative assessment, improving the transparency of AI-generated recommendations, and ensuring that learners understand how feedback is generated and applied. Additional suggestions included incorporating differentiated support for learners with varying levels of digital competence, strengthening collaborative learning activities, and embedding mechanisms that promote learner reflection, self-regulation, and critical thinking. These recommendations were incorporated into the final version of the framework, resulting in a more comprehensive and pedagogically balanced model.

The findings indicate that the proposed framework has considerable potential for supporting teaching and learning across a variety of higher education contexts, particularly in online, blended, and flexible learning environments. By combining constructivist instructional principles with intelligent educational technologies, the framework promotes active knowledge construction, collaborative learning, continuous formative assessment, and personalized instructional support. The integration of AI enables learning experiences to be dynamically adapted to individual learner needs while maintaining the central role of educators in facilitating learning, interpreting AI-generated insights, and making pedagogical decisions.

From an institutional perspective, the implementation of the framework may produce several important educational benefits. Personalized learning support and adaptive scaffolding can increase learner engagement, motivation, self-regulated learning, and academic achievement across diverse student populations. Automated feedback generation, routine assessment support, and continuous monitoring of learner progress can reduce instructor workload associated with repetitive administrative tasks, allowing educators to devote more time to mentoring, facilitating discussions, providing individualized guidance, and designing meaningful learning experiences. Learning analytics generated by the AI system can provide educators, program coordinators, and institutional leaders with evidence-based insights that support early identification of at-risk students, timely interventions, curriculum improvement, and informed resource allocation.

The framework also contributes to educational inclusion by providing continuous academic support to learners regardless of geographical location or institutional resources. This is particularly relevant for remote, under-resourced, and non-traditional learning environments where access to experienced instructors may be limited. Furthermore, the proposed framework explicitly incorporates ethical principles governing the responsible use of artificial intelligence, including transparency, fairness, data privacy, accountability, and human oversight. These principles are essential for building trust among learners, instructors, and institutions while ensuring that AI technologies remain aligned with educational values and regulatory requirements.

Another significant contribution of the framework is its scalability and flexibility. The modular architecture allows educational institutions to gradually implement AI-supported learning services according to their technological infrastructure, institutional

priorities, and pedagogical practices without compromising teacher autonomy or contextual adaptation. Such flexibility facilitates sustainable implementation across diverse educational settings while preserving the essential human role in teaching and learning.

The research contributes to both the theoretical and practical advancement of artificial intelligence in education. Theoretically, it synthesizes the contemporary literature on constructivist learning, educational technology, and AI-supported instruction to develop a coherent conceptual framework that addresses existing research gaps. Practically, it offers educators, instructional designers, educational technology developers, and policymakers a validated framework that can guide the design, implementation, and evaluation of AI-supported educational environments.

The findings of this study should be interpreted in light of several limitations. The proposed framework was evaluated through qualitative expert assessment involving six experts and was not empirically validated with students in educational settings. Therefore, the findings provide evidence of the framework's pedagogical suitability and practical feasibility rather than its effectiveness across diverse higher education contexts.

## 6. Future Works

Given the limitations of the present study, future research on AI-based educational support systems in higher education should focus on strengthening pedagogical impact, transparency, and long-term sustainability. First, further research is needed to improve adaptive analytics models by incorporating multimodal data sources, such as learning artifacts, peer interaction patterns, and reflective writing, to obtain a more holistic representation of learner progress. These models should move beyond performance prediction toward explanatory analytics that clearly justify recommendations and make underlying assumptions visible to both students and instructors.

Second, real-time feedback mechanisms should be extended to support higher-order learning outcomes, including critical thinking, methodological reasoning, and collaborative knowledge construction. Future systems should combine automated feedback with structured instructor moderation, allowing teachers to refine feedback templates and intervene at key learning moments. Longitudinal studies are required to examine how continuous formative feedback influences self-regulated learning skills, motivation, and academic persistence across multiple courses or programs.

Third, teacher-centered design must remain a priority. Future work should emphasize participatory co-design with instructors from diverse disciplines to ensure that dashboards and analytics align with pedagogical practices and assessment cultures. Professional development frameworks should be developed to support teachers in interpreting analytics, making evidence-based interventions, and critically evaluating AI recommendations rather than relying on them unreflectively. Additionally, ethical and governance considerations require deeper attention. Future systems should embed privacy-by-design principles, bias detection mechanisms, and student agency features that allow learners to understand, contest, or opt out of certain automated decisions. Cross-institutional validation studies are also needed to assess transferability and scalability across different educational contexts.

Finally, future research should explore the integration of educational support systems within broader digital learning ecosystems, ensuring interoperability with learning management systems and institutional data infrastructures. By addressing these directions, future work can contribute to more trustworthy, pedagogically grounded, and human-centered AI support systems in higher education.

**Author Contributions:** Conceptualization D.G., R.K., V.J., S.D., E.S. and J.Č.; methodology, D.G.; software, S.D.; validation, D.G. and R.K.; formal analysis, R.K. and V.J.; investigation, R.K. and V.J.; resources, D.G. and J.Č.; data curation, J.Č.; writing—original draft preparation, E.S., R.K. and J.Č.;

writing—review and editing, D.G.; visualization, S.D.; supervision, D.G.; project administration, D.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** Partly funded by Lithuanian Research Council project “Renewable Energy for Bolstering Ukraine’s Infrastructure by Learning and Design”, REBUILD, No.: IMPRESS 246.

**Institutional Review Board Statement:** Ethical review and approval were waived for this study based on the guidelines of Kaunas University of Technology (<https://en.ktu.edu/research/research-ethics/> (accessed on 14 July 2026)). In the case of research involving human participants (except for research falling within the scope of bioethics) and research including the collection and/or processing of personal data, it is mandatory to fill in the Research Ethics Self-Assessment Questionnaire. Based on the result of the completed Research Ethics Self-Assessment Questionnaire, the University’s employee or doctoral student makes a decision whether to apply to the Commission. In the case if committee sees that it could be necessary, they ask to fill self assessment questionnaire. During the research, the author did not collect any biometric data, in which cases there is necessary to get permission from the national Ethical committee. In our case, the research does not have any influence on the research participants, and their personal data are not collected or the data is anonymised; we do not need permission from the ethics committee.

**Informed Consent Statement:** Informed consent for participation was obtained from all subjects involved in the study.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy concerns.

**Acknowledgments:** The scientific paper was developed in the framework of the international project “Renewable Energy for Bolstering Ukraine’s Infrastructure by Learning and Design”, REBUILD, No.: IMPRESS 246. During the preparation of this manuscript, the authors used the Chatbase platform for the purposes of [educational support framework for a master’s-level online module that integrates Adaptive Learning Pathways, AI-driven formative feedback, learner analytics, and an instructor dashboard]. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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