



Article

# Building an Adaptive AI-Powered Higher Education Class for the Future of Engineering: A Case Study from NTUA

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## Featured Application

This study contributes significantly to higher education, particularly within engineering disciplines, by proposing a personalized and adaptive learning framework supported by artificial intelligence and virtual reality technologies.

## Abstract

This study presents the outcomes of the Erasmus+ European project Higher Education Classroom of the Future (HECOF), with a particular focus on chemical engineering education. In the digital era, the integration and advancement of artificial intelligence (AI) in higher education, especially in engineering, are increasingly important. The main goal of the HECOF project is to establish a system of new higher education teaching practices and national reforms in education. This system has been developed and tested through an innovative personalized and adaptive method of teaching that exploited digital data from students' learning activity in immersive environments, with the aid of computational analysis techniques from data science. The unit operations—extraction process course—a fundamental component of the chemical engineering curriculum, was selected as the case study for the development of the HECOF learning system. A group of undergraduate students evaluated the system's usability and educational efficiency. The findings showed that the HECOF system contributed positively to students' learning—although the extent of improvement varied among individuals—and was associated with a high level of satisfaction, suggesting that HECOF was effective in delivering a positive and engaging learning experience.



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## 1. Introduction

A conventional chemical engineering curriculum is built on fundamental concepts such as mass and energy balances, transport phenomena, thermodynamics, reaction engineering, separations, and process control. Today, these thematic areas have been oriented toward subjects that support a more sustainable society, focusing on clean energy, climate change, well-being, and digital intelligence. Furthermore, shifting from traditional, static teaching evaluation methods to a dynamic, iterative approach in curriculum development is essential [1].

Furthermore, curriculum reconstructions are now designed to prepare students to navigate the challenges and opportunities presented by the new digital era revolution. The transition from traditional educational practices and tools into a digital format has become an unavoidable challenge for teaching methods within the field of chemical engineering. However, there are open challenges regarding how this transition will stay on track, what the legal framework will be, and who is going to have control of it. The digital age of education is here, bringing artificial intelligence (AI), collective intelligence, machine learning (ML), deep learning, and the concept of the extended mind. However, it is crucial to ensure that these new tools serve as a means of reinforcement rather than a substitute for the human mind. In the future, we must reconsider the definitions and use of terms like ‘mind’ and ‘intelligence’ and explore whether intelligence can truly be replicated through technology [2].

Most chemical engineering processes aim to “simulate” physical phenomena, develop mathematical models for better understanding, test different scenarios, make predictions, and serve educational purposes. The use of digital tools for such simulations has been practiced in chemical engineering education for decades. Characteristic examples include older programming languages like Fortran, as well as software platforms such as MATLAB and Python, representing the latest iteration of this trend [3]. As demonstrated by numerous studies and reviews available in the literature, the current trend is the application of AI to model the behavior of chemical systems, process scheduling, control, and more [4]. The possibilities that AI offers to education are enormous, especially for tutoring, assessment, and the personalization of education, and most of these are yet to be discovered [5]. Furthermore, many authors support the creation of a more specialized AI course within the chemical engineering curriculum, with higher relevance to chemical applications or the chemical industry [6].

The application of AI in chemical engineering is not a recent development—it has been an active area of research and practice for over 40 years, marked by several notable achievements. The application of AI in Process Systems Engineering (PSE) dates back to the late 1960s and early 1970s, when pioneering researchers began exploring its potential in the field [7]. Currently, four different stages of the evolution of AI can be found [8]:

#### -1st Stage: Expert Systems (early 1980s to mid-1990s)

This phase marked the first widespread effort to apply AI in chemical engineering. Research focused primarily on rule-based expert systems, aiming to encode human expertise into decision-making tools. For education purposes, programs like CHEMEX were used, which was an expert system developed to assist students in understanding chemical process synthesis and design [9]. Also, several flowsheet simulators were being developed, including PACER, CHES, and FLOWTRAN [10].

#### -2nd Stage II: Neural Networks (~1990 to ~2008)

During this period, interest shifted toward data-driven approaches, particularly artificial neural networks. These models were applied to tasks such as process modeling, control, and fault detection, benefiting from their ability to learn complex nonlinear relationships from data [11]. One example involves combining expert systems and neural networks in a process called hybridization, used both in practice and to teach students about the complexities of process fault detection and the advantages of combining different AI approaches [12]. Another example is a feed-forward neural network for knowledge acquisition and storage, and subsequent use was developed for a chemical reactor selection expert system [13].

For the first two periods, the main problems and limitations were [7] as follows:

- Insufficient data availability, restricted data access, limited computational resources, and underdeveloped programming environments and paradigms.

- The presence of competing, successful, emerging technologies in chemical engineering, especially mechanistic modeling, optimization, and model predictive control.

#### -3rd Stage: Deep Learning Data Science (~2005 to present)

This phase is defined by the rise of deep learning and the integration of data science into chemical engineering. Improved computing power, data availability, and algorithms have enabled accurate, data-driven models for process design and optimization. AI now captures both numerical and symbolic knowledge, bridging data- and knowledge-based methods [8]. Machine learning techniques have become increasingly popular in chemistry and chemical engineering for uncovering patterns in data that often elude human researchers [14,15]. However, one of the primary limitations of these approaches lies in their “black-box” nature—while they can produce outputs from given inputs, the underlying decision-making processes remain opaque [16].

A representative example of hands-on activities introduced in an undergraduate chemical engineering course to teach machine learning was developed using Google Colaboratory, a free cloud platform for AI and ML. These activities can also be executed in a local Python environment and use public datasets from sources such as Kaggle and the UCI repository [17].

And what comes next?

#### -4th Stage: Hybrid and Generative AI Era (~2023–Future)

In this emerging phase, AI is transitioning from a tool for prediction and optimization to a creative collaborator in chemical engineering. It now plays an active role in generating novel chemical pathways, proposing innovative process designs, and autonomously planning experiments. Foundation models, such as GPT and graph-based models, are fine-tuned with domain-specific data to serve as intelligent copilots for engineers and researchers. As generative AI becomes increasingly embedded in professional chemical engineering roles, it is essential that students learn to use these tools ethically, responsibly, and effectively. An example is the research that adopt the IDEE framework (Identify desired outcomes, Determine level of automation, Ensure ethics, Evaluate effectiveness), to develop a chemical engineering lab session which is augmented by large language models (LLMs) [18].

One example of this shift is a problem-based learning (PBL) initiative using ChatGPT 4.0 in a unit operations course, where students designed an industrial dryer for socially and economically relevant applications in Brazil. The project supported key undergraduate outcomes such as solving open-ended problems, gathering diverse data, and applying mathematical and simulation tools [19]. Another early example comes from the Technical University of Denmark (DTU), where a Good Manufacturing Practice (GMP) course is exploring “ChatGMP,” a digital audit tool. This tool simulates a fictional company, allowing students to conduct audit exercises by questioning the system about documentation and practices, potentially replacing instructors in the simulation [20].

Table 1 below summarizes these four stages along with representative examples of AI applications in chemical engineering.

Furthermore, virtual reality (VR) was first introduced in the 1960s in chemical engineering education in the Department of Chemical Engineering at the University of Michigan in Ann Arbor [21]. Since its introduction, VR has rapidly advanced in the field of education. A major boost in adoption occurred around 2015, driven by the release of cutting-edge devices from leading tech companies. By 2018, research began to focus more deeply on incorporating VR into engineering education. As of 2023, over 80 scholarly articles across more than 30 academic journals had explored this topic. In engineering education, VR applications generally fall into five main categories: head-mounted displays (HMDs),

360-degree videos and cameras, augmented and mixed reality (AR/MR), 3D modeling and design tools, and interactive simulators [22]. Initially, most VR applications focused on reproducing single experiments or unit operations [23].

**Table 1.** Description of AI phases in chemical engineering education over the years.

| Time                  | Stage                      | Enabling Technology  | Education Chemical Engineering Examples   |
|-----------------------|----------------------------|--|---|
| Early 1980s–Mid-1990s | Expert Systems             | Expert systems, rule-based inference   | CHEMEX for process synthesis and design, flowsheet simulators PACER, CHES, FLOWTRAN |
| ~1990 to ~2008        | Neural Networks            | Feed-forward/recurrent neural networks, hybrid models                                    | Hybridization process—complexities of process fault detection                       |
| ~2005 to present      | Deep Learning Data Science | Deep learning, GNNs, transformers, knowledge graphs                                      | Chemical reactor selection expert system  |
| ~2023–Future          | Hybrid/Generative AI       | Foundation models, generative AI (e.g., GPT, GNN+LLM), causal AI, neuro-symbolic systems | Revealing patterns in data  |
|                       |                            |  | Unit operations course, industrial drier fictional company                          |

Currently, there is a shift from using VR solely for single experiments or unit operations toward simulating entire processes and realistic industrial scenarios [24,25]. This allows students to be trained in virtual factories, using 3D visualization and simulation tools [26]. Moreover, integrating VR with real-world scenarios can engage students more deeply and promote sustainable behaviors by facilitating education and knowledge transfer within the framework of the digital era and sustainability [27]. Recent empirical studies validate the growing impact of AI, adaptive learning, and VR in STEM and engineering education in terms of both survey reviews [28–34] and individual empirical studies [35–38].

For example, AI tutors were found to make learning more efficient, motivating, and engaging compared to active learning [39]. In another study [37], the findings revealed a generally positive outlook on the role of generative AI in education, where most of the students reported feeling more comfortable seeking help from the AI assistant than from instructors or teaching assistants. AI-based adaptive learning was found to enhance learning outcomes and student satisfaction [38] and to positively impact students' learning and improvement [40]. Furthermore, a meta-analysis of 45 studies found that AI-based adaptive learning platforms produce substantially better cognitive outcomes than non-adaptive methods, with a medium-to-large effect size ( $g \approx 0.70$ ) on student learning performance [34]. Moreover, various studies have shown empirically the benefits of using VR, including significant improvement in performance accuracy and speed, higher satisfaction and engagement levels, enhanced learning of mechanical skills, and offering an effective and engaging approach [35]; improved learning, engagement, immersion, motivation, and perceived learning effectiveness [41]; and helping students to learn better and be more prepared for real-life situations [36].

Despite growing evidence that AI, generative AI, adaptive learning, and VR each enhance learning outcomes when used independently, there is limited research on their combined or integrated application, particularly within chemical engineering education. While studies have demonstrated the individual effectiveness of these technologies across cognitive and affective learning dimensions, their hybridization into a unified system remains rare. This lack of integrated research represents a notable gap in literature. The HECOF

system is designed to address this by combining AI-driven personalization, generative tools, and immersive VR environments into a cohesive platform tailored for engineering education. Based on the increasing demand for effective digital tools in engineering education, this study investigates the potential of a unified, AI-driven learning environment that integrates AI-based adaptive learning, VR, and generative AI. While prior research has explored these technologies in isolation, few systems have examined their combined impact in a single framework. To address this gap, this study poses the following research question:

To what extent does integrating AI, adaptive learning, and VR enhance student engagement, conceptual understanding, and perceived instructional effectiveness in chemical engineering education?

This question guides the system's design rationale and informs the pilot evaluation, focusing on both cognitive and affective outcomes of student interaction with the platform.

Furthermore, this study aims to explore the effectiveness of HECOF, a system that integrates artificial-intelligence-driven adaptivity, a retrieval-augmented virtual tutor, and immersive virtual reality modules, in the context of chemical engineering education. The purpose is to assess whether this integrated system can enhance student engagement, support personalized learning experiences, and contribute to a conceptual understanding in a complex, process-oriented domain. Given the exploratory nature of this work, the following additional research question guides this study:

To what extent does the HECOF system support learner engagement, personalized progress, and perceived learning improvement in higher education chemical engineering courses?

Based on prior research in adaptive learning and virtual tutoring systems, we propose the following expectations:

**H1:** *Students using the HECOF system will report high levels of engagement, satisfaction, and perceived learning improvement with the AI-based adaptive features.*

**H2:** *Students will demonstrate measurable learning gains across sessions, as estimated by the system's internal knowledge model.*

These hypotheses are evaluated through a combination of system-generated metrics and student self-reports in a pilot implementation.

In this work, the Higher Education Classroom of the Future (HECOF) project is presented. The main goal of the HECOF initiative is to create systemic changes in higher education teaching practice and national reforms in education by developing and testing an innovative personalized, adaptive method of teaching that exploits digital data from students' learning activity in immersive environments and uses computational analysis techniques from data science and AI. HECOF also aims to foster the development and uptake of safe and lawful AI that respects fundamental rights by providing insights into ethical and legal issues around the design of the system. It will drive the policy agenda by formulating recommendations on the role and use of AI for personalized, adaptive learning. HECOF technology has clear potential to be mainstreamed in vocational education and the training sector for employees in the chemical engineering sector.

In the EU, the agenda for Higher Education (European Commission, 2017) stresses the need for higher education institutes to address digital transformation, implement digital learning strategies, and exploit the potential of technology to the benefit of their staff and students [42]. Another challenge is the effective adaptation of the education and training systems of EU Member States (as outlined in the Digital Education Action Plan, 2021–2027) to the digital age [43]. Green and digital transitions are the core focus of the Union's

agenda for the next decade. Progress towards the full integration of digital technologies in education and training is still needed in many European countries.

Therefore, HECOF supports the first strategic priority of the Digital Education Action Plan (2021–2027), namely the development of a high-performing digital education ecosystem. It will do so by building capacity and critical understanding in all types of education and training institutions on how to exploit the opportunities offered by digital technologies for teaching and learning at all levels and for all sectors, and to develop and implement digital transformation plans for educational institutions.

AI can serve as an excellent assistant in students' education by supporting these types of simulations, rather than replacing traditional learning. It acts as a tool for realistically modeling physical phenomena, rather than merely a conventional classroom substitute. Additionally, the implementation of adaptive learning methods can serve as a continuous knowledge stream tailored to students' needs and interests. Symbiotic collaborations between teachers and machines, governed by ethical guidelines, can lead to the development of new educational programs, ushering us into a new era.

The project has a conceptual focus on two “chemical engineering” schools in the EU academic discipline and engages teaching staff and students. The National Technical University of Athens (NTUA), School of Chemical Engineering, is one of the pilot Universities of the project, and Politecnico di Milano-School of Chemical Engineering is the second. This work presents a case study of NTUA, concerning a unit operation lesson and the extraction process as the main subject of learning element.

## 2. Materials and Methods

### 2.1. NTUA Chemical Engineering School Curriculum

Two chemical engineering academic disciplines/units have participated in the HECOF project from two different EU countries, Greece and Italy. The main aim is the adoption of the HECOF integrated system into their daily practices. Moreover, HECOF will support higher education systems in Greece and Italy with findings and lessons learned on the use of AI-enhanced pedagogies in the pilot HEIs from these two countries, aiming to augment personalized adaptive learning, while also maintaining its human dimension and social relevance. HECOF will improve the 21st century skills that students need to succeed in their careers during the Information Age. Therefore, it supports the implementation of country recommendations from the European Semester related to paying particular attention to young people and women, who are more affected by a lack of employment opportunities, as well as to increasing the quality and labor market relevance of education and training [44].

NTUA is the most prestigious and competitive academic institution in engineering sciences in Greece. The School of Chemical Engineering at NTUA implements chemical engineering laboratory courses. The Undergraduate Curriculum of the School of Chemical Engineering aims to provide a high level of education to students of chemical engineering, enabling them to acquire the knowledge, skills, and ability to apply the principles of science—mathematics, physics, chemistry, and biology—as well as engineering and economics/social sciences, in their fields of activity.

Among the different courses in the School of Chemical Engineering, unit operations is one of the most important, providing the fundamental knowledge and practical skills necessary for understanding and designing industrial processes. Unit Operations Courses I and II are offered in the 5th and 6th semesters, accordingly, and include both theory teaching and laboratory exercises.

The theory is conducted by the professor for 4 h per week, for a total of 52 h per semester. The course, which enrolls approximately 200 students, aims to introduce process

design, analyze fundamental physical processes, and develop the theoretical background necessary for the courses in the upcoming semesters, such as Safety of Industrial Facilities and Process Design I & II. Students are expected to have prerequisite knowledge in mass and energy balances, thermodynamics, and transport phenomena. The course covers a broad scope, including process analysis and design (introduction, basic principles, and examples), thermal processes (heat exchange, evaporation, freezing, and drying), particle techniques (sieving, filtration, and centrifugation), and key separation processes (distillation, absorption–desorption, and extraction), focusing on process descriptions, basic principles, design, modeling, equipment, and practical exercises. The course follows a structured teaching approach that combines theoretical instruction with computational exercises, including problem-solving sessions and hands-on practice in a personal computer lab.

In addition, the laboratory exercises of the unit operations course are conducted in the 5th and 6th semesters, comprising a total of 12 h per semester in the Laboratory of Process Analysis and Design (LPAD). Each week, two shifts of 3 h each take place, with six different laboratory exercises being performed simultaneously in both shifts. The students work in groups of five, under the supervision of PhD students and technical laboratory staff.

The scope of the laboratory exercises covers key experimental studies, including the following:

- Fluid–Solid Bed: Experimental study of the phenomenon of particle bed fluidization and determination of their fluid dynamic characteristics.
- Heat Exchange: Experimental operation and investigation of the characteristics of an exchanger.
- Hot Air Drying: Study of the change in the parameters that affect the process.
- Distillation: Study of continuous fractional distillation for binary separation mixture.
- Crystallization: Study of basic principles of the crystallization phenomenon using an intermittent cooling crystallizer.
- Extraction: Study of basic principles of the extraction process.

The assessment of the course is carried out through a final mandatory written examination, including the solving of a unit operations design and analysis problem, laboratory exercises that require the performance of 5 unit operations laboratory exercises, the delivery of a group report, and the individual oral presentation and discussion of results exercises from the students.

## 2.2. NTUA Use Case: Extraction

Out of the various processes taught in the unit operations course, solid–liquid extraction is selected as the use case for the adaptive AI-powered learning system, since it offers several benefits. First, it is a widely used process in various industries, such as food and beverages, pharmaceuticals and cosmetics, chemicals, petrochemicals, and environmental sectors, thanks to its key advantages, namely high efficiency, protection of thermolabile compounds of high value, high selectivity, and easy scalability [45,46].

Furthermore, there are many extraction techniques, both conventional (such as maceration and Soxhlet extraction) and innovative (such as ultrasound-assisted extraction—UAE, microwave-assisted extraction—MAE, ultrasound- and microwave-assisted extraction—UMAE, pressurized liquid extraction—PLE, and pulsed electric fields—PEF). This variety gives the students the opportunity to explore different methods, understand their principles, and compare their pros and cons. In addition, extraction presents high flexibility, since it involves various factors that influence the final yield, including the extraction method, the type of solvent, the particle size of the solid matrix, the temperature, the solid material humidity, the extraction time, and the solvent/solid ratio [46–48]. This fact provides a rich learning opportunity for students and allows them to apply their theoretical knowledge

in practice and find the best combination of parameters to maximize the efficiency of the process and optimize the recovery of compounds.

Another reason why the solid–liquid extraction method was selected as the case for this study is the expertise and long experience of the staff of the Laboratory of Process Analysis and Design (LPAD) in performing this process for various purposes. The extraction has been studied in LPAD for the recovery of carotenoids and proteins, as well as omega-3 from microalgae, the obtaining of glycosides from stevia leaves, the isolation of phenolic compounds from fruit bio-products, the yielding of antioxidant compounds from olive pomace, and the recovery of starch from potatoes [49–55]. Finally, LPAD is equipped with various extractors, such as Soxhlet, UAE, MAE, UMAE, PLE, and PEF extracting systems. Therefore, students can go beyond theoretical learning and have the chance of hands-on experience, which improves their understanding.

### 2.3. Adaptive System Description

Education has often implemented one-size-fits-all models that prioritize fixed outcomes rather than focusing on individual learners and their needs. However, AI-adaptive learning has been developed as an alternative, offering a personalized approach to meet each student's unique needs through tailored teaching methods. AI-enabled adaptive learning systems apply AI to customize the educational journey for each student. They analyze data on students' performance and then adjust the learning path and content accordingly.

HECOF integrated the Adaptemy AI-Adaptive Learning Engine to build accurate learner models and to provide recommendations. The Adaptemy AI Engine creates and updates accurate learner models and provides multi-layered adaptation and recommendations that encapsulate effective learning strategies. The engine makes use of a learner model, a curriculum model, and a content model. The Adaptemy AI-Adaptive Learning Engine makes use of content and curriculum modeling to support its applicability across different courses. Furthermore, it uses machine learning to continuously update the models. Item Response Theory (IRT), Bayesian Networks, and Knowledge Space Theory are the underlying foundations of the Adaptemy AI-Adaptive Learning Engine. A student's response to an assessment item gives probabilistic evidence related to one concept. This evidence further updates the learner model across the whole curriculum.

The curriculum model defines the prerequisite relationships between the knowledge items (concepts). The content model encapsulates metadata that reflects how content objects are used and learner content metrics. Content objects may have some intended sequence and are linked to curriculum concepts. The learner model encapsulates ability estimates on skills and knowledge in an overlay to the curriculum model [56–58]. The Adaptemy AI-Adaptive Learning Engine structure aligns with the classical adaptive learning system (ALS) architecture, which typically consists of a Domain Model (DM), a learner model (LM), and an Adaptation Engine [57]. The Domain Model represents the formal structure of the knowledge domain. It contains both the content model, including content metadata, and the curriculum model, including conceptual relationships and learning objectives. The learner model stores information about the student's knowledge state, misconceptions, preferences, and learning history. The Adaptation Engine uses AI techniques to personalize content sequencing, assessments, and feedback in real time and to orchestrate the learning experiences and learning strategies.

To better support complex task decomposition and micro-level diagnostics in STEM domains, this framework has been extended to include a Sub-skills Model, which captures fine-grained skill mastery using data-driven inference. As a result, HECOF maintains fidelity to a well-established adaptive learning framework while enhancing its precision

and transparency, key features for domains requiring stepwise conceptual and procedural understanding.

The learning experiences in the HECOF system were designed within Adaptemy's adaptive learning design framework, and the Adaptemy AI Engine was configured using the designed learning experiences to personalize the curriculum sequence and content sequencing, to provide real-time feedback, and to support individualized progression based on learner performance data.

Adaptemy's adaptive learning design considers adaptive learning design a thought process, rooted in asking questions like 'what should the learning experience depend on?' and 'If you were the learner's personal tutor, how would you help them?' when creating learner-centered experiences. The learning experience design is created through designing learning loops, which are then used to configure the AI-Adaptive Learning Engine to orchestrate the learning experiences for students.

Learning loops are definable sub-components that encapsulate a learner-centered learning experience with a defined goal and a given rationale in the given context. Using learning loops, the learner-centered design shifted the focus from instruction to learner-driven construction of an experience that is meaningful, engaging, and satisfying. It includes an understanding of the learner through the learner model and an empathetic understanding of the learner in the sociocultural and technical context through the extended learning model.

As mentioned, the focus of the design is the learning experience rather than the learning tools or materials, and it is focused not on the learning materials only, but builds on top of the learning goals of promoting the acquisition of knowledge and skills (as learning outcomes) with goals that are meaningful and relevant to the learner, aligning with the trajectory of their individual purpose and internal influences (i.e., cognitive, emotional).

The pedagogical principles underpinning the HECOF NTUA inherit the Adaptemy AI Engine pedagogical principles, as follows: (1) getting attention—capturing learner focus and stimulating curiosity and readiness to learn, (2) creating active engagement—by providing a clear goal and relating to aspects that would increase intrinsic motivation and support metacognitive judgments, (3) keeping learners "in flow"—maintaining an optimal balance between challenge and skill level keeps learners immersed and motivated, (4) providing effective feedback—timely and specific feedback is crucial for guiding learners toward the desired outcomes, and (5) enabling reinforcement and interleaved practice—incorporating reinforcement through spaced repetition and interleaved practice enhances long-term retention and the ability to apply knowledge across varied contexts.

In addition to its adaptive learning architecture and learning design described above, through the Adaptemy AI-Adaptive Learning Engine, the HECOF system integrates an AI virtual tutor. The AI virtual tutor is based on a retrieval-augmented generation (RAG) approach. RAG is a method that combines information retrieval with generative AI, as follows: instead of relying solely on pre-trained language models, RAG retrieves relevant documents or knowledge chunks from curated database documents and then uses a generative model (e.g., a transformer-based LLM) to construct personalized, context-aware responses [59]. This architecture enables the HECOF tutor to answer student questions by grounding responses in instructional content, improving both factual accuracy and relevance. This design minimizes hallucinations and enhances traceability, essential in safety-critical disciplines like chemical engineering. Furthermore, in the context of engineering education, this approach is particularly valuable for supporting open-ended inquiry, just-in-time explanations, and dynamic scaffolding.

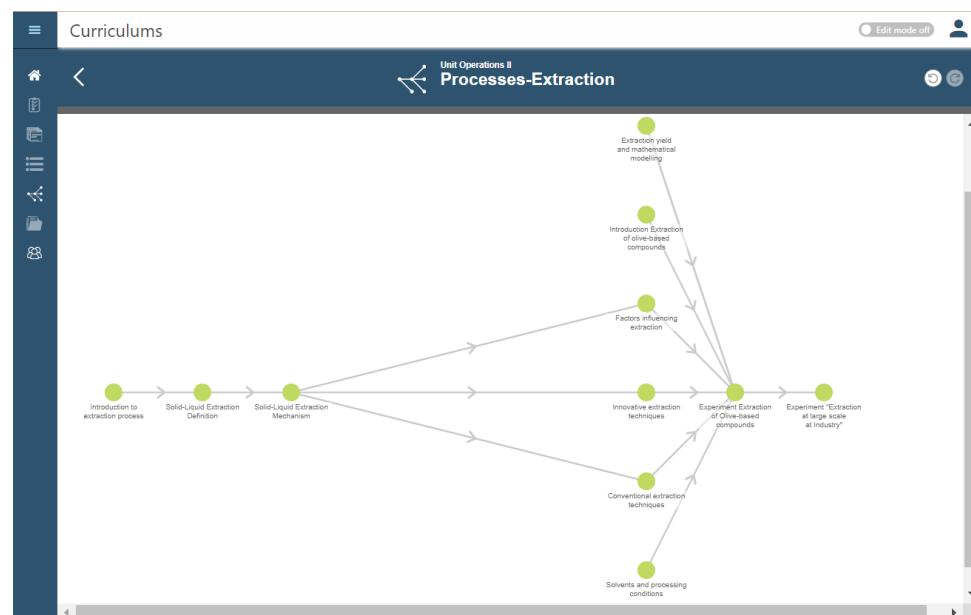
### 3. Research Design

#### 3.1. Overview of the Curriculum and Content for the HECOF NTUA Pilot

The development of the course's curriculum for AI-based adaptive learning experiences of the course was structured on the axis of solid–liquid extraction and the following concepts were identified:

1. Solid–liquid extraction definition: Introduction of the concept of extraction and definition of solid–liquid extraction and its components, examples, and applications
2. Solid–liquid extraction mechanism: Explanation of extraction phenomena and kinetics
3. Factors influencing extraction: Discussion of the influence of the solvent, particle size, temperature, solid material humidity, time, and solid to solvent ratio on the extraction yield
4. Conventional extraction techniques: Overview of principles and mechanisms of percolation, maceration, hydro-distillation, and Soxhlet extraction
5. Innovative extraction techniques: Overview of principles and mechanisms of UAE, MAE, UMAE, PLE, PEF, high-pressure homogenization, and combined methods and comparison with conventional techniques
6. Extraction of olive-based compounds: Introduction (preparation for the laboratory exercise) of phenolic compounds in olive leaves and their health benefits.
7. Solvents and processing conditions (preparation for the laboratory exercise): Presentation and explanation for choosing the solvents and parameters in the experiment
8. Extraction yield and mathematical modeling (preparation for the laboratory exercise): Presentation and calculation of extraction yield and kinetics, with mathematical modeling to predict the yield.

Furthermore, a prerequisite network that defines the necessary prerequisite relationships between concepts was created. The prerequisite networks facilitate misconception detection and enable multiple layers of personalization and adaptation in learning. Figure 1 presents the prerequisite view of the NTUA curriculum in the Adaptemy curriculum authoring tool, where a concept is represented as a circle and the prerequisite link is represented through an arrow from concept to concept.



**Figure 1.** NTUA curriculum in the Adaptemy curriculum authoring tool—Prerequisite view.

A Learning Activity Matrix (LAM) was configured for the learning experiences. A LAM is a metadata tagging framework that is used to tag content and will be further used in learning loop creation. It contains the activities (or learning phases) that will more likely form a sequence in the learning loop (i.e., instructional assessment). LAM's primary purpose is to organize the content and illustrate the range of learning activities that will be used. The matrix helps educators and instructional designers to ensure that a variety of learning experiences are provided to meet the diverse needs of learners. Additional metadata can be added to each learning phase.

In practice, a Learning Activity Matrix might take the form of a table or grid, where each cell of the matrix then describes a specific activity that contributes to the corresponding learning experiences.

The Learning Activity Matrix for the NTUA pilot is composed of the following: (1) instructional content—as is the primary source of new information or skills for learners and usually includes material that introduces and explains the subject matter, (2) assessment items—used to evaluate the learner's understanding and mastery of the instructional content, (3) instructional remediation—provided when the assessment results indicate that a learner has not fully understood a concept or skill, (4) VR lab—used to create immersive, interactive environments for practice, exploration, and simulation of real-world scenarios, mainly for the lab-based experiments, and (5) summary—often provided at the end of a learning unit, which succinctly reviews the key points and concepts covered. Figure 2 presents a high-level illustration of the Learning Activity Matrix for the NTUA pilot.



**Figure 2.** High-level illustration of the Learning Activity Matrix for the NTUA pilot.

The NTUA team created one instructional and approximately ten assessment items for each concept. The existing content was then used by the Adaptemy AI-Adaptive Learning Engine for its large language model in-context learning that will facilitate content optimization for AI-enabled adaptive learning experiences and chat-based interactions with the students. Regarding upfront content generation, multiple versions of instructional and remedial instructional, and summaries were generated and reviewed, with each content type having a minimum three versions—one for each difficulty level—including easy, medium, and hard. After the subject expert review, a total of 157 versions across instructional, remedial and summaries were kept. Both multiple choice questions and open-answer questions were generated at three difficulty levels. After the expert review, a total of 321 generated questions were kept.

### 3.2. Overview of the Learning Loops for the HECOF NTUA Pilot

The following learning loops were designed for NTUA: guided mastery, reinforcement practice, practice through VR and think-pair-share. Table 2 presents a summary of the learning loops in terms of goals, rationale, benefits to students, adaptivity, and format.

Guided mastery includes a concept-level mastery strategy and progress in map-order through concepts in the topic towards mastery coverage. The NTUA guided mastery learning loop is a structured learning experience that ensures students achieve concept-level mastery by progressing through topics in a curriculum map sequence. The learning loop implements a balanced adaptive learning approach based on all available content towards mastery of the lesson and knowledge acquisition. A strong student will most

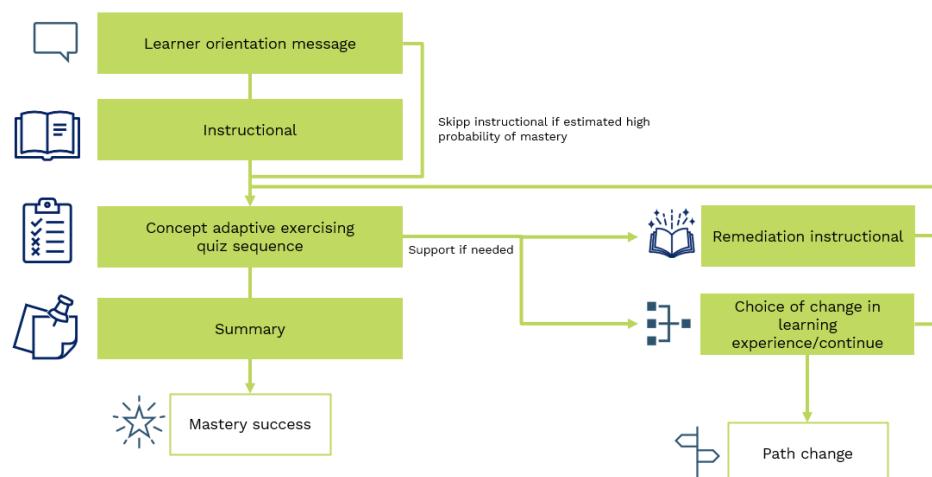
likely go through instructional tasks and exercises (quizzes) and, as soon as there are signs of a low success rate (lower probability to pass), alternative paths with remedial instructional content are given to the students. The rationale for this loop is rooted in the mastery learning theory [60–62] and in previous research in adaptive and intelligent tutoring [58,63–65]. Figure 3 presents the schematic adaptation of the guided mastery loop that was configured using the AI Engine. The learning loop takes students through instructional content and exercises (quizzes) through easy, medium, and hard quizzes (exercises). The students will go progressively through easy, medium, and hard levels of knowledge acquisition. At each level, if the students show a lower probability to pass, remedial instructional content is presented, followed by an additional exercise (quiz). Additional path change is available if the students struggle again.

**Table 2.** Summary of learning loops HECOF NTUA.

| Loop           | Strategy                       | Goals  | Rationale   | Benefits for Students  | Adaptivity  | Context and Format  |
|----------------|--------------------------------|--|---|--|---|---|
| Guided mastery | Concept-level mastery learning | Build towards the mastery of the topic<br>Create self-awareness of progress            | Implement balanced adaptive learning for mastery<br>Provide remedial content upon low success<br>Ensure lesson mastery before progression       | Personalized learning paths enhance engagement<br>Improved academic performance and confidence   | Progress through increasingly difficult levels<br>Responsive adjustments to learner performance<br>Offer remedial instruction when needed | Schedule-aligned concept-level mastery learning, exercise questions, guidance messaging, and adaptive-instruction   |
| Reinforcement  | Interleaved reinforcement      | Reinforce and consolidate prior learning   | Implement spaced repetition for retention   | Enhances long-term information retention<br>Strengthens recall through systematic review   | Adjusts review intervals based on performance<br>Targets areas needing reinforcement  | Topic (chapter)-level spaced repetition of recently acquired concepts, where content includes assessment items, summary instructions, and guidance messages |
| Practice VR    | VR Practice                    | Facilitate hands-on experiment practice<br>Enhance understanding of practical concepts | Provide practical experience through VR<br>Improve comprehension of experimental procedures<br>Increase accessibility to laboratory experiments | Engaging, immersive learning experiences<br>Safe environment to practice experiments., Access to virtual labs irrespective of location | Progress from guided to independent experimentation<br>Adjust VR scenarios based on student performance                                   | Available at concepts tagged as experiments<br>Interaction through VR-based content objects   |

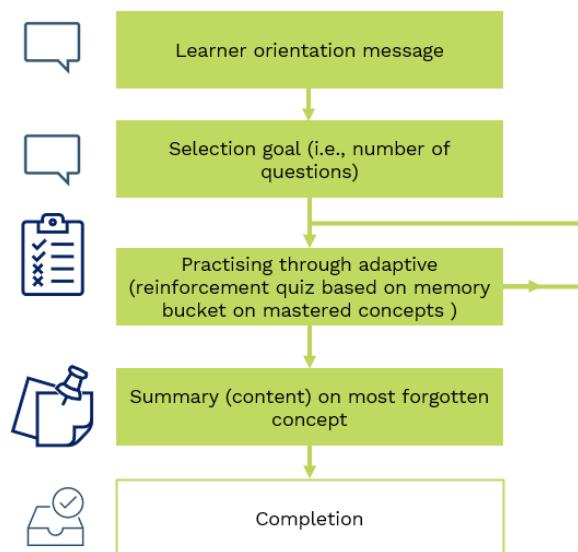
**Table 2.** Cont.

| Loop             | Strategy  | Goals   | Rationale   | Benefits for Students  | Adaptivity   | Context and Format   |
|------------------|---|---|---|--|--|--|
| Think-pair-share | Collaborative Virtual Subject Expert based on LLM and learner model | Provide explanations and study support through an AI learning companion | Facilitate student reflection on course material Encourage sharing of notes and insights Enhance understanding through collaborative learning | Personalized explanations tailored to individual needs Opportunities for active engagement with course content Improved comprehension through articulation of thoughts | The AI agent reviews recent student responses to identify areas requiring further explanation Engages students in dialogue as a Virtual Subject Expert to address specific questions Encourages students to document reflections, promoting deeper understanding | Conversations with Virtual Subject Expert based on LLM structured in a loop at a topic (chapter) level |

**Figure 3.** Guided mastery loop (NTUA pilot)—Schematic adaptation.

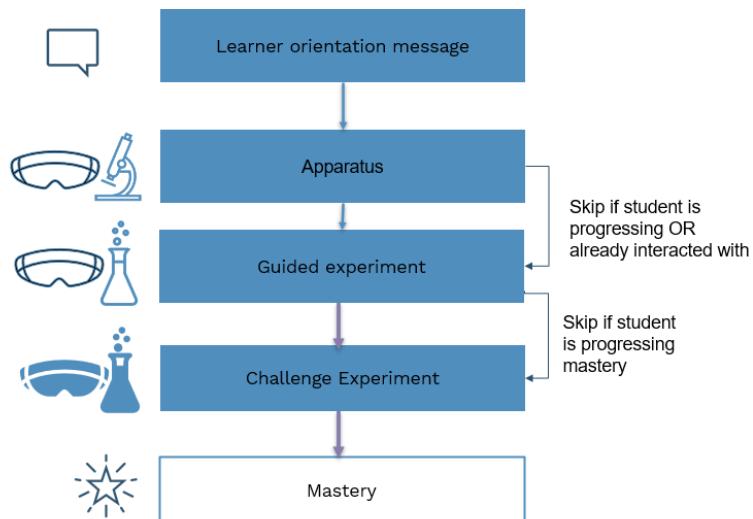
The reinforcement revision loop includes an interleaved reinforcement strategy and performs a course-level spaced revision of recently acquired concepts to reinforce and consolidate previous learning. The loop uses mainly assessment items and is aimed at giving course-level spaced repetition of acquired concepts following a memory bucket approach after students have mastered the concepts. Furthermore, a summary of each concept is provided for the most forgotten concept. The rationale for this loop is rooted in previous research of model forgetting and spaced repetition [66–71].

Figure 4 presents the schematic adaptation of the loop that was configured. Students will start by selecting their goal (i.e., number of questions to revise) and will answer questions from the already mastered concepts. As mentioned, the concepts will be selected following the space repetition approach with the most overdue for revision being priorities first. In addition, a summary of the most forgotten concept will be presented to students.



**Figure 4.** Reinforcement loop (NTUA pilot)—Schematic adaptation.

The practice (VR) loop includes a VR experience to enable the practice of experiments. This loop enables students to gain practical experience, enhance comprehension about practical aspects, and makes the experiments accessible to students. Practice (VR) will include VR content objects. The rationale of this loop is rooted in virtual labs and VR-based education [72–77]. Figure 5 presents the schematic adaptation of the practice VR loop. Inside the VR learning loop, students will proceed through the following: (1) apparatus investigation—with the role to allow students to accommodate VR and the apparatus used in VR; (2) guided experiment—with the role to allow students to perform an experiment in a guided mode, where, step by step, the experiment is explained to them; and (3) challenge experiment—with the role to allow students to perform an experiment on their own.

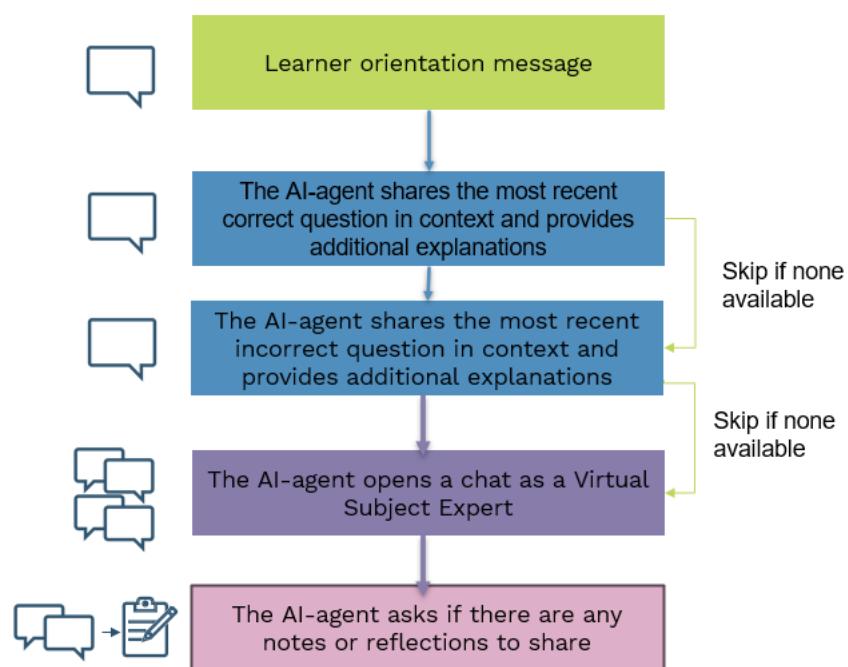


**Figure 5.** Practice (VR) (NTUA pilot)—Schematic adaptation.

Think-pair-share includes interactive explanations and study support through an AI-driven learning companion to help students to reflect on their understanding, exchange insights, and engage in discussions about key concepts in a think-pair-share approach. The AI agent presents students with their recent correct and incorrect answers, providing targeted explanations. It then facilitates a chat-based interaction as a Virtual Subject Expert—an AI Agent—offering personalized responses and encouraging reflections to deepen understanding. Think-pair-share is a learning loop that offers explanations based on the

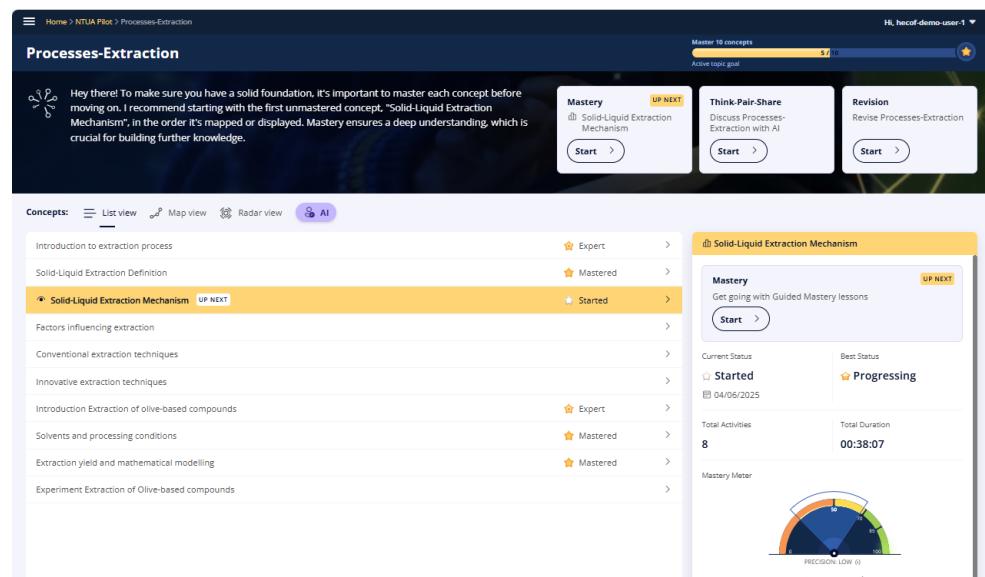
course material and learner model, including the estimated mastery level on concepts and evidence of previous mistakes and successes when interacting with the system; moreover, it makes students reflect, share notes on concept-specific learning, and focus on how the learning experience helped them to understand the concept. Think-pair-share makes use of content from a large language model trained on the course material. The rationale and fundamentals of the loop are rooted in previous research of the think-pair-share approach as a strategy [78–80] and large-language-model-based virtual tutors [81–86].

Figure 6 presents the schematic adaptation of the think-pair-share loop. During the think-pair-share learning experience, the AI agent shares the most recent correct and incorrect question and provides additional explanations. The AI agent then opens a chat as a Virtual Subject Expert and provides answers to student questions. In the end, the AI agent will ask for any notes or reflections that the student might want to share. The existing content is used by the Adaptemy AI-Adaptive Learning Engine for its large-language-model in-context learning, where the AI agent is built as a Virtual Subject Expert for chat-based interactions with the students.



**Figure 6.** Think-pair-share loop.

Figure 7 presents an example of student interface, on the topic view, using Adaptemy course player. The list of concepts is presented, with the estimated mastery level. It also contains recommendations, explanations of the current recommendations through an Explainable AI (XAI) principle. Furthermore, once a concept is selected, full details of the concept including mastery level and precision is presented in the panel as can be seen in the right panel.



**Figure 7.** Example of student interface—topic view—using Adaptemy course player, highlighting recommendations.

### 3.3. Methodology

The approach for HECOF evaluation employs a mixed-methods approach, combining quantitative metrics from system performance and learning analytics with qualitative feedback from users. This study employed a quasi-experimental pilot design to evaluate the HECOF system's impact on student learning and engagement in a higher education chemical engineering course. The intervention was conducted over an 8-week period, during which students interacted with the HECOF platform, including adaptive learning content, VR modules, and an AI-powered virtual tutor. The participants were undergraduate students enrolled in a senior-level chemical engineering course at NTUA, recruited through class invitation. Participation in this study was voluntary, and all participants provided informed consent. The inclusion criteria required that the students had basic knowledge of online learning environments and chemical process concepts. Students who did not complete both the pre- and post-surveys were excluded from the final analysis. A total number of N=10 students filled in both the pre- and post-surveys. Data were collected through multiple instruments to assess both cognitive and affective learning outcomes, mainly through usage logs and pre- and post-surveys. The HECOF system automatically recorded interaction data using the XAPI standard, including evidence of each interactivity (i.e., an XAPI for each question, each instructional) and VR module interactions. The students completed a structured questionnaire containing Likert-scale pre- and post-use surveys, given the presented evaluation framework. The surveys also included open-ended questions to gather qualitative feedback on the learning experience.

The methodology integrates current AI-adaptive learning and VR training research to assess the system's impact [66–68]. The evaluation dimensions include the pedagogical impact—learning improvements and effectiveness, satisfaction, and perceived usefulness—student experience, and usability evaluation—learning experience in learning loops and overall system usability.

The pedagogical impact of the HECOF AI experience was measured through key metrics that track learning improvements and overall effectiveness. One of the primary indicators of learning effectiveness was the learning gain per session per concept, which measures how much students improve in their understanding of specific concepts after each learning session. This was closely monitored through learning analytics, which provide insights into student progress and mastery of concepts, allowing us to track incremental

improvements over time. Additionally, the students' perceived improvement was evaluated through surveys.

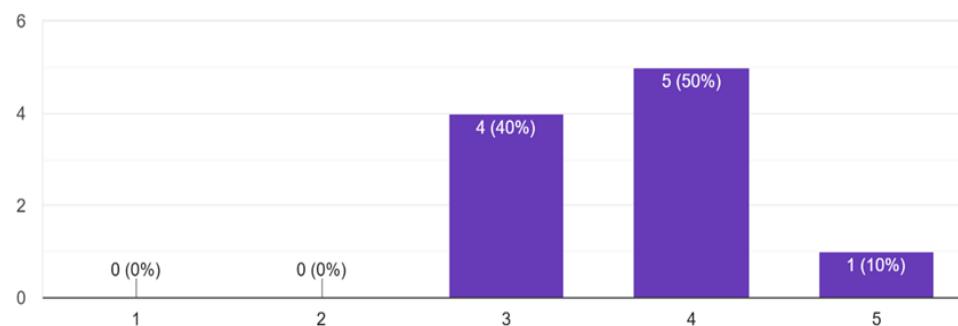
The satisfaction and perceived usefulness of the HECOF system are essential for ensuring both students and teachers have a positive experience with the system. This dimension evaluates the perceived usefulness, where students and teachers evaluate how beneficial the AI-driven personalization and exercises were in achieving their learning and teaching objectives. Lastly, the evaluation focused on overall user satisfaction, evaluating how satisfied the students were with the platform's ability to enhance their learning and experiences without overwhelming them with complexity or technical difficulties. The usability evaluation of the HECOF system focused on how effectively it supports seamless learning experiences through adaptive learning loops, the integration of VR, and overall system usability. In the context of learning loops, the goal is for students to progress through these loops without disruptions.

#### 4. Results

This section presents the results based on the post-survey (i.e., in terms of perceived improvement in subject understanding, perceived effectiveness of AI-based adaptive learning in achieving learning goals, engagement level, and overall perceived experience), as well as in terms of learning analytics through objective metrics computed through logs of the XAPI statements.

The participants assessed how much their understanding of the subject improved after using the HECOF system. Half of the respondents (50%) reported a significant improvement (4—very much), while 40% indicated a moderate improvement (3—moderately). A smaller portion (10%) felt their understanding was extremely improved (5). Notably, no participants rated their improvement as slight (2) or nonexistent (1) (see Figure 8). These findings indicate that the HECOF system contributed positively to students' learning, though the extent of improvement varied among individuals.

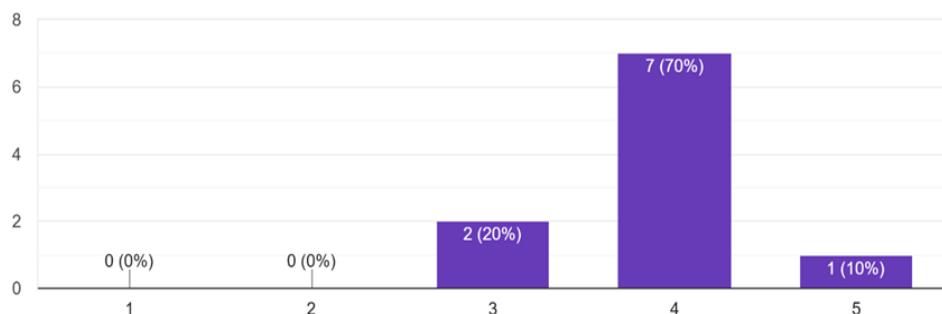
How much do you feel your understanding of subject has improved after using the HECOF system?  
10 responses



**Figure 8.** Post-survey—Perceived improvement in subject understanding after using HECOF—NTUA.

The participants evaluated how well the AI-based adaptive learning features helped them to achieve their learning goals. The majority (70%) reported that the features were considerably helpful (4), while 10% found them fully effective (5), a smaller portion (20%) felt that they were only somewhat helpful (3), and no participants rated them as slightly helpful (2) or not helpful at all (1) (see Figure 9). These results indicate that most students found AI-based adaptivity beneficial for their learning or completely effective.

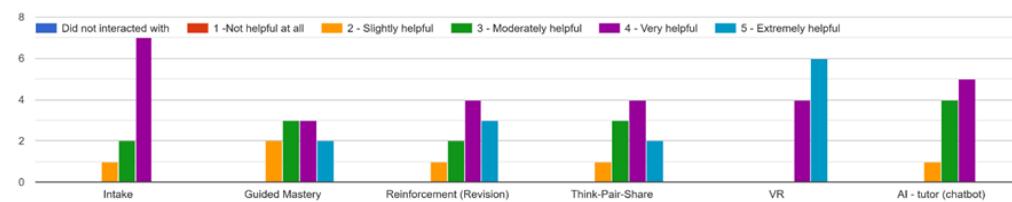
To what extent do you feel that the AI-based adaptive learning features helped you achieve your learning goals?  
10 responses



**Figure 9.** Post-survey—Effectiveness of AI-based adaptive learning in achieving learning goals.

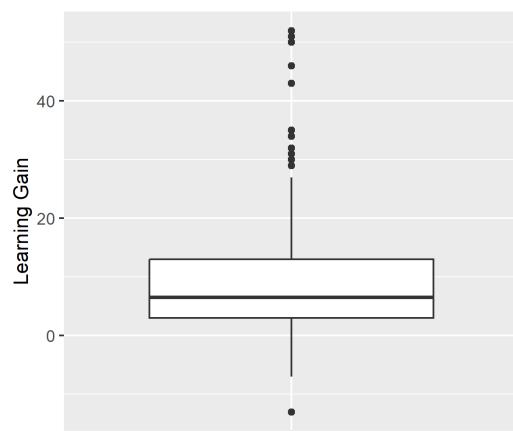
The participants rated how the different HECOF learning experiences contributed to their understanding and retention of material (see Figure 10). The VR learning experience received the highest ratings, with a majority marking it as extremely helpful (5). The AI tutor (chatbot) was also well received, with many participants rating it very helpful. Guided mastery, reinforcement (revision) and think-pair-share activities were generally rated moderately to very helpful, with only a few students finding them slightly helpful.

Please rate the following HECOF learning experiences based on how much each contributed to your understanding and retention of the material.



**Figure 10.** Post-survey—Engagement levels across HECOF learning experiences.

Good learning gain can also be seen through learning analytics. Students acquire learning through learning experiences structured as “learning loops.” During each instance of a “learning loop,” students interact with a structured sequence of instructional items (activities) and assessment items (questions) aligned as per the learning design above. Each loop targets one or more active concepts, defined as the knowledge components explicitly engaged and assessed during that session. The reinforcement loop was employed periodically to consolidate prior knowledge before introducing new material. Learner ability was estimated by the system’s AI Engine, which continuously updates an estimation per concept based on response correctness and system-inferred previous estimation using Item Response Theory and Bayesian Networks as underlying approaches. Learning gain per session was computed as the difference in estimated ability for each active concept from the start to the end of the session. Figure 11 presents a boxplot of learning gains across sessions and concepts. The median learning gain was 9 points, indicating a moderate improvement in concept mastery per session. While most sessions showed positive learning progress, some yielded negative gains, which may reflect knowledge decay, distractions, or incomplete engagement with activities. Sessions with low or negative gains were more likely to involve either review material perceived as easy, leading to disengagement, or complex concepts introduced without prior scaffolding. Overall, the gain estimates provide a quantitative basis for evaluating adaptivity and session effectiveness within the HECOF system.



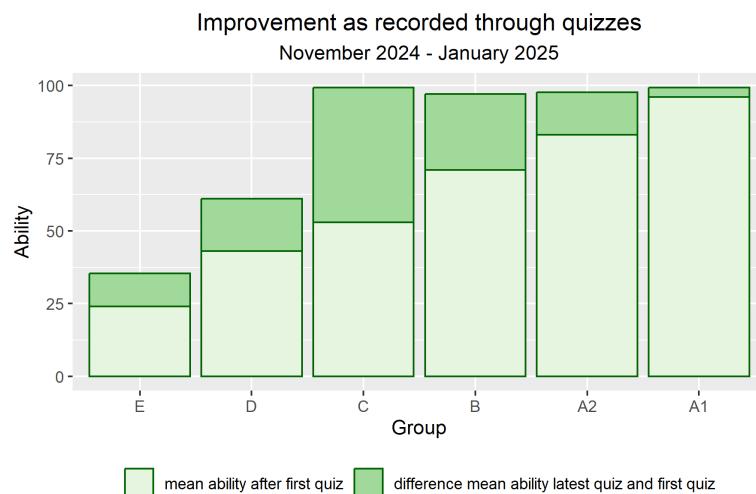
**Figure 11.** Learning gain as seen through learning analytics.

Overall, this pattern supports HECOF's goal of enabling personalized, data-informed adaptive learning experiences, not only for learners who may struggle in traditional settings, but also for those who are more advanced and at risk of becoming disengaged, as well as those steadily progressing through their development. This approach aligns with Vygotsky's Zone of Proximal Development (ZPD) [87], which emphasizes the importance of targeting instruction just beyond a learner's current level of independent competence, allowing for growth through guided support. Simultaneously, the AI Adaptive Learning Engine reflects key principles from Csikszentmihalyi's Flow Theory [88,89], which posits that optimal learning and engagement occur when the challenge of a task is well matched to the learner's ability. By dynamically adjusting difficulty, pacing, and feedback, the HECOF system helps learners to remain in this productive "flow state," avoiding both the frustration of overwhelming content and the boredom of overly simple tasks. Together, these frameworks support a robust instructional model that nurtures engagement, persistence, and meaningful learning across a diverse range of student profiles in chemical engineering education.

Figure 12 presents the improvement as recorded through quizzes for different student groups. The graph presents the mean ability after first quiz and the difference mean ability between the latest quiz and the first quiz across all concepts—student pairs for each group. The group was created based on the student ability in the first quiz per concept, where A1—has ability over 90 (including 90), A2—has ability between 75 (including 75) and 90, B—has ability between 60 (including)-75, C—has ability between 50 (including)-60, D—has ability between 35 (including)-50, E—has ability lower than 35. As can see from the graph, improvement was recorded across all groups, with lower improvement on the A1 group due the already high ability in that group.

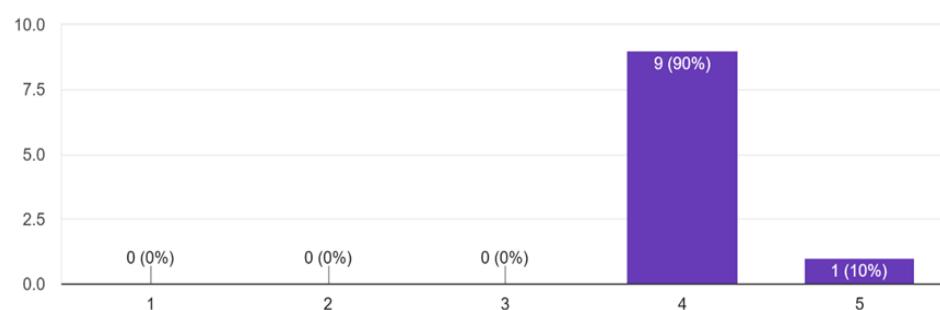
The participants rated their overall experience with the AI-based adaptive learning technology in the HECOF course (see Figure 13). The majority (90%) rated their experience as good (4), while 10% found it excellent (5). Notably, no participants rated the experience as fair (3), poor (2), or very poor (1) (see Figure 13). These results suggest that the students had a generally positive experience with the AI-driven adaptive learning technology.

The participants rated their overall satisfaction with their learning experience using HECOF (see Figure 14). The majority (80%) reported being satisfied (4), while 20% were very satisfied (5). No participants rated their experience as neutral (3), somewhat dissatisfied (2), or very dissatisfied (1) (see Figure 14). These results indicate a high level of satisfaction among the students, suggesting that HECOF was effective in delivering a positive and engaging learning experience.



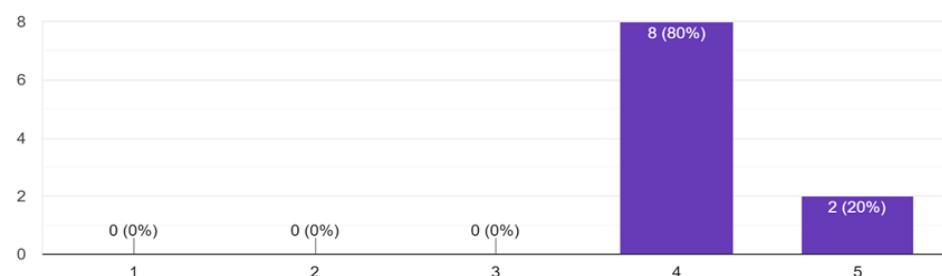
**Figure 12.** Improvement as recorded through quizzes.

How would you rate the overall experience of the AI-based adaptive learning technology in the HECOF course?  
10 responses



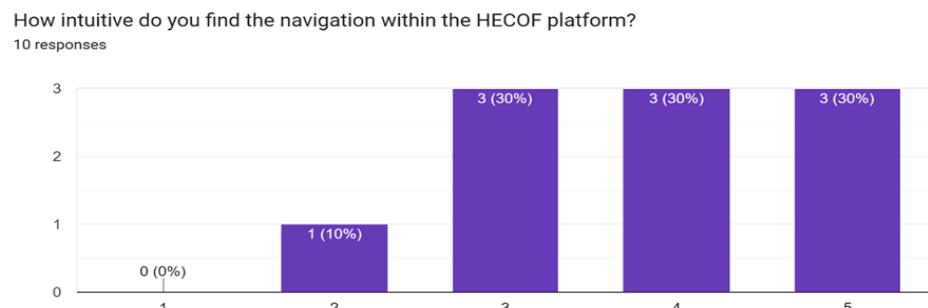
**Figure 13.** Post-survey—Overall experience with AI-based adaptive learning technology.

Overall, how satisfied are you with your learning experience using HECOF?  
10 responses



**Figure 14.** Post-survey—Overall satisfaction with HECOF learning experience.

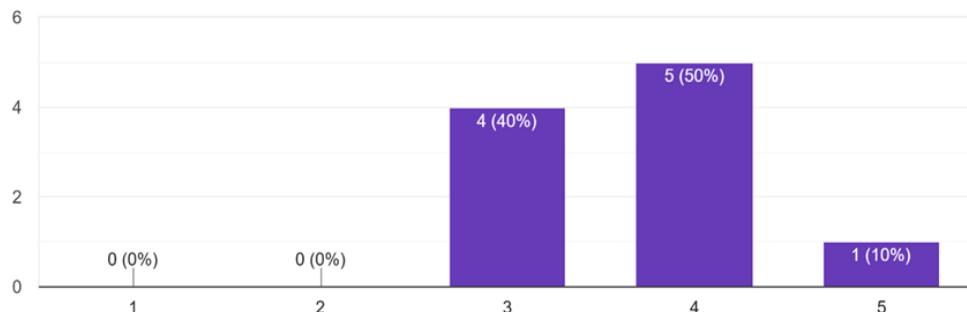
The participants rated the intuitiveness of navigation within the HECOF platform (see Figure 15). Most responses were distributed across neutral (30%), easy (30%), and very easy (30%), suggesting that most users found the platform relatively straightforward to navigate. However, 10% of the participants found navigation difficult (2), while no one rated it as very difficult (1). These results indicate that, while the platform was generally intuitive for most users, some encountered minor difficulties that could be addressed for a smoother experience.



**Figure 15.** Post-survey—Intuitiveness of navigation in the HECOF-platform—NTUA pilot.

The participants rated the ease of understanding and using the system's learning loops (guided mastery, revision, think-pair-share, etc.) (see Figure 16). The majority (50%) agreed (4) that the learning loops were easy to use, while 10% strongly agreed (5). Another 40% remained neutral (3), with no participants disagreeing (2) or strongly disagreeing (1). These results suggest that most students found the learning loops accessible and functional, but a significant portion remained neutral, indicating potential areas for refinement to improve usability.

Do you feel that the system's learning loops experiences (i.e., guided mastery, revision, think-pair-share) were easy to understand and use?  
10 responses

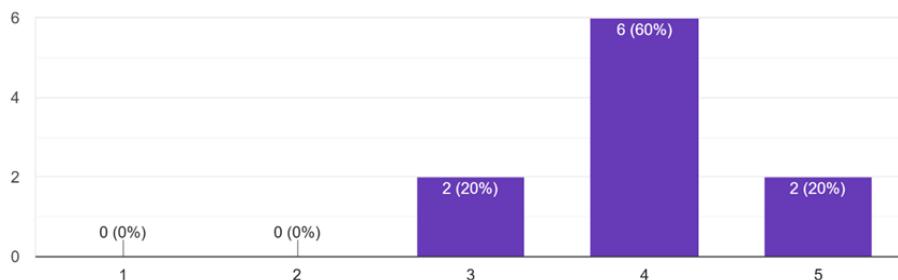


**Figure 16.** Post-survey—Ease of understanding and using learning loops.

The participants rated the usefulness of AI-based adaptive learning recommendations and learning loops in guiding their learning and identifying areas for improvement (see Figure 17). The majority (60%) found them very useful (4), while 20% rated them as extremely useful (5). Another 20% considered them moderately useful (3), with no participants rating them as slightly useful (2) or not useful at all (1). These results suggest that AI-driven adaptivity played a significant role in enhancing the students' learning experiences, with most finding it to be a valuable tool for improvement.

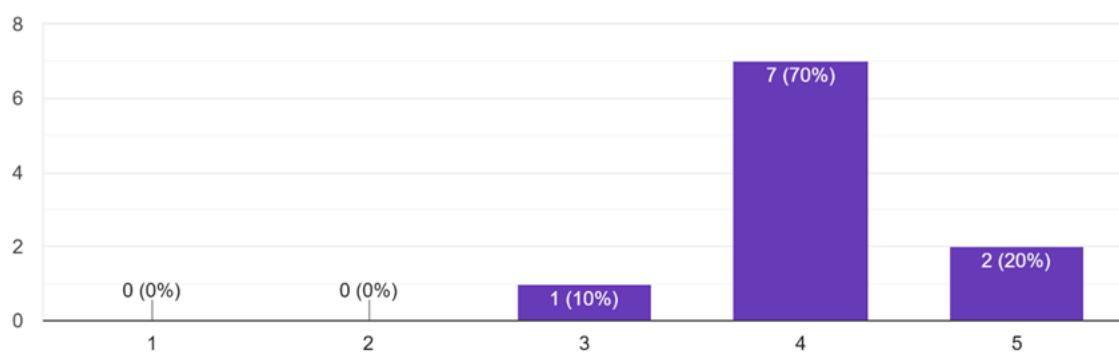
The participants rated the ease of interacting with the AI-based adaptive learning technology and understanding its recommendations (see Figure 18). The majority (70%) found it easy to use (4), while 20% rated it as very easy (5). One participant (10%) remained neutral (3), and no participants found it difficult (2) or very difficult (1). These results suggest that the AI-based adaptivity was generally user-friendly and accessible, though some minor improvements could enhance clarity and interaction.

How useful was the AI-based adaptive learning recommendations and learning loops in guiding your learning and helping you identify areas for improvement?  
10 responses



**Figure 17.** Post-survey—Usefulness of AI-based adaptive learning recommendations.

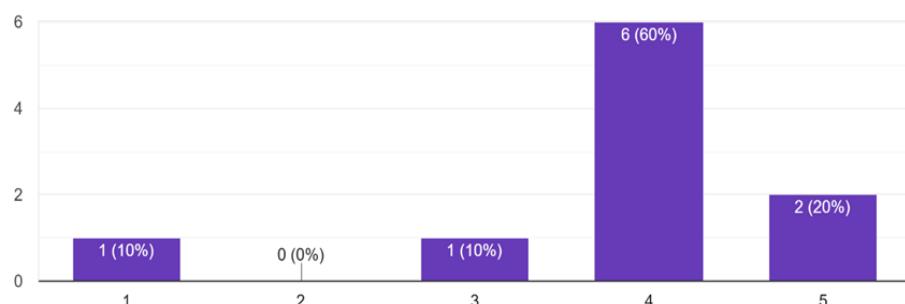
How easy was it to interact with the AI-based adaptive learning technology and understand its recommendations?  
10 responses



**Figure 18.** Post-Survey—Ease of interaction with AI-based adaptive learning technology.

The participants rated the ease of interacting with the AI tutor (chatbot) and understanding its answers (see Figure 19). The majority (60%) found it easy to use (4), while 20% rated it as very easy (5). A small percentage (10%) remained neutral (3), while another 10% found it very difficult (1), with no participants selecting difficult (2). These results suggest that while most students found the AI tutor accessible and understandable, some faced challenges that may require improvements in clarity and responsiveness.

How easy was it to interact with the AI tutor (i.e., chatbot) and understand its answers.  
10 responses

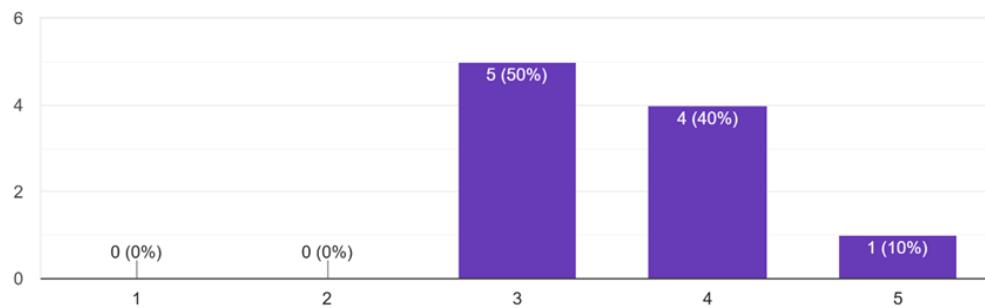


**Figure 19.** Post-survey—Ease of interaction with AI-based adaptive learning technology.

The participants reflected on how using HECOF improved their confidence in understanding and mastering course topics (see Figure 20). The majority (50%) rated their confidence improvement as moderate (3), while 40% found it significant (4). A smaller

portion (10%) reported an extreme confidence boost (5), and no participants rated their improvement as slight (2) or nonexistent (1). These results suggest that HECOF contributed positively to the students' confidence levels, however, for most, the improvement was moderate to high rather than transformative.

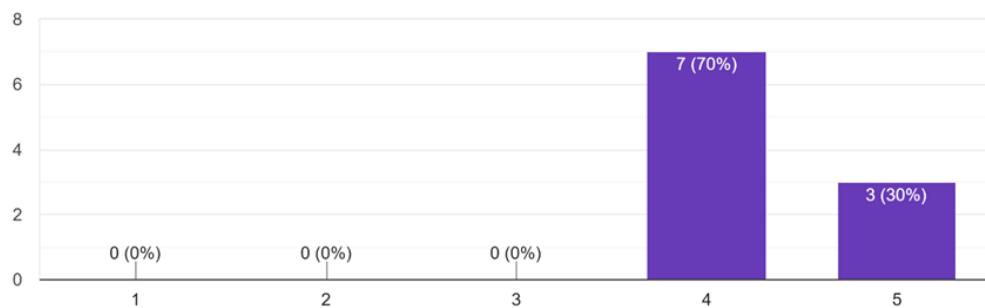
To what extent do you feel that using HECOF has improved your confidence in understanding and mastering topics in the course?  
10 responses



**Figure 20.** Post-survey—Improvement in confidence in understanding and mastering topics.

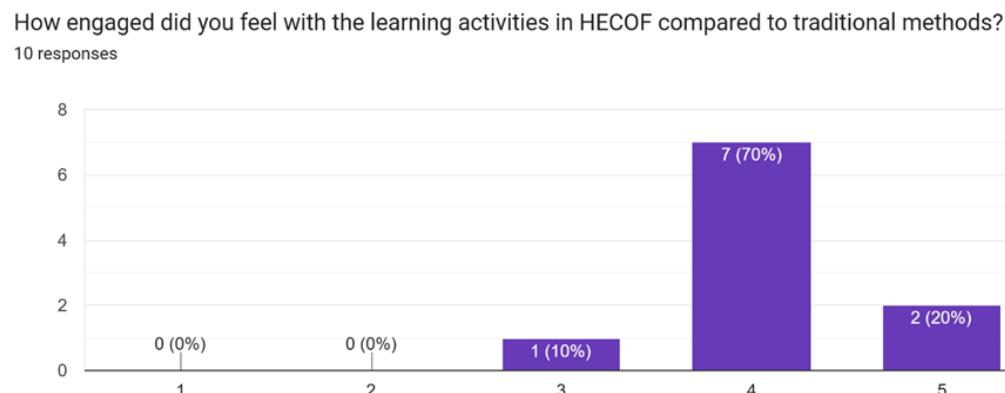
The participants rated their confidence in approaching new learning challenges independently after using HECOF (see Figure 21). The majority (70%) felt confident (4) in their ability to tackle new challenges, while 30% reported feeling very confident (5). Notably, no participants rated their confidence as neutral (3), somewhat confident (2), or not confident at all (1). These results suggest that HECOF had a strong positive impact on the students' self-reliance in learning, equipping them with the skills and confidence to navigate new academic challenges independently.

After using HECOF, how confident do you feel in your ability to approach new learning challenges independently?  
10 responses



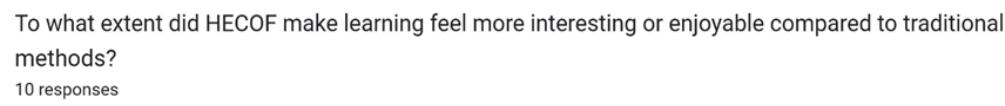
**Figure 21.** Post-survey—Confidence in approaching new learning challenges independently.

The participants rated their engagement with HECOF learning activities compared to traditional methods (see Figure 22). The majority (70%) found the HECOF activities very engaging (4), while 20% rated them as extremely engaging (5). A small percentage (10%) reported moderate engagement (3), and no participants rated their engagement as low (1 or 2). These results indicate that HECOF provided a significantly more engaging learning experience compared to the traditional methods, with most students feeling highly involved in the interactive activities.



**Figure 22.** Post-survey—Engagement with HECOF compared to traditional learning methods.

The participants assessed how HECOF made learning more interesting or enjoyable compared to the traditional methods (see Figure 23). The majority (60%) rated it as considerably more engaging (4), while 40% found it greatly more enjoyable (5). No participants rated the experience as moderately (3), slightly (2), or not at all enjoyable (1). These results indicate that HECOF significantly enhanced student engagement and enjoyment, making learning more interactive and appealing compared to the traditional methods.



**Figure 23.** Post-survey—Perceived enjoyment of learning with HECOF compared to traditional methods.

The findings of this pilot case study provide initial support for the hypotheses outlined at the start of the research. Consistent with H1, the participants reported high levels of engagement, satisfaction, perceived learning improvement, and perceived usefulness of the AI-based adaptive features. Regarding H2, measurable learning gains were observed across sessions, based on the system's internal ability estimates, with consistent upward trends in concept mastery.

It is important to acknowledge that the sample size used in this study was modest, consistent with the scope and purpose of a pilot or exploratory evaluation. While the findings provide initial evidence of the HECOF system's effectiveness in enhancing engagement and learning outcomes, they should be interpreted with caution and not generalized beyond the study context. The primary aim of this investigation was to assess the feasibility, usability, and pedagogical alignment of the system in a real-world educational setting. The insights gained from this pilot will directly inform the design of a larger-scale study with expanded participant cohorts, improved controls, and more robust statistical power to validate and extend these preliminary results.

## 5. Discussion

The findings from this exploratory study suggest that the HECOF system, integrating AI, adaptive learning, and VR, can provide a meaningful and engaging learning experience in chemical engineering education. Students demonstrated measurable learning gains per session, particularly among those who started with lower initial ability levels, supporting the system's ability to personalize instruction and scaffold learning appropriately. These results are consistent with the system's design principles, which aim to align instructional content with each learner's current mastery level and dynamically adjust feedback and pacing through AI-driven adaptation.

In addition to the system-generated performance data, the participants' subjective evaluations provided valuable insight into the perceived effectiveness, usability, and impact of the HECOF system. Most students (70%) rated the AI-based adaptive learning features as considerably helpful in achieving their learning goals, with 10% finding them fully effective. Although 20% found adaptivity only somewhat helpful, no participants reported it as unhelpful or ineffective, suggesting generally positive perceptions of the adaptive features (see Figure 9). Similarly, 90% of students rated their overall experience with the AI-based adaptivity as good or excellent (Figure 13), and 80% reported being satisfied with their learning experience (Figure 14). In terms of learning outcomes, 50% of participants reported a significant improvement in subject understanding, while 40% noted moderate gains, and 10% reported extreme improvement (Figure 8). Furthermore, 90% of respondents found easy or very easy to use the AI-based adaptive learning technology and its recommendations (Figure 18), indicating that the adaptive interface was largely accessible and well-integrated.

Taking together, these results reflect a consistently positive user experience, with most students finding HECOF to be both supportive and effective, though with some variation in perceived learning impact. Importantly, the observed learning gains and engagement patterns reinforce the potential benefits of AI-based personalization in complex and hierarchical domains like chemical engineering. By leveraging learner modeling, learning loops, and a retrieval-augmented AI tutor, HECOF was able to respond to student performance in real time, providing differentiated support without sacrificing content depth.

While these findings are promising, they should be interpreted within the scope of a pilot study, where the absence of a control group and the modest sample size limit the generalizability of the results. Nonetheless, the patterns observed provide a strong foundation for future research and suggest that HECOF may offer a scalable and effective model for delivering an adaptive, learner-centered classroom experience in the future of higher education.

The use of AI-driven educational technologies like HECOF raises important ethical concerns, including transparency, data privacy, fairness, and learner autonomy. A recent systematic review of AI in education emphasizes that systems must be designed for explainability, allowing students to understand how and why the system generates recommendations or feedback. In HECOF, transparency is supported through visible exposure of the learner model (i.e., students can see the estimation updated in real-time through updates on the mastery meter and through the learner dashboard), content model (i.e., the content item difficulty is exposed to the students together with the content type), and curriculum model (both the hierarchy and the prerequisite networks are presented to the students). Furthermore, students are exposed to progress indicators (i.e., locally, in each learning experience and overall, across the curriculum) and to the justification of the transitions in the learning experiences within the learning loop.

Additionally, learner autonomy must be preserved. While AI can guide, it should not override student agency. HECOF incorporates learner input by allowing students to

select from learning strategies (e.g., reinforcement practice, guided mastery) and topics and concepts in the curriculum and to reflect on system estimations through a dashboard. AI augmentations serve educators rather than replace them, reflecting a human-centered pedagogical mode.

Beyond individual interactions, broader social and pedagogical implications must be addressed. AI systems can inadvertently reinforce inequities if access to necessary infrastructure is uneven, a concern corroborated by global analyses of ethical AI use in education [90,91]. HECOF's design explicitly includes measures to mitigate such risks, as follows: it can run on low-bandwidth platforms and is accompanied by institutional recommendations for equitable deployment. Furthermore, the VR experiments are also provided in desktop mode, allowing students to experiment without a VR headset.

As per the OECD recommendations that AI should serve as a complement and not a replacement of educators [92], HECOF incorporates teacher oversight mechanisms, including human-designed learning experiences and granting instructors control over content banks. This ensures that AI augments pedagogical decision making without displacing the educator's essential role.

### Limitations and Future Research

The HECOF system demonstrated promising results in enhancing students' learning outcomes by integrating AI-based adaptive learning; however, several limitations should be acknowledged in this initial innovative work.

Firstly, the evaluation relied on a relatively small sample size of participants, which may affect the statistical significance of the results. Nevertheless, the students who participated in the evaluation process were carefully selected so that they represented a heterogeneous group in terms of gender (both males and females), academic performance (high and low grades), and prior familiarity with AI (none, moderate, and high familiarity). In the future, the implementation of HECOF will be expanded to a wider population of students with various characteristics, e.g., learning styles, disciplines, and institutions, to investigate the influence of these factors in the effectiveness of the adaptive learning system, as well as to test its scalability.

Furthermore, while acknowledging that the sample size used was modest, it is worth noting that it was consistent with the scope and purpose of an exploratory pilot evaluation. The primary aim of this investigation was to assess the feasibility, usability, and pedagogical alignment of the system and its AI technologies in a real-word educational settings. The insights gained from this pilot will directly inform the design of another future evaluation with expanded cohorts and greater statistical power to validate and extend these preliminary results.

In addition, another limitation of this study could be the fact that it did not include a longitudinal component to assess sustained learning or long-term retention. Therefore, the next aim of the work is to add longitudinal analyses to better understand user adaptation and the lasting impact of the system over time.

Finally, in this initial study, there was no comparative control group using conventional learning methods, which limits the ability to determine whether the improvements are uniquely due to the HECOF system. However, the learner gains and self-reported outcomes suggest positive trends. Future research will include a comparative study with traditional teaching to explore the added value and effectiveness of AI-driven adaptive learning.

The working group of the development of this system consisted of different disciplines. Co-designing the system with participation from both chemical engineering educators and information technology experts proved to be a significant strength of the proposed approach. It is no longer sufficient to simply know how to use machine learning tools, understanding the chemical processes that they are applied to is equally important. As a

result, chemical engineering programs must incorporate deeper training in AI and statistical methods. Additionally, stronger collaboration between computer scientists and domain experts is essential. Without this, researchers may misuse tools, and data scientists may misinterpret results. Interdisciplinary research and close cooperation between both fields are crucial to avoid ineffective outcomes and disappointment [16].

## 6. Conclusions

HECOF is an innovative, personalized, adaptive teaching program that can contribute to the transformation of traditional educational models and practices to fit the requirements of the digital era in engineering and higher education in general. Specifically, in chemical engineering education, it can contribute to better teaching and understanding of complex process phenomena—such as extraction, a commonly used method in the industry with a variety of applications—and prepare students for solving real industrial problems, especially in processes with hazardous materials or with high safety risks.

The HECOF system builds on existing adaptive learning models and architecture, educational psychology, and ethical AI guidelines. Specifically, HECOF builds upon the classical framework comprising the Domain Model, learner model, and Adaptation Engine, as described in the established literature of AI-enabled adaptive learning systems [61,93–95]. Furthermore, its scaffolding and adaptivity reflects Vygotsky's Zone of Proximal Development [87] and Csikszentmihalyi's Flow Theory [88], which emphasizes optimal learner support through tailored challenge and feedback. Finally, consistent with OECD's "Trustworthy AI in Education" framework [96], HECOF ensures that data handling occurs via transparent and explainable AI mechanisms, while maintaining learner autonomy. The underlying theoretical framing of HECOF enables HECOF to align with broader pedagogical and ethical principles in education technology.

The case study presented in this paper has provided an initial evaluation of HECOF and its AI-driven adaptive learning and virtual tutoring learning experiences developed for chemical engineering education. The preliminary results suggest that the system supports engagement, perceived learning improvement, and differentiated instruction across ability levels. Although the current pilot study does not include a traditional control group, objective learning analytics, such as concept-level gain estimates and usage patterns, have been introduced to strengthen the internal validity. These metrics complement the self-reported survey data, enabling a more nuanced understanding of student progress. Therefore, while limited in scope, this pilot study offers valuable insights into the feasibility and potential of the platform. We also situate our findings within the context of prior empirical research [97–104], which has identified improved learning performance, satisfaction, and engagement in adaptive learning systems.

The participants in the evaluation of the system provided diverse recommendations for enhancing the HECOF system, particularly regarding VR experiences, AI adaptivity, and overall usability. Regarding AI-driven adaptivity, suggestions included better question structuring and more interactive learning approaches. The usability and accessibility of HECOF were also discussed, with proposals for allowing both hands to be used simultaneously in the VR lab, integrating a voice feature in the chatbot for greater inclusivity, and offering a less guided experience to encourage independent exploration and problem solving.

Collectively, the results of this pilot study suggest that HECOF and its AI-based adaptivity offer a promising direction for AI-enhanced, adaptive learning in chemical engineering education, particularly in its ability to scaffold learning across diverse ability levels and promote learner engagement. However, we fully acknowledge that the current study represents a case study evaluation through a pilot framework and demonstrates

the system's technical feasibility, alignment with pedagogical theories, and positive early feedback from learners. These insights are valuable for informing future system refinement and for guiding the design of larger evaluations. This paper contributes meaningfully to the iterative research and development processes of enhancing the higher education classroom of tomorrow with AI-based adaptive learning technologies.

Future work will involve expanded evaluations across diverse learning contexts using mixed methods, enabling deeper analysis of the learning impact and instructional integrations. These case study evaluations will guide the continued refinement of HECOF into a robust, scalable, and pedagogically grounded system for AI-supported engineering education.

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