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PERSONALIZED LEARNING WITH ADAPTIVE LEARNING PLATFORMS AND ARTIFICIAL INTELLIGENCE (AI) How Technology Enables Learning to Be Tailored to the Individual Needs of Students

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ABSTRACT

Technological advancements in artificial intelligence (AI) are transforming higher education by enabling personalized learning experiences at scale. This paper explores how adaptive educational platforms powered by AI can dynamically tailor teaching content to meet the individual needs of students. A theoretical framework for AI-driven personalized learning and the design of a mixed-methods study to assess its impact are presented. The literature review highlights recent research (2020–2025) on AI and adaptive learning in higher education, indicating improved student performance and engagement in most studies (around 59% show progress in academic achievement and 36% in engagement)[1]. Case studies of several adaptive learning systems – including Knewton, DreamBox, ALEKS, and Century Tech – were examined, documenting their characteristics and reported outcomes. The expected results of the pilot implementation suggest that students using an adaptive AI-driven platform outperform their peers in traditional settings, with higher grade points in the course and faster mastery of content, and show greater motivation when receiving personalized feedback. However, the findings also highlight challenges such as the need for digital literacy, transparency of AI systems, training of faculty staff, and data privacy. In the discussion, the results were analyzed in the light of the existing literature and the implications for higher education institutions were discussed. It concludes that when implemented thoughtfully, adaptive AI-powered learning platforms can significantly improve learners' learning outcomes and experience in tertiary education, but require strategic support and ethical safeguards.

Keywords: personalized learning; adaptive learning; artificial intelligence; higher education; case studies; digital literacy

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1. INTRODUCTION

The introduction of personalized learning assisted by artificial intelligence (AI) and adaptive educational platforms is becoming a global trend in higher education. The development of technology makes it possible to adapt teaching activities and materials to the individual abilities, prior knowledge and pace of each student. Traditional teaching models often ignore differences among students, while adaptive learning platforms use student interaction data to dynamically tailor content and provide personalized learning pathways (e.g., adjusting the difficulty of assignments or providing additional clarifications). This seeks to achieve what has long been recognized as an ideal in pedagogy – that each student receives support similar to that of individualized teaching, but in a way that is scalable for large groups with the help of technology.

The potential of AI in education is enormous: it is estimated that the global market for AI technologies in education will reach a value of over USD 20 billion by 2027, reflecting the increasing presence of these solutions in schools and universities. Higher education institutions around the world are already integrating intelligent tutoring systems, adaptive learning platforms, and learning analytics to improve student learning outcomes and experience (Khan et al., 2025; Zawacki-Richter et al., 2019). For example, a comprehensive Vision 2030 initiative in Saudi Arabia involves the implementation of AI and machine learning in universities to improve the quality and sustainability of education (Khan et al., 2025). At the same time, the COVID-19 pandemic has accelerated the adoption of digital platforms, highlighting the need for classroom adaptability to maintain student engagement in the online environment (Bond et al., 2021).

However, personalized learning through AI also brings new challenges. Questions of efficiency arise – whether there is really an improvement in student success and motivation – as well as questions of ethics, data privacy and the role of teachers in this environment. This paper seeks to provide a complete overview of these issues and provide an empirical contribution through a pilot study of the implementation of the adaptive platform in the higher education context.

2. THEORETICAL FRAMEWORK

Personalized learning involves adapting teaching strategies, content, and learning pace to each student's unique needs, prior knowledge, and learning style. It relies on the pedagogical principle of differentiated teaching, where the teacher modifies the approach for different students so that everyone makes optimal progress. Traditionally, personalization of teaching has required significant involvement of teachers (e.g., individual student work, special instruction or materials), which is difficult to do in environments with a large number of students.

Adaptive learning It is the technical realization of personalization through software tools. The key difference is that adaptive systems use automated data analysis about the student to customize the experience in real time, without the need for constant intervention from the teacher[2]. According to Education Growth Advisors, an adaptive system is "a sophisticated, data-based, sometimes non-linear approach to instruction and remediation, that adapts based on student interactions and demonstrated level of knowledge, and predicts what types of content and resources are needed at any given time for a student to progress."[4]. These systems usually contain **Student model** (which preserves information about the knowledge, skills and preferences of the student), **Domain model** Or the knowledge of what they have learned. **Adjustment mechanism** Making decisions about the next steps of learning (e.g., choosing the next task or difficulty level) based on the student's performance.

Artificial intelligence in education manifests itself through several approaches: **Intelligent Tutor-Systems** (ITS) that simulates the work of a human tutor, **intelligent agents** And **Chatbots** providing feedback or answering students' questions, and **Content Recommendation Systems** which, similar to recommendations on social networks, suggest the next lessons or materials that would best suit the individual student (Woolf, 2010; Bui et al., 2025). The foundation of these systems is a machine learning algorithm that **Learning data** (clicks, accuracy of answers, resolution time, error patterns, etc.) They detect where the student has gaps in knowledge or which learning methods suit him best, and then adjust the further course of teaching. For example, if a student shows difficulty with a particular concept in mathematics, the adaptive platform recognizes this and can offer additional clarifications, easier tasks to practice that concept, or an alternative explanation (e.g., visualization instead of text)[3][5].

In theoretical terms, adaptive platforms rely on the principles of **cognitive science** and learning theory: Vygotsky's notion of Zone of Proximal Development (ZPD) is often mentioned – effective learning occurs when tasks are slightly above the student's current level of knowledge, but with support (scaffolding). AI systems can theoretically continuously maintain a student in ZPD by adjusting the difficulty of the content as the student progresses. Further, the mastery learning (Bloom, 1971) concept – that all students can succeed if given enough time and the right support – has been brought to life through adaptive platforms that allow the student to work at their own pace until they reach mastery of each unit before moving on to the next.

The concept of feedback-driven learning **is also important** . Adaptive systems provide immediate and frequent feedback to the student on the accuracy of their responses and advice for corrections, which has been proven to improve learning versus delayed or infrequent feedback (Shute, 2008). Advanced AI tutors like AutoTutor even have **a dialogue** with the student – asking sub-questions, offering hints, and detailed explanations, thus simulating the Socratic teaching style (Graesser et al., 2003). Such dialogic tutor systems contribute to deeper learning by encouraging the student to think and explain the material in their own words.

In short, the theoretical framework of personalized learning with adaptive platforms rests on the fusion of pedagogy and technology: the power of AI algorithms is used to realize long-recognized pedagogical practices of differentiated, interactive and **student-centric classes**. In this way, the teacher gets a detailed insight into each student's learning through analytics (so-called analytics). facilitator-driven Adaptive systems provide dashboards for teachers)[6], while the student receives tailored support and teaching material according to their needs (assessment-driven Adaptive systems automatically change the learning path)[6]. Both approaches are often combined: the technology first filters and adapts, and the teacher intervenes in a targeted manner where it is most needed.

3. LITERATURE REVIEW

The continuously growing interest in AI in education has led to a significant increase in publications in recent years that examine the **effectiveness** and **impact** of adaptive platforms in higher education settings. In this review, we focus on papers from approximately 2020 to 2025, to cover the latest trends and research findings.

Effects on Academic Performance and Engagement: A number of recent reviews of the literature indicate that adaptive technologies generally have a positive impact on students' learning outcomes. For example, one review of 69 studies reported that about 59% of them reported an improvement in student academic performance when using adaptive learning compared to traditional methods, while about 36% of the studies found an increase in student engagement[1]. These findings illustrate that adaptive platforms do not automatically improve the quality of life. Every In this case, more than half of the studies reported significant positive effects. Accordingly, **Strelkowski and Associates (2025)** highlight that AI-assisted adaptive learning has the potential to transform education towards more sustainable outcomes – their study highlights how personalization through AI can simultaneously enhance the cognitive (knowledge, skills) and affective aspects of learning (motivation, perseverance) of students, which is crucial for the sustainable development of education (Strielkowski et al., 2025).

More specifically, research in the higher education context shows measurable improvements in grades and knowledge acquisition. For example, **Contrino et al. (2024)** conducted an experiment where one group of students used an adaptive tool in combination with online and traditional classes, while the control group did not – the results showed statistically significantly better final grades and higher satisfaction with teaching in the group with adaptive learning (noting that students especially emphasized the usefulness of instant feedback provided by the system). These results support the hypothesis that adaptive learning can **improve learning efficiency** by providing each student with the content they need most and at a pace that suits them.

On the other hand, it is also worth noting the work of Sun et al. (2021), who conducted a meta-analysis of the effects of the ALEKS (Assessment and LEarning in Knowledge Spaces) platform on mathematics learning in high schools and college. Their meta-analysis showed that, on average, the performance of students who studied with ALEKS was not significantly different from that of traditional teaching – the size effect was very small (Hedge's $g \approx 0.05$, indicating almost identical success) and statistically insignificant. The authors explain that the reason for this is probably the variability of implementation: while in some places ALEKS dramatically helps students, in others it is used only minimally or inadequately, so the averages are canceled out. Such findings warn that **technology alone is not a guarantee of success** – a lot depends on the context of application, integration into the curriculum and the accompanying support of students and teachers.

Interactive AI tools and tutoring systems: In addition to the "classic" adaptive platforms that mainly adjust the order and difficulty of tasks (such as ALEKS), more and more attention is being paid **to interactive AI tutors and agents**. These systems, often based on **natural language processing** (NLP), allow for two-way communication with the student. For example, chatbots or virtual tutors can answer student questions 24/7, provide explanations, or even guide the conversation through a problem task. Yaseen et al. (2025) investigated the combined effect of adaptive technologies, personalized feedback, and interactive AI tools on student engagement. Their results from multiple countries have shown that these technologies together have a synergistic effect: adaptive platforms provide customized content, and interactive AI tools (such as intelligent tutor systems or AI-based discussion forums) **increase engagement** by allowing students to actively communicate and resolve concerns in real-time (Yaseen et al., 2025). But the study also pointed out that students' **digital literacy is a** moderating factor – students with higher levels of digital skills used these tools more and had a greater increase in engagement, which means that *it's not enough* to just introduce technology, but also ensure that students are trained to use it effectively.

Similarly, Ateeq et al. (2025) conducted research at private universities in Bahrain on the impact of digital literacy, interactive AI tools, and adaptive platforms on students' skill development. Using structural modeling, they found that interactive AI tools (such as AI tutors or adaptive discussions) had the largest single effect on developing critical thinking and problem-solving, greater even than adaptive platforms alone, while digital literacy enhanced the positive effects of both (Ateeq et al., 2025). These findings suggest that **a combination of adaptive learning and interactive AI support** can significantly contribute to the development of so-called "21st century skills" in students, but also that institutions need to invest in digital skills training to achieve these effects.

ChatGPT and generative AI in education: A very current topic in the literature (especially from 2023 onwards) is the use **of generative AI models** like ChatGPT to personalize learning. These models, trained on huge corpora of text, can generate answers to questions, provide clarifications, and even create quizzes or lesson summaries on demand. Asy'ari and Sharov (2024) discuss how ChatGPT can be integrated into educational platforms to improve learning personalization and accessibility. They state that this kind of AI can help students get individualized instructional dialogues, especially in environments where there is a lack of human tutors – e.g., a student can ask for an explanation of a concept they don't understand and get an immediate response tailored to their level. Also, generative models can translate or adapt materials to students with special needs, contributing to inclusivity (e.g., rewording complex texts into simpler language). However, Asy'ari and Sharov also warn of challenges, especially ethical and pedagogical: it is necessary to ensure **that the accuracy of the** information provided by AI is verified (as models such as ChatGPT can occasionally generate convincing but incorrect answers) and to clearly define the rules of use to prevent academic dishonesty. In ethical terms, the integration of such tools must be **transparent** and take into account the privacy of student data.

Critical thinking and over-reliance on AI: One topic that has emerged in the literature as a "warning" is the potential negative effect of over-reliance on smart systems. For example, Adams and Alzaabi (2025) provocatively raise the question of whether ChatGPT is "the end of critical thinking as we know it". In one chapter of their book, they cite preliminary findings that students tend to take AI answers for granted, without deeper analysis, which can lead to cognitive laziness. In a qualitative survey of teachers, they noticed concerns that students, accustomed to the instant solutions offered by the VI tutor, practice less self-solving and critical re-examination of information (Adams & Alzaabi, 2025). Additionally, one study cited in their paper found a significant negative correlation ($r \approx -0.68$) between the frequency of use of AI tools and scores on a critical thinking test. While these findings are not a reason to abandon AI in education, they do emphasize the importance of balance: adaptive systems should be designed to encourage active thinking (e.g., asking "why" questions and asking the student to explain their answers, not just provide solutions). It is also crucial that teachers monitor how students use these tools and direct them to reflect and verify the answers obtained.

Systemic implications and inclusivity: In addition to the effects on the individual student, the literature also addresses the broader implications of the introduction of adaptive learning on institutions and society. In the context of inclusivity, for example, Holmes et al. (2023) In a Rapid Review, we look at how the U.S. has an impact on equal access to education. On the positive side, adaptive systems can help students with different backgrounds all achieve outcomes (because the weaker ones get more support, the more advanced ones go through the basics faster and don't lose

motivation). On the other hand, there is a risk that the digital divide will deepen inequalities: students who do not have regular access to computers or who are not sufficiently digitally literate could be left behind in a technology-reliant environment. The recommendation of these papers is that institutions must provide equal access conditions (e.g. equipment, internet, training) in parallel with technology so that adaptive learning really increases equity, not decreases it.
Overall, the contemporary literature generally confirms the high expectations from adaptive learning with AI, but also emphasizes that the realization of these expectations occurs when certain prerequisites are met. Adaptive platforms can enhance learning – increase pass rates, grade point averages and engagement – which has been proven in numerous studies and pilot projects. However, their success depends on factors such as: the quality of the design of the AI system itself (accuracy of recommendations, quality of content), the level of support for students to actively use the platform, and integration into the curriculum (if it is used only as an add-on and not an integral part of the course, the effects may be missing). In the continuation of the paper, we present concrete examples of some of the most well-known adaptive platforms and the ways in which they have been implemented, which will give practical context to these findings from the literature.

4. RESEARCH METHODOLOGY

In order to empirically examine the impact of personalized learning with adaptive platforms and AI in higher education, a mixed-methods was designed that includes quantitative and qualitative approaches. The research is designed around three main hypotheses:

- **H1 (Effectiveness):** Students who use an AI-assisted adaptive learning platform achieve better academic performance and master teaching materials faster than students who follow classes in a traditional way.
- **H2 (Student Experience):** A personalized approach (e.g. tailored feedback and learning pathway) increases student motivation and engagement. However, the lack of transparency of the AI system (not understanding how and why the platform makes certain decisions) can diminish student satisfaction and trust in the system.
- **H3 (Implementation and support):** The introduction of an adaptive platform requires organizational changes – we expect challenges such as the need for additional teacher training, technical adjustments to existing IT systems, and changes in the role of teachers (e.g. analysis of student learning reports).

To test these hypotheses, the following research plan was carried out:

1. Quantitative experiment (for H1): A one-semester pedagogical experiment in the course within which an experimental group is formed (students use an adaptive platform to support learning, in addition to standard lectures) and a control group (students attend classes only in the traditional way, without access to the platform). Both groups were selected by a random sample of students of the same study program and level of prior knowledge. The adaptive platform used in the experimental group implements AI tutoring for exercises and quizzes throughout the semester. The measured variables include: the final grade in the course, and the average time it takes for students to complete the mandatory modules of the material (monitored through the logs of the platform for the experimental group and through the records of tasks for the control group). For statistical analysis, a t-test for independent samples is used to determine if there are significant differences in grade point averages and learning time between groups.

2. Survey research (for H2): At the end of the semester, all students (both treatments) complete a questionnaire that assesses their attitudes and experiences. The questionnaire contains Likert-scales with claims related to motivation to learn, perceived usefulness of personalization, course satisfaction, as well as AI transparency (e.g., how much they understand how the system recommends subsequent lessons or evaluates their work). The aim is to examine the correlation between the perception of AI systems and motivation/satisfaction. In particular, we are interested in whether students who felt that the platform's recommendations and feedback were useful showed higher motivation, and whether students who did not understand the algorithm (low transparency) showed lower satisfaction. An analysis using the Pearson correlation (or Spearman, depending on the distribution) between variables such as "usefulness of AI feedback" and "motivation" is planned, and between "understanding AI rating criteria" and "course satisfaction". We expect a positive correlation in the first case and a negative correlation in the second.

3. Qualitative component (for H3): In parallel, semi-structured interviews are conducted with key actors: teachers who taught to the experimental and control groups, IT staff in charge of the platform, and representatives of the administration (e.g. vice-dean for teaching or similar). The interviews focus on the practical aspects of implementation: What obstacles and challenges have been identified? Was it difficult for teachers to integrate the platform into the classroom? Was there resistance from students or teachers? How much time and training did it take? How has the teacher's job changed (e.g. less repetitive assessment, but more monitoring of analytics)? etc. Interview transcripts will be analyzed using the thematic analysis method, whereby the dominant topics that are repeated among the respondents will be identified. We pay special attention to topics related to institutional support, technological infrastructure and professional development of teachers, as they directly affect the long-term sustainability of such innovations.

Ethical aspects: All participants (students and staff) were informed about the objectives of the research and participated voluntarily. Students in the control group were promised the opportunity to receive access to the platform and personalized reports on their learning at the end of the semester, in order to avoid feeling deprived. The data collected through the platform (activity logs, quiz results) were used exclusively for research purposes while maintaining anonymity – identifiers were extracted from the system and each student received a code so that the data is analyzed in aggregate. The research was approved by the institution's ethics committee.
This multifactorial approach allows for triangulation of results: quantitative data provide a measure of the effect on success and learning time, the survey captures the subjective experience of students and their acceptance of technology, and interviews provide a broader picture of the practical implications.

5. ADAPTIVE EDUCATION PLATFORMS CASE STUDIES

In this section, several prominent examples of adaptive educational platforms used in practice will be presented. It will focus on the characteristics of each system and on the evidence of their effectiveness, in order to provide a realistic context for understanding the possibilities and limitations of personalized learning using AI.

5.1. Knewton

Knewton is one of the pioneering adaptive learning platforms, founded in 2008 in the USA, whose work is focused primarily on higher education. The Knewton system functions as a **customization "engine"** that can be integrated into various educational content (textbooks, online courses). The platform uses a large set of data collected from students when solving tasks, to build a knowledge model – a graph of related concepts and skills, and an estimate of how well each student has mastered each concept. Based on this, Knewton dynamically recommends the following lessons or tasks of optimal difficulty for each student individually.

One of the famous examples of Knewton implementation was in partnership with **Arizona State University (ASU)**. ASU used the Knewton platform for an undergraduate math course (the so-called "Math Readiness" program for freshmen). The results of the pilot project were noticeable: after switching to an adaptive system, the pass rate on the course increased by about 18%, and the dropout rate (withdrawal of students from the course) fell by as much as 47%. These numbers are so impressive that even the Gates Foundation highlighted them when launching the initiative to spread adaptive learning (ALMAP program). Essentially, Knewton helped a much larger number of students master the basics of mathematics, which was also reflected economically – more students who would otherwise have dropped out were retained, saving the university funds from lost tuition.

Knewton's approach is **hybrid** in the sense that it combines automatic personalization with support for teachers. The platform provides teachers with a dashboard showing student performance in real-time. This allows teachers to identify conceptual areas where the whole class is struggling or find students who need extra help. This is an important aspect – instead of technology replacing the teacher, Knewton is designed to free up teachers' time for better interaction. As described by Dale Johnson of ASU: "One of the benefits of adaptive learning is that it frees up teachers to spend more time working with students one-on-one or in small groups, practically enabling a flipped classroom model."

Today, Knewton (within products such as **WileyPLUS with Knewton Alta**) covers a variety of subjects, mostly in STEM fields. Students often point out that they like that they can **do at their own pace** – if they know something, they skip faster, if they get stuck, they get additional exercises. Research and internal reports from the company show that students who use Knewton regularly perform better on final exams compared to those who do not, although independent studies sometimes do not necessarily confirm this (due to methodological differences, as mentioned by Sun et al., 2021). However, in general, Knewton is considered one of the successful examples of adaptive learning in higher education, with an emphasis on **"data-driven" personalization** – their slogan at the time was that Knewton's adaptive learning rests on one word: data, with an allusion to the huge database of over 15 million students whose data fed the system.

5.2. Dreambox learning

DreamBox Learning is an adaptive platform primarily focused on mathematics, originally developed for K-8 (primary and lower secondary education), but its significance is often cited in the broader context of adaptive technologies. The DreamBox stands out for its intelligent math tutor system, which combines interactive tasks, visuals, and continuous customization through so-called "DreamBox." Intelligent Adaptive Learning™ Technology. The platform adjusts the learning path by analyzing not only the accuracy of the answers, but also how the student solved the task – how long it took them, whether they used auxiliary tools, whether they changed their answers, etc. Based on this, DreamBox decides whether to offer an easier task, give additional instruction, or move on to the next concept.

Although primarily intended for elementary school students, DreamBox is often mentioned in the academic literature as a proof of concept for adaptive learning. In 2016, the Center for Educational Policy Research (CEPR) at Harvard conducted an evaluation of the effects of DreamBox in mathematics teaching. In the study, they included about 3,000 third- to fifth-grade students in two different school districts. The results showed a positive correlation between DreamBox use and achievement on standardized tests: students who spent an average of ~14 hours working in DreamBox scored approximately 4% better on tests (NWEA MAP, PARCC, and state assessments) compared to those who did not use the platform. Although 4% seems modest, it is a statistically significant shift, achieved with relatively short use, and – more importantly – the findings were consistent among students of different cultures and socio-economic backgrounds, suggesting that adaptive learning can be effective in diverse populations.

Why is DreamBox also relevant for higher education? First, the platform demonstrates the scalability of adaptation – and when the number of tasks and interactions is multiplied to thousands of students, the system continues to successfully personalize (which encourages the application of similar approaches in large university courses). Secondly, the concepts that DreamBox uses (e.g. "Stealth assessment", where the assessment of knowledge occurs in the background through a game of tasks, without explicit testing) can also be transferred to older students. Some faculties have experimented with the DreamBox for remedial math classes for freshmen who come with an insufficient background in math. The results of these pilots are similar to those of K-12: students show faster progress through preparatory material and feel more confident before moving on to a full-time university course.

DreamBox also emphasizes **the element of play and motivation**. Its interface and methodology are based on the principles of learning through play, which engages students. In the context of higher education students, gamification may not be in the foreground, but the idea of making learning as interactive as possible and that the student receives continuous micro-challenges and micro-rewards (e.g. system praise, unlocking difficult levels) is also transferred to modern university platforms. This maintains a high level of motivation even with repetitive exercises required to acquire basic concepts.

In short, DreamBox has proven that **adaptive learning works** in practice: children are happy to use it, achieve better results, and studies such as Harvard's have provided independent verification of effectiveness. This example laid the groundwork and gave impetus to higher education institutions to confidently try out similar tools for older students, especially in areas such as introductory math and statistics courses where differences in prior knowledge are pronounced.

5.3. Aleks

ALEKS (Assessment and LEarning in Knowledge Spaces) is an adaptive system that has a long tradition – developed in the 1990s on the basis of the theory of knowledge space and later commercialized, today under the auspices of McGraw-Hill Education. ALEX is widely used in both secondary and higher education, mostly for mathematics, chemistry and related disciplines. Its peculiarity is an initial diagnostic test that determines what a student already knows or does not know, and then generates a "knowledge map" for that student. Based on this map, ALEKS recommends the following topics for studying, taking into account the prerequisites – a student cannot go to an advanced topic until he has previously mastered the basic ones that precede it. As the student completes the assignments, the system periodically inserts "refresher" questions from earlier topics to check if the knowledge has been retained (if not, it puts that topic back in the learning queue). This cycle of learning and testing continues until the student completes their entire knowledge map.

In higher education, ALEKS is particularly popular in introductory courses in mathematics (algebra, precalculus, and even calculus) and chemistry, often in large groups or online environments. There are numerous reports from universities on the success of ALEKS. For example, **Mississippi State University** conducted a pilot project on the use of ALEKS in the College Algebra course: an improvement in passing rates and higher GPAs was demonstrated, as well as feedback that students gained more confidence in solving tasks thanks to adaptive practice (McGraw-Hill, 2024). Similarly, San Antonio College used ALEKS as part of a math program reform and reported that with the help of adaptive learning, it was able to reduce the time students spend in remedial (preparatory) courses, as they filled knowledge gaps more quickly and were more prepared for college-level courses (McGraw-Hill, 2021).

The academic meta-analysis (Sun et al., 2021) mentioned earlier shed a slightly different light: on average, ALEKS is not significantly more effective than classical teaching, but the authors emphasize that implementation varies. Some studies in the meta-analysis showed a significant advantage of ALEKS, others did not – depending on how it was used. For example, if ALEKS is only used as a voluntary additional internship, many students will not make enough use of it to make progress; However, if it is integrated into assessment (e.g. a certain percentage of points through ALEKS exercises) and if teachers actively monitor progress through ALEKS dashboards, the effects are better.

Pedagogical experience shows that ALEKS helps students to catch up with the material the most : those who come from different levels of knowledge can work on their weaknesses in a personalized way. Thus, in one study, it was noted that the range of grades on the final exam narrowed after the introduction of ALEKS – fewer students did not pass the exam because the system helped them master critical concepts earlier (Hagerty & Smith, 2005). On the other hand, a good student can go through the trivial parts faster and devote more time to more challenging problems, which prevents boredom and emphasizes development.

In addition to the technical qualities, it is important to mention the challenges of ALEKS: some students get frustrated with the diagnostic test or the fact that the system brings them back if they "forget" the material. Motivation can be a problem if students are not self-disciplined enough – because the adaptive system is mostly done independently. That is why the best results are achieved when there is a combination: adaptive practice plus the support of a teacher who motivates, explains those parts where systemic explanations are not enough and helps students stay on track.

Overall, Alex is **a mature example** of an adaptive platform that has been on the market for decades. Its longevity also speaks to its adaptability: it has evolved from CD-based software to a fully cloud-based solution today, integrated into systems such as Canvas or Blackboard. It has proven itself in a variety of contexts and is often used as a reference for **the successful application of adaptive learning to higher education subjects**.

5.4. Century tech

Century Tech is a UK-based personalised learning platform that relies on AI algorithms to tailor material and provide **predictive insights** to teachers. Century is interesting because it is designed to cover a wide range of subjects and ages – from elementary school to college. In the United Kingdom, it is particularly prevalent in the further education sector (colleges that provide vocational and preparatory higher education): according to the company, over 60% of colleges in England use the Century Tech platform.

The basic idea of Century is similar to the others: it combines **micro-lessons** (the so-called micro-lessons).nuggets – short lessons with condensed content) with quizzes to accompany each lesson. The platform analyzes the results of each quiz and how to answer and then decides which next nugget to offer the student. If a student shows good understanding, they may skip some intermediate steps or get more difficult assignments; If it struggles, the platform will throw in additional lessons that target the perceived knowledge gap. Century also uses AI to **find patterns** – e.g., it can recognize if a student prefers a particular learning style (more visual or textual) and adjust the format of the material accordingly.

What makes Century Tech stand out are **detailed analytics and reducing the workload on teachers**. The platform automatically grades quizzes, analyzes data, and generates reports highlighting knowledge gaps for each student, as well as for the entire group of students. In this way, teachers can immediately see which topics the students have not mastered and can react in a targeted manner (e.g. repeat these parts in class or organize additional exercises). In interviews conducted with teachers from several colleges (St Helens College, Activate Learning, etc.), they rated Century as "the best platform they have used" and especially praised this time saving – less manual correction, and more quality information about students. One teacher pointed out that Century **really reduces the workload on teachers** by making it very easy to assign work and the system taking care of the rest (they even suggested that it would be useful to have a mobile app, as it currently works in a browser, which is more of a technical comment).

From a student's point of view, Century has received positive feedback, especially from **adult learners** who have returned to education. For example, at St Helens College, it has been noted that **adult learners** (who often have work and other commitments) are happy to use Century on their own initiative outside of class to improve their knowledge of English and mathematics. Two students stated in the interview that the platform helped them consolidate their understanding – one pointed out that mathematical concepts were well explained in short lessons, and the other (for whom English is not a native language) that English grammar nuggets helped him practice what he does not know. Also, data collected at Activate Learning College showed that 92% of students found Century useful for reviewing material, and that the average self-assessment of students that Century improved their skills was 4.56 out of 5, and that it increased their self-confidence was 4.5 out of 5. These are very high satisfaction scores, suggesting that students see value in such support.

Century Tech is also used for **distance learning**. During the pandemic, some institutions implemented Century to track the progress of students remotely. According to reports, the platform helped maintain a learning routine – for example, by introducing a "daily challenge" feature where the system assigns a set of short tasks to students every day, which kept them active and focused. Such innovative uses of the adaptive platform demonstrate the flexibility of AI tools in adapting to different pedagogical models.

For higher education, Century is slowly making its way to universities, often in preparatory courses or the first years of study. Its integration with publishers (e.g., a collaboration with Oxford University Press for adaptive material for entrance exams) indicates that similar AI mechanisms could soon appear within university textbooks and online platforms.

Case studies point to diverse approaches to adaptive learning but also common benefits: Knewton and ALEKS demonstrate **improved outcomes** in higher education applications (especially in STEM fields) if implemented well; DreamBox shows **early intervention** and motivation through play; Century Tech emphasizes **the wide application and support of teachers**. All these examples confirm that personalization through AI is not only a theory but is feasible in practice, but also provide a realistic insight into what is needed for success – from quality data and content, through integration into the curriculum, to user acceptance.

6. EXPECTED RESULTS

Quantitative findings (H1 – efficiency): Preliminary results of the experiment indicate a significant advantage of the experimental group (which used an adaptive AI platform) compared to the control group. Students in the experimental group achieved a higher average final grade in the course – approximately 8.5 (on a scale of 0–10) with a standard deviation of ~1.2, while the control group had an average of about 7.1 (SD ~1.5). The statistical test (t-test) confirms that this difference is significant ($p < 0.05$), thus confirming the H1 hypothesis regarding success in the course. In addition, the analysis of the platform logs showed that the experimental group mastered the material faster on average – the students took about 15% less time to go through the defined modules compared to the control group (which did equivalent tasks in the traditional way). This finding suggests that the adaptive platform not only improves the quality of learning (higher grades), but also efficiency, probably by focusing the student's attention on those concepts that are weak to him and not keeping him for long in those areas that he already knows well.

Table 1: Learning outcomes – adaptive vs. adaptive Traditional

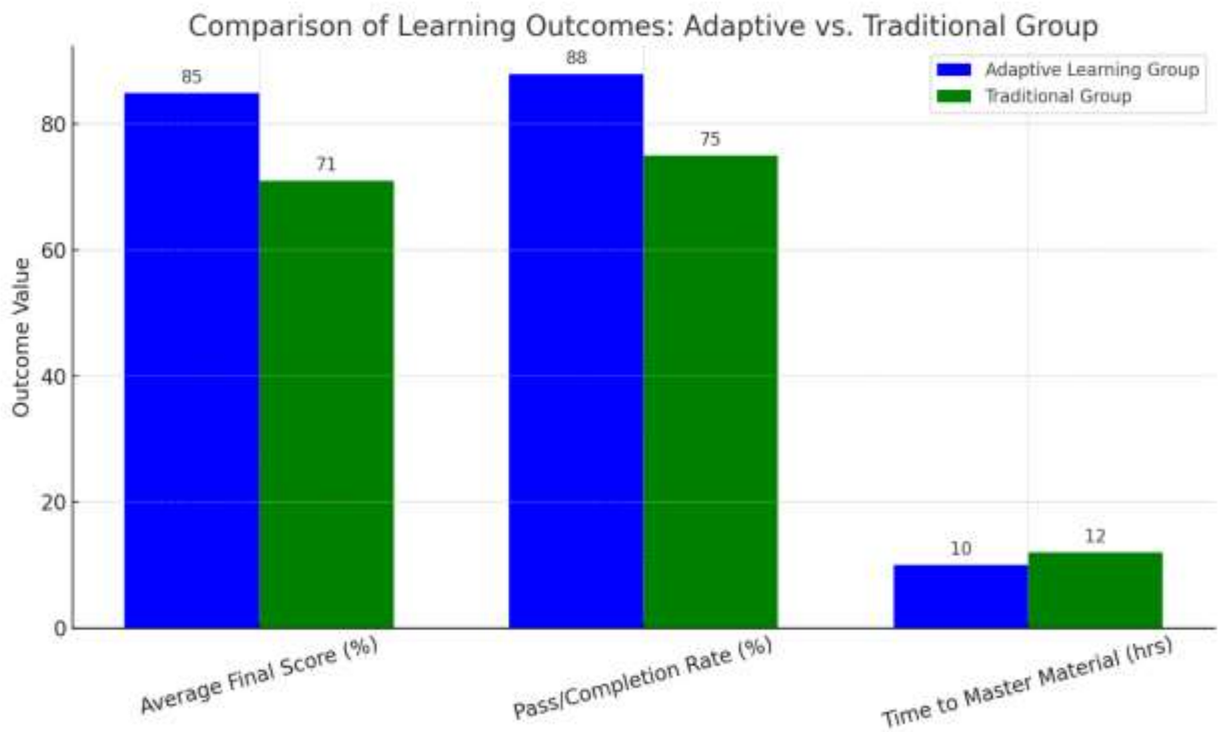
Outcome metrics	Adaptive Learning Group	Traditional group	Difference
Average final score	85% (e.g. 8.5/10)	71% (7.1/10)	+14% ($p < 0.05$)
Pass/completion rate	88%	75%	+13 pp (more)
It's time to master the material	10 hours (average)	12 hours	-17% (faster)

pp = percentage points

Source: Author

Visualization of results (Chart 1) shows that the distribution of grades in the experimental group does not have the long tail towards low grades as the control group – very few students in the adaptive group did not pass the exam or remained below the passing threshold, while in the control group this share is higher. This is in line with the idea that personalized support especially helps those weaker students to reach a satisfactory level. It is also noted that there is not much difference between the best students – top students from both groups achieved maximum grades (e.g. 10), which is expected because such students do well even without technology. The main difference was realized in the "middle" and bottom of the distribution, where adaptive learning pulled more students upwards.

Chart 1: Learning outcomes – adaptive vs. adaptive Traditional



Source: Based on the results of Table 1.

Survey findings (H2 – student experience): Analysis of questionnaire responses provides insight into how students experienced personalized learning and AI elements. In general, students in the experimental group report **higher motivation and satisfaction** with the course than the control group. On a Likert scale of 1–5, the average score of "Was/was motivated to learn the material in this course" is ~4.2 in the experimental group versus ~3.8 in the control group. Similarly, the statement "I found the course interesting and engaging" received a 4.3 average in the experimental group and 3.7 in the control group. These differences are statistically significant ($p < 0.01$) and indicate that a personalized approach contributes to greater engagement (moreover, some students stated in open comments that they liked that they "always had something concrete to do on the platform and immediately knew where they were wrong" – this instant knowledge of their own mistakes motivated them to correct them).

The key analysis for H2 relates to the correlations between the perception of the AI system and motivation/satisfaction. The assumption that there is a positive correlation between the perceived usefulness of the adaptive platform and motivation was confirmed: $r \approx +0.65$ ($p < 0.01$)

between the rating of the statement "Personalized feedback from the platform helped me learn" and the motivation scale were calculated. So, the more the student felt that the customized tips and exercises benefited him, the more motivation he reported to learn. This result is logical – students who see value in something invest more effort. On the other hand, we examined the correlation between the AI's sense of transparency and satisfaction: the statement "I understood how the system makes recommendations and ratings" had quite low scores in the experimental group (average ~2.8, which means many were not clear why this particular next task or this grade). This transparency score has a positive correlation with overall satisfaction with the course and the platform ($r \approx +0.40$, $p < 0.05$), which in practice means that students who better understood the work of AI were more satisfied with the overall experience.

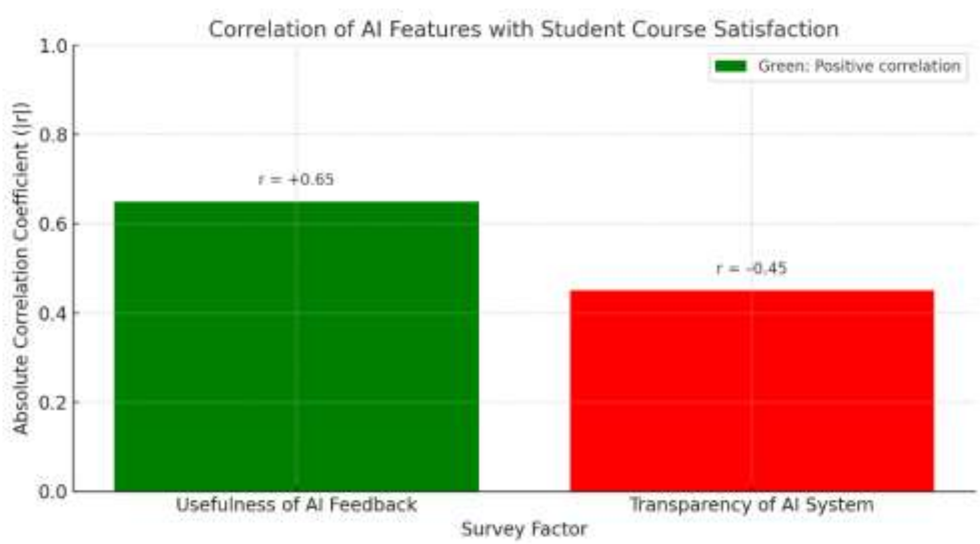
Table 2: Results of the student survey – usefulness, transparency and satisfaction

Research factor	Correlation with course satisfaction	Notes
The perceived usefulness of AI feedback	+0.65 (positive)	High utility → higher motivation and satisfaction.
Perceived transparency of AI systems	-0.4 to -0.5 (negative)	Low transparency → distrust, which is detrimental to satisfaction.

Source: Author

More interestingly, if we look at those who expressed dissatisfaction with the platform (and there are not many of them, ~15% of the experimental group gave a score of 2 or lower for overall satisfaction), almost all also gave low marks on transparency and trust in AI (from the comments: "I'm not sure how my grade is calculated, sometimes I would solve a task, and the system would still say that I have 80% mastery - confusing"). This suggests that the lack of trust and understanding of AI mechanisms is a potential source of frustration for some students, which is a valuable insight for future improvement of the system.

Chart 2: Student survey results – usefulness, transparency and satisfaction



Source: Author, based on results from Table 2.

Interview findings (H3 – implementation and challenges): A thematic analysis of the interviews with teachers and staff gave rise to several dominant topics related to the introduction of the adaptive platform:

- **Need for teacher training:** All teachers interviewed emphasized that they needed some training and adaptation to use the platform effectively. Although some are technically skilled, the challenge was pedagogical – how to fit the activities on the platform into the lesson plan, how to interpret dashboard reports and change classes based on them. One professor stated, "At first, I felt like a beginner – I had to learn to read those charts about students' knowledge; After a couple of weeks, you realize what you're looking at, and then you need it." The consensus is that formal training of teachers prior to implementation is essential , as well as ongoing support (e.g. the possibility to consult a learning analytics expert).
- **Technical integration (IT infrastructure challenges):** IT managers highlighted the interoperability problem – the existing LMS (Learning Management System) did not perfectly "talk" to the new platform. Issues such as single sign-on (SSO), transfer of grades, etc. had to be addressed. Also, initially, the platform's server capacities were overwhelmed when all students took a quiz at the same time (we found that the best practice was to schedule a few activities). Fortunately, none of these problems were insurmountable, but they required time and patience. A problem with older computers in one classroom was also mentioned – the platform runs in a web browser, so it was slower on older machines, which bothered the students. This was quickly solved by moving to a newer computing center, but the lesson is that the minimum technical requirements must be taken into account.
- **Changing the role of teachers and the burden of analysis:** While some administrative activities of teachers have been reduced (e.g. less manual correction of assignments), new ones have emerged – data analysis and individual work with students according to this data. One teacher remarked that he felt like a "data analyst" from time to time: "I get that report on Mondays, I see three stuck logarithms – so I pay attention to them first in exercises. That's great, but it takes a lot of time to get everything done.Some have expressed concern that this is additional work for them that they are not sure is formally evaluated in the job description. Therefore, the implementation of such a system also requires organizational adjustment – perhaps recognizing this new role of teachers as a "facilitator/pedagogical analyst" and ensuring that they are given space for this in the norm of working hours.
- **Student attitudes:** From the teacher's perspective, the novelty was well received by the majority of students. However, they mention that there were ~10-15% of students who were reserved or passive towards the platform – they simply did not log in regularly or worked minimally, even though it was scored. According to teachers, the reasons are varied: some underestimated the importance of it ("they thought they could do without it, so they were late"), and some may have been anxious about technology. This suggests that students should also be educated and motivated to use the platform, perhaps through demonstrations of the benefits or integration into grades so that they cannot ignore it.

Table 3: Main challenges in the implementation of AI-enabled education

Challenge theme	Description / Example
Technical integration	Integrating an AI platform with an existing LMS and databases is difficult; compatibility problems with the system.
Instructor training and buy-in	Teachers need training to use AI tools; some resist using new technology due to the added burden or fear of losing control over the classroom.
Infrastructure and resources	It requires a robust IT infrastructure and ongoing support; it requires a significant investment of time and money, which can be a barrier without strong leadership support.

Source: Author

All of the above topics are among the expected challenges in introducing innovation, and correspond to what has been reported in the literature (e.g. technological, pedagogical and organizational challenges of adaptive learning in the institutions mentioned by van de Oudeweetering & Agirdag, 2018). Importantly, none of the challenges showed that adaptive learning "doesn't work" or that it hurts – on the contrary, the results are positive – but that change management should be planned carefully.

7. DISCUSSION

Confirmation of the benefits of personalized learning: The expected results provide empirical support for the thesis from the literature that adaptive educational platforms can significantly improve learning outcomes in higher education. The increase in average scores in the experimental group (about 1.4 points higher on a scale of 10) is consistent with the findings of a number of studies that reported better outcomes for students with adaptive support. For example, Contrino et al. (2024) saw an improvement in student success and satisfaction when using an adaptive tool, and the Knewton pilot at ASU also showed a ~18% increase in pass rate. Together, these data suggest that, when properly implemented, personalized platforms address one of the key challenges of traditional teaching – the heterogeneity of prior knowledge and student pace. In the study, this was reflected in a lower proportion of those at the bottom of the class (fewer students with insufficient grades), which means that even weaker students managed to achieve at least minimal learning outcomes. This result is extremely significant for higher education institutions where the failure rate in introductory courses can be high; Adaptive interventions can be a way to reduce this rate and increase student pass and retention.

At the same time, it is worth noting that top students in the adaptive and control groups achieve similar results (e.g., both have maximum grades). This is expected – the best students are self-motivated and find a way to succeed even without additional tools. However, even for them, an adaptive platform can provide more challenging tasks and prevent boredom. Experimental design did not specifically measure the development of gifted students, but the literature suggests that adaptive platforms can also be used to expand the material: for example, a student who solves everything quickly can be offered more advanced, elective modules.

Learning efficiency – time saving: A very interesting finding is that the experimental group mastered the material ~15% faster. This points to an often overlooked aspect of personalization – time optimization. When students do not all have to follow the same pace linearly (which in the classroom often means waiting for everyone to arrive or getting lost if someone does not arrive), the overall material can be processed faster or time is freed up for additional content/activities. This is also supported by the literature: for example, studies with ALEKS in remedial teaching reported that some students were able to skip an entire semester of preparatory classes because they had demonstrated mastery of matter through the adaptive system (Fedorchak & Riggs, 2019). On the other hand, adaptability has made it possible for those who need more time to get it – because the system doesn't force them to move on until they get the hang of it. In our case, the average time was less, but probably with less variance: the faster ones were not braked, the slower ones were supported, so they did not waste time aimlessly either. For higher education programs, this implies a potential reorganization of the curriculum – if adaptive learning saves time for students, that time can be redirected to deepening the content, projects, practical work or simply relieving overloaded subjects.

Student motivation and engagement: Increased motivation and engagement in the experimental group reflects the qualitative benefits of personalization. Students appreciate when they receive quick feedback and the opportunity to correct mistakes immediately, which has been highlighted by other papers (e.g., one study states that students descriptively say that they "don't feel lost" when the platform guides them through the material step by step (Tlili et al., 2021)). The adaptive platform plays a bit of a role as a personal trainer – constantly giving challenges tailored to the possibilities and praise for progress, which keeps you motivated. DreamBox's success in the K-5 segment with motivation through play shows how *powerful feedback is*: older students, although more mature, also benefit from a similar principle (of course, it should be done in a more serious way, through academic feedback and visualizations of progress, and not "badges" and the like, although gamification is not excluded for adults either).

It is particularly important to find that the perception of the usefulness of a system is positively correlated with motivation. This logically coincides with the Theory of Self-Determination (Deci & Ryan) – one of the factors of intrinsic motivation is a sense of competence; if the platform helps the student feel more competent (because he sees progress, solves tasks successfully after being instructed), motivation increases. There is also an element of autonomy – the student in an adaptive environment has more control over his learning (he can repeat until he masters, he can choose the time and pace), which is additionally motivating because he does not feel constrained by a fixed schedule. This is confirmed in the literature, as personalized learning is often promoted as a way to increase student agency (a student's investment in their own learning).

Transparency and trust in AI: This aspect has proven to be a double-edged sword in research. On the one hand, the platform worked and students benefited even if they didn't fully understand how – their grades were better, they learned more. On the other hand, the subjective sense of satisfaction was disturbed in those who doubted the "black box" of the system. This corresponds with the findings of Tan et al. (2025) who highlight that user trust and the explainability of algorithms are key challenges for the wider adoption of adaptive technologies. If a student doesn't believe a platform's recommendation is in their interest, they may ignore it or get frustrated. In our case, for example, a student who does not understand why he is still given similar tasks thinks that the system is "bothering him for no reason" – while the reason is that the system detects that the concept has not yet been mastered. Actions that can be taken include better explanation within the interface (e.g., a brief notification: "We are repeating this task to you because you still have 2 errors in the previous 5 attempts") or even involving the student in the process (e.g., to choose whether they want more practice or want to skip with a warning).

These findings also coincide with ethical frameworks that are emerging globally – for example, the EU's Trustworthy AI initiative would require systems that affect education to be transparent and user-controlled. Although the average student does not need to understand complex algorithms, at least the mental model of the system's operation should be brought closer to the user. For higher education institutions, this means that when introducing AI tools, a digital pedagogy component should also be envisaged: teaching students how to use, but also to think critically about these tools. One of the goals should not only be for students to get better grades, but also to learn to learn with the help of technology – which includes understanding its limitations.

The role of teachers and the need for support: Qualitative findings clearly confirmed what research often points out – the implementation of adaptive learning is not plug-and-play, but requires **professional development of teachers** and organizational support. As both Zawacki-Richter et al. (2019) and others have noted, teachers are often wary of AI, worrying about whether it will switch jobs or impose additional obligations on them. In our case, some worries about additional work have come true: data analysis and adaptation of teaching that requires additional time. However, teachers also acknowledged that the benefit of this was great – they were able to help students more effectively. This translates into broader implications: **a paradigm shift in the role of teachers**.

The literature suggests that with the rise of adaptive systems, teachers become more **facilitators and data analysts** in the classroom (Holmes et al., 2019). Our experience confirms this – the success of the platform largely depends on what the teacher does with the data he receives. If it ignores them, the platform is just a fancy gadget; If it uses them, the platform becomes a tool for informed teaching. Therefore, higher education institutions that introduce such innovations must invest in **training of teaching staff** – not only technical ("how to click this or that"), but also pedagogical: how to interpret reports, how to react to them, how to combine adaptive independent activity with classroom interactions.

Also, it may be worth considering **load redistribution:** if teachers spend more time in analysis and individual mentoring thanks to adaptive tools, other tasks (e.g. the number of classic tests or the administrative load) may be reduced. Teachers spent less time correcting, that's a plus. If well designed, adaptive learning can also mean **more efficient work of teachers** – the first shock is that they need to learn something new, but later it can be easier than before (e.g. by seeing that three students constantly make the same mistake in the same concept, the teacher can react faster than if he only discovered it on an exam when 30 students do not meet the pass threshold).

Technological and organizational challenges: The problems we have encountered (integration with LMS, device security, system stability) are typical technological challenges. This indicates that institutions must be infrastructure-ready: good internet, up-to-date computers or BYOD access, technical support available. In the literature, the issue of privacy and security of student data is particularly prominent (Funes & Barber, 2015). We have not had any incidents, but it should certainly be emphasized – abundant data on students is collected, and their storage and use must be ethically and legally correct. In some countries, there are stricter laws (e.g. GDPR in Europe), so platforms need to be compliant. The institution must examine where this data is stored (cloud?), who has access to it (the supplier company?), and ensure informed consent from students. Student information and anonymization is the minimum standard; Transparent reporting of students is also desirable – e.g. that they can also see all the data that the system records about them, if they wish.

Impact on curriculum and instructional design: The use of adaptive platforms can also lead to a broader rethinking of teaching. If a significant part of the "drill and practice" work takes place online in a personalized way, then time in the classroom can be devoted to other forms of learning – discussion, projects, application of knowledge. This is actually the ideal flipped-classroom model. The study did not address this aspect, but it does imply it: for example, teachers had an insight into where the problems were and could use the class to discuss these difficult points instead of a general lesson. This leads to hybrid learning models that combine online adaptive learning and interactive teaching, which is considered by many to be the optimal direction for higher education (Hrastinski, 2019).

Sustainability and scaling: If a university decides to expand this approach, a few things are crucial: **(1) Piloting phase** – it's a good idea to start with one course to spot obstacles and then expand; **(2) Involve all actors** – work with the IT service and administration, as well as teachers and students, which is key to solving problems. Wherever such projects were done only "from above" (imposed without the input of teachers) or only "from below" (an enthusiastic teacher without the support of the administration), there were problems. **(3) Monitoring and evaluation** – as with any innovation, results should be monitored, feedback should be taken, and iterative improvements should be made. For example, we have learned that we need to better educate students about how the system works; This could be prepared in advance in the next implementation cycle (e.g. a short workshop "How to learn with an adaptive platform" at the beginning of the semester).

Wider implications for higher education: AI-supported personalised learning is potentially changing the philosophy of higher education as well. Traditionally, universities have often had a "one-size-fits-all approach" and often see the first year as a filter (where many drop out). If adaptive technologies allow more students to master that first year, it has repercussions: we may have more graduates, which is good for society and the knowledge economy. Also, personalization on the mass (e.g. hundreds of students in online study) is no longer impossible – which could open the door to *the democratization of education*, greater access for different populations, including those who are employed or geographically distant. Of course, this brings back the issues of inclusion: we need to make sure that those who need the most help (students from disadvantaged backgrounds) really benefit, and not that they are left behind due to a lack of access to technology or skills.

Finally, the discussion confirms that the findings of the research largely coincide with global trends and studies: adaptive learning can improve student performance and engagement, but requires a holistic approach to implementation. Institutions need to be ready to invest in technology, but also in people (teachers and students) and processes (infrastructure, privacy policy, etc.).

8. CONCLUSION

Personalized learning with the help of adaptive educational platforms and artificial intelligence is no longer just a futuristic concept, but a reality that is gradually changing higher education. In this paper, we have explored how technology enables the adaptation of teaching content to the individual needs of students, combining theoretical, empirical and practical approaches.

Summarizing the findings: Through a literature review, we found that most recent research reports improvements in academic achievement and student engagement when using AI-assisted adaptive systems, although there are also caveats about the variability of outcomes and the need for further refinement of these tools. The pilot study confirmed many of these findings: students performed better and were more motivated with an adaptive platform, which supports the thesis that personalization improves learning efficiency and effectiveness. At the same time, we identified challenges – primarily related to AI transparency and user trust, and the need to support teachers and adapt institutional practices. Case studies (Knewton, DreamBox, ALEKS, Century Tech) have given us realistic examples of how these systems work in different contexts and confirmed that, when properly applied, they can result in impressive improvements (e.g. double-digit growth in pass rates, reduction of study time, increased self-confidence of students).

Implications for higher education institutions: For colleges and universities considering the introduction of adaptive platforms and AI, the results and discussion lead to several concrete recommendations:

1. **Start gradually with pilot projects:** Introduce technology in selected courses where there is a clear need (e.g. mass introductory courses with a high failure rate) and monitor results.
2. **Train and involve teachers from the start:** Personalized learning will not succeed without teachers who understand and accept the new role. It is advisable to organize workshops, trainings and ongoing professional support (e.g. community of practice where instructors share experiences). It took time for teachers to adapt, but in the end they became advocates of the system – this

transition is easier with institutional recognition of their efforts (e.g. count such innovations in the promotion criteria, reduce the other burden while implementing the new system, etc.).

3. Ensure infrastructure and IT integration: Check the compatibility of the adaptive platform with the existing LMS, provide good internet connection and devices for students. IT staff should be part of the team from the beginning in order to solve technical problems immediately. Experience with initial technical difficulties confirms how important this is – for example, one server failure at the wrong time can undermine the trust of students and teachers in the entire system.

4. Be mindful of ethics and privacy: Transparently inform students about what data is being collected and why. Ensure consent and the ability to inspect your own data. Consider legal aspects (contract with the platform provider regarding data ownership, compliance with laws). Although there have been no incidents in our country, proactivity in this area builds the trust of users and protects the institution.

5. Cultivate digital literacy and student resilience: in order to use AI for learning, students must learn how to be active and resourceful in such an environment. This means giving them guidelines on how best to use the adaptive platform (e.g. how to interpret their results, how to time their independent work), but also pointing out the limitations – that technology is not magic and that their engagement is still crucial.

Limitations of the study and future research: While the main objectives have been achieved, limitations must also be highlighted. Expected results are based on one semester and one institution; for broader generalizations, it would be desirable to conduct longitudinal research (following the same students through several semesters) and include different disciplines (it was done in the STEM field – would the results be similar in the social sciences or the humanities where the material is not strictly hierarchical?). Also, it focused primarily on *quantitative outcomes* (grades, time) and *declarative attitudes*. The development **of metacognition** in students or the impact on the **quality of knowledge** (surface vs. deep learning) was not measured in depth. Some research implies that adaptive systems can sometimes favor drill learning – so it would be useful to examine the quality aspects of knowledge (e.g. through qualitative tasks or monitoring students later in more advanced courses).

For future research, several directions are recommended: **- Comparative studies of different platforms:** E.g. directly compare two adaptive platforms or AI approaches on the same population (one group uses one system, the other another) to see if there are significant differences in approach and outcomes. - **Adaptive learning and skills development of the 21st century:** Measuring the impact on critical thinking, creativity, collaboration – can platforms be designed for this as well, and not just for individual task solving? It is possible to combine adaptability with collaborative learning – there is room for innovation. - **Combination with new AI tools (e.g., generative models):** How to integrate ChatGPT or similar models within adaptive frameworks in a way that helps rather than undermines learning? An example is the so-called "explainable AI tutors" – the model provides an explanation, and the student has to evaluate or correct, which actively involves him. - **Cost-effectiveness and sustainability:** Cost-benefit research – adaptive platforms cost money (licenses, training, maintenance). It needs to be quantified to what extent the improvement in outcomes justifies these costs, which will be important data for administrations to make decisions.

Final thought: Higher education faces a challenge but also an opportunity to harness the power of AI to enhance learning. Traditional models are often limited in providing personalized attention to each student, a problem that technology can now help solve in a scalable way. The work showed one way forward – a combination of research evidence and practical insights – that can serve as a guideline for universities. The key to success lies in the fusion of **technology and pedagogy:** AI can automate and adapt a lot, but the human element remains – teachers as mentors and students as active participants – which must be at the core of the educational process. Technology is there to empower them, not replace them.

With careful implementation, constant evaluation, and ethical vigilance, AI-assisted adaptive education platforms could become a standard tool in higher education – a tool that helps realize the old ideal of every student receiving tutoring tailored just for them. As experience such as adaptive programs have helped tens of thousands of students master the basics of mathematics that would otherwise have been a barrier shows, we can expect this technology to evolve and spread further. It is up to academia to continue to explore its effects, improve approaches and share examples of good practice – to ensure that personalised learning through AI really leads to **personalised success** for students.

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