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WP2 LEADER AI Toolkit

Transnational Report



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Project Information

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Introduction to the report

The strategic framework for European cooperation in education and training towards the European Education Area and beyond (2021-2030) highlights the importance of providing learners with adaptable and appropriate learning environments, materials and teaching methods. In line with this, the LEADER AI project aims to build the capacity of Higher Education Institutions (HEIs) to personalise digital learning (technology-enhanced face-to-face and fully

online) through AI-based tools and data-driven decision-making. To achieve this and ensure that all project results address the current needs of Higher Education Institutions (HEIs), the LEADER AI partnership conducted desk and field research, which was mixed methods. Mixed-methods research identifies the participants' reflections, opinions, and views through an evidence-based approach and provides a concrete image that might be limited if only one type of data is collected (Wisdom & Creswell, 2013). In this context, the current research aimed to investigate the existing practices, challenges, and needs of the HE staff about personalised instruction and AI- and data-based technologies. First, all partners reviewed the literature on personalised instruction, AI, and analytics on national and European levels. Then, adding to the dialogue, the consortium conducted national field research involving distributing questionnaires and running focus groups with target group members (HE faculty, staff, learning designers, leadership teams, educational technologists, researchers, and academics). As a result, the current report compares and synthesises the findings of the transnational research, which is the foundation for developing Work Package 2 – Toolkit and all upcoming results.

This report provides fascinating insights into the differences and common issues all institutions must overcome, as recorded through mixed-method research. The current report is organised in the following way:

- **Chapter 1: Literature review.** Each partner was responsible for reviewing their country-specific literature along with literature from specific European countries assigned to them. This allowed the partnership to cover various European countries regarding geographical and cultural aspects, some more and some less advanced regarding the technologies and methodologies under discussion. The first section of this report presents the cumulative literature review to compare the practices, challenges, and barriers HEIs across Europe follow and face regarding personalised learning, AI-based, and data-based technologies.
- **Chapter 2: Mixed methods research.** The second section includes the results from the online survey, which comprised of questionnaires and focus groups distributed and conducted by each partner. On the one hand, the consortium distributed an online questionnaire to target group members based on the thematic categories derived from the literature review. The total sample that filled in all the questionnaires was 180 people. On the other hand, the consortium held focus groups in their countries with a team of representatives of the target group to record their experiences. In total, 36

people participated in the focus groups that were carried out. The results are presented separately to allow anyone interested to easily navigate and sport the results from the respective country. Below (Table 1) is an overview of the number of people participating in each part of the survey.

Table 1. Number of focus groups and questionnaires completed by each and all partners.

Partner Country	Focus group	Questionnaire
Cyprus	8	50
Greece	8	51
Estonia	8	15
Romania	9	50
Portugal	3	14
Overall	36	180

Executive Summary

The current report presents the results from the transnational research conducted in the framework of the LEADER AI project. The consortium has undertaken desk and field research on European and national levels (Cyprus, Greece, Estonia, Romania, Portugal). The adoption of Learning Analytics (LA), Artificial Intelligence (AI), and Personalised Learning (PL) in Higher Education Institutions (HEIs) varies, with research showing the potential of these technologies to improve learning outcomes. One of the main findings is that data-based technologies can be used to identify at-risk students and provide timely support. By analysing student behaviour and identifying the participants' reflections and perceptions data, educators can identify early warning signs of academic struggles and provide targeted interventions. Additionally, AI-

powered adaptive learning systems that use data from digital environments can customise the learning experience for each student, providing a more personalised approach to education. Other tools that are freely available now, like ChatGPT, BingAI, and Grammarly, can also add to the effort of personalisation by freeing up instructors' time from hectic tasks to engage deeply with their students. At the same time, they help students themselves with personalised guidance and support. However, the research also revealed several challenges hindering the widespread adoption of these technologies. One major challenge is the lack of infrastructure and technical support to implement and maintain these systems. Many HEIs face budget constraints and lack the necessary expertise to integrate LA and AI into their curriculum. Furthermore, there are concerns regarding data privacy and security and the potential for bias in algorithmic decision-making. Another challenge is the need for instructor and student preparation. Both educators and students require higher-order thinking skills to evaluate and utilise these technologies effectively, yet many feel overwhelmed or tend to rely too much on these technologies. To address the challenges and reap the benefits of these technologies, the consortium recommends that policymakers, educators, and technologists work together to develop effective implementation strategies while quality training, infrastructure and support are given to all critical stakeholders for the transition to an AI- and data-driven personalised learning.

Chapter 1: Literature Review

The partnership conducted a literature review investigating the status quo regarding Learning Analytics (LA), Artificial Intelligence (AI), and Personalised Learning (PL) in Higher Education Institutions (HEIs) across Europe. The databases accessed were SCOPUS, EBSCO, Semantic Scholar, and Google Scholar. The partners used a combination of the following keywords:

- personalised, individualised, differentiated, customised, adaptive learning
- online learning, distance education, blended learning
- learning design process, framework, model
- Artificial Intelligence
- learning analytics, data-driven practices, data-driven technologies
- Higher Education, Higher Education Institutions, Universities, colleges
- challenges, obstacles, barriers, limitations
- benefits, advantages, impact

All collected papers should be published between 2018 and 2023, written in English and national languages. Context: Higher Education. All the papers collected should be conducted in the context of HE. The countries reviewed were the Republic of Cyprus, the Netherlands, the Czech Republic, Ireland, Greece, Italy, Malta, Denmark, Estonia, Finland, Sweden, Norway, Slovenia, Poland, Hungary, Croatia, Romania, Germany, Lithuania, Slovakia, Portugal, Spain, France, Belgium. The partners accessed journals, papers in conference proceedings, Theses/Dissertations, and grey literature such as reports, working papers, government documents, and white papers. The results are presented below, divided into the topics they covered.

Studies' frequency per country

Most studies were recorded in Germany (6), Finland (5), Sweden (5), Romania (4), Croatia (4), Portugal (4), Spain (4), The Netherlands (3), Norway (3), Estonia (3), Lithuania (3) followed by Ireland (2), France (1), Poland (2), Slovenia (2) - the rest namely Hungary, Belgium, Slovakia, Cyprus and the Czech Republic had only 1 study each. These results can potentially be linked to the progress of Western European countries and the underdevelopment of research and/or emerging technologies for personalised teaching and learning in central and southern Europe. However, many studies such as the ones from Gubiani et al. (2020), Guzsvinecz and Szucs (2021), Kadoić and Oreški (2021) and Smyrnova-Trybulska et al. (2022) were connected to the adoption of eLearning during and due to the COVID-19 pandemic. As such, using analytics and AI in online learning (either in blended or fully online formats) for personalisation to occur is still in its infancy, a transition that may be possible after the massive, global transition to online formats brought by the pandemic. Another paradoxical finding is that Slovakia was labelled by McKinsey & Company in its 2018 report "The Rise of Digital Challengers" as a "Digital Challenger" demonstrating strong potential for growth in the "digital economy", and yet, the available literature on AI within Higher Education was poor.

Research methodologies adopted

A lot of papers are theoretical papers on existing approaches. For example, some papers are work-in-progress, theoretical positionings or conceptual framework propositions. Various systematic literature reviews have been published on the topic (see Nouri et al., 2019; Ley et al., 2023; Khor & Mutthulakshmi, 2023). For instance, a study through literature review presents the use of Intelligent Tutoring Systems (ITS), Smart Learning Management Systems (SLMS) and Adaptive Learning/Technologies (AL/T) to provide individualised support and feedback to

students based on their learning needs and preferences and improve learning achievements (Holmes et al., 2018). Keller et al. (2019) performed literature review, document analysis and expert interviews to investigate how AI, Big Data, Learning Analytics and Predictive Analytics are applied in German universities. They also found that chatbots and dropout detectors are used in German HE. Kurilovas & Kubilinskiene (2020) used a combined method of literature review and *applied computing approach* to assess in terms of suitability, acceptance and use two IT tools (“Axure RP Pro” and “Balsamiq Mockups”) that are popular while studying Human-Computer Interaction design course at Lithuanian Universities.

The studies that investigated analytics also used such data as a research method. The data was gathered from the students themselves, either directly (for example, through a registration process) or indirectly (for example, logged via a Learning Management System such as Moodle). More specifically, implicit and explicit information, such as information through browsing history and bookmarking events or learning analytics within the learning environment such as students’ written exercises, online quizzes completion, access to educational content such as quizzes, videos, external links, documents in different formats, etc. (see Carannante et al., 2021; Gkontzis, 2018; Ifenthaler et al., 2019; Mah & Ifenthaler, 2018; Montebello, 2021; Rentz et al., 2020). In these cases, the data could show, for example, the patterns of students’ behaviour, such as participation in the platform where a course was hosted (Guzsvinecz & Szucs, 2021). Other data sources examined are the university database and administration office (see Agrusti et al., 2020; Iatrellis et al., 2021).

From those papers that collect primary data, the research designs vary. Chounta et al. (2021) conducted a quantitative survey to understand the teachers’ perceptions of using AI tools in education. Van der Vorst & Jelcic (2019) interviewed various stakeholders (academics, researchers, school leaders, teachers, and experts). Interviews were also chosen for Moşteanu (2022) and Tsai et al. (2020), whose research included a survey distributed to 249 HEIs across Europe in the context of a large-scale mixed-method study. A randomised controlled experiment was applied by Hellings & Haelermans (2020) when investigating the impact of an intervention to yield more accurate results. Some studies used mixed methods approaches since they were trying to identify opinions, perceptions, and expectations using surveys and interviews or focus groups (e.g., Belda-Medina & Calvo-Ferrer, 2022; Brdnik et al., 2022; Giuliani et al., 2020; Moltudal et al., 2020) with descriptive statistics, correlation and rules analysis in some cases (e.g., Kadoić & Oreški, 2021) or simply surveys (e.g., Rako et al., 2022; Smyrnova-Trybulska et al., 2022; Vrkić,

2019). One study deployed action research using the think-aloud protocol (e.g., Marković et al., 2018), a helpful method when trying to evaluate the use of technology tools or to make salient underlying thoughts and hidden behaviours. Others implemented both quantitative and qualitative research methods in exploring the topic. To elaborate on a few of the chosen methodologies, Nguyen et al. (2023) used triangulated data collection, including data from stakeholder groups, interviews, and expert evaluations. Additionally, participatory design in developing technological and otherwise data-driven solutions was used in the analysed studies.

Definition of personalised learning

Since not all papers examined the application of AI or LA for personalisation per se, the definition of personalisation is not found throughout. In most cases where a definition is dispersed, personalisation is conceptualised as adaptive learning, individualised support targeted at meeting students' preferences and needs (Kazoun et al., 2022; Khan & Bose, 2021; Logan-Phelan, 2018; van der Vorst & Jellic, 2019). It relates to an approach that responds to individual differences (Tsai et al., 2020), where students become central agents of the learning process. The student organises their learning autonomously and understands that it occurs in various educational contexts, whether formal and informal (Junior, Silva, 2021). Therefore, they consciously assume responsibility for their learning process, self-assessing and reorganising their learning paths. As such, personalised learning is conceived as individual, student-focused learning. It is a process-orientated approach to learning where the teacher makes data-driven and evidence-based decisions in guiding the learner. In contrast, the student is aware of the alternative approaches and different aspects of the meaningful learning experience. In parallel with the personalised learning concepts used, the analysed literature also looks into self-regulated learning as a similar concept. Emphasising that PL is complicated and complex, Holmes et al. (2018) define it as:

“a range of learning experiences, instructional approaches, and academic support strategies intended to address the specific learning needs, interests, aspirations, or cultural backgrounds of individual students”. These researchers show that “many authors use personalised learning and the terms differentiation and individualisation synonymously” and point out about their study that it “mostly uses the term personalised learning interchangeably with the wider understanding of inner differentiation” (p. 18).

The concept of PL is linked to creating and/or adapting individual learning plans for students, identifying the best way to teach materials (audio, video, e-book), or using AI to tailor the

learning process (Bucea et al., 2022). The notion of personalisation as adaptation is supported by Belda-Medina and Calvo-Ferrer (2022) when they highlight the need for personalisation and adaptation of a chatbot for language learning to the users' language level. On another note, personalisation in the study of Brdnic et al. (2022) is linked with the provision of recommendations, such as showing different data to students based on students' psychological profiles to increase motivation and adaptations of content. When automated technology is used (e.g., LA, adaptive learning pathways with AI), that technology is responsible for adaptation; otherwise, the instructor adapts the content, method or material to respond to students' emerging needs. Moşteanu (2022) uses the term hyper-personalisation, which is enabled through machine learning. In this case, artificial intelligence is incorporated to design a dedicated learning profile for each student and tailor-made the teaching and learning materials. Machine learning will consider each student's social identity, the mode of learning, the student's experience in the field of specialisation, the student's ability and preference in learning and assessment delivery approach – within listening, watching videos, role-playing, learning, and gaming. Ciolacu et al. (2018) propose an adaptive learning environment based on AutoTutor (an intelligent tutoring system that provides immediate and customised instruction or feedback to learners), while Renz et al. (2020) support the idea that PL can be achieved with educational robots that provide students with tailored educational contents according to their unique needs. Another perspective is that of supervised learning, which focuses on students' learning habits and adaptation to new learning habits (Topîrceanu & Grosseck, 2017). Some researchers (Ifenthaler et al., 2019) explain that the personalisation of learning can be achieved through the LA platform (Student Relationship Engagement System), which is designed to be adaptable by teachers to diverse contexts (teachers can collect, curate, analyse, and act on data of their choosing that aligns to their specific contexts). In the opinion of Keller et al. (2019), individually tailored learning proposals can be achieved through Learning Analytics that provide students with performance feedback and learning recommendations by uncovering patterns in their learning behaviours.

Teaching and learning, based on personalisation, requires environments whose opportunities are fair and accessible to all, without prejudice or discrimination. Personalised education, mediated by digital technologies or not, is vital in including students with disabilities. Thus, the insertion of digital technologies in education should not be an opportunity for stigmatisation and labelling but a resource capable of facilitating the possibilities of learning, socialising, and

collaborating among students. Therefore, environments enhanced by digital technologies offer rich possibilities for adapting and optimising learning, considering students' different knowledge levels, interests, and experiences with technologies.

AI and data-driven technologies used

The most frequently used technology-based approach for the personalisation of learning is learning analytics. Learning analytics occurs in three steps: data collection, learning analytics, and intervention. Specific LA techniques and tools to process data are available, such as network analysis, user modelling or knowledge domain modelling. The prime objective of LA is to monitor individual learners' progress and behaviour continuously to explore factors that may influence learning efficiency and effectiveness. The most common tools used are those offered by the Virtual Learning Environment (VLE) or LMS, along with existing data management system and in-house developed tools, focusing on integrating more data-driven solutions into a variety of pedagogical practices, i.e., collaborative learning (Kurilovas, 2018; Kurilovas & Kubilinskiene, 2020; Mah & Ifenthaler, 2018; Renz et al., 2020; Tsai et al., 2020). Specifically, learning analytics dashboards (LADs) are tools that visualise students' digital footprint from an online environment through pies, charts, and progress lines (van der Vorst & Jelicic, 2019). These systems use student performance and engagement data to provide instructors with insights into students' progress, strengths, and weaknesses (Ifenthaler et al., 2019) or to predict students' final scores before participating in final examinations (Ciolacu et al., 2018). An example is given by Hellings and Haelermans (2020), who used a dashboard which exploited data mining technologies for a predictive model, gathering student data (student characteristics such as specialisation and past education level, demographic data such as gender, age, ethnicity, order of registration and their behaviour measured with three indicators, namely the assignment completion, average grade on quizzes and average online mastery exercises). With this information, the LAD gave students insights into their weekly progress, expected grades and class average grades. Similarly, Gkontziz (2019) used Moodle's Learning Analytics Dashboards (LADs) that aim at visualising students' activities and facilitate students and tutors to have a quick and direct view of their performance, and, in turn, to assist them in making the right decisions to improve their educational process while Rako et al., (2022) who proposed a LA-based dashboard as a Moodle plug-in that provides students with prompts and teachers with real-time insights into the students' digital footprint and responses to those prompts. Of course, apart from LADs, there are other tools which use analytics, like that of Logan-Phelan (2018), a personalised learning tool called CLARA

(<https://cic.uts.edu.au/tools/learning-power/>) which summarises visually (using analytics) a learner's profile in terms of specific criteria, i.e., curiosity, creativity, sense-making, belonging, collaboration, hope and optimism, mindful agency and openness to change.

The instructors can manually access the data instead of having them visualised. Guzsvinecz and Szucs (2021) accessed specific data from Moodle (number of clicks on the material) and the YouTube platform (number of clicks on the videos, watching time and average duration of viewing the videos) to identify students' behaviour, such as what they did before an exam, what material they read based on the type of subject (theoretical where the students tended to focus on reading presentation slides or practical where the students managed to watch videos). YouTube and Moodle analytics were also used by Kadoić and Oreški (2021) for the same reason. Other data sources which can be exploited for LA are scores from assessments, Student Information Systems (SIS), student surveys (e.g., evaluation), library systems (Amare & Simonova, 2021; Tsai et al., 2020) and even external content from social media platforms and Internet of Things (IoT) (Amare & Simonova, 2021). The researchers highlighted the potential of analytics in enhancing teacher-student communication (e.g., students cannot lie by saying that something is difficult if they have not seen it).

Data and information collected through AI and data-driven technologies can be utilised to guide the development of personalised interventions and support for students and inform teaching and assessment strategies. In these terms, data from the learning process (e.g., time spent) or students' individuality (e.g., personal characteristics) can become input for an adaptive model (van der Vorst & Jelcic, 2019). For example, Educational Data Mining (EDM) is used to understand the students' needs and classify them based on individual traits (Topîrceanu & Grosseck, 2017) or to emphasise EDM's advantages when used together with Case-Based Reasoning (CBR) for student profiling and designing a personalised intelligent learning system (Mamčenko et al. 2019). Algayres & Triantafyllou's (2020) proposed model relies on learning analytics to provide students with a fully personalised adaptive learning experience. In Κανελλοπούλου's thesis (2020), Learning Analytics and Educational Data Mining were used, and the user was provided with a list of recommended courses to choose from; the system gathered students' ratings and progress statuses from currently taken courses and merges this information with courses' metadata to offer the mentioned recommendations. Similarly, Marković et al. (2018) also referred to an AI system since they investigated the adaptivity criteria students prepare to

develop an Intelligent and Adaptive Hypermedia eLearning system that is a System for Dynamic Generating of Learning Objectives for personalised learning. Moreover, Brdnik et al. (2022) developed a system that merges learning analytics with an AI model that uses classification and regression techniques which show students a predicted grade they might receive based on their progress at the time to help them take action and self-regulate their learning throughout the semester.

Even though not linked with personalisation, Brdnik et al. (2022) proposed a system based on an AI model for predicting at-risk students and notifying them accordingly. The system uses classification and regression techniques to show students a predicted grade they might receive based on their progress to help them take action and self-regulate their learning throughout the semester (Brdnik et al., 2022). Another way is combining 5G networks with AI-based data mining algorithms to uncover unseen patterns, unexpected associations, and inadvertencies in the collected data to design a personalised curriculum (Opincariu, 2019). In addition, the e-learning Platform of Comenius University in Bratislava at

(<https://www.distancelearningportal.com/?redirect=false>) delivers personalised content and assessments based on the needs and performance of individual students, and the *e-learning Analytics System* developed by the Faculty of Informatics and Information Technologies at the Slovak University of Technology in Bratislava (STU) uses *Educational Data Mining* techniques to analyse students' online behaviour and generate personalised recommendations for learning activities. Finally, Herbert Simon Personalised Learning Laboratory, also at STU, is a research centre of user experience and interaction, exploring methods for computer-supported learning that are tailored to each student based on various inputs from the *Adaptive Learning* systems and sensors in the laboratory: achievements of learning goals, emotional responses, eye gaze tracking, mouse movements, etc. The laboratory has 20 workstations, each with an array of sensors for conducting observations. These can potentially provide targeted support to students based on what they need.

In addition, a few papers refer to specific tools based on AI or types of AI technologies that can be used for teaching and learning, particularly personalisation. Khan & Bose (2021) present the following AI-enabled software: Classcraft, Alta, Squirrel AI learning and various chatbots. First, Classcraft is a gamified platform that offers personalised gamified quests related to learning (adaptive gamification), promoting a behavioural management approach to teaching. Classcraft

also offers an LA analytics tool for data-driven decisions. AI has been integrated into gamified approaches, but other emerging technologies like VR and AR have also added to the immersive learner experiences (e.g., seeing instructions in a VR system) (van der Vorst & Jellicic, 2019). Second, Alta (<https://marketing.knewton.com/what-is-alta/>) offers personalised learning to HE students, which is linked to improved scores and reduced dropouts. Third, Squirrel AI learning (<http://squirrelai.com/>) offers students personalised learning (adaptive learning), facilitating the lack of individual attention teachers can pay within a huge classroom. Finally, chatbots are common AI tools used in HE, mainly for language learning. Belda-Medina and Calvo-Ferrer (2022) used three chatbots, namely Kuki (kuki.ai), Replika (replika.com) and Wysa (wysa.io), for language learning. Another existing approach is using chatbots and virtual assistants (e.g., SEB, viLTè, SIMAS – not for HE) to provide personalised support and feedback to learners. Hybot (<https://hybot.eu/>) is a prototype chatbot developed within an Erasmus+ project to support enhancing hybrid teaching in Higher Education. It can also be said that the articles included in this literature review did not only look into designing and developing new technologies but rather making use of the existing technological tools and building a change in pedagogical and methodological approaches around the tool to complement the learning process (Apiola et al., 2019).

Besides these specific tools, AI technologies can support personalisation in various ways. The most common case is that of adaptive learning systems, where the learning process changes to fit students' needs. Behind an adaptive system are three models, the expert, student and instruction model, which are combined to offer an interface with which the students interact and experience adaptive learning (van der Vorst & Jellicic, 2019). In these terms, AI can also support differentiation within educational levels (e.g., students who should be in Grade B but are not ready yet can experience differentiated instruction to reach that level) (van der Vorst & Jellicic, 2019). Besides, AI tools can automate hectic tasks (e.g., grading, administration) and reduce workload so that the teachers have more free time for demanding tasks, including coaching and guiding the students or personalising instruction (van der Vorst & Jellicic, 2019).

The learning design process followed.

According to van der Vorst and Jellicic (2019), design thinking can be valuable for successfully integrating AI. Design thinking is a collaborative approach to solving open, complex problems (Dijksterhuis & Silviu, 2022). Collaboration among all is required, for example, educational

technologists, learning designers and instructors (Logan-Phelan, 2018), along with students' involvement, especially in the decision-making with LA (Tsai et al., 2020). Thus, design thinking can inform the learning design sequence one can apply when designing personalised learning.

Regarding which steps to follow, only one study from those we have examined (Mamčenko et al., 2019) explicitly presents a model for the learning design process in college that implies data-driven technologies (Educational Data Mining combined with Case-Based Reasoning). The design of personalised learning process modelling described by the authors is based on the development of a curriculum which considers several factors that affect the choice and content of a personal program. The process consists of 11 steps:

- (1) Determine learning objectives.
- (2) Ask students to complete questionnaires to identify the Index of Learning Styles.
- (3) and (4) – Determine students' learning styles using CBR and Data Mining to prepare personalised profiles.
- (5) Learning profiles development using received results.
- (6) Design profiled course content.
- (7) Examination process after study by personalised profiling.
- (8) Exam results evaluation.
- (9) Learning profiling improvement depending on received exam results.
- (10) and (11) – Improved course profiles saving system.

It should be noted, though, that various researchers have criticised learning styles, and as such, relying on them can result in strictly categorising and profiling students.

Even though the rest of the papers examined were not directly connected to a course or activity development, relevant approaches for learning design practices emerge. For example, the analysed literature includes collaboration (e.g., computer-supported collaborative learning) (Andersen et al., 2022) as a part of the primary design process and highlights that pedagogical-psychological models should be part of the intelligent learning system design (Ley et al., 2023). Marković et al. (2018) investigated the HE academics' frequency of using specific adaptivity criteria for learning, to use them when developing an Intelligent and Adaptive Hypermedia eLearning system that is a System for Dynamic Generating of Learning Objectives for personalised learning. The researchers measured teachers' use of the following adaptivity criteria in direct, individual and group teaching: learning goals, motivation, learning and cognitive

style, prior knowledge, acquired knowledge through the learning process, psychophysical abilities, learning materials availability, and students' emotions. Most of these were used very frequently. However, on top of the list were the learning goals followed by knowledge acquired during teaching and acquired before and the students' psychophysical abilities (Marković et al., 2018). The new system to be designed by the research team will include the following criteria: learning goals, cognitive and learning style (using the VARK method) (Marković et al., 2018). The system already includes other criteria such as prior knowledge (level of expertise through a text in an LMS), while the psychophysical abilities along with emotions will not be included; this requires interdisciplinary knowledge, and it is a complicated process to identify such skills, and states (Marković et al., 2018).

A more traditional approach is that of Smyrnova-Trybulska et al. (2022), where the students were presented with specific sets of activities based on the mark they received in a quiz or lesson (e.g., above 50, they progress, below 50, they restudy the content) (Smyrnova-Trybulska et al., 2022). After studying the material, they could take the same or another quiz, but they would proceed only when they meet the acceptable score the instructor has set (Smyrnova-Trybulska et al., 2022). Similarly, the content can appear based on students' pre-test results or preferences (Smyrnova-Trybulska et al., 2022). The above examples show that identifying students' characteristics to design personalised learning is critical and should be part of any learning design sequence.

Furthermore, designing digital learning should include a stage where appropriate technological tools like LA and AI are used. Kazoun et al. (2022) proposed a conceptual framework that offers an overview of the factors that play a role in adopting AI chatbots for adaptive learning. Their proposed framework is based on the Unified theory of acceptance and use of technology (UTAUT), which includes the following factors:

- Performance expectancy (a user would accept and use a tool if it performs well)
- Effort expectancy (a user would accept and use a tool if not much effort is needed)
- Social influence (a user would accept and use a tool if others believe s/he should use it)
- Facilitating conditions (a user would accept and use a tool if the relevant conditions – hardware, software – are in place).

To these, Kazoun et al. (2022) add the following:

- Security and privacy (data collected)

- Trust in technology (confidence in AI, whether users trust it to share their personal data)
- Individualised education (teaching and learning tailored to students)
- Equality and fairness
- Engagement

The above framework could be turned into a checklist, with the factors turned into criteria, to guide the selection of AI-powered technologies. Other criteria which can be added related to the degree of autonomy offered by AI applications, i.e., whether the system or the human decides for adaptation, with three levels being pertinent: providing insights (low autonomy), interpreting data and offering insights to teachers (medium autonomy), directly adapting or offering recommendations (high autonomy) (van der Vorst & Jelicic, 2019). In addition, the motivation for learning (why use a tool) needs to be identified (Kazoun et al., 2022). In another study carried out by Montebello (2021), the design and implementation of the Personalised Learning Environment (PLE) was based on the personalisation principle provided through the integration of AI machine learning techniques to address the following three e-learning concerns: (a) Isolation and Connectivism, (b) Motivation and Self-Determination and (c) Impersonal Environment and Adaptivity. The tool selection is part of an online or blended course design and is crucial for smooth development and delivery.

AI applications and LA need to be selected based on the roles they fulfil, the context where they are embedded, and the teaching modality followed. Tsai et al. (2020) highlight the importance of using learning sciences as the foundation of technology. In these terms, AI applications can undertake didactical roles (e.g., choosing material, giving feedback, reviewing assessment) but even pedagogical roles, beyond simple knowledge transfer to the teaching of complex skills (e.g., collaboration with AI tools that divide students into proper groups based on their characteristics or performance) based on how or why they are used (van der Vorst & Jelicic, 2019). Based on the context, AI systems can be used within a specific subject or across the curriculum, personalising the content, respectively; this is especially useful for personalisation since students' skills are observed across subjects (van der Vorst & Jelicic, 2019). Lastly, AI can be used across various teaching models, including blended and distance learning (van der Vorst & Jelicic, 2019). For the personalisation of learning, whether with the support of LA or AI, redesign is required along with support from educational technologists, learning designers and experts. The redesign process varies from simple substitution (online used as traditional setting), augmentation (slight changes) and complete modification (reform of teaching and learning practice) (Logan-Phelan, 2018).

These indicators can be part of a rubric when evaluating the integration of AI technologies in digital teaching and learning.

Benefits of PL, AI and data-driven technologies

There are a lot of benefits associated with the use of LA and AI in university education. Regarding LA, the critical benefit reported by end-users is that it allows teachers to understand better how students learn and have the opportunity to intervene to satisfy their needs (Bjælde & Lindberg, 2018; Tsai et al., 2020). Thus, it supports using the vast amount of existing data and knowledge on student learning and making more informed decisions in preparing for the data collection to support the learners. For example, even though Guzsvinecz and Szucs (2021) did not use analytics for personalisation, they highlight that LA can be used to see the students' motivation (decreased as the materials are accessed less as time passes) and studying patterns (students squeeze studying time before the exams based on the number of clicks, they spotted). Similarly, Gkontzis (2018) noticed that student participation can indicate educational progress: participation in the forum and increased student activity in the course shift trainees from the base and lead them to higher grades, improving their retention in the educational process.

The potential to oversee students' work and engagement in an online environment benefits many teachers (Guibiani et al., 2020). Using LA to identify students at risk of failing or dropping out is critical to offer relevant support in time (Guibiani et al., 2020) and potentially minimise the dropout rates (Demetriadis et al., 2018). To that end, LA dashboards can also be a supportive tool. The teachers may monitor students' progress (i.e., real-time insights into their digital footprint and responses to prompts generated) and use such input to improve their course (Gkontzis, 2019; Rako et al., 2022). Yet, data outside the eLearning platform is also valuable. First, Kadoić et al. (2021) further suggest that by using YouTube analytics, we may identify students' use of educational videos, find the patterns related to the time of use and compare this use and the videos' complexity to students' performance. Second, Vrkić (2019) highlights the potential of using and reaching data collected by libraries with LA to improve teaching and learning, for instance, by identifying trends and suggesting what to change. Learning Analytics can help students with performance feedback and learning recommendations by uncovering patterns in their individual learning behaviours (Keller et al., 2019) and continuous assessment with feedback loops (Bjælde & Lindberg, 2018).

The LA-driven insights can also be helpful to students who may use LA-based prompts for self-regulation during blended learning (Rako et al., 2022). The students can monitor their performance through a progress bar that promotes self-assessment (Gkontzis, 2019). Technology-enhanced personalised learning offers insights to the students so that they can become independent learners, achieve the aims of the given curriculum, or achieve an academic qualification (Holmes et al., 2018). New technologies make the learning process more meaningful for students and teachers, supporting the new generation of self-directed learners. Hence, it is concluded that LA can make some actions more salient to many stakeholders.

In addition, data-driven insights into the students' learning process become a more "objective" interpreter of the current status (e.g., what students have seen and completed), tackling potential biases or misconceptions of instructors (van der Vorst & Jelacic, 2019). The precision of the AI networks can critically enhance the decision-making processes for more accurate predictions and recommendations in student performance (Opincariu, 2019), for instance, with the prediction of students' final score before participating in the final examination to create an adaptive learning environment, focusing on students' success (Ciolacu et al., 2018). This also promotes transparent learner-instructor communication. In Hellings & Haelermans' research (2020), using an intervention system with a LAD showing students' progress and expected grades was linked with positive effects on students' performance throughout the online course. Intelligent tools support generating more intuitive decision tree learning models and making student profiling more sensitive and specific (Topîrceanu & Grosseck, 2017). This can enhance inclusivity, as, according to Morin (2019), AI can assist with getting rid of the stigma associated with disabled students since everyone works at their own pace and ability level on tasks they are interested in.

Besides the technologies that directly respond to students' needs (e.g., adaptation based on knowledge level), AI tools can automate repetitive tasks. This way, they free up teachers' workload to proceed to demanding tasks, constructively engaging with students, monitoring, coaching and guiding them for personalisation to be supported (van der Vorst & Jelic, 2019). AI can help teachers personalise the learning process by identifying the best way to teach materials (audio, video, e-book), significantly contribute to the quality of teaching, choose materials for lecture content, make fewer mistakes, analyse students' incorrect answers and suggest which teaching units require additional instruction, use the system to automatically provide warnings for students' risky behaviours (Bucea et al., 2022). In addition, AI applications can allow for

authentic assessment, replacing the standardised tests with observation and performance monitoring in the form of formative evaluation (van der Vorst & Jellicic, 2019). Moşteanu (2022) concludes that artificial intelligence and machine learning can help higher education in several ways: assisting the admission and registration process, monitoring attendance, and aiding professors in students' evaluation process.

Challenges of PL, AI and data-driven technologies

As with any other technology, the adoption of LA and AI is accompanied by challenges. Most challenges seem to relate to the degree of readiness of all stakeholders. On the one hand, Gubiani et al. (2020) state that teachers need to prepare for their changing role due to new technological solutions such as learning analytics and using ICT for personalisation. The teachers need relevant knowledge to properly benefit from such technology, using AI to support pedagogy with a balance between human-machine tasks (van der Vorst & Jellicic, 2019). The same readiness applies to the university as a whole: the lack of infrastructure (i.e., for digital tracking) and financial support can be among the main challenges for both the outdated tracking methods and innovative exploitation of data such as that of libraries to connect them with the students' learning activity (Vrkić, 2019). Adequate infrastructure and funding are required, with leadership teams overseeing this change (Holmes et al., 2018; Tsai et al., 2020). Sufficient knowledge for all will tackle the issue of power, where one agent might have more power than the others (van der Vorst & Jellicic, 2019). Yet, most Croatian librarians lack a basic understanding of what LA includes, and they especially cannot distinguish between learning and academic analytics (i.e., use of analytics for institution-wide policy information) (Vrkić, 2019). Similarly, Smyrnova-Trybulska et al. (2022) report that there is an additional need to teach teachers a methodology on how to introduce personalisation in line with students' abilities and preferences since teachers are the main drivers of change. On the other hand, students are not prepared yet to respond to such changes. The study of Beld-Medina et al. (2022) indicates that most students' knowledge of chatbots is limited to Intelligence Personal Assistants like Siri and their use in e-commerce.

For skills related to the use of AI and data, training for both teachers and students is vital. Particularly for LA, students need training since, currently, most initiatives focus on teachers (Tsai et al., 2020). Additional support and collaboration among various stakeholders (teachers, support staff, IT), including students often excluded from the decision-making, is required (van der Vorst & Jellicic, 2019). Such support can allow the users to recognise the benefits and

limitations. For instance, LA has been linked with constraints such as the lack of accuracy (e.g., in terms of prediction) (Hellings & Haelermans, 2020). This will support careful data-driven decision-making.

Nevertheless, the most essential aspect to be considered is the ethics underpinning the use of emerging technologies. Technology-enhanced personalised learning can require massive amounts of student data, compromising student privacy (Holmes et al., 2018; Renz et al., 2020). This can also amplify potential users' negative attitudes regarding using Learning Analytics and AI in Education (AIED) and scepticism about data collection (Renz et al., 2020). For instance, when it comes to chatbots, for example, the students surveyed in the study of Beld-Medina et al. (2022) were concerned about the way their data is stored as well as the way language was used (i.e., lack of inclusivity, potential gender stereotyping, lack of appropriate humour). This is why the students in the same study were reluctant about the future use of chatbots since they preferred human-human interaction. Similar concerns were evident for the use of an AI system where students focused on privacy, being concerned about the way their data will be used and wanting to be in control of who and why can access it (i.e., knowing why they use it) (Brdnik et al., 2022). Data privacy is an issue raised, with researchers suggesting that higher-order measures are required along with policies and standards with which LA should comply on an institutional level (Amare & Simonova, 2021; Ifenthaler et al., 2019). For this, it is essential to consider AI's transparency, explainability and predictability (van der Vorst & Jelicic, 2019). AI should be challenging to manipulate, accountable for mistakes or biases, not prejudiced, respecting an individual's privacy and self-determination and supporting the educational goals for which it was chosen in the first place (van der Vorst & Jelic, 2019). Since AI is a machine, the person behind AI could be the one responsible for its use and, therefore, potential consequences. GDPR, education laws, laws on liability, and general regulations (e.g., copyright and database law) seem to apply (van der Vorst & Jelicic, 2019). Studies on ethics can support this with ethical frameworks following the Kantian perspective (having predetermined principles), the utilitarian perspective (deciding based on the outcomes), or virtue ethics (judging the importance of a goal) (van der Vorst & Jelicic, 2019).

Additionally, data is not always accurate, and the footprint might not be interpreted similarly. For instance, recommendation systems used for personalisation may not provide accurate suggestions based on students' needs (Smyrnova-Trybulska et al., 2022), and the algorithms can reproduce existing stereotypes (Holmes et al., 2018). In the study of Kadoić et al. (2021), teachers'

notion of how complex a video was different when compared to the dips (i.e., moments skipped or moments where viewers stopped watching) and spikes (i.e., moments rewatched) spotted in a YouTube video; thus, interpretation is challenging and possibly subjective. This is why Carannante et al. (2021) highlight that the quantity of actions taken by users, measured in frequency and time, appears more important than engagement, synthesising how a learner organises the study path. The most common learning analytics applications related to MOOCs refer to indicators based on the frequency of actions. Therefore, frequency-based activity indicators are considered good predictors of performance and learners' dropout and allow identification of the learners' profiles. Additional information, such as those relating to time spent in activities and interaction, improves the learning construct and provides better predictions about learners' performance. Even if not all the considered time-based indicators are statistically significant, they improved performance measurement. Yet, even if these tools have limitations or teachers have trouble using the more advanced ones (Smyrnova-Trybulska et al., 2022), researchers argue that personalisation with AI tools can save teachers great time (Brdnik et al., 2022). Thus, it is crucial to proceed with caution, acknowledging both the benefits and limitations, to fully exploit the potential of these tools. Well-thought-out, evidence-informed and guided decision-making by all stakeholders involved is vital.

Chapter 2: Mixed methods research

To investigate the practices and challenges of Higher Education Institutions (HEIs) in the partner countries, the consortium followed a mixed methods research approach to collect quantitative and qualitative data. The research was implemented between January and May 2023. Regarding the quantitative study, a questionnaire was constructed with 20 closed and open-ended statements or questions in English, following the nominal scale (select options), the 4-point Likert scale (i.e., for familiarity with the critical research terms where one corresponds to not at all and 4 to a lot) and the 5-point Likert scale (i.e., for the tools' frequency of use, where 1 corresponds to daily and 5 to never) (see Annex 1). The statements were grouped into three parts. The first part gathered demographic information (e.g., the sample's expertise and university profile) to inform other researchers. The second part investigated the participants' practices concerning LA and AI for personalised learning and focused on the learning design process. The last part explored the participants' perceptions, particularly the barriers, facilitators, drawbacks, and challenges related to emerging technologies for personalised learning. Excel and IBM SPSS Statistics 25 were used to analyse the closed-ended data, employing descriptive statistics such as the means and percentages depending on the statement type. Thematic analysis was used to analyse the open-ended data, uncovering response patterns and grouping them inductively into themes. To ensure construct validity, the questionnaire was aligned with the literature review (Cohen et al., 2007) on practices and approaches related to personalisation with LA and AI, while for content validity, an adequate number of questions was assembled, both closed and open-ended, while the questionnaire was piloted with five experts for modifications as needed.

Regarding the qualitative research, the partnership conducted focus groups to collect data from representatives of the target group. The focus group followed a semi-structured interview, and the questions covered various areas that constitute the field: learning analytics, data-driven approaches, artificial intelligence, personalised or adaptive or differentiated or customised or individualised learning (see Annex 2). The focus groups were implemented between January and May 2023 in an online and face-to-face context, with the support of web conferencing tools such as ZOOM, Skype, or Google Meet. Throughout the survey, the partnership complied with the GDPR, asking for the respondents' written permission to participate and record the focus group sessions (see Annex 3). Ethical issues were considered; anonymity, confidentiality, and objectivity were maintained.

Research in Cyprus (CARDET and UNIC)

Focus group

Focus group information

The focus group participants were eight (8) 1 full-time and three part-time academics/instructors in the field of Education, two online learning support officers and two researchers. All participants reported their experiences from private and public Universities in the Republic of Cyprus. Having a group of people representing various roles and positions in a university, with solid experience in distance learning programmes, allowed us to form a comprehensive yet multifaceted picture of the context.

Focus group results

The focus group analysis revealed nine themes categorised into three broader categories (Table 2). The participants referred to the definition and techniques of personalised learning, mentioning tools and applications they had used. In addition, they reported the challenges they faced with personalised learning using LA and AI, along with the associated benefits.

Table 2. Thematic analysis from focus groups

Categories	Themes
Personalised learning background	Personalised learning definition
	Personalised learning techniques
Technology tools	Artificial Intelligence tools
	Learning analytics applications
Challenges related to personalisation with LA and AI	Lack of skills, knowledge and attitudes
	Technical and language issues
Benefits of using LA and AI	Observations to intervene and adopt
	Improved communication and interaction
	Automation of tasks and learning design

Personalised learning background

Personalised learning definition

A shared definition sets a common ground for the focus group unfolding. The participants defined personalised learning as learning that adapts to each learner's prior and ongoing needs and background, such as knowledge, skills, and preferences. It is a process of modifying teaching and learning based on the learners' profile, in advance or as the learning process unfolds. The following excerpt summarises the definition:

[personalised learning] refers to adapting teaching and goal setting in your class based on learners' readiness level [...] to respond to all needs and promote learning. (T5)

Personalised learning techniques

The participants mentioned different techniques they used to personalise learning, even without advanced technologies. Specifically, they asked learners to keep a (e-)diary to document their thoughts and feelings during learning. Additionally, they might offer different resources and activities while using the Universal Design for Learning, an established framework to enhance accessibility for all. The participants also dedicated time to getting to know their learners through one-to-one communication, mentoring and tutoring while offering flexibility and autonomy. As such, most techniques related to exploring learners' individuality:

I dedicate the first week of a semester to diving deeper into learners' interests, preferences, and difficulties so that I can accommodate teaching and meet these needs. (T1)

We try to allow learners to take initiative and be autonomous in terms of the way they will work in the different activities we give. (T5)

Technology tools

Artificial intelligence tools

The participants explored various AI tools. The most common were the adaptive systems, chatbots and generative AI. For instance, they used ChatGPT for recommendations on how to modify teaching. The Frequently Asked Questions (FAQ) chatbots offered by the universities provided students with personalised administrative support 24/7, without having to contact someone during working hours. The participants also used Grammarly for personalised writing support and Duolingo and Speakly for personalised language learning.

I use those AI tools that support my teaching within and outside the classroom. (T3)

Learning analytics applications

Regarding learning analytics, the participants' process included the collection, analysis, and interpretation of the footprint left in digital learning environments. This included data from an LMS like Moodle and Blackboard. They tracked who logged in, when and how many times, what grades they received, what activities they clicked on and whether they viewed recorded sessions. Such data could be extracted into tables and turned into graphs. Generally, most digital tools, within or outside an LMS, report learners' activity (e.g., scores, time spent, etc.).

I use all types of data that show how a person reacts to a certain task at their time. (T2)

Challenges related to personalisation with LA and AI

Lack of skills, knowledge, and attitudes

When using artificial intelligence and learning analytics for personalised learning, the participants referred to learners' and instructors' lack of proper knowledge, skills, and attitudes as a barrier. According to them, lacking the know-how for terms and techniques could result in misusing these tools. For example, in generative AI like ChatGPT, instructors and learners should be able to evaluate the content they receive critically. Otherwise, wrong interpretations might be drawn, with the learners relying on cheating and spoon-feeding. These challenges are summarised in the following excerpts:

Having access to all this information [as in the case of generative AI] might be a general drawback, considering that not all individuals will use it with integrity. (D1)

The human factor is crucial as the individual will have to review the results produced and use them according to their purposes. (T6)

It is important that these tools do not deprive learners of the essential process of studying, researching, analysing, thinking critically, and synthesising through trial and error, as this will have a negative impact in the long term. (T5)

The use of these tools requires having acquired the foundational knowledge (T4)

Similarly, some participants were unsure whether the tools could be purposefully integrated into teaching or used for daily life assistance. They were not fully aware of the way learning could be enhanced, advocating instead for practical training:

Train academics and learners on when to deploy these tools and whether their recommendations or results are truthful and accurate to use them and progress. (T3)

Technical and language issues

Additional challenges were the technical issues. Tools might crash without responding, be unavailable in need, and produce inaccurate results. This might lead to frustration or lack of interest. In addition, many tools had fees while being available only in English. In case a translated version existed, there were localisation issues, lack of natural speech flow, or proper cultural interpretation.

[In the case of ChatGPT], it is crashing, not loading conversations, or having a long waiting list. (T1)

[In the case of ChatGPT], it might use words that do not fit the context or do not respond to the question. In Greek, we have different interpretations of the words, as you know. (T4)

Benefits of using LA and AI

Observations to intervene and adopt

The participants referred to the multiple benefits of using LA. The analytics allowed them to observe learners' progress and engagement. Engagement relates to actions completed within the environment, such as accessing the material or contributing to the learning community's discussions. Such data helped modify the teaching method and resources, guiding the learners further. In addition, a knowledge database was created, and the developers could use the information retrieved to improve the digital applications.

Using digital data allows us to track the progress or even effectiveness of lessons [...], building a database that the instructor can use as feedback to improve. (D1)

Improved communication and interaction

Tracking learners' activity could promote transparent communication between the instructor and the learners, as there was evidence of actions. For instance, the instructor could spot if a learner responded to forum activities online without studying the material first to recognise further whether the response was original or copied by other learners. When learners tracked their activity and saw a lack of engagement, they might also seek to increase interaction with classmates.

I have observed that a certain person responded to activities without accessing the material [...] I started looking further and discovered that someone from a previous semester had sent the solutions. (T1).

Automation of tasks and learning design

In addition, AI tools were beneficial for task automation. The instructors reported having time for more complex actions, such as building personal relationships with learners. This included receiving automatic translations, answers to questions, content paraphrasing or summarising. In addition, generative AI tools were used for lesson design by offering instructors learning activities examples or personalised language learning.

We can now [use generative AI to] search for anything, get answers to all our questions whether these relate to education per se or technical aspects, anything anyone can think of. (D2)

Questionnaire

Questionnaire information

Excel and IBM SPSS Statistics 25 were used to analyse the closed-ended data, employing descriptive statistics such as the means and percentages depending on the statement type. Thematic analysis was used to analyse the open-ended data, uncovering response patterns and grouping them inductively into themes.

Questionnaire results

Based on the demographic data, more than half of the participants (62.2%) were working in private Higher Education Institutions (HEIs) and half in medium-sized universities with 5,000-15,000 students (55.6%). Regarding their profession, 29 were involved in teaching and 28 in research. There was also one participant in a leadership position. Half of the participants had a doctorate (51.1%), while only one had a bachelor's degree. The sample's average age was 36 years.

When it comes to their knowledge of the key research terms (Table 3), on average, the participants were moderately to very familiar with personalised learning ($M=3.7, SD=1.01$) and educational data ($M=3.28, SD=1.12$). Considering the high standard deviation number, the responses were quite different. Yet, on average, they were from "not at all" to "slightly familiar with" learning analytics ($M=2.97, SD=0.97$) and artificial intelligence ($M= 2.95, SD=0.92$).

Table 3. Participants' degree of familiarity with the research terms

Demographics		Mean	Std. Deviation
Degree of familiarity with terms	Personalised learning	3.7	1.01

Educational data	3.28	1.12
Learning analytics	2.97	0.97
Artificial Intelligence	2.95	0.92

In addition, more than half of the participants who were using learning analytics for personalised learning monthly to annually (68%) were using artificial intelligence for personalised learning monthly to annually (52%) (Table 4).

Table 4. Participants' frequency of technology use for personalised learning

Demographics		N	%
Frequency of use: LA for PL	Never	8	16
	Daily	1	2
	Weekly	8	16
	Monthly	20	40
	Annually	14	28
Frequency of use: AI or PL	Never	11	22
	Daily	5	10
	Weekly	8	16
	Monthly	9	18
	Annually	17	34

Regarding the processes followed, most respondents (52.8%) stated that the teacher makes the decisions regarding personalisation (Figure 1). About half the participants (47.3%) reported that the adaptations occur within the whole course and during instruction (44.7%) compared to only ten stating that adaptations occur in the entire programme (Figure 2).

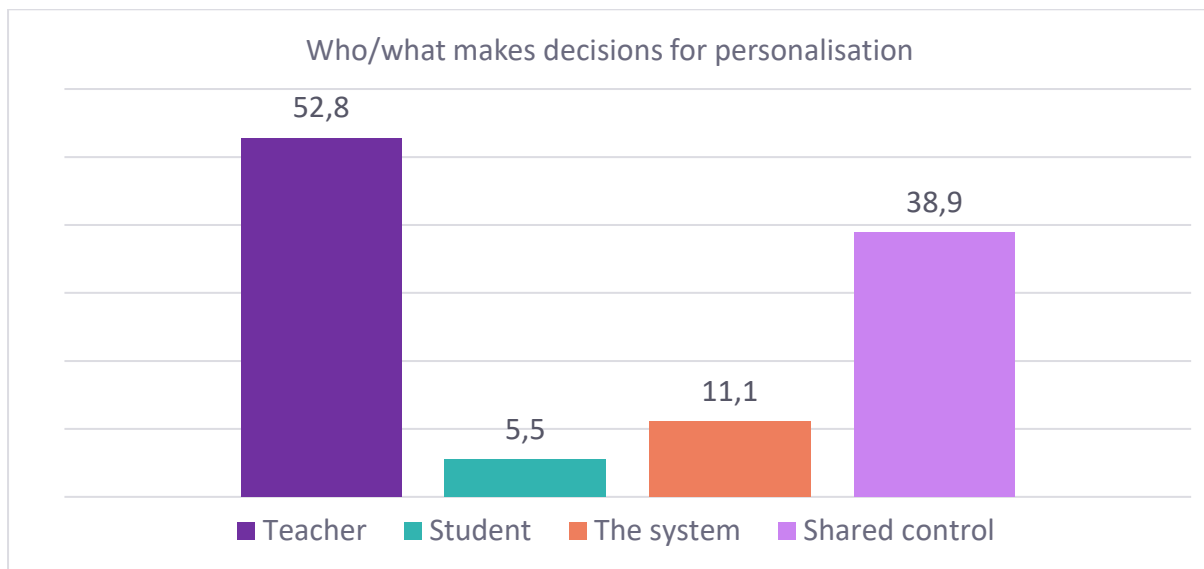


Figure 1. Participants' choices about who/what makes decisions for personalisation.

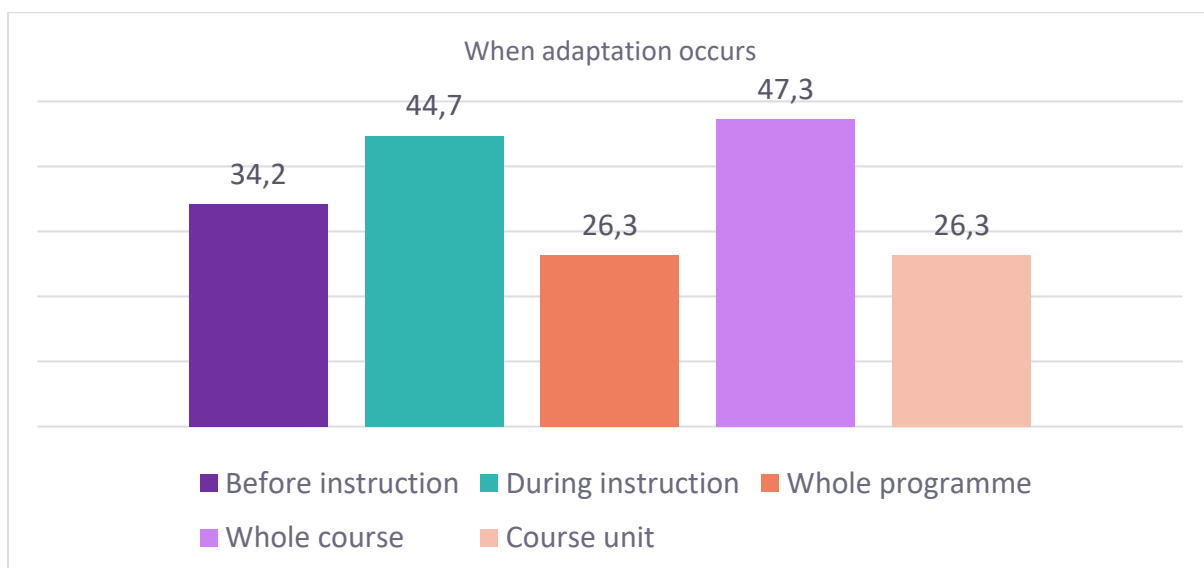


Figure 2. Participants' choices about the timing of personalisation.

The most common type of information used to make decisions for personalisation (Figure 3) is learners' performance (80%), followed by cognition (e.g., mental processes) (34.3%), data patterns (e.g., data scores) (34.2%) and individual goals (31.4%). Only seven individuals referred to learners' psychology and demographic profiles as sources for adaptations. In addition, more than half the participants stated that they adapt how the content is presented and the teaching method chosen (59% and 51.3%, respectively) (Figure 4).

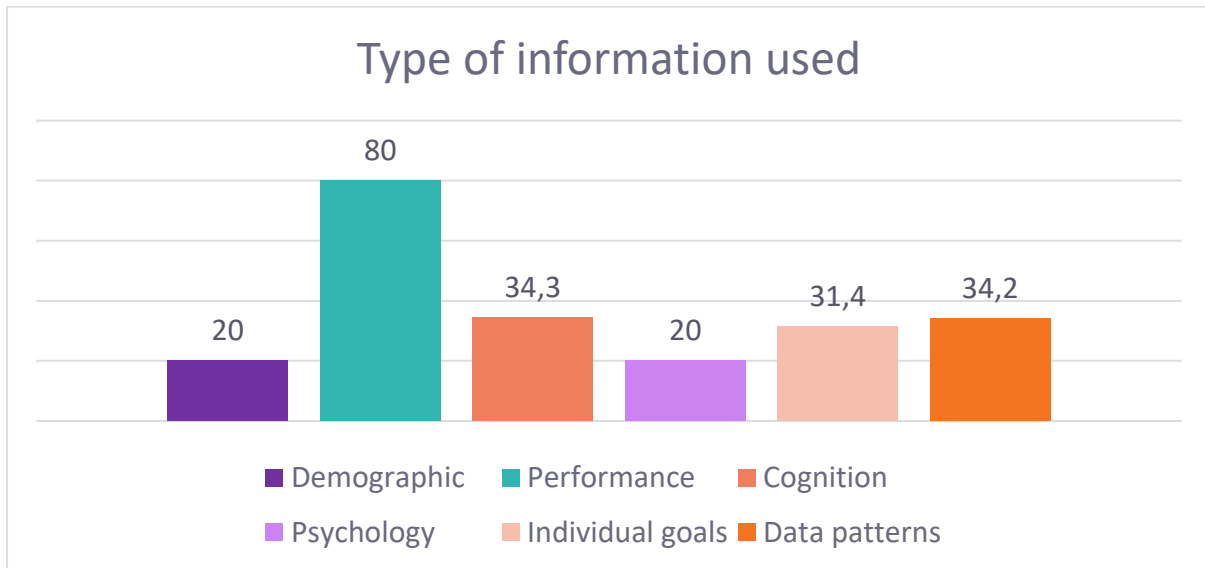


Figure 3. Participants' choices about the type of information used for personalisation

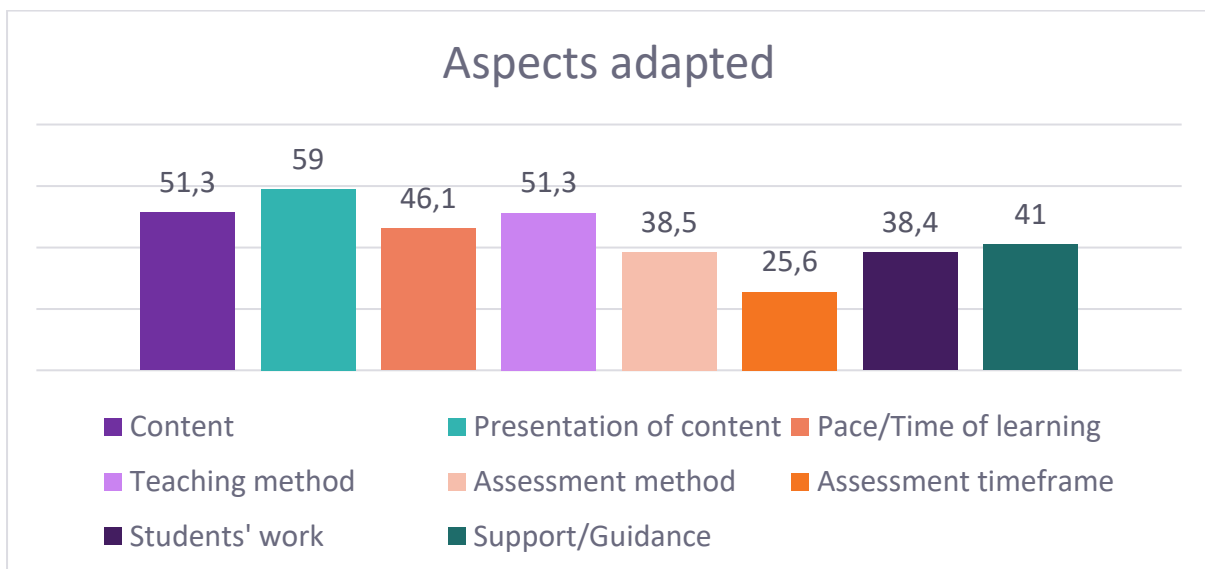


Figure 4. Participants' choices about the aspects adapted.

The lack of training offered was the most common reason not to use LA and AI for personalised learning (Figure 5) for more than half of the participants (54.3%). In addition, for one out of two participants, the lack of adequate infrastructure and university support were common reasons not to use these technologies. About half added the lack of skills or knowledge (48.7%) and time to explore (41.3%). In contrast, most participants who use these technologies for personalisation do so because it is an approach that aligns with the pedagogical purposes (62.5%) they want to fulfil.

They find it beneficial for their learners (59.4%) (Figure 6).

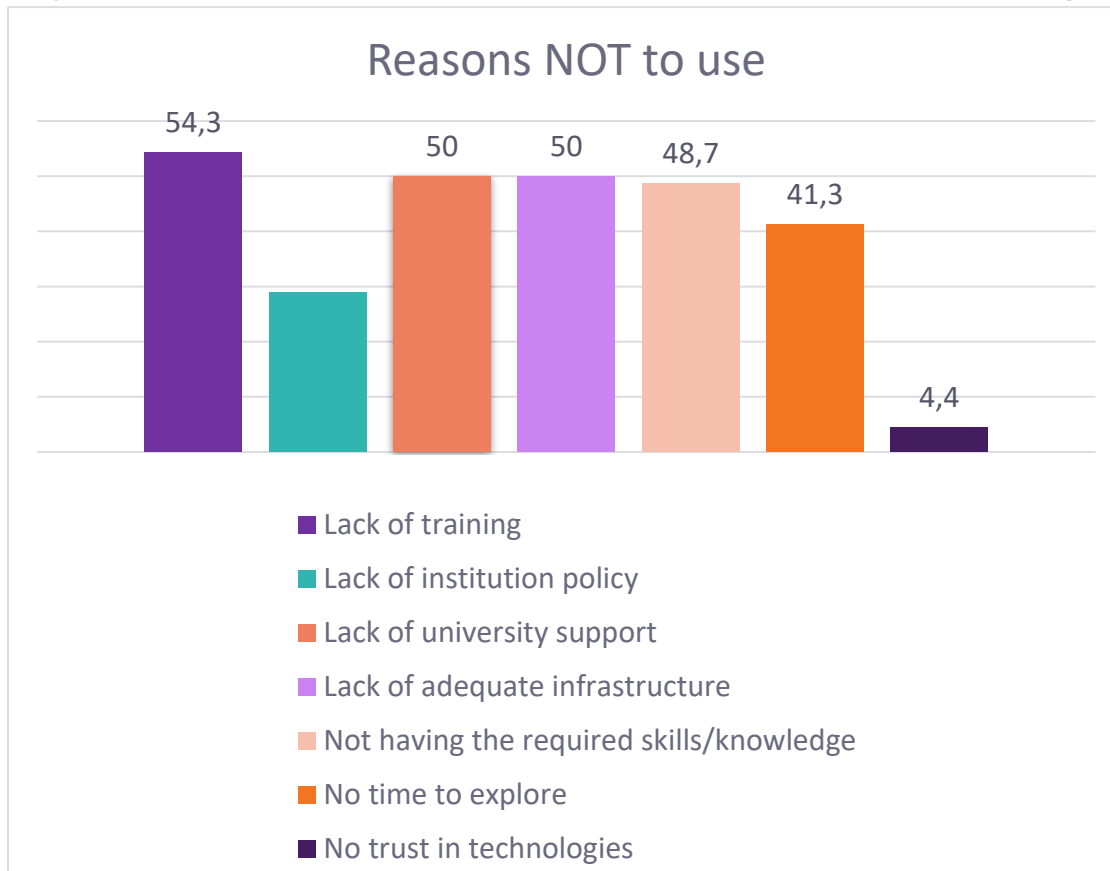


Figure 5. Participants' opinions about the barriers related to applying personalised learning with the emerging technologies

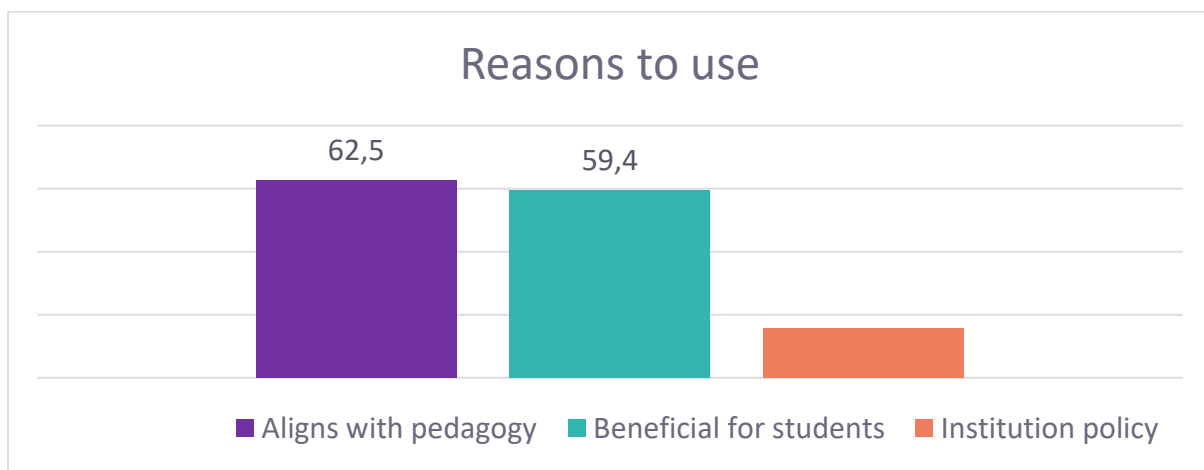


Figure 6. Participants' opinions about the facilitators related to applying personalised learning with the emerging technologies

Those who use personalised learning have spotted several benefits (Figure 7), including enhanced motivation (60.5%), engagement (55.2%) and performance (47.4%) for approximately half of the sample. In contrast, only three participants have seen increased well-being as a deriving benefit.

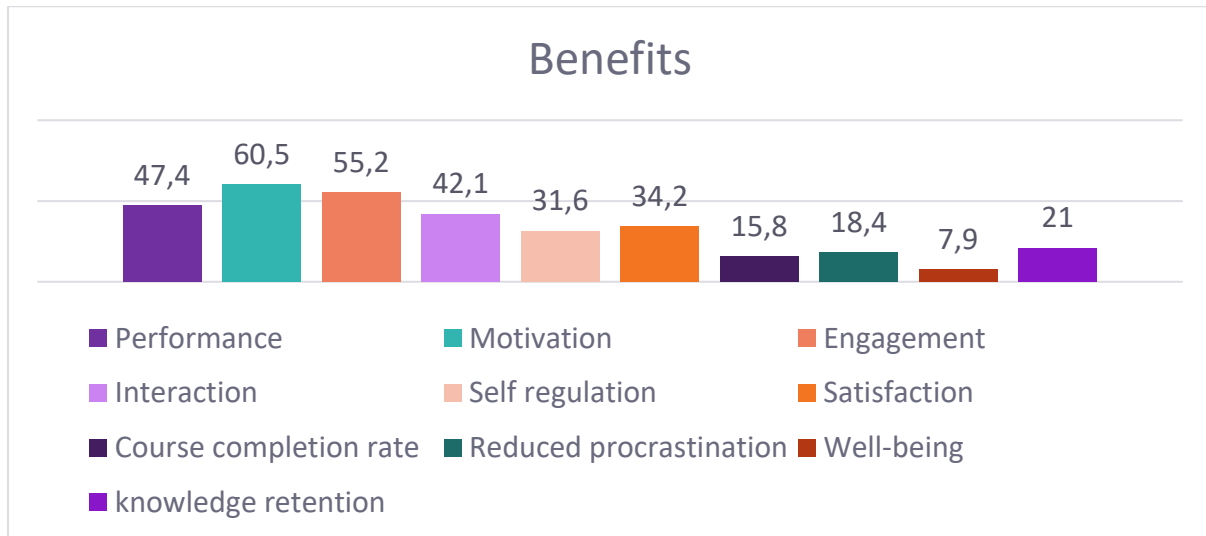


Figure 7. Participants’ opinions about the benefits of applying personalised learning with the emerging technologies

Finally, the questionnaire included two open-ended questions for insights regarding any drawbacks and challenges related to using LA and AI for personalisation. Through thematic analysis (Table 5), three drawbacks were evident. Six respondents reported ethical concerns about data collection and learners’ lack of academic integrity when using tools like generative AI. In addition, these technologies were not always considered accurate, producing invalid results. Regarding the challenges they faced, respondents reported a lack of AI-related knowledge, including its positive contribution and the fact that extra time is required for effective personalisation.

Table 5. Participants’ opinions about the drawbacks and challenges related to personalised learning with the emerging technologies

Perceptions	n participants contributing	
Drawbacks	Accuracy and validity	3
	Ethics	6
	Learners’ lack of initiatives	3



Challenges	Time-consuming	4
	Training	2
	Language issues	1
	Technical support and funding	4
	Technical issues	1
	Know-how	5
	Engaging students	1
	Colleagues' negative feelings	1

Research in Estonia (Tallinn University)

Focus group

Focus group information

According to the project proposal, HE faculty members were invited to participate in the focus group in a semi-structured interview format. Six people attended the 40-minute virtual focus group and two face-to-face. Out of the eight participants (one male and seven female), six instructors have a doctoral degree, one is a doctoral student, and one is a learning designer with an MA. All are engaged in teaching at the university, and one person was on a sabbatical then (and had not had much chance to apply AI in her teaching). The questions used in the focus group were derived from the project research guidelines and have been replicated in the results section.

Focus group results

The responses were analysed using thematic analysis. Due to the nature of the questions, the following themes emerged about the use of learning analytics (LA) and AI for personalised learning (PL):

Awareness: the teaching staff are generally aware of PL, LA, and AI concepts.

Usage: PL and LA are seldom used; AI is used more often.

Benefits: AI for writing and editing, language learning, workshop preparation, etc.; some usefulness of LA data (e.g., demonstrating students' desire to learn).

Challenges: uncertainty (about skills and usefulness), hallucinations (by AI), ethical considerations, and trust.

Needs: availability (of data), accessibility (paid subscriptions), time (to redesign learning).

An overview of the results is provided with examples from the interview questions.

1. Are you aware of the term personalised learning (or individualised, customised)? What do you think it refers to?

All participants were aware (or a bit aware) of personalised learning. However, they highlighted the issues linked to terminology: 'It should be referred to as adaptive, NOT personalised learning, as students' learning objectives, personal feedback, and learning process will be adapted'. It was also acknowledged that people talk about different things using these terms. Mostly, personalised learning was defined as 'adapting learning based on students' needs'; however, the 'Importance of adapting the lessons, feedback, and assessment based on students' strengths (not only needs)' and 'finding a personal way to learn, using all kinds of technologies (including books and libraries)' were also offered as clarifications to the term.

2. When teaching online (distant or blended mode), do you apply strategies for personalisation? If yes, could you give examples?

Some respondents had not used any strategies for personalisation: 'I don't use personalisation mostly because of a lack of tools; all adaptations are without technology; I just allow choosing the focus of learners' projects or how they choose to do them'. Others claim to have used adaptations to assignments, their own teaching, differentiating tasks (providing a choice to students), etc. For example, one instructor is personalising language learning by using AI-produced transcripts or by providing open-ended questions to stronger students and multiple-choice questions to weaker students.

One associate professor said that his teaching is not aligned with personalised learning but with self-regulated learning. He uses personal study contracts and environments (every learner uses a personal blog with other environments linked to this; the whole course is open). Also, students can choose some tasks or topics and build different learning pathways in the course.

1. Are you aware of the term "educational data"?

The respondents had quite a good understanding of this term. They could even elaborate on different types of educational data: 'Educational data is related to school-level data, subjects,

students (demographic), anything that can be used from the pedagogical point of view to prepare better learning experience for students, or teacher professional development and skills'. These data can be extracted from different sources, including course-level data, open educational data from university systems, Learning Management Systems (e-Didacticum, Moodle) and national surveys. General consent was that educational data is 'some big data about how students learn, which can be collected digitally or using LMSs, depending on the focus.'

4. Do you use data (e.g., LMS log data) to personalise learning? If yes, how? Do you use learning analytics (data collection, analysis, report and action) for personalisation? If yes, how?

Although all focus group instructors are aware of educational data, they hardly ever use it for personalised learning. At the same time, they use data to teach students about the possibilities of data use: 'I use data, yes, but not for personalised learning. We took students' self-reports and e-Didacticum data about their progress and gave it back to them so they could see the easy ways to collect data and learn from it (triangulate different data sources). However, we did not use the data to change anything.'

The main reason for scarce data use seems to be its limited value for the instructor's use: 'Moodle provides data about submissions, digital trace about who was late, how much time they spend in Moodle, etc.; I don't use it much, it's just an indication of which student is more eager to study.' Another instructor put all his class recordings in Panopto to get statistics about who are the students who watch the videos, but this information was not very helpful.

5. Are you aware of the term "Artificial Intelligence" (AI)?

All participants are familiar with the term; however, not all have used the technology in their teaching or for the personalisation of learning.

6. Do you use any AI tools in your teaching? In what way?

All instructors but one have used AI for teaching. The examples of AI use in teaching are varied, from digital photography to language learning, especially when the AI has been incorporated into some pre-existing tools used by these instructors (e.g., Padlet, Miro). One of the instructors has been on a sabbatical since spring (when AI became wide-spread), and although interested in its application, has not had a chance to try it out for teaching. However, she has used AI to facilitate the supervision of thesis writing, especially regarding academic integrity and hallucinations (which AI is very good at).

7. Do you use any AI tools for personalisation? In what way?

As the focus group participants have not really been focused on personalised learning, the closest response to this question comes from a language teacher: 'I teach teachers to teach and students to learn; with teachers, we have learned how to adapt texts, change the genre, write formal/informal texts, generate materials for debates/arguments, create fake news for critical analysis; with learners, we have explored how to ask good feedback to texts they have produced, and how to learn from the answers. I have also used Padlet images for digital story-telling, and to facilitate discussions.'

8. Are there any benefits/ challenges related to the use of these technologies? If yes, please elaborate

The benefits in using AI-driven tools vary. The main benefits mentioned by the instructors include possibilities to improve writing and editing: 'When supervising, I suggest using Grammarly to improve their writing'; Instructors also generate materials or questions for students, create assignments, and spark discussions; one person uses AI to answer 'stupid' e-mails.

Mostly, AI is used for workshop preparations: 'When delivering or designing workshops, I have used ChatGPT to check clarity or get inspiration, e.g., which activities might be more engaging or effective'. 'I have used it in teaching very little, but I have some ideas about what the task could be, and then I talk to ChatGPT to discuss what the task might be like to get inspiration. I just insert an idea and the outcome I want to achieve; I also check the clarity of my own instructions to students, but I have not used it for assessment or feedback.'

The instructors are also confident in expressing the need for students to learn how to use AI: 'Encourage students to use AI, feel confident with it, female students do not want to experiment that much; students report that AI has extended their understanding of a case or a concept, formulated their thoughts, and also developed technical skills (first-year law students); how to prepare a professional opinion (feed into AI who their audience is to express a legal opinion).'

The participants saw uncertainty about how to use AI tools as the main challenge. They expressed an opinion that lots of staff haven't used AI at all and that discovery and finding out about the tools should be the first step forward. People are unsure how to write the prompts so that the response would be useful; therefore, it is seen as a challenge and 'not a technical issue'. The instructors also expressed concern about students' use of AI: 'Some students don't like it; they cannot write the prompts'. There is also the challenge of availability (accessibility to the paid

versions); also, 'some students are ashamed of using AI and try to conceal it, which leads to cheating' - so instructors expect more openness!

9. What do you think about using these technologies? Do you expect any benefits/ challenges?

As to the people who have not used AI and data in their teaching, the results demonstrate doubt and inaptitude to try it: 'I guess in some cases it is useful. However, it takes quite some time to understand and re-design teaching and learning activities.'; 'There might be some benefits; however, so far, I haven't felt the need to use them.' 'Probably there will be many challenges, my own personal skills to properly use it, ethical considerations, and data management issues.'

10. What are your needs when using these technologies for personalised learning?

Apart from the instructors who currently do not feel the need to use these technologies, the respondents expressed some needs. First, the availability of tools for AI and learning analytics, especially in open courses (plugins). It's time to get familiar with the fast-emerging opportunities. Also, universities should be paying for the subscriptions, not the instructors. Regarding personalised learning, the instructors expressed an opinion that 'students should be able to personalise their learning paths as well, not only me'.

Questionnaire

Questionnaire information

The questionnaire, compiled and piloted by partners, was distributed to Tallinn University staff through targeted e-mails. As the response time was only two weeks, 15 responses were obtained.

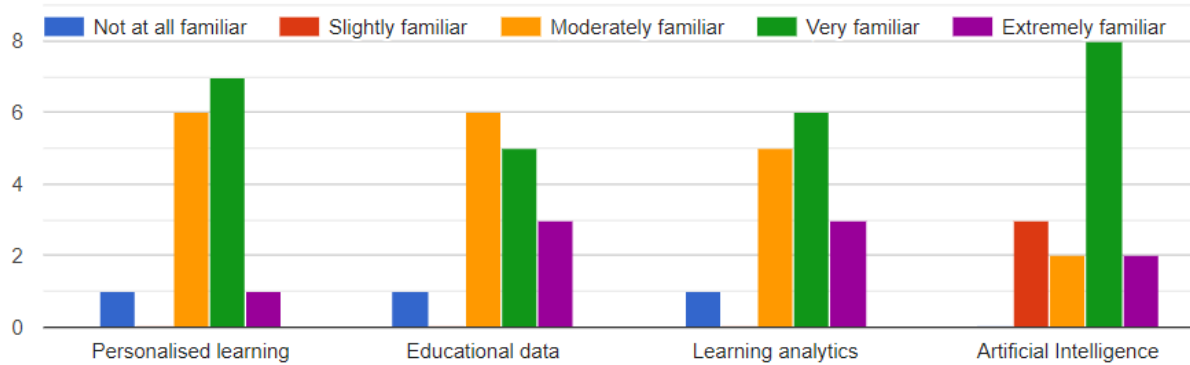
Questionnaire results

Participants

Of the 15 respondents, eight are female, and five are male (others are non-binary or prefer not to say). The age varies from 28 to 71 (five people between 28 and 40, five people between 41 and 49, and four people 50 or older). All work at a public university with over 500 staff and 5,000 and 15,000 students. One respondent belongs to the tech staff, two have leadership positions, eleven are involved in teaching, and eleven are engaged in research. Nine have a doctoral or post-doctoral degree, one has a professional diploma, and five have a master's degree.

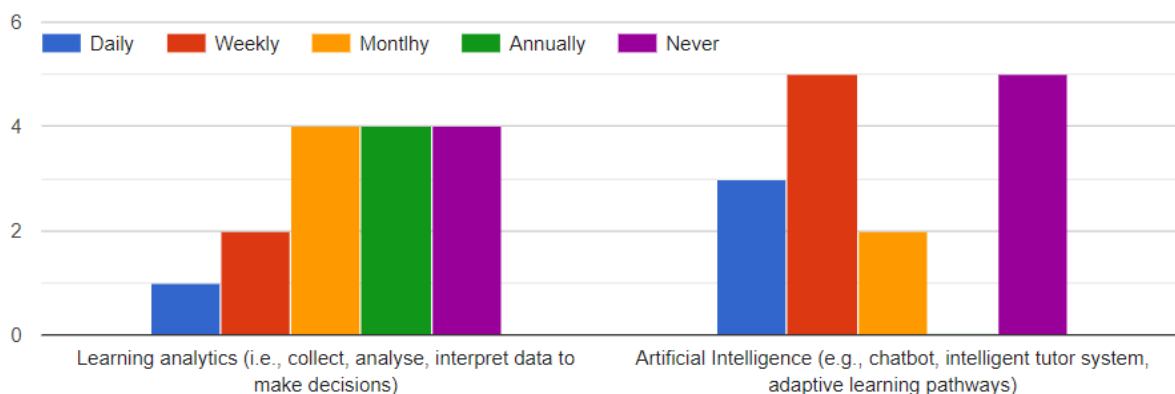
Familiarity with the terms

One person is not familiar with the terms personalised learning (PL), educational data (ED), and learning analytics (LA). Others claim good familiarity with these terms, and all are familiar with the term artificial intelligence (AI).



Technology usage

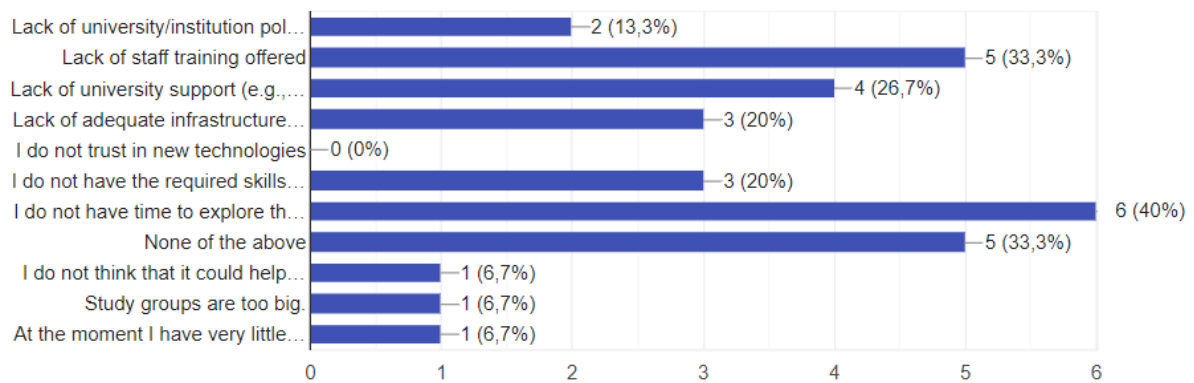
Four people do not use LA, and five do not use AI. Only one instructor uses LA daily, and three use AI daily. The weekly usage of AI is also higher than that of LA (probably because AI is used for teaching rather than pedagogical decision-making).



Specifically, instructors use Graph algorithms, Minimax, Poe, Quizlet, and CoTrack. The technology is used to propose discussion topics or for thesis supervision. Also, AI is used to create personalised tasks, answers, reports, and feedback.

There are several barriers to the use of these technologies. Most often (6 responses), respondents cannot find time to explore these tools for personalisation. Similarly, lack of staff training (5 responses) and university support (technical team) also hinder adoption (4 responses). Three people lack the required skills or technology.





However, eight people who use the technologies find it beneficial for their students, and six people find that these technologies align with their pedagogical purposes. No-one says that it is university policy, and one person does not use the technologies at all.

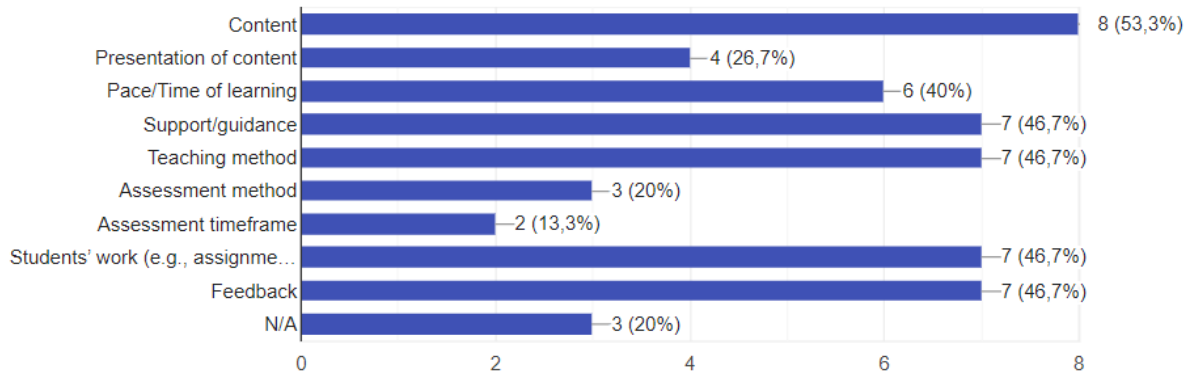
Personalisation

When it comes to personalising learning, ten responses reveal that the teacher makes decisions for personalisation; in nine cases, it is the student, and in three cases, it is the system. Only one response demonstrates shared control among teachers, students, and the system.

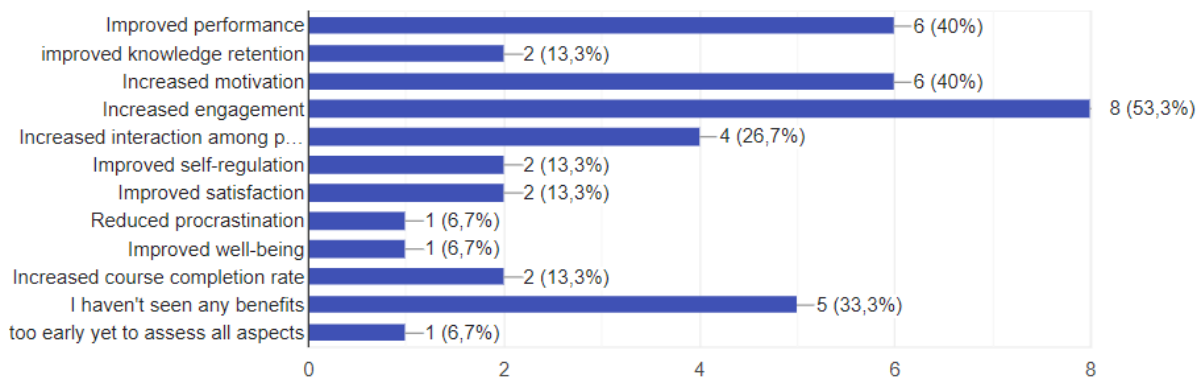
Mostly, personalisation is decided based on the performance (10 answers) and individual goals (9 responses). In four cases, personalisation depends on psychological aspects (motivation, interests) and data patterns (e.g., achieved scores or repeated behaviours). Three responses demonstrate the use of cognition, and two responses reveal the use of demographic profiles; one response also addresses emotional needs (stress).

The adaptations mostly occur during instruction (9 responses) and within a course unit (7 responses). However, some adaptations are also made before instruction (4 responses), in the whole programme (3 responses), or in the whole course (2 responses). In one case, adaptations are carried out afterwards.

When it comes to the aspects that are adapted, eight respondents picked content, and students' work, support/guidance, teaching method, and feedback were all picked by seven respondents. Presentation of content and pace are also often considered (4 and 6 responses, respectively). The assessment method (3 responses) and assessment timeframe (2 responses) are not adapted that often.



As to the benefits of using these technologies for personalised learning, instructors mostly notice increased engagement (8 responses), followed by improved performance, increased motivation (six responses), and interaction between participants (four responses).



Drawbacks and challenges

The responses to these questions are not very informative, as many of the respondents do not use these technologies for personalisation. Problems with the internet and too general feedback provided by AI are mentioned as drawbacks. Regarding personalisation, one drawback is avoidance: 'Students try to avoid what they are not very familiar with and try to select what they know well already (e.g., for selecting tasks)'. One response clarifies that 'change decisions should not be based only on numbers'.

Challenges connected with using these technologies include low equipment and technological support, inadequate skills or knowledge to implement them, some accessibility issues and the fact that 'they do not fit all purposes'.

Research in Greece (UAegean)

Focus group

Focus group information

To communicate with the target groups, UAegean internally circulated emails through the university's mailing lists. After a two-week effort and having preliminary discussions with more than twenty (20) persons, UAegean gathered eight (8) participants for the focus group: 1 assistant professor (male), two teaching and research staff (males), 3 PhD candidates/educational technologists (2 males, one female), one e-learning expert (male), 1 PostDoc researcher/teaching staff (male). The sample was heterogeneous concerning job description, not balanced concerning gender, and the mean age of participants was between 40 and 45 years. The focus group session was delivered via ZOOM meeting, lasted almost 1 ½ hour and was recorded after the participants' agreement. A project team member served as the facilitator/moderator of the discussion, and another member served as the note-taker to record critical issues of the participant's answers. The facilitator explained the project's aims to the participants transparently and understandably, as well as how and where the collected data will be used and disseminated. Moreover, all the procedures during the study were initially presented to the participants. All the participants have filled in the consent form to participate in the focus group. The group work was generally successful because all the participants could share opinions and attitudes about the proposed topics.

Focus group results

The data was analysed following the logic behind the initial questions (Q1 – Q10) to have a structured procedure. Afterwards, the findings were summarised in various significant themes.

Participants' familiarity with terms

All participants were familiar with the term, perhaps in different contexts (undergraduate, postgraduate, non-formal education, etc.). They suggested that personalised learning is a generic educational methodology aiming at an individual's preparation, regardless of the means and the context, considering educational needs, personality, learning styles and background. Moreover, according to their experience, there hadn't been any systematic initiatives for personalised learning in higher education in Greece.

Strategies for personalisation

None of the participants was using strategies for personalisation. They were using strategies for e-assessment, monitoring/tracking, and control of the educational procedure in the context of blended or online distance courses, using various LMSs, like Moodle. Moreover, this type of monitoring refers to the class, not on a student level. Only one of the participants referred to selective-release criteria in the LMS, which can help instructors design differentiated learning paths with an e-course according to various rules, like answering intermediate questions or student performance in intermediate e-tests. Also, he referred to the absence of the institution's guidelines, policies and instructional strategies for this type of course design. He suggested that this type of design (i.e., applying selective-criteria rules in the course's flow) implies control of students' behaviour. He had the impression that this type of rule was familiar among students, but he could not document/justify any learning potentials, and this type of e-course design requires more effort.

Awareness about "educational data"

All the participants were familiar with the term and agreed that educational data could add value to e-learning. Moreover, they mentioned that educational data are already used, not for personalisation, but rather for monitoring/tracking students' performance during the semester, either in summative or formative assessment settings. Most participants mentioned that log data from platforms like Zoom and Webex are not available to the teachers, which is an inherent problem. One solution could be using open teleconference platforms like BigBlueButton (BBB).

Data used for personalisation of learning

Log data are used mostly offline, either from LMS like Moodle or virtual spaces like VRChat and OpenSim. All the participants agreed on the importance of digital learning environments' log data.

Awareness of "Artificial Intelligence" (AI)

All the participants were familiar with the term. In some cases, they included examples or case studies in their courses about the potential use of AI in education in the context of the 4th Industrial Revolution and Pedagogy 4.0.

Use of AI tools in teaching

They were not using AI tools to support their teaching or design practices. One professor mentioned ChatGPT as an experimentation platform during the last months to create scenarios for interactive games, which he then adapted and tested accordingly.

Use of AI tools for personalisation

All of the participants agreed that they are not using any AI tools for personalisation in their courses, and they also mentioned that it is mostly unlikely for the Greek universities. In some cases, they include in their course examples or case studies about the potential use of AI in online distance education and e-learning.

Benefits related to the use of these technologies

In cases where simple learning analytics were used, like monitoring essays, assessments, participation, etc., all the participants mentioned possible benefits, as long as the reported data could have a “meaning” for the teachers and the students, i.e., if they would be able to interpret the data in a meaningful manner to improve themselves. One of the participants, whose field of expertise is e-assessment, mentioned that learning analytics were used for reflection, i.e., re-evaluating the credibility and accuracy of the e-tests within the context of the actual course syllabus. Moreover, machine learning algorithms were used using Weka software to calculate predictive models for the undergraduate students in his department. Those are settings that cannot be established within the traditional offline assessment context and could potentially support and enhance summative evaluation and more focused didactic interventions and designs.

Challenges related to the use of these technologies

In cases where simple learning analytics were used, like monitoring essays, assessments, participation, etc., students reported that they felt someone was spying on them when they found out their actions within an LMS were recorded. One of the participants in the focus group mentioned a case where trainees referred to this type of logging as a violation of their rights. One of the participants, whose field of expertise is virtual (3D) worlds in education, stated that log data were not correct (mostly “fake”) because that data mainly corresponded to the avatar’s actions, performance, and interactions and not the student’s themselves. Also, another participant specialised in MOOC platforms like OpenEdx, raised an issue about the credibility of log data. For instance, the system could log how many times a user is watching a video, but this user could have only opened the video and left the computer.

Expectations for benefits and challenges

Regarding using AI tools, some participants highlighted potential applications like automating email responses and feedback to the students during the online courses. As with every technological innovation, the main issue is to use it correctly. For instance, AI tools should be used as cognitive tools, not tools to replace students' learning efforts. One challenge is the credibility, validity, and eligibility of the results when you incorporate AI tools in educational settings with open issues of authorship and agency that have not yet been solved. The second challenge is the low level of technological readiness of the involved personnel (academic, research, technical and administrative staff) in the universities in Greece. The third challenge is the ethics of using AI and learning analytics in education, as a clear and transparent legislation framework is missing. The fourth challenge is data privacy and security issues in the context of GDPR. The fifth challenge is technology maturity and trustiness because AI tools can distort reality (i.e., fake photos, videos, etc.). Concerning chatbots like ChatGPT, one question raised by the participants is how reliable/unreliable those technologies are, to which degree chatbots could replace traditional search engines for "smarter" results and what about the plagiarism effect.

Participants' related needs

All the participants highlighted the need for training on using AI tools and learning analytics, as well as using good case studies. There is a need not only to use learning analytics in a course but also to have the skills to interpret the results and reflect and organise the course and the didactic approaches accordingly. Moreover, the participants stressed the need for support at an institutional level and a transparent legislation and technical framework on how to embed and use AI and learning analytics in everyday teaching practice.

Questionnaire

Questionnaire information

The University of the Aegean implemented the application of the online questionnaire in February and March 2023. An email was sent to all the faculty of the University of the Aegean (and to other HEIs) containing a short description of the LEADER AI project and the questionnaire's aim. This resulted in the completion of the questionnaire by 50 participants. An Excel file containing the responses of the 50 participants was downloaded.

Questionnaire results

A total of 50 people filled in the questionnaire, with 36 of them being males and 14 of them females. The age span was from 37 to 65 years old. All but one participant worked at a public university. Half the institutions the participants worked in had less than 500 staff, while 18 had more than 500 people. Regarding the number of students, 14 institutions had less than 5000 students, 21 had 5000-15000 students, and 15 had more than 15000 students. Most participants had a teaching position in the university; about half of them were researchers, four were in eLearning development, 4 were instructional designers, and 3 had a leadership position. More than half of them had a PhD degree, and 14 had a postdoctoral degree.

Regarding their familiarity with the terms inquired, Most of the participants were very familiar (19 out of 50) or highly familiar (16 out of 50) with the term “personalised learning”. The term “educational data” was very familiar to 21 participants and extremely familiar to 14 participants. Many participants said that they were moderately familiar with the term “learning analytics” (17), while 16 of them were very familiar and only 6 of them extremely familiar. Surprisingly, 13 participants said that they were not familiar with the term “artificial intelligence” and 21 participants were extremely familiar with the term.

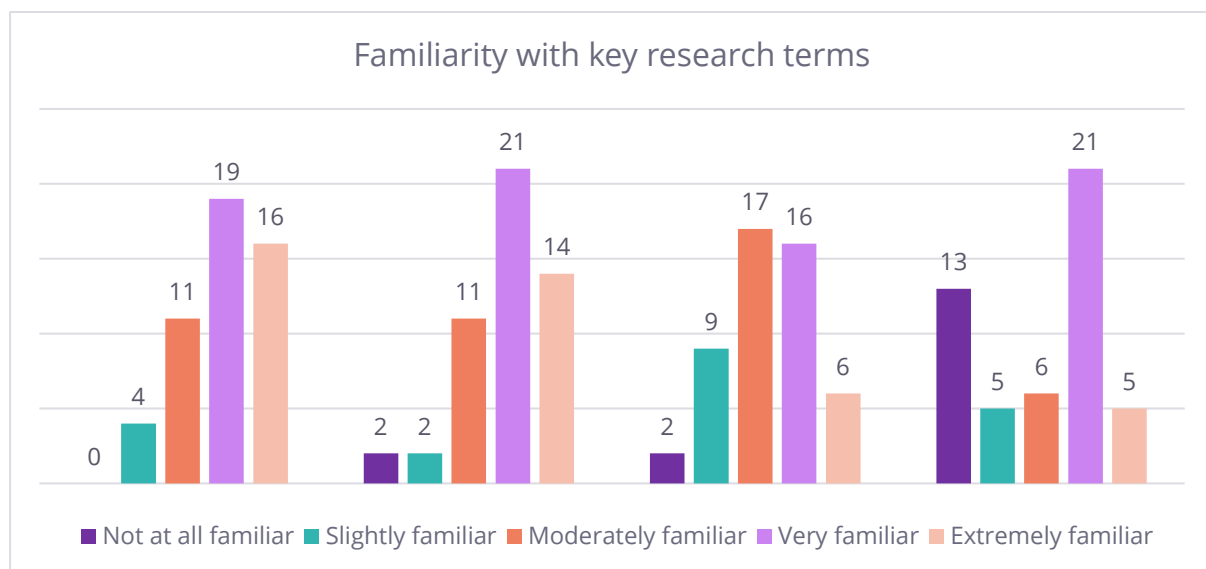


Figure 8. Participants’ degree of familiarity with the research terms.

38 respondents said that they never used learning analytics, or they used them annually, while 12 of them used them monthly with only 7 used them weekly and 3 daily. As far as AI is

concerned, more than half of them (26) never used AI and 13 of them used it annually. 4 respondents used AI monthly, 6 weekly and just one daily.

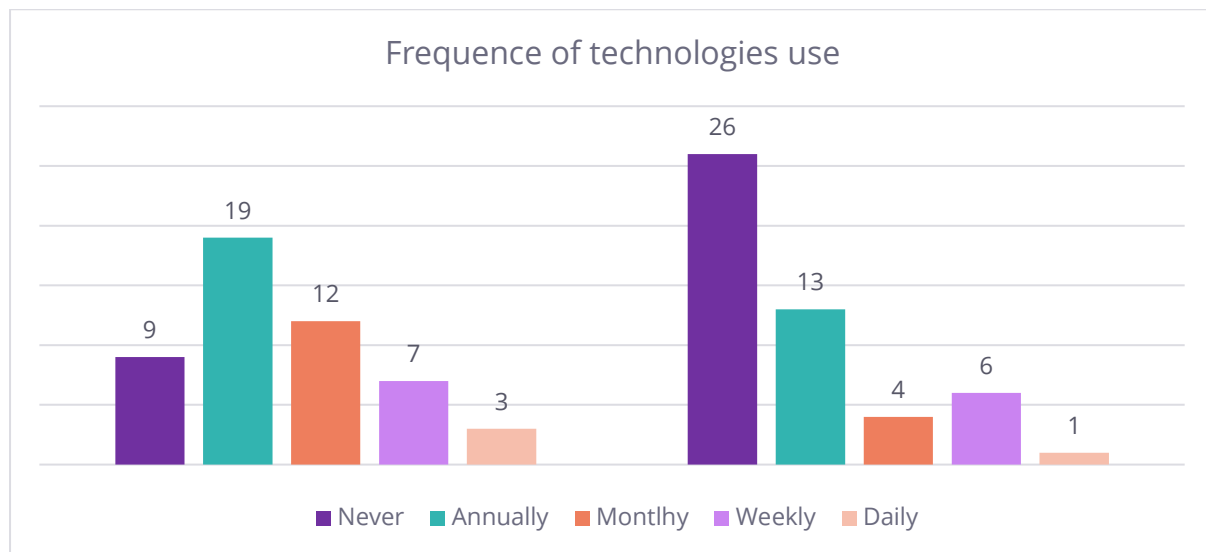


Figure 9. Participants' frequency of technology use for personalised learning

The main reasons the staff do not use these technologies for personalisation is the lack of university support (selected by 33 respondents) and the lack of training offered (same), while 26 mentioned the lack of university/institution policy. Other reasons selected were the lack of adequate infrastructure (23 respondents), lack of time (18) and lack of skills (17).



Figure 10. Participants' opinions about the barriers related to applying personalised learning with the emerging technologies

The respondents used these technologies, based on the open-ended questions, for self-assessment, for supervised learning, for statistical reasons, use of chatbots in conversations, for research reasons and analysis of student data to predict the duration of studies/ academic degree grade. When asked why they use these technologies for personalisation, 3 respondents said it had been a university policy, 26 of them believed that it applied to their pedagogical purposes. At the same time, 29 thought that the approach had been beneficial for their students.

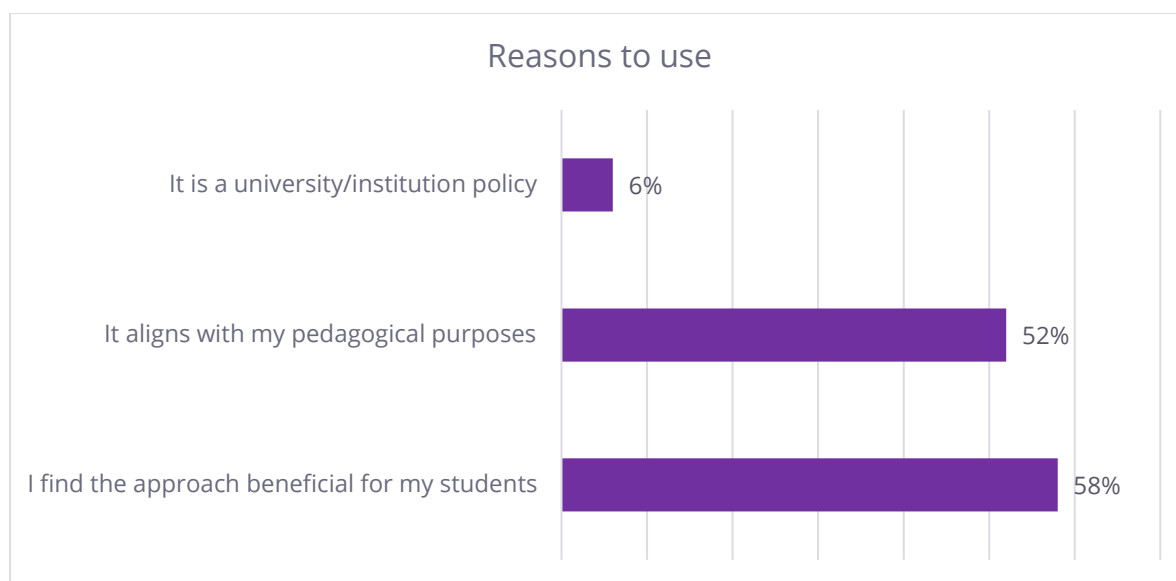


Figure 11. Participants' opinions about the facilitators related to applying personalised learning with the emerging technologies

The inquiry regarding who-what makes decisions for personalisation, was answered as follows: Most respondents (28) said that the teacher decides, 6 said that the student decides and 9 that the system decides. 11 of them said that there is shared control among them.

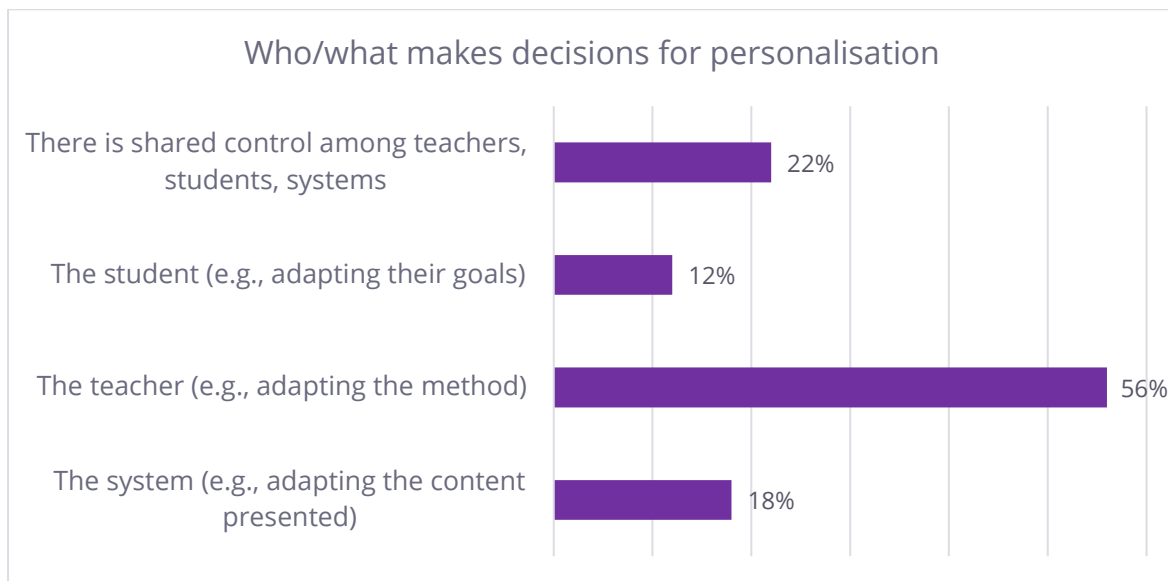


Figure 12. Participants' choices about who/what makes decisions for personalisation.

As far as the type of student information that the decisions for personalisation are made is concerned, most participants (38) said that these decisions were based on performance, half of them (24) that they were based on data patterns, 20 of them on individual goals, 19 of them on psychology, 17 of them on cognition and 16 of them on demographic profile.

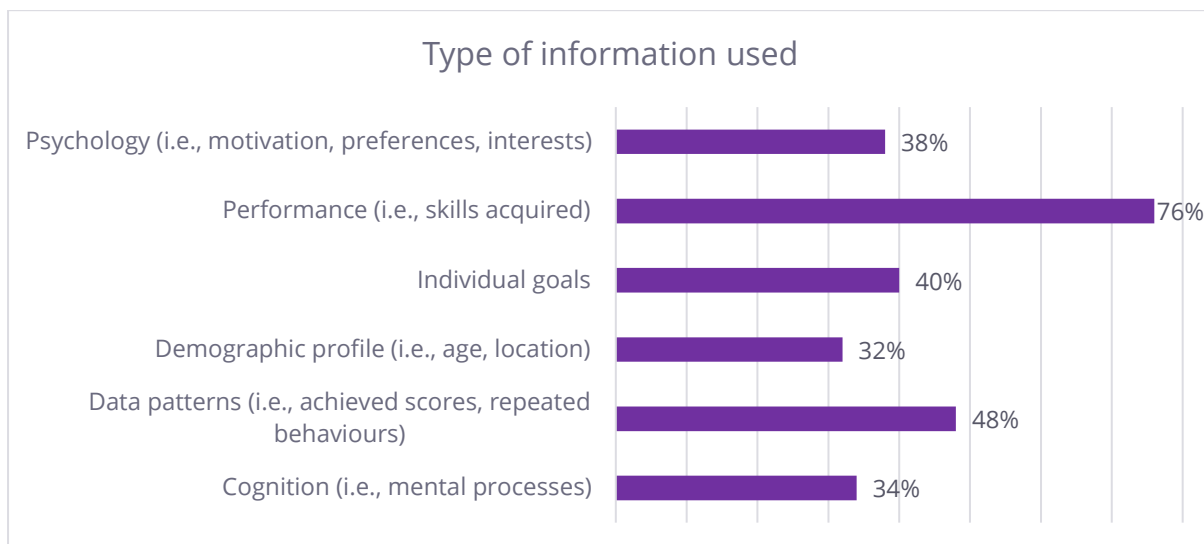


Figure 13. Participants' choices about the type of information used for personalisation

According to the replies of the participants, these adaptations occurred before the instruction (14 replies), during instruction (15 replies), within a course unit (12 replies), in the whole course (20 replies), and in the whole programme (14 replies).

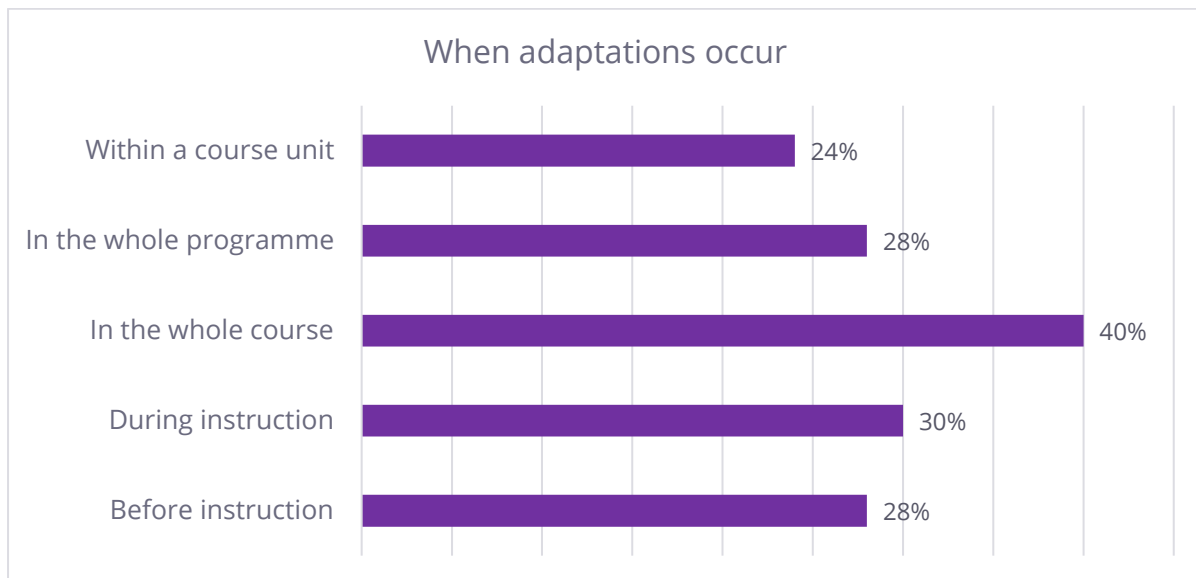


Figure 14. Participants' choices about the timing of personalisation.

The participants said that they personalised and adapted the pace/time of learning (33 replies), the assessment method (27 replies), the teaching method (25 replies), the presentation of content (22 replies), the content (23 replies), support/guidance (21 replies), feedback (19 replies), students' work (18 replies) and the assessment timeframe (13 replies).

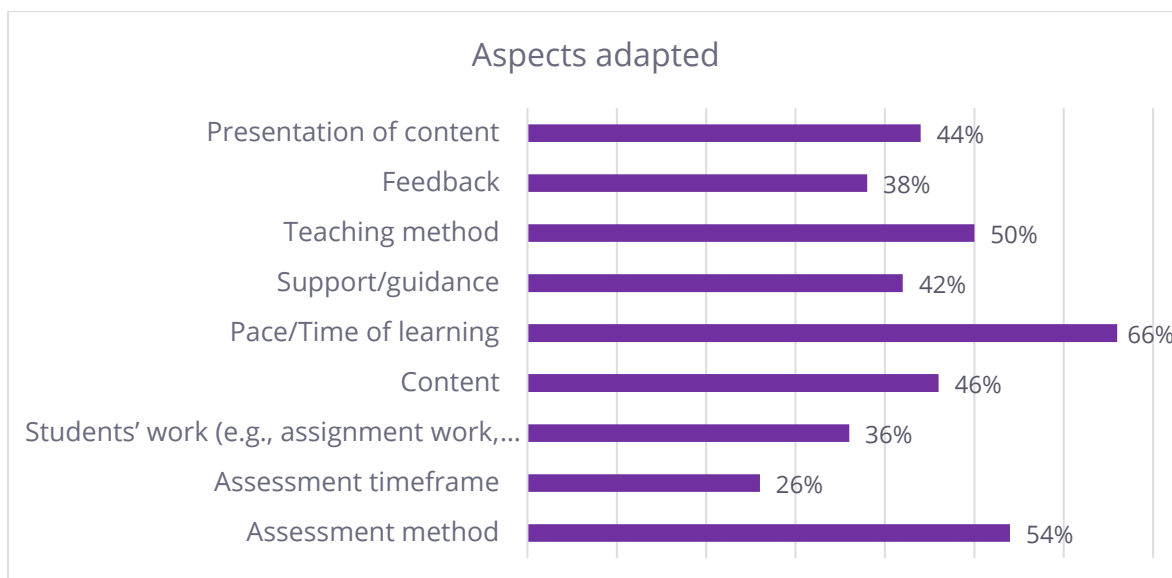


Figure 15. Participants' choices about the aspects adapted.

The participants mentioned the following benefits as a result of personalisation with the mentioned technologies: improved performance (28 replies), increased motivation (25 replies), increased engagement (24 replies) and improved satisfaction (19 replies). Some mentioned increased interaction among participants (14 replies), increased course completion rate (11 replies), improved knowledge retention (11 replies) and improved self-regulation (11 replies). Reduced procrastination (5 replies) and improved well-being (5 replies) were also mentioned, while 9 participants said they hadn't seen any benefits.

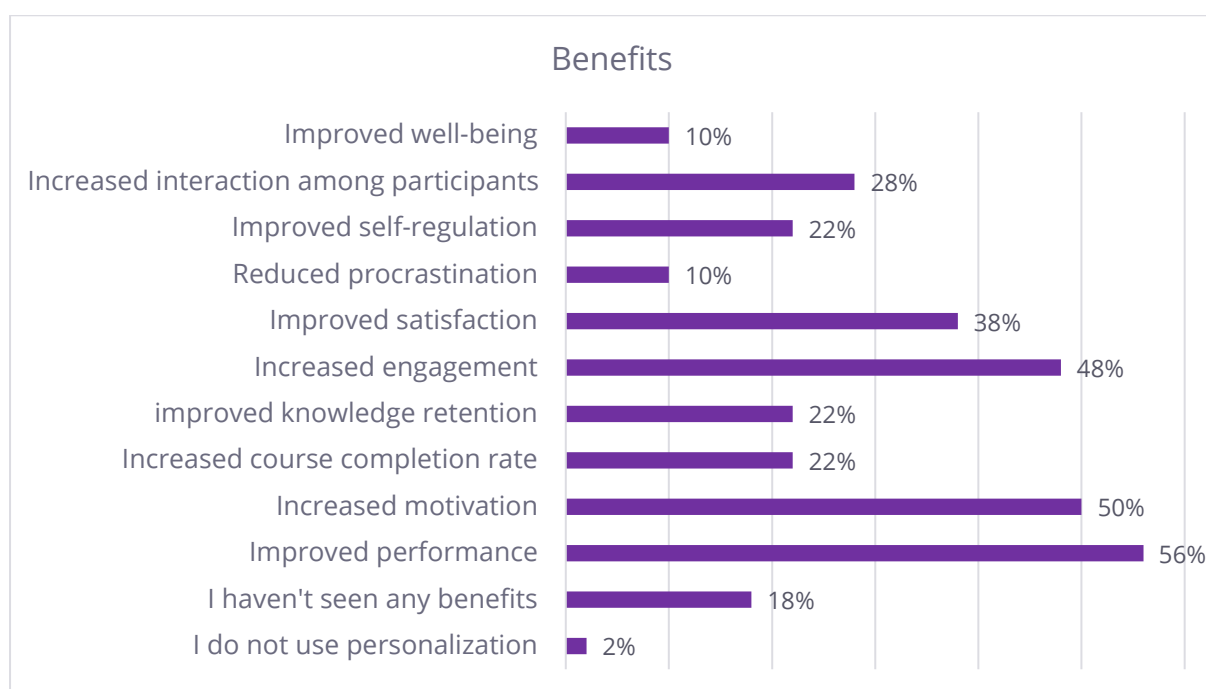


Figure 16. Participants' opinions about the benefits of applying personalised learning with emerging technologies.

An open question inquired about drawbacks that might result from the personalisation. More than half of the respondents said they couldn't think of any. The drawbacks mentioned were the increased workload, the human isolation, the bad quality data (for example, incorrect or irrelevant data) and the lack of technical support, organised policies, equipment, training, and university infrastructure. A participant claimed these technologies are new methods in a traditional teaching/learning environment, without new policy, new infrastructure, different assessment methods and support for students and teachers.

Research in Romania (UPIT)

Focus group

Focus group information

The focus group was held face-to-face, on March 7th, 2023, in the premises of the University of Pitesti, Building B, and lasted approximately 45-50 minutes. There were 9 participants belonging to different university staff categories: 1 Vice-Rector for International Relations, 1 Head of the International Relations Centre, 1 Dean, 4 teaching staff members, and 1 PhD student. There was 1 facilitator and 1 note-taker (both were women, HE teaching staff with over 20 years of experience in academic environment).

The nine FG participants were recruited based on their academic experience within UPIT and their openness to the issue of personalised learning and to the topic of AI tools in general and as integrated in education on a specific level. Eight of them are members of the academic staff of UPIT, three of which also hold management positions (1 Vice-rector for international relations, 1 faculty dean and 1 head of the centre for international relations) and there was also 1 PhD student. They were invited to participate via telephone or email, and they all showed their complete willingness to participate in the activity. Of the nine FG participants in Romania, two of them were men, and seven were women. The HE teaching experience of the FG participants is varied. It ranges from only 2 years to 25 years; therefore, an average would be 14-15 years.

Focus group results

A synthesis of the participants' answers to the questions addressed by the facilitator follows.

Participants' familiarity with terms

The Romanian respondents stated that they were familiar with this concept of Personalised Learning. They described it as aiming to customise learning for each student's strengths, needs, skills, and interests. While it may already be implemented outside Romania to a greater degree (one of the participants studied in France during their PhD some 10-15 years ago and told the rest of the colleagues that the teaching approach at that French university was personalised), and for a long time, in Romanian higher education institutions it is difficult to implement it because of time constraints, as well as syllabus constraints and teaching staff constraints (not enough in point of number). However, efforts are being made to make it more present in the

institution as well because personalised learning has obvious advantages (it increases student engagement, motivation and achievement, to mention just one).

Strategies for personalisation

The FG participants stated that UPIT had been delivering lectures online since the beginning of the pandemic (2020) and the staff had been trying to apply some strategies for personalisation (such as allowing students to come up with their ideas on how to solve a problem or reach a specific goal, to take part in online conferences etc.). Personalisation is made easier in this online environment.

Awareness about “educational data”

The RO participants knew the meaning of the “educational data” phrase and stated that it covers quite a wide scope, ranging from information on the student background, to wellbeing data (connectedness to school, student morale, student safety, perceptions of relationships and classroom behaviour) or achievement data. Overall, they appreciated that educational data could be connected with personalisation as they have a tailored nature and are specific to each student.

Data used for personalisation of learning

Within the University of Pitesti, data were collected periodically (for instance, at the admission process, when students have to introduce some data about themselves, or throughout the year using the tutoring activity). This allowed the teaching staff to know when they are dealing with a student who has a particular problem (for instance, leaves outside the city and has to commute to university or had a medical problem) and adapt their teaching process accordingly.

Awareness of “Artificial Intelligence” (AI)

The FG participants knew the meaning of the Artificial Intelligence term as the simulation of human intelligence processes by machines, especially computer systems.

Use of AI tools in teaching

Only 1 FG participant, belonging to the field of Engineering, reported more experience in the field of AI (approximately 10 years of research), but without incorporating it too much in the teaching activity. The other FG participants only reported using AI at the minimum level (for instance, the mere use of a browser), or the use of MOOCs in their activities. In real life, the participants reported using AI for GPS navigation systems.

Use of AI tools for personalisation

AI tools would definitely be a great asset for personalisation purposes in the education system because it would increase engagement of the students and teachers alike - both classes would be more interested to work with new tools and better results may be obtained. However, in the RO university the use of AI in teaching was not very wide.

Expectations for benefits and challenges

The RO respondents agreed that using these technologies in the teaching process would be highly beneficial: they can help students learn better and faster, produce good feedback on the students' performance and help the teacher identify quite rapidly the areas in which the students need further work. Despite these benefits, there were also clear concerns. One major issue is related to privacy and protection of personal data, which is the European policy our university adhered to. Secondly, there is the very human experience of education, which is changed by the introduction of machines. And, thirdly, the respondents stated that adequate infrastructure is key to implementing AI tools in our university and legislation at the national level to regulate its use.

Some testimonials of participants in the FG are rendered below:

"Personalised learning is essential for improving students' performance as it means putting the needs of individual students first. It is even more suitable in the context of online education." (D.A., teaching staff)

"Artificial intelligence is everywhere, from the smallest to the most important aspects of human life. It brings about visible benefits, but also important challenges that need to be addressed." (L.B., teaching staff)

Participants' related needs

The respondents stated that there is a need for adequate infrastructure to implement AI tools in our university, as well as legislation at the national level to regulate its use.

Questionnaire

Questionnaire information

The University of Pitești applied the online questionnaire between February 27, 2023, and March 2, 2023. 60 teachers and researchers belonging to the project's target group were invited to participate in its completion. 50 of them responded positively to the invitation sent to their email

address. To facilitate and shorten the time to complete the questionnaire, the UPIT team translated the questions into Romanian and uploaded them to Google Forms. The questionnaire was translated into Romanian language. Also, another preliminary activity consisted in presenting the participants the theme, partnership, objectives and expected results of the LEADER AI project. The aim of our questionnaire-based research has been also explained to them. They received information on how they must fill in the online questionnaire, about data anonymisation and processing.

Questionnaire results

The data collected and analysed demonstrated the interest of teachers in the use of Artificial Intelligence during courses and other learning activities in HE, due to the benefits it brings especially to students, as can be seen in the section below.

Regarding the demographics of the participants, 30 of them are female and 20 are male. The age of the participants was between 34 and 64 years. All participants worked within a state, public university. The number of staff in their institution was about 500 people, and the number of students was between 5000 and 15,000, according to the information provided by the participants. 86% of the participants are teaching staff, 12% represent people with management positions (vice chancellor, dean, department director), and 2% of them fall into 'other categories' (namely, they are researchers). All 50 participants answered that the last completed form of education was doctoral studies.

Regarding the familiarity with key terms and technology used - PL, educational data, LA, AI - most respondents stated that they knew 'a lot' and 'somewhat' the meaning of the following concepts: personalise learning, educational data, learning analytics, artificial intelligence. Also, extremely few participants answered that they had 'little' or 'no' knowledge of the previously mentioned concepts.

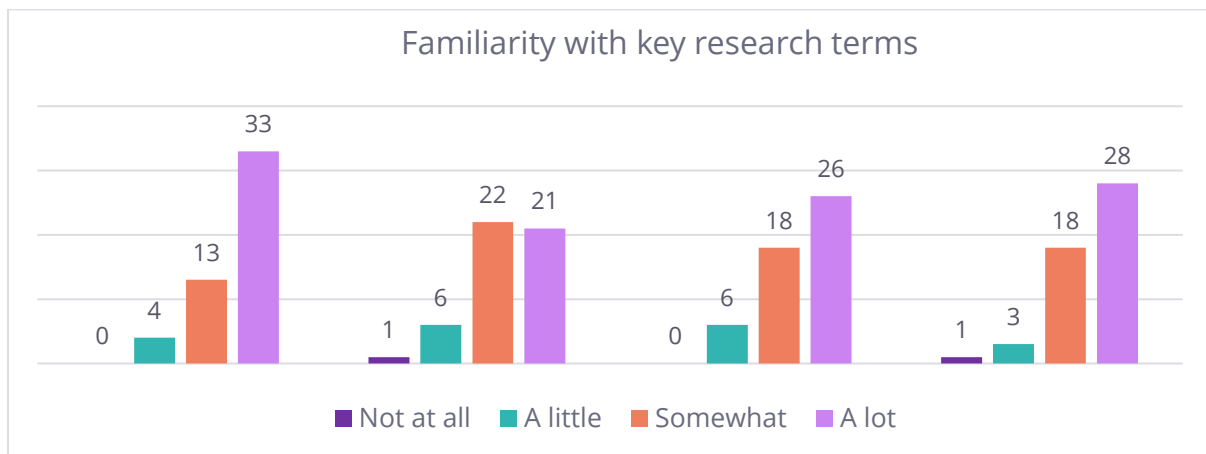


Figure 17. Participants’ degree of familiarity with the research terms.

58% of respondents said that they used AI tools (e.g. chatbot, intelligent tutor system, adaptive learning pathways) or Learning Analytics (i.e., collect, analyse, interpret data to make decisions), to personalise their educational process teaching-learning-assessment and adapting it to students' needs. Conversely, 42% of them did not use such tools in the classroom.

The reasons why 48% of participants did not use AI or Learning Analytics tools are as follows:

- Non-existence of a university policy;
- Lack of specialised training to be offered to teachers and researchers;
- Lack of university support;
- Lack of adequate infrastructure;
- Distrust in new technologies;
- Lack of time to explore these new technologies.

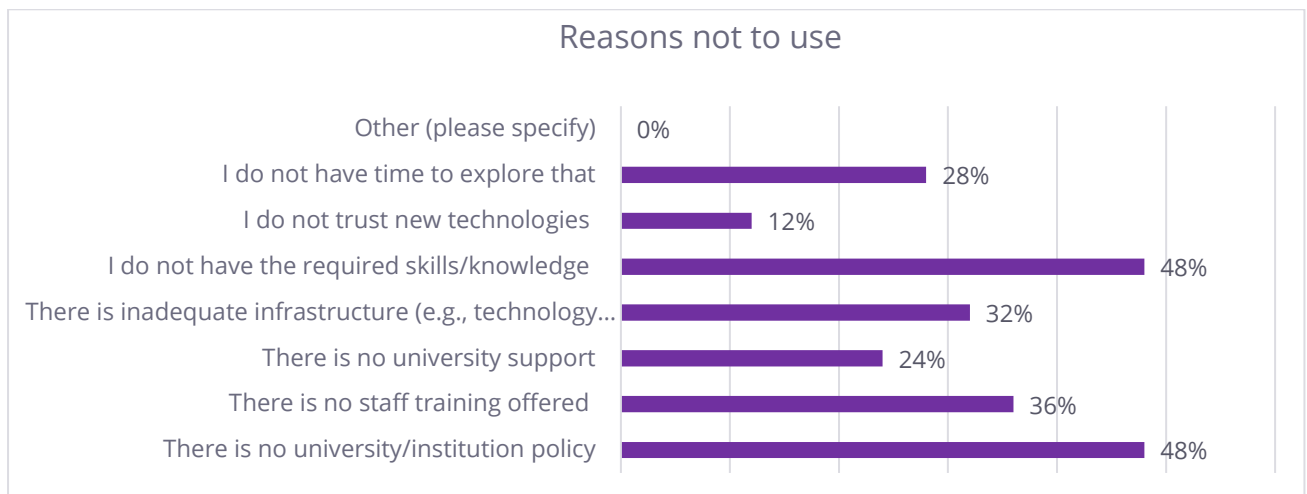


Figure 18. Participants’ opinions about the barriers related to applying personalised learning with the emerging technologies

Regarding the use of Artificial Intelligence and Learning Analytics to personalise the educational process, 66.7% of participants used AI tools and 69.4% used Learning Analytics tools.

Among the specific examples provided by the participants, we mention:

- Moodle platforms;
- Management methods: application and interpretation of questionnaires; statistics; Chat GPT;
- Chatbots;
- University's eLearning platform;
- Software specific to students' specialisations.

When asked why they use these technologies for personalisation, 8.6% of respondents said it had been a university policy; for 80% of them it aligned with pedagogical goals, and 71.4% believed that this approach was beneficial to students.

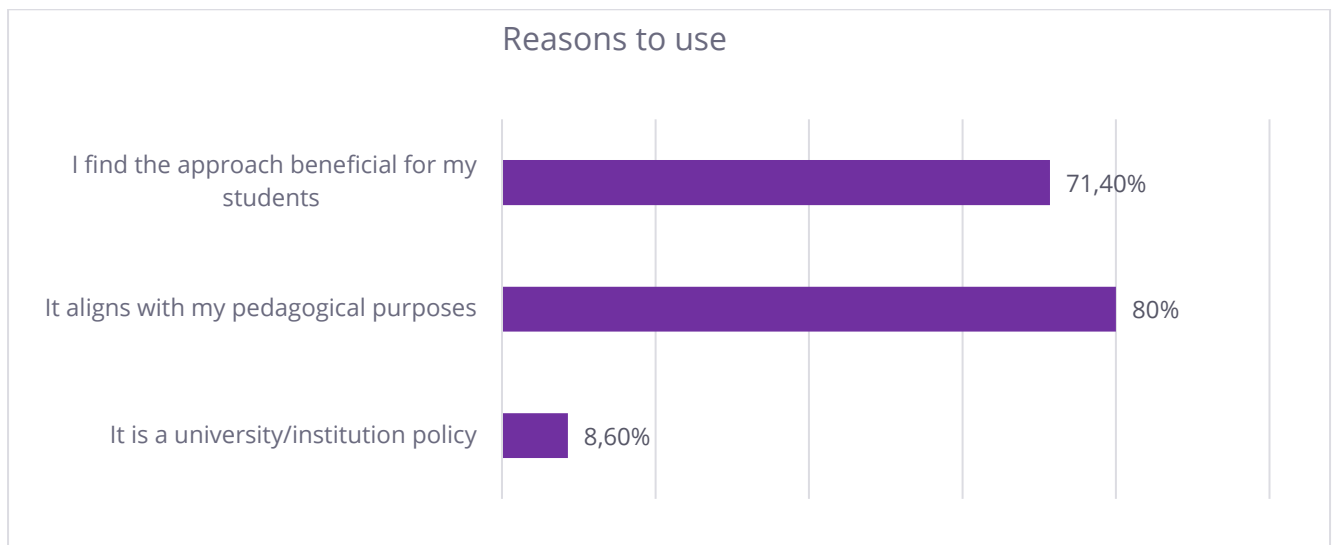


Figure 19. Participants' opinions about the facilitators related to applying personalised learning with the emerging technologies

The decisions for the personalisation process were made either only by the student (5.7% of respondents allow students to make such decisions), or by teachers (as is the case with 60% of respondents), or there had been shared control among teachers, students, systems (42.9% of respondents chose this answer).

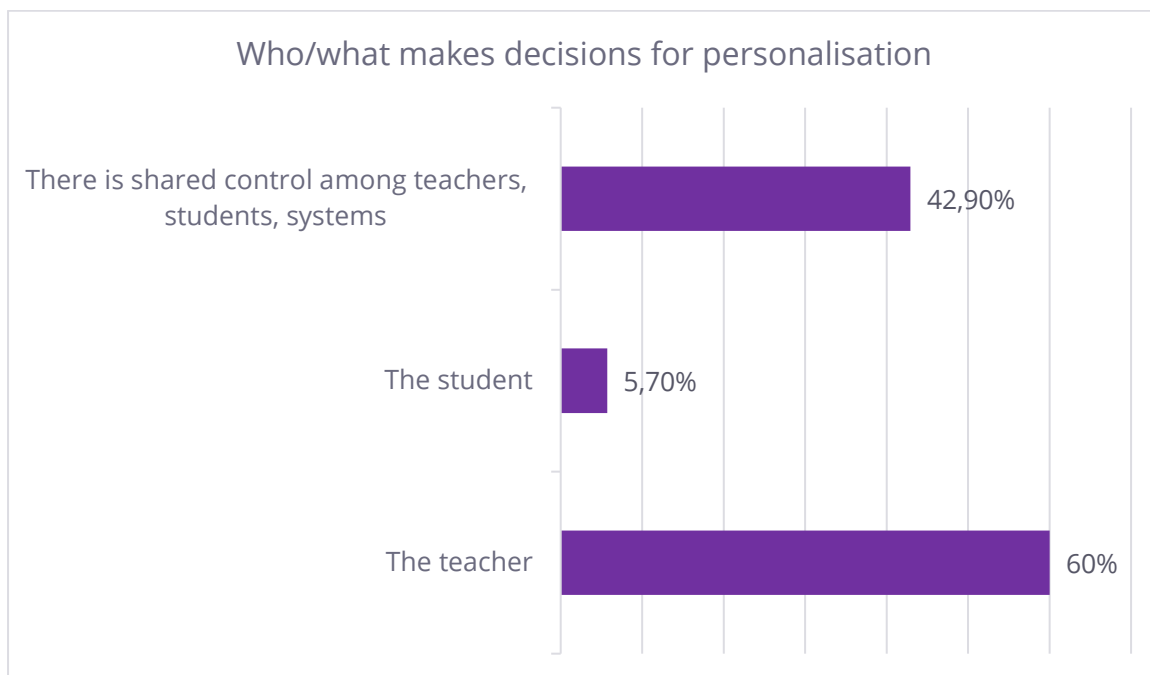


Figure 20. Participants' opinions about the facilitators related to applying personalised learning with the emerging technologies

The respondents agreed that there was some information based on which decisions for personalisation were made. 94.3% of them considered performance (skills acquired), 62.9% - psychology (i.e., motivation, preferences, interests), 60% - individual goals; 60% - cognition (i.e., mental processes). Only 20% of respondents considered data patterns (i.e., achieved scores, repeated behaviours), and 17% considered the demographic profiles (i.e., age, location).

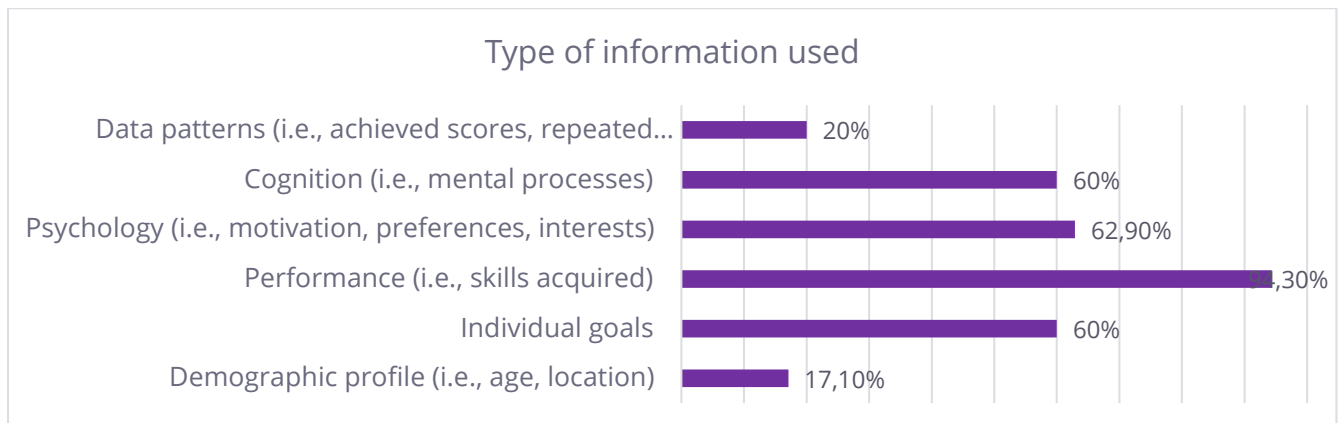


Figure 21. Participants' choices about the type of information used for personalisation

The previously mentioned adaptations appeared, for most of the respondents (54.3%) during the entire course. 37.1% of them said that adaptations occurred during the training process and 34.3% - during the entire program. Only 11.4% chose 'Before instruction' and 2.9% the option 'Within a course unit'.

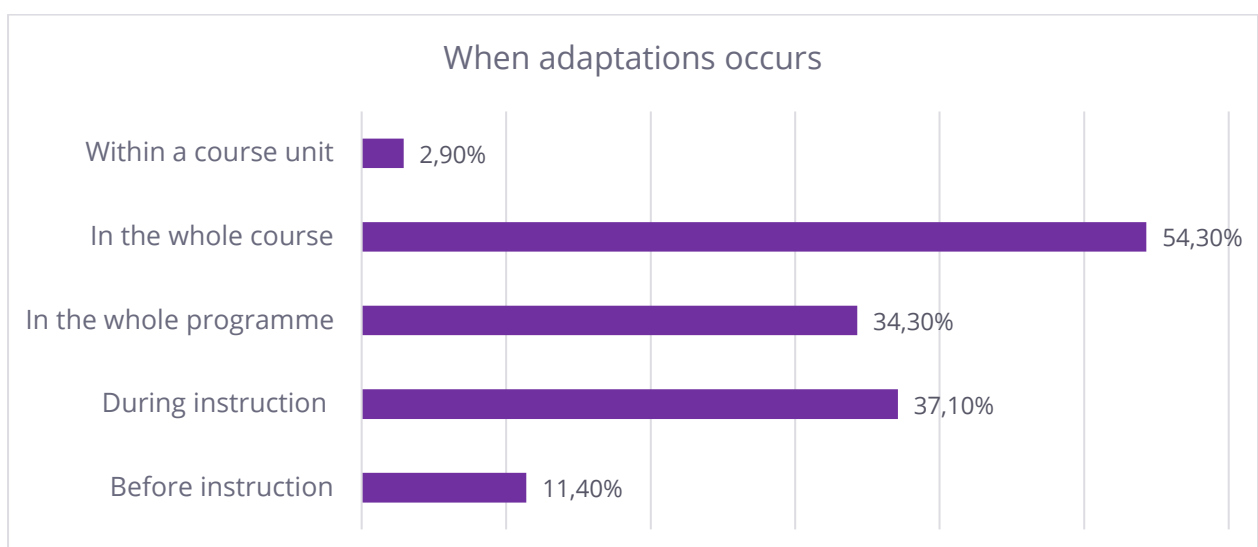


Figure 22. Participants' choices about the timing of personalisation.

The teachers and researchers who responded to this survey said that they mostly personalised and adapted:

- Teaching method (85.7%);
- Content presentation (77.1%);
- Support and guidance activities (71.4%);
- Content (68.6%).

In contrast, only 20% of respondents said they adjusted the time frame and 31.4% said they adjusted student work.

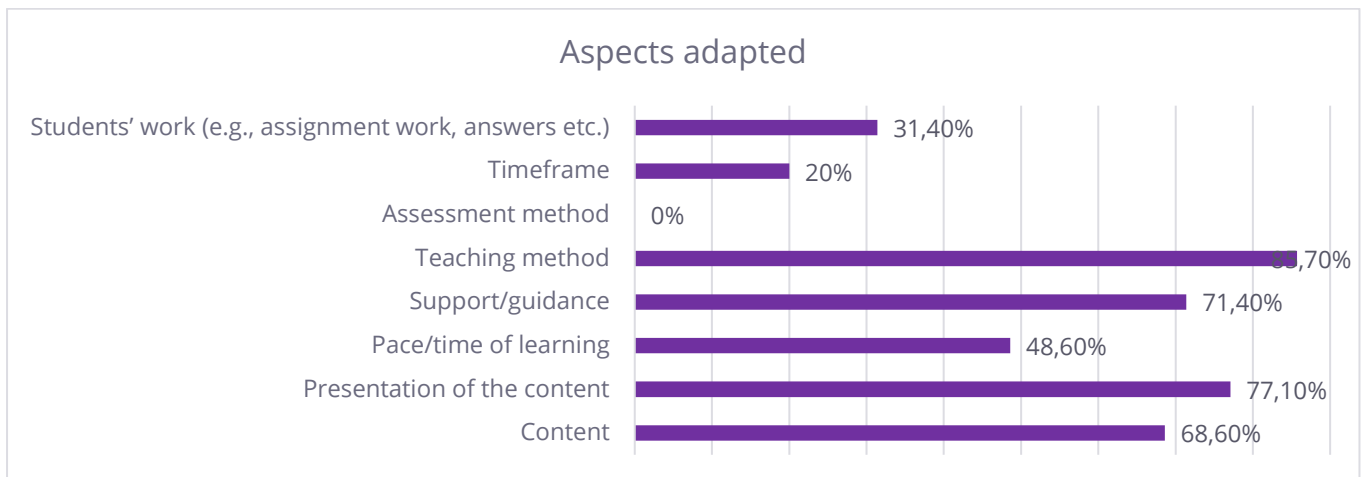


Figure 23. Participants' choices about the aspects adapted.

All the teachers and researchers who used these technologies in the classroom had observed some benefits for the student, the most important being:

- Increased motivation (65,7%);
- Increased engagement (62,9%);
- Improved performance (57,1%);
- Increased interaction among participants (54,3%);

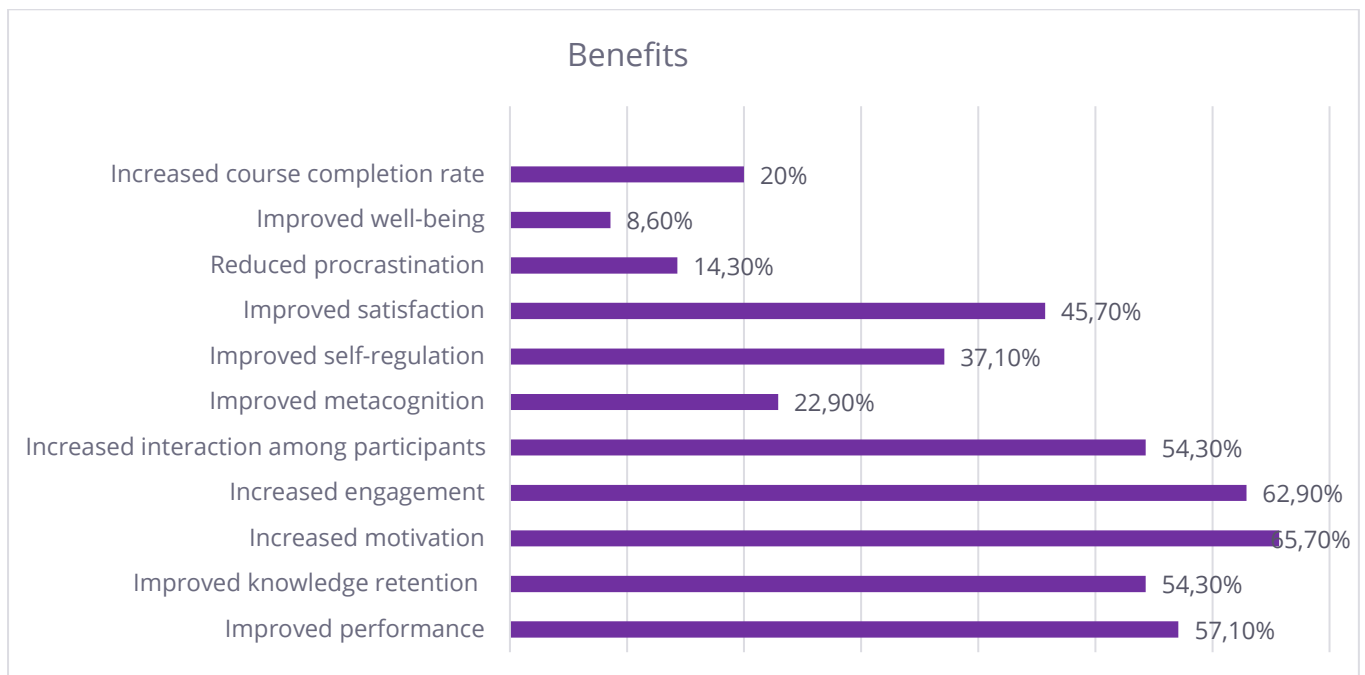


Figure 24. Participants' opinions about the benefits of applying personalised learning with the emerging technologies

However, teachers and researchers also faced challenges when using technologies for personalisation. Some of these challenges were:

- The difficulty of creating contents in a professional form;
- Lack of adapted devices;
- Lack of skills to use devices;
- The low level of adaptability of students;
- Lack of time to explore and apply technologies for personalisation in the classroom;
- Initial student reluctance.

Research in Portugal (Virtual Campus)

Focus group

Focus group information

Our focus group was made up of 3 professors, all from different fields of study. The originally proposed structure for the focus group was followed, using the ten questions in the "WP2 LEADER AI Toolkit Research Guidelines and Templates" made by the consortium of the project. The questions helped to outline the main topics of the discussion. The focus group was held in teams and had a duration of 30 minutes. The questions were translated to Portuguese

Focus group results

Participants' familiarity with terms

All of the participants said they were familiar with the concept. They added that personalised learning was learning that is more targeted to the type of student. They also consider that personalised learning creates the need to get away from classes in which only a general PowerPoint is presented to all students.

Strategies for personalisation

The answer to this question was negative from two professors, only one professor said they used Karrot in their theoretical-practical classes.

Awareness about “educational data”

The participants were not familiar with the term.

Data use for personalisation of learning

The participants did not use data.

Awareness of “Artificial Intelligence” (AI)

All the participants were aware of this term. The participants, often, did not use AI in their teaching. Only one said they used AI in the production of flashcards.

Use of AI tools in teaching

The participants said “no”.

Expectations for benefits and challenges

The participants pointed out that the use of Artificial Intelligence can accelerate personalised learning since AI will have the ability to provide personalisation tools. Teachers indicated as benefits the effectiveness of teaching, adaptive teaching, and the greater ease on the part of the students in acquiring knowledge. As challenges, the participants identified the elevated costs and the security of the data.

Questionnaire

Questionnaire information

Virtual Campus implemented the application of the online questionnaire that was translated to Portuguese to be easier to disseminate. The target audience was reached by e-mail and by the Virtual Campus' social media. As a result, 14 participants completed the questionnaire.

Questionnaire results

A total of 14 people filled in the questionnaire, with 7 of them being males and 7 of them females, with ages between 33 and 69 years old. The participants were equally divided between public university and private one and the majority work in HE institutions with more than 500 staff. Regarding the number of students, half of the participants said their institution had between 5 000 and 15 000 students. All the participants had a teaching position in the university and most of them had completed their doctorate.

In regards of their familiarity with the terms asked: half of the participants were very familiar (7) with the term "personalised learning". The term "educational data" was very familiar to half of the participants and, also, half were familiar with the term "learning analytics". 6 participants said they were familiar with the term "artificial intelligence" and 6 said they were more or less familiar with the same term.

In regards to using learning analytics, most participants said they often used it (10). The main reasons the staff did not use these technologies for personalisation was the lack of university/institution policy (8) and 6 participants highlighted the lack of staff training. The inquiry regarding who-what makes decisions for personalisation, was answered as follows: Most respondents (6) said that the teacher decided and 1 said that there was shared control among teacher, students and system. The participants noted that they personalised and adapted the pace/time of learning (1), the assessment method (1), the teaching method (2), support/guidance (2) and students' work (2). The participants mentioned the following benefits because of personalisation with the mentioned technologies: Many mentioned improved performance (1), increased motivation (3), and increased engagement (1). One also mentioned increased interaction among participants (1).

Chapter 3: Discussion

The literature review and mixed-methods national research uncovered practices related to the adoption of learning analytics (LA), artificial intelligence (AI), and personalised learning (PL) in higher education institutions (HEIs). In the literature so far, various research methodologies have been employed, including data analysis (when LA was the focus), surveys, interviews, and mixed methods approaches. For instance, some studies analysed students' behaviour patterns on platforms like Moodle and YouTube, while others explored opinions, perceptions, and expectations through surveys and interviews. A few papers were also theoretical, in line with the principles of Systematic Literature Review. The national research used mixed methods to exploit the benefits of both qualitative and quantitative approaches.

The definition of personalised learning varies across the literature, while most do not specifically refer to a definition. Personalisation was generally linked to student-focused learning that caters to individual needs, aligns with their strengths and modifies teaching and learning accordingly. The term was often used interchangeably with adaptation and differentiation. In all partner countries, the respondents in the field research agreed with the literature since they perceived personalisation as an approach that caters to students' individuality. It is worth mentioning that, to a certain extent, the concept of personalisation is still ambiguous. This is evident in Estonia and Greece. In Estonia, the participants talk more about self-driven learners and adaptive learning, referring to personalised learning as "finding a personal way to learn, using all kinds of technologies (including books and libraries)". In Greece, where, even if the participants were generally familiar with the concept of personalisation, they suggested that personalised learning is just another generic educational methodology; according to their own experience, there aren't any relative systematic initiatives in their national higher education context. Similar difficulties were faced by the Cypriot HE staff, who mentioned the problem of providing fully personalised teaching in higher education due to limited contact with students, time constraints, and lack of university-wide practices, training, and support.

Most studies did not extensively use AI or learning analytics for personalisation, but they used these technologies as general tools in the teaching and learning process. However, some studies incorporated AI models and learning analytics to identify students' digital behaviour and offer personalised support. The learning design processes might include developing adaptive hypermedia eLearning systems based on specific adaptivity criteria or manual (traditional)

approaches to personalisation, such as tailoring content and activities based on student's performance or preferences. Yet, a similar reluctance to use these emerging technologies is also reflected in all partner countries (Cyprus, Estonia, Greece, Romania, and Portugal). In most partner countries, the participants were primarily aware of "Educational Data" and "Artificial Intelligence" concepts. This does not equate, though, to direct use. For instance, although all focus group instructors were aware of educational data in Estonia, they hardly ever used it for personalised learning. In there, AI's weekly usage was higher than LA's, probably because AI is used for teaching rather than pedagogical decision-making. The main reason for scarce data use seems to be its limited value for the instructor's use. Similarly, in Greece and Portugal, though, the HEI staff had a significantly lower awareness of using learning analytics and AI in education.

On the one hand, the participants in the countries had been using strategies for personalisation such as spending time to get to know their students, offering personalised guidance, presenting material in different formats, adjusting the course organisation based on student response, monitoring/tracking and controlling the educational procedure in the context of blended, or online distance courses, using various LMS while experimenting with LA and AI tools. For instance, some participants mentioned AI tools like Duolingo, Speakly, Google Translator, DeepL, ChatGPT, Grammarly, and Turnitin, which assist in tasks such as editing texts, detecting plagiarism, and providing solutions to various questions they might have. However, they did not use these technologies specifically for personalisation, showing slower progress.

Of course, these technologies had both benefits and challenges. The European literature shows that learning analytics is associated with having insights into students' digital footprints to identify their motivation, studying patterns, interaction, and engagement, which help identify at-risk students and provide timely support (see Ciolacu et al., 2018; Gkontziz 2019; Guzsvinecz & Szucs, 2021; Hellings & Haelermans, 2020; Kadoić & Oreški, 2021). Kurilovas, 2018; Kurilovas & Kubilinskiene, 2020; ah & Ifenthaler, 2018; Rako et al., 2022; Renz et al., 2020; Tsai et al., 2020; van der Vorst & Jelcic, 2019). Such data are also combined with adaptive systems offering targeted recommendations to students, creating an adaptive learning environment, and focusing on students' success (see Algayres & Triantafyllou, 2020; Brdник et al., 2022; Mamčenko et al., 2019; van der Vorst & Jelcic, 2019). LA helps teachers provide students with performance feedback and learning recommendations while students themselves can self-reflect on their progress. As for AI per se, the literature review showed a connection with personalisation in the form of chatbots to engage students in personalised language learning and intelligent tutor

systems. In general, similar benefits were reported by the national field research participants. The participants highlighted several benefits of using AI tools, including time-saving, quick access to information, automation of tasks, improved thinking and structure, translation capabilities, and the opportunity for personalisation and communication. AI-driven tools seem to be linked to improved writing, editing, and thesis supervision.

Most challenges related to using these advanced technologies, as identified in the desk and field research, revolved around stakeholders' readiness, infrastructure and financial support, ethical concerns, and the tools' accuracy. A lot of instructors do not have time to explore and apply technologies for personalisation in their cohorts. In contrast, they and their students do not have adequate skills and awareness about both theory and practice (what and how, respectively). Both instructors and learners need higher-order thinking skills to evaluate and use these technologies effectively. Infrastructure is not present at this stage, as there is low equipment and technological support. At the same time, technical difficulties are present, as in other technologies so far (e.g., lack of translation and proper localisation, along with software bugs).

Given the presence of data and algorithms, there are issues with trustworthiness, credibility, accuracy, and validity, including both machine errors and reality distortion (e.g., fake photos, videos, misinformation) and human errors in interpreting the results. There is uncertainty about how to use AI tools (e.g., prompt writing), with participants stating that tools do not fit all purposes and have accessibility issues. This amplifies the negative attitude and scepticism of potential users while it might lead to potential harm in the form of plagiarism and misuse of AI-generated content. There are concerns related to privacy, personal data protection and power imbalance. Legislation at the national level to regulate its use, in line with European policy, is vital for trustworthy AI and data-based technologies that do not exacerbate exclusion or discrimination in any form.

In conclusion, adopting AI, analytics, and data-driven technologies for personalised learning in HEIs is still in its early stages. The studies highlighted these approaches' potential benefits and

challenges, emphasising the need for careful consideration and further exploration of their capabilities.

Conclusions and Recommendations

This study aimed to investigate the adoption of learning analytics (LA), artificial intelligence (AI), data-driven technologies and personalised learning (PL) in higher education institutions (HEIs). To achieve this aim, the project team conducted desk and field research at European and national levels.

The literature reviews revealed that using LA, AI, and data-driven technologies for PL in HEIs is still in its early stages, with various benefits and challenges associated with these approaches. The studies highlighted the potential of these technologies to provide insights into student motivation, studying patterns, engagement, and performance and offer personalised support and feedback based on student progress, preferences, and goals. However, the studies also emphasised the need for careful consideration and further exploration of these technologies' capabilities, accuracy, ethical implications, and infrastructure requirements. It is concluded that there is a need for more studies and/or practices that:

- evaluate the effectiveness, impact, and outcomes of using LA AI or data-driven technologies for PL in HEIs.
- compare different types of AI tools or LA applications for PL in terms of their accuracy, reliability, validity, usability, accessibility, affordability, scalability, interoperability, privacy, transparency, explainability, accountability, and fairness, among others.
- explore how different stakeholders such as instructors, students, administrators, policymakers, researchers, developers, and designers can collaborate, co-design, co-evaluate, and co-implement LA and AI-driven technologies for PL in HEIs.
- examine how different pedagogical approaches such as constructivism, cognitivism, connectivism, social learning, experiential learning, inquiry-based learning, project-based learning, game-based learning, etc., can be integrated or aligned with LA AI or data-driven technologies for PL in HEIs for a concrete learning design process.

Based on these gaps or limitations, the study provides the following recommendations for future research, policy, and practice:

- rigorous and robust experimental quasi-experimental or mixed-methods studies that measure and compare the effects of using different LA AI or data-driven technologies for PL in HEIs on various learning outcomes and indicators.
- holistic and systemic perspective that considers the interplay and interdependence of different LA, AI or data-driven technologies for PL in HEIs and the roles and responsibilities of various stakeholders.
- participatory and collaborative approach that involves and empowers different stakeholders and contextual factors in designing, developing, implementing, and evaluating LA, AI or data-driven technologies for PL in HEIs to provide adequate infrastructure.
- pedagogically driven and learner-centred approach that aligns and integrates different LA or AI-driven technologies for PL in HEIs with appropriate and effective teaching and learning strategies.
- effective teacher and student training and support that tackles theory and practice to recognise the nuances of personalised learning, AI, and LA and their interconnectedness.
- ethical guidelines and policies development and adoption on institution, national and European levels (all aligned with each other).

References

Amare, M. Y., & Šimonová, S. (2021b). Learning analytics for higher education: proposal of big data ingestion architecture. *SHS Web of Conferences*, 92, 02002.

<https://doi.org/10.1051/shsconf/20219202002>

Andersen, R., Mørch, A. I., & Litherland, K. T. (2022). Collaborative learning with block-based programming: investigating human-centered artificial intelligence in education. *Behaviour & Information Technology*, 41(9), 1830–1847. <https://doi.org/10.1080/0144929x.2022.2083981>

Apiola, M., Karunaratne, T., Kaila, E. & Laakso, M-J. (2019). Experiences from digital learning analytics in Finland and Sweden: a collaborative approach. 2019 *42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, Opatija, Croatia, 2019, (pp. 627-632), <https://doi.org/10.23919/MIPRO.2019.8757204>

- Bogdan R. & Biklen, S. (1994). *Investigação qualitativa em educação*. Porto Editora.
- Bogdan, R. & Biklen, S. (2013). *Investigação Qualitativa em Educação*. Porto Editora.
- Belda-Medina, J., & Calvo-Ferrer, J. R. (2022). Using chatbots as AI conversational partners in language learning. *Applied Sciences*, 12(17), 8427. <https://doi.org/10.3390/app12178427>
- Bjælde, O. E., & Lindberg, A. B. (2018). Using continuous assessment with feedback loops to generate useful data for learning analytics. In M. Campbell, J. Willems, C. Adachi, D. Blake, I. Doherty, S. Krishnan, S. Macfarlane, L. Ngo, M. O'Donnell, S. Palmer, L. Riddell, I. Story, H. Suri, & J. Tai (Eds) *35th International conference of innovation, practice and research in the use of educational technologies in tertiary education* (pp 53-62). ASCILITE.
[https://pure.au.dk/portal/en/publications/using-continuous-assessment-with-feedback-loops-to-generate-useful-data-for-learning-analytics\(282128ee-b4bf-4a4a-9e76-6c1106fac62b\).html](https://pure.au.dk/portal/en/publications/using-continuous-assessment-with-feedback-loops-to-generate-useful-data-for-learning-analytics(282128ee-b4bf-4a4a-9e76-6c1106fac62b).html)
- Brdnik, S., Šumak, B., & Podgorelec, V. (2022). Aligning learners' expectations and performance by learning analytics system with a predictive model. *ArXiv (Cornell University)*.
<https://doi.org/10.48550/arxiv.2211.07729>
- Bucea-Manea-Țoniș, R., Kuleto, V., Gudei, S.C.D., Lianu, C., Lianu, C., Ilić, M. P., & Păun. D. (2022). Artificial intelligence potential in higher education institutions enhanced learning environment in Romania and Serbia. *Sustainability*, 14(10), 5842.
<https://doi.org/10.3390/su14105842>
- Bunting, L., af Segerstad, Y. H., & Barendregt, W. (2021). Swedish teachers' views on the use of personalised learning technologies for teaching children reading in the English classroom. *International Journal of Child-Computer Interaction*, 27, 100236.
<https://doi.org/https://doi.org/10.1016/j.ijcci.2020.100236>
- Chounta, I., Bardone, E., Raudsep, A., & Pedaste, M. (2021). Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in Estonian K-12 education. *International Journal of Artificial Intelligence in Education*, 32(3), 725–755.
<https://doi.org/10.1007/s40593-021-00243-5>
- Ciolacu, M., Tehrani, A. F., Binder, L. and Svasta, P.M. (2018). Education 4.0 - Artificial Intelligence Assisted Higher Education: Early recognition System with Machine Learning to support Students' Success. IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), Iasi, Romania, 2018, 23-30. doi: 10.1109/SIITME.2018.8599203
<https://ieeexplore.ieee.org/document/8599203>
- Cope, B., & Kalantzis, M. (2023). Generative AI comes to school (GPT and all that fuss): what now?, *Educational Philosophy and Theory*, (forthcoming).

https://cgscholar.com/community/community_profiles/new-learning/community_updates/168819

Dias, A. A. & Gomes, M.J. (Eds.). (2004). E-learning para e-formadores. TecMinho.

Dijksterhuis, E., & Silvius, G. (2022). The design thinking approach to projects. *The Journal of Modern Project Management*, 4(3).

<https://journalmodernpm.com/manuscript/index.php/jmpm/article/view/JMPM01205>

Gkontzis, A. F., Panagiotakopoulos, C. T., Kotsiantis, S., & Verykios, V. S. (2018). Measuring engagement to assess performance of students in distance learning. *2018 9th International Conference on Information, Intelligence, Systems and Applications (IISA)*, 1–7.

<https://doi.org/10.1109/IISA.2018.8633607>

Gkontzis, A. F. (2019). *A big data analytics framework to support adaptive and personalized learning environments*. <https://apothesis.eap.gr/archive/item/160648>

Gubiani, D., Cristea, I., & Urbančič, T. (2020). Introducing e-learning to a traditional university: a case-study. *Studies in Systems, Decision and Control*, 225–241. https://doi.org/10.1007/978-3-030-18593-0_18

Guzsvinecz, T. & Szucs, J. (2021). Using analytics to identify when course materials are accessed relative to online exams during digital education, *Education Sciences*, 11, 576.

<https://doi.org/10.3390/educsci11100576>

Hellings, J., & Haelermans, C. (2022). The effect of providing learning analytics on student behaviour and performance in programming: a randomised controlled experiment. *Higher Education*, 83, 1–18. <https://doi.org/10.1007/s10734-020-00560-z>

Herbert Simon Personalized Learning Laboratory (Research center of user experience and interaction UXI@FIIT, Faculty of Informatics and Information Technologies from the Slovak University of Technology in Bratislava - STU). https://www.stuba.sk/english/science-and-research/other-research-centres-and-laboratories/herbert-simon-personalized-learning-laboratory.html?page_id=10594

Holmes, W., Anastopoulou S., Schaumburg, H. & Mavrikis, M. (2018). Technology-enhanced personalised learning: untangling the evidence. Robert Bosch Stiftung. <http://www.studie-personalisiertes-lernen.de/en/>

Ifenthaler, D., Mah, D., & Yau, J. Y. (2019). Utilizing learning analytics to support study success. In *Springer eBooks*. <https://doi.org/10.1007/978-3-319-64792-0>

- Kadoić, N. & Oreški, D. (2021). Learning analytics of YouTube videos linked to LMS Moodle, *44th International Convention on Information, Communication and Electronic Technology (MIPRO)* (pp 570-575). IEEE. <https://doi.org/10.23919/MIPRO52101.2021.9597168>
- Kazoun, N., Kokkinaki, A. I., & Chedrawi, C. (2022). Factors that affects the use of ai agents in adaptive learning: a sociomaterial and mcdonaldization approach in the higher education sector. In *Springer eBooks* (pp. 414–426). https://doi.org/10.1007/978-3-030-95947-0_29
- Keller, B., Baleis, J., Starke, C., & Marcinkowski, F. (2019). Machine learning and artificial intelligence in higher education: a state-of-the-art report on the German university landscape. Heinrich-Heine-Universität Düsseldorf. 1-31.
https://scholar.google.com/citations?view_op=view_citation&hl=fr&user=KUg7olUAAAAJ&citation_for_view=KUg7olUAAAAJ:d1gkVwhDpl0C
- Khan, P. F., & Bose, D. (2021). Artificial Intelligence enabled Smart Learning. *ETH Learning and Teaching, ICED 2020 Proceedings*, 153-156. <https://doi.org/10.48550/arXiv.2101.02991>
- Khor, Ean Teng, and Mutthulakshmi K. (2024). A Systematic Review of the Role of Learning Analytics in Supporting Personalized Learning, *Education Sciences*, 14(1), 51.
<https://doi.org/10.3390/educsci14010051>
- Kurilovas, E. (2018). Advanced machine learning approaches to personalise learning: learning analytics and decision making. *Behaviour & Information Technology*, 38(4), 410-421,
<https://www.tandfonline.com/doi/full/10.1080/0144929X.2018.1539517>
- Kurilovas, E., & Kubilinskiene, S. (2020). Lithuanian case study on evaluating suitability, acceptance and use of it tools by students – an example of applying technology enhanced learning research methods in higher education. *Computers in Human Behavior*, 107,
<https://doi.org/10.1016/j.chb.2020.106274>
- Ley, T., Tammets, K., Pishtari, G., Chejara, P., Kasepalu, R., Khalil, M., Saar, M., Tuvi, I., Väljataga, T., & Wasson, B. (2023). Towards a partnership of teachers and intelligent learning technology: A systematic literature review of model-based learning analytics. *Journal of Computer Assisted Learning*, 39(5), 1397–1417. <https://doi.org/10.1111/jcal.12844>
- Liu, S., Chen, Y., Huang, H., Xiao, L., & Hei, X. (2018). Towards Smart Educational Recommendations with Reinforcement Learning in Classroom. *Proceedings of the 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, 1079–1084. <https://doi.org/10.1109/TALE.2018.8615217>

- Logan-Phelan, T. (2018). The buzz around learning analytics – Enablers and challenges identified through the #VLEIreland project. *Irish Journal of Technology Enhanced Learning*, 3(2). 77- 85.
<https://doi.org/10.22554/ijtel.v3i2.46>
- Ma J., Park S., Shin J., Kim N., Seo J., Lee J., & Sa J. (2018). AI based intelligent system on the EDISON platform. *Proceedings of the 2018 Artificial Intelligence and Cloud Computing Conference*, 106-114. <https://doi.org/10.1145/3299819.3299843>
- Mah, D.-K., & Ifenthaler, D. (2018). Students' perceptions toward academic competencies: *The case of German first-year students. Issues in Educational Research*, 28(1), 120-37.
<http://www.iier.org.au/iier28/mah.pdf>
- Mamčenko, J., Kurilovas, E., Krikun, I. (2019). On application of case-based reasoning to personalise learning. *Informatics in Education - An International Journal*, 18(2), 345-358.
<https://www.ceeol.com/search/article-detail?id=804179>
- Marković, M., Kadoić, N., & Kovačić, B. (2018). Selection and prioritization of adaptivity criteria in intelligent and adaptive hypermedia e-learning systems. *TEM Journal*, 7(1), 137-146.
<https://doi.org/10.18421/tem71-16>
- Moltudal, S., Høydal, K., & Krumsvik, R. J. (2020). Glimpses into real-life introduction of adaptive learning technology: a mixed methods research approach to personalised pupil learning. *Designs for Learning*, 12(1), 13-28. <https://doi.org/10.16993/df.138>
- Moşteanu, N. R. (2022). Machine learning and robotic process automation take higher education one step further. *Romanian Journal of Information Science and Technology*, 25(1), 92-99.
<http://www.romjist.ro/contents-88.html>
- Nouri, J., Ebner, M., Ifenthaler, D., Saqr, M., Malmberg, J., Khalil, M., Bruun, J., Viberg, O., González, M. Á. C., Papamitsiou, Z., & Berthelsen, U. D. (2019). Efforts in Europe for data-driven improvement of education – a review of learning analytics research in seven countries. *International Journal of Learning Analytics and Artificial Intelligence for Education*, 1(1), 8.
<https://doi.org/10.3991/ijai.v1i1.11053>
- Nguyen, A., Lämsä, J., Dwiarie, A., & Järvelä, S. (2023), Lifelong learner needs for human-centered self-regulated learning analytics", *Information and Learning Sciences*,
<https://doi.org/10.1108/ILS-07-2023-0091>
- Opincariu, M. (2019). Education in the 5G and the AI Context. *Journal Plus Education*, 97-103.
<https://www.uav.ro/jour/index.php/jpe/article/view/1266>

- Rako, S.; Šimić, D. and Rienties, B. (2022). Supporting self-regulated learning in a blended learning environment using prompts and learning analytics. In *CEUR Workshop Proceedings*, 3292 (pp. 66–71). https://ceur-ws.org/Vol-3292/DCECTEL2022_paper09.p...
- Renz, A., Krishnaraja, S., & Gronau, E. (2020). Demystification of artificial intelligence in education – how much ai is really in the educational technology?. *International Journal of Learning Analytics and Artificial Intelligence for Education (ijAI)*, 2(1), 14–30. <https://doi.org/10.3991/ijai.v2i1.12675>
- Statement of the Slovak Accreditation Agency for Higher Education, 17/02/2023. <https://saavs.sk/en/statement-of-the-slovak-accreditation-agency-for-higher-education/>
- Smyrnova-Trybulska, E., Morze, N., & Varchenko-Trotsenko, L. (2022). Adaptive learning in university students’ opinions: Cross-border research. *Education and Information Technologies*, 27(5), 6787–6818. <https://doi.org/10.1007/s10639-021-10830-7>
- Toprceanu, A., & Grosseck, G. (2017). Decision tree learning used for the classification of student archetypes in online courses. *Procedia Computer Science*, 112, 51–60. <https://doi.org/10.1016/j.procs.2017.08.021>
- Trindade, A.R. (coord.). (2001). *New learning*. UAb.
- Tsai, Y. S., Rates, D., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Jivet, I., Scheffel, M., Drachsler, H., Kloos, C. D., & Gašević, D. (2020). Learning analytics in European higher education—Trends and barriers. *Computers and Education*, 155, 103933. <https://doi.org/10.1016/j.compedu.2020.103933>
- van der Vorst, T. & Jelacic, N. (2019). Artificial intelligence in education: Can AI bring the full potential of personalized learning to education?, *30th European Regional ITS Conference, Helsinki 2019 205222*. International Telecommunications Society (ITS). <http://hdl.handle.net/10419/205222>
- Velander, J., Taiye, M. A., Otero, N., & Milrad, M. (2023). Artificial Intelligence in K-12 Education: eliciting and reflecting on Swedish teachers’ understanding of AI and its implications for teaching & learning. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-023-11990-4>
- Vrkić, D. (2019). Learning analytics and academic libraries in Croatia - are we ready for it?, *42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)* (pp. 812-817). IEEE. <https://doi.org/10.23919/MIPRO.2019.8756857>

Zhang, L., Basham, J. D., & Yang, S. (2020). Understanding the implementation of personalized learning: a research synthesis. *Educational Research Review*, 31, 100339.

<https://doi.org/10.1016/j.edurev.2020.100339>

ANNEX 1 Questionnaire

Description

This survey is conducted as part of the Erasmus+ Programme – “LEADER AI: LEarning analytics and AI for personalised LEarning”.

The project aims to address the need for effective Higher Education (HE) digital learning that responds to students’ needs, strengths, and skills, through the proper exploitation of advanced technologies (i.e., Artificial Intelligence, analytics). To better understand the current practices, needs and challenges, we ask HE staff (instructors, researchers, academics, eLearning designers, developers), to provide us with some feedback through this survey. We kindly ask you to answer honestly and base your answers on your experiences. The estimated time to complete this questionnaire is 10 minutes.

GDPR: All data gathered through this survey will be strictly used explicitly for the research. The responses will be handled in a discreet manner, and responses are completely anonymous. The answers will be saved in a properly secured place, with no authorization to anyone apart from the Research Team. Our consortium complies with the GDPR regulation and the protection and processing of personal data.

For any inquiries, feel free to contact representatives of the research team:
nisiforou.e@unic.ac.cy, konstantinidou.a6@live.unic.ac.cy

CONSENT. By clicking the "Agree" button, you indicate that: you have read all the information above, the privacy policy and you agree to participate voluntarily, you are at least 18 years old. If you do not wish to participate in this survey, please click the "disagree" button.

- Agree
- Disagree

Demographic data

Country (place of work):

- Cyprus
- Greece
- Estonia
- Portugal
- Romania

Gender:

- Male
- Female
- Non-binary
- I prefer not to say

Age: (open ended)

What is the type of your Higher Education Institution?

- Public university
- Private university

Number of staff in your institution:

- ≤ 500
- ≥ 500
- I do not know

Number of students in your institution:

- Less than 5,000 students
- 5,000 – 15,000
- More than 15,000
- I do not know

What is your job position in the university? Select all that apply.

- Researching
- Teaching
- Leadership
- Learning/Instructional design
- eLearning development

What is your highest degree of formal education?

- Professional diploma
- Bachelor's Degree or equivalent
- Master's Degree
- Doctorate
- Post-doctoral

How familiar are you with the following terms? (Not at all familiar, Slightly familiar, Moderately familiar, Very familiar, Extremely familiar)

- Personalised learning
- Educational data

- Learning analytics
- Artificial Intelligence

How often do you use these technologies for personalisation? (Daily, Weekly, Monthly, Annually, Never)

- Learning analytics (i.e., collect, analyse, interpret data to make decisions)
- Artificial Intelligence (e.g., chatbot, intelligent tutor system, adaptive learning pathways)

Could you provide a specific example? (open ended)

Which of the following are barriers for not using these technologies for personalisation? Select all that apply.

- Lack of university/institution policy
- Lack of staff training offered
- Lack of university support (e.g., technical team)
- Lack of adequate infrastructure (e.g., technology tools)
- I do not trust in new technologies
- I do not have the required skills/knowledge
- I do not have time to explore these tools for personalisation
- None of the above

Why do you use these technologies for personalisation? Select all that apply.

- It is a university/institution policy
- It aligns with my pedagogical purposes
- I find the approach beneficial for my students
- Not applicable (N/A)

Who/what makes decisions for personalisation? Select all that apply.

- The teacher (e.g., adapting the method)
- The student (e.g., adapting their goals)
- The system (e.g., adapting the content presented)
- There is shared control among teachers, students, systems
- N/A

Based on what type of student information are the decisions for personalisation made? Select all that apply.

- Demographic profile (i.e., age, location)
- Individual goals

- Performance (i.e., skills acquired)
- Psychology (i.e., motivation, preferences, interests)
- Cognition (i.e., mental processes)
- Data patterns (i.e., achieved scores, repeated behaviours)
- N/A

When do the adaptations occur? Select all that apply.

- Before instruction
- During instruction
- In the whole programme
- In the whole course
- Within a course unit
- N/A

When personalisation occurs, what aspect is adapted? Select all that apply.

- Content
- Presentation of content
- Pace/Time of learning
- Support/guidance
- Teaching method
- Assessment method
- Assessment timeframe
- Students' work (e.g., assignment work, answers etc.)
- Feedback
- N/A

Have you spotted any of these benefits as a result of personalisation with these technologies? Select all that apply.

- Improved performance
- improved knowledge retention
- Increased motivation
- Increased engagement
- Increased interaction among participants
- Improved self-regulation
- Improved satisfaction
- Reduced procrastination
- Improved well-being
- Increased course completion rate
- I haven't seen any benefits

Have you spotted any drawbacks, as a result of personalisation with these technologies? (open ended)

Any challenges you face when using these technologies for personalisation? (open ended)

ANNEX 2 Focus group

Each partner will conduct a **focus group** with members of the target groups – **8 members per partner**. The focus group shall not exceed 30 – 40 minutes. The aim is to collect data regarding the readiness of HEIs (current state, practices followed and what is needed). The research questions take the form of semi-structured questions, and each partner can slightly adjust the list according to their needs.

The examples in the brackets next to the questions are there for guidance and clarification to the interlocutors. Make sure that you do not “direct” participants to specific answers.

The target groups include:

- Higher education faculty and staff (leadership teams, instructors/lecturers, academics, researchers, learning scientists, Ph.D. Candidates)
- Learning designers and educational technologists

Semi-structured Questions

Please adjust the below suggested list of semi-structured questions based on your target group needs. The word “you” refers to both individual and university-wide practices.

1. Are you aware of the term personalised learning (or individualised, customised)? What do you think it refers to?
2. When teaching online (distant or blended mode), do you apply strategies for personalisation? If yes, could you give examples?
3. Are you aware of the term “educational data”?
4. Do you use data (e.g., LMS log data) for personalisation of learning? If yes, how?
[if Q4 does not lead to learning analytics]:
 - Do you use learning analytics (data collection, analysis, report and action) for personalisation? If yes, how?
5. Are you aware of the term “Artificial Intelligence” (AI)?
6. Do you use any AI tools in your teaching? In what way?
7. Do you use any AI tools for personalisation? In what way?

8. *If they **use** learning analytics and AI tools:*
 - a) Are there any benefits related to the use of these technologies? If yes, please elaborate
 - b) Are there any challenges related to the use of these technologies? If yes, please elaborate
9. *If they are **not using** learning analytics and AI tools:*
 - c) What do you think about using these technologies?
 - d) Do you expect any benefits?
 - e) Do you expect any challenges?
10. *If **not extracted** from Q7 and 8:*
 - f) What are your needs when it comes to using these technologies for personalised learning?

