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Personalisation of Education

Enhancing Equity, Learner Agency and Academic Success

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Introduction

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Personalisation has become one of the central ambitions of contemporary higher education, particularly in online and distance learning. The shift towards flexible, digitally enhanced education offers unprecedented opportunities to respond to learner diversity — enabling students to progress at their own pace, follow pathways aligned with their goals, and engage with content that matches their prior knowledge and preferences. At the same time, these opportunities raise challenges for universities, requiring new pedagogical approaches, institutional strategies, technologies, and ethical frameworks.

Recognising the strategic importance of this topic, EADTU established the Task Force (TF) on Personalisation of Education in 2024. This task force brings together experts from thirteen EADTU member universities and associations across the EU, as well as partners from Canada (Université TÉLUQ), the United Kingdom (the Open University) and Turkey (Anadolu University). Its members contribute expertise in pedagogy, curriculum design, educational technology, learning analytics, and artificial intelligence, ensuring that the work is informed by both cutting-edge research and practical institutional experience.

The TF was convened to share experiences, identify good practices, and co-develop a reference model for personalisation that can guide institutions in designing meaningful, scalable, and inclusive approaches. Over the course of its meetings and peer-learning activities, the task force explored how universities can define personalisation, address diverse learner profiles, integrate technological solutions, and create organisational conditions that support its sustainable implementation.

This report synthesises the work of the TF, presenting both a knowledge base and a strategic guide for higher education institutions seeking to advance their efforts in personalisation. It captures conceptual foundations, institutional practices, and technological enablers, aiming to inspire member institutions and the wider higher education community to adopt approaches that enhance engagement, equity, and learner success.

Structure of the Report

This report is organised into six chapters that collectively provide guidance for understanding and implementing personalisation in online and distance higher education.

- **Chapter 1** sets the scene by clarifying what personalisation means in the context of online and distance higher education, exploring its pedagogical foundations and distinguishing it from related approaches.

- **Chapter 2** moves to the institutional level, examining strategies, frameworks, and maturity models that support the implementation of personalisation and discussing the challenges institutions face.
- **Chapter 3** looks at the technological dimension, describing tools and systems — including AI, analytics, and adaptive environments — that enable personalised learning at scale.
- **Chapter 4** focuses on curriculum design, showing how personalisation can be embedded into programmes and courses through flexible pathways, learner agency, and innovative approaches to assessment.
- **Chapter 5** addresses the ethical dimension of personalisation, highlighting issues of privacy, transparency, bias, and human oversight.
- **Chapter 6 o**ffers a conclusion and reflection, synthesising the insights from the previous chapters and highlighting overarching lessons.
- Finally, **Chapter 7** provides practical guidelines and recommendations for institutions and policymakers, with a focus on sustainable and responsible implementation of personalisation.

Together, these chapters offer a comprehensive roadmap for institutions seeking to translate the ambition of personalisation into actionable strategies that enhance student success and equity.

Looking Ahead: Enhancing Equity, Learner Agency, and Academic Success

Personalisation is shaping the future of higher education. As universities adopt more flexible and hybrid learning models, the ability to provide individualised pathways will increasingly define educational quality. The work of the TF shows that personalisation can enhance equity by addressing diverse learner needs, foster agency by giving students voice and choice, and strengthen academic success through higher achievement, employability, and lifelong learning. These benefits, however, depend on robust institutional strategies, ethical use of data, and ongoing professional development for educators.

By combining conceptual insights, practical examples, and strategic perspectives, this report seeks to inspire universities to design learner-centred approaches that not only advance academic outcomes but also prepare students for lifelong learning in a complex and rapidly evolving world.

1. Personalisation in the context of Online and Distance Higher Education

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Introduction

In recent years, personalisation has emerged as a cornerstone of educational transformation, especially in online and distance learning environments. Within the broader context of this report, which explores digital transformation and innovation in higher education, personalisation represents a key area where pedagogy, technology, and learner diversity converge. As higher education institutions worldwide continue to adopt and expand flexible and digital learning models, the possibility to tailor educational experiences to individual learners' needs, preferences, and circumstances has become increasingly apparent. This chapter examines how personalisation is conceptualised and implemented in online and distance higher education (ODHE), analysing its pedagogical foundations, technological enablers, and strategic implications.

The concept of personalised learning (PL) has gained prominence in education policy, institutional strategies, and academic research. However, despite its widespread use, there is still limited consensus on its definition and operationalisation (Walkinton & Bernacki, 2020; Zhang et al., 2020). In some cases, personalisation is broadly understood as any educational effort that seeks to adjust instruction to learners' individual traits. In others, it refers specifically to technologically mediated adaptations based on data-driven profiling. Bartolomé et al. (2018) emphasise that PL is a multifaceted and complex construct, whose theoretical and empirical development has spanned several decades. While early research highlighted pedagogical intentions, more recent approaches often privilege technological innovation, potentially weakening the pedagogical grounding of PL initiatives.

Educational researchers typically define personalisation in relation to students' interests, prior knowledge, and learning goals, aiming to increase engagement and improve learning outcomes (Spector, 2015). Meanwhile, in fields such as computer science and engineering, personalisation regularly focuses on learning styles and preferences—an approach that, while innovative, has been questioned for its lack of empirical validation (Bernacki et al., 2021). Furthermore, the literature reveals a fragmented landscape, where PL is approached through multiple disciplinary lenses, often without a shared theoretical foundation. As Shemshack and Spector (2020) point out, this lack of coherence underscores the need for a robust conceptual framework to guide research and practice in personalisation.

In the context of ODHE, personalisation takes on particular relevance. Online environments naturally offer flexibility in terms of time, space, and pace, making them ideal for adapting instruction to learner needs. However, this flexibility also poses challenges—particularly in ensuring meaningful engagement, learner autonomy, and sustained motivation. In this regard, PL can provide powerful strategies to enhance the online learning experience by incorporating adaptive learning technologies, intelligent tutoring systems, learning analytics, and AI-driven tools. These technologies enable real-time adjustments to content, feedback, and learning pathways, aligning the educational experience more closely with each learner's trajectory (Nguyen & Nguyen, 2023; Bayly-Castaneda et al., 2024).

This chapter has three main objectives. First, it aims to clarify the concept of personalised learning by reviewing definitions, key components, and current debates. Second, it examines the similarities and differences between personalised and adaptive learning, identifying points of convergence and distinction. Third, it explores how personalisation is being implemented in ODHE through the use of learning analytics and AI, while also reflecting on the challenges, ethical implications, and practical strategies for effective adoption.

The chapter is organised into five sections. *Section 1.1* introduces and contextualises the concept of personalisation, including a review of key literature. *Section 1.2* analyses the relationship between personalised and adaptive learning, clarifying conceptual overlaps and differences. *Section 1.3* discusses related terms such as differentiated and individualised learning, situating them within the broader framework of PL. *Section 1.4* explores the role of artificial intelligence in enabling PL, with a focus on adaptive systems and machine learning. *Section 5* highlights the contributions of learning analytics to PL design, followed by recommendations and implications for educational practice and policy. The chapter concludes with reflective questions to support further discussion and inquiry into the future of personalisation in ODHE.

Addressing these dimensions, the chapter contributes to a more nuanced and critical understanding of how personalisation can shape the future of online and distance higher education, enhancing equity, learner agency, and academic success.

1.1 Personalisation

Conceptualisation of personalised learning

Personalised Learning (PL) has emerged as a key approach in contemporary education due to its ability to address student diversity, adapt to individual preferences and needs, and leverage advanced technologies such as Artificial Intelligence (AI) (Nguyen & Nguyen, 2023; Xie et al., 2019). Studies highlight PL's effectiveness not only in improving academic performance, student engagement, and motivation, but also in narrowing educational gaps and promoting more equitable learning experiences (Bayly-Castaneda et al., 2024; Walkinton & Bernacki, 2021).

According to Bernacki et al. (2021), one of the most influential definitions of PL comes from the U.S. Department of Education's Office of Educational Technology (2016). It defines personalisation as a student-centred approach that adapts instruction to individuals' needs, preferences, and interests by adjusting learning goals, content, methods, pace, flexible pathways, and strategic technology use. Nguyen and Nguyen (2023) note that this definition has served as a foundation for many research efforts and practices in the field, with a significant rise in publications on the topic since 2011.

Spector (2015) expands the concept of personalisation, considering it a broad set of practices that involve adjusting learning activities and resources based on individual or group parameters. PL thus adapts both content and instructional methods to students' preferences, needs, prior knowledge, and learning pace, which requires adaptive learning environments based on learning analytics, dynamic feedback, and student modelling (Shemshack & Spector, 2020; Spector, 2015).

Zhang et al. (2020) offer an emerging definition of PL as a systematic design focused on tailoring teaching to students' strengths, preferences, needs, and goals. This approach promotes comprehensive educational experiences, supporting flexibility in what is learned, how it is learned, and how learning is demonstrated. It also emphasises the use of technology to improve access and quality, support educators, and strengthen school tech infrastructures.

Other studies, like those by Peng et al. (2019), introduce adaptive personalised learning as an approach that combines adaptive pedagogical strategies and advanced technology to dynamically adjust teaching methods. This includes accounting for individual differences (strengths, preferences, motivations), individual performance (student progress and learning goals), and personal development (interests and desires), through adaptive adjustments. This approach includes learning profiles, student progress tracking, and strategic adjustments based on continuous analysis.

Definitions of PL vary across pedagogical approaches, sets of practices, or educational strategies. For instance, Cheng and Wang (2020) view PL as a pedagogical approach that allows students to reach their goals at their own pace, emphasising individual differences. Bernacki et al. (2021) define it as an educational practice that addresses students' needs. Khor and Mutthulakshmi (2024) describe PL as an educational strategy that adapts pacing, content, and teaching to learners' specific needs and interests. However, Nguyen and Nguyen (2023) caution that despite theoretical advances, PL remains an ambiguous concept in some studies, often functioning as an umbrella term for educational strategies aiming to be fair and adaptable to learners' capacities and needs (Schmid & Petko, cited in Nguyen & Nguyen, 2023).

Goals and roles in personalised learning

Broadly speaking, Personalised Learning (PL) aims to tailor the educational experience to the individual strengths, needs, and interests of each student (Bernacki et al., 2021). This approach necessitates a flexible learning process and encourages active student participation in determining the content, methods, timing, and context of their learning. According to Cheng and Wang (2020), the primary objective of PL is to enable learners to achieve educational goals at their own pace, thereby enhancing effectiveness through the customisation of pedagogical strategies to align with each learner's unique profile. From the perspective of Shemshack and Spector (2020), the ultimate aim of PL is to foster increased motivation, engagement, and comprehension among students, thereby optimizing both satisfaction and learning outcomes. Within this approach, the teacher assumes the role of a guide throughout the learning process, assessing each student's strengths and needs to develop learning plans that align with both their interests and academic standards. The teacher facilitates content delivery and supports students in making informed decisions about their learning by providing appropriate tools and contextual information (Bernacki et al., 2021). According to the framework of Personalised Adaptive Learning proposed by Peng et al. (2019), the teacher functions as both a facilitator, while the student takes on an active and autonomous role in their educational journey. From the learner's perspective, Walkington and Bernacki (2021) emphasise that student agency and control are central themes in PL. However, its implementation is not without challenges, as it often involves navigating tensions between efficiency, autonomy, and structure. One such tension arises from the balance between offering students' choice (adaptability) and prioritising system efficiency (adaptivity) (Plass & Pawar, 2020). Furthermore, granting students greater choice can create conflicts with curricular requirements, pedagogical approaches, and certain teaching-centred practices, posing significant challenges within traditional educational systems.

According to Walkinton and Bernacki (2020), technology has transformed PL by enabling student-device interactions (tablets, laptops, phones) that collect data on students' knowledge, interests, and preferences to tailor content and predict academic success through learning analytics and AI. Despite this adaptive potential, studies like Xie et al. (2019) have shown that technology is often used for routine tasks or relies on traditional computers, despite advances in AR, VR, and mixed reality.

Technological platforms have the following uses in PL (Walkinton & Bernacki, 2020):

- **Adaptive tool**: Platforms automatically adjust content and learning pathways to meet student needs.
- **Facilitating medium**: Technology organises student work without adapting content to individual characteristics.
- **Socio-technical ecosystem**: Approaches integrating digital tools to transform teaching and actively engage students in creative digital environments.

Components and dimensions of personalised learning

Bernacki et al. (2021) identify several key components in PL definitions: student characteristics, learning design elements, and expected outcomes. Among student characteristics, interests and needs are frequently mentioned, followed by prior knowledge, goals and preferences, learning styles, and individual abilities. However, aspects such as cultural background and physical disabilities are often omitted (Cheng & Wang, 2020). Spector (2015) addresses personalisation dimensions, referring to individual differences that can serve as a basis for PL. These include cognitive (prior knowledge, areas of interest, self-efficacy, preferences), affective (motivation, attitude, self-esteem, emotional maturity), cultural (language, nationality, religion), demographic (age, gender, location), disability (hearing, vision, mobility), and personal (values, leisure time use, preferences).

In terms of learning design, what is personalised, elements include content, activities, instructional methods, assessment, feedback, learning objectives and goals, pacing, sequencing, and the use of technology (Bernacki et al., 2021; Spector, 2015).

Regarding the personalisation of expected outcomes, factors include motivation, skills development, and academic achievement, although implementation complexity remains a major challenge. Spector (2015) also points out who or what can perform personalisation: an automated system, the teacher, or the learner.

1.2 Personalised learning and adaptive learning: similarities and differences

Xie et al. (2019) and Shemshack & Spector (2020) caution against the interchangeable use of personalisation-related terms, especially PL and adaptive learning, the latter being more associated with technology-driven learning. Both terms aim to meet diverse learning needs using advanced technologies like intelligent tutoring systems to offer meaningful educational experiences, including the optimisation of materials and activities based on student characteristics (Xie et al., 2019).

While previous sections provided general definitions and characteristics of PL, it's important to reiterate that PL focuses on adapting learning objectives, methods, and content based on individual traits, interests, and goals. Adaptive learning, on the other hand, emphasises the system's ability to monitor real-time student performance and dynamically adjust activities and materials based on progress and skill level. A major difference lies in the data used: while PL incorporates personal characteristics, adaptive learning may function solely based on observable performance (Xie et al., 2019).

Adaptive learning is a pedagogical approach that employs advanced technologies—particularly artificial intelligence (AI) and machine learning algorithms—to dynamically tailor educational content, instructional strategies, and assessments to the unique needs of individual learners. Rather than requiring students to conform to a fixed instructional model, adaptive systems adjust in real time based on the learner's goals, preferences, knowledge level, and learning style (Brusilovsky & Peylo, 2003; Gligorea et al., 2023; Psyché, 2025).

This adaptation is achieved through AI algorithms that analyse both pre-existing learner models and real-time interaction data. These systems infer the learner's cognitive state by interpreting behaviours such as response time, error patterns, and interaction choices. For instance, the time taken to answer a question may indicate confidence or difficulty, while cognitive diagnosis techniques can identify specific misconceptions based on error types. Such data-driven insights enable the system to personalise the learning experience continuously, enhancing engagement and effectiveness (Somyurek et al., 2020).

Finally, it is important to distinguish between adaptivity and adaptability. Adaptivity refers to the system's capacity to adjust to each student's knowledge and skills. This includes modifications based on prior knowledge, errors, strategies, motivation, metacognition, and self-regulation (Plass & Pawar, 2020). Adaptivity is seen as a continuum, where systems vary in responsiveness to student characteristics, essential for PL experiences (Bernacki et al., 2021; Walkinton & Bernacki, 2020). Plass & Pawar (2020) propose a taxonomy of adaptivity with dimensions including: cognitive (knowledge and skills), emotional (emotional state during learning), motivational, and sociocultural variables. Adaptivity can be micro-level (real-time adjustments to specific tasks) or macro-level (general adaptations like course sequencing).

Adaptability, in contrast, focuses on learner-driven adjustments, allowing students to control their learning process. This involves tailoring experiences to individual needs to enhance learning outcomes and self-regulation (Plass & Pawar, 2020). It requires the development of diverse materials and learning environments tailored to students' preferred modalities (Murtaza et al., 2022).

1.3 Related Terms

Terms such as differentiated learning and individualised instruction have specific meanings within the broader PL framework (Spector, 2015).

Differentiation

Both differentiated learning and instruction involve group-based practices tailored to students' skills, levels, and learning needs (Spector, 2015). Linder & Schwab (2020) explain that differentiation addresses diverse needs within inclusive classrooms, requiring strategic design, varied activities, difficulty levels, and assessment types to ensure educational equity. Walkinton & Bernacki (2020) and Peng et al. (2020), referencing the U.S. Department of Education (2016), note that while all students have the same goal in differentiation, instructional methods vary. Both PL and adaptive learning incorporate differentiation, though it's traditionally associated with special education.

Individualisation

Focuses on individuals rather than groups, typically referring to special education needs (Spector, 2015). Shemshack & Spector (2020) reaffirm that individualised instruction is common in special education or where students face specific challenges. According to Linder & Schwab (2020), individualisation occurs at the micro-level, tailoring content, materials, and assessments to each learner's pace and characteristics.

Table 1: *Comparative dimensions of related concepts: Personalisation, individualisation, differentiation, and adaptive learning*

LEARNER-CENTRED PROCESS

CONCEPTS	TEACHER'S ROLE	STUDENT'S ROLE	WHEN TO USE	EXAMPLES
Personalisation **Student-driven.** Tailoring learning to each student's strengths, needs, and interests.	**Facilites individualized path for each student. High flexilibity**	**Takes ownership of learning goals and methods.**	Students have diverse interests and you want to increase engagement by allowing them to choose their learning paths	Project-based learning, choice boards, personalized learning plans.
Differentation **Teacher-driven.** Tailoring insruction to meet the needs of different groups of students	**Guides group progress with some flexibility.**	**Works within general framework with some choice.**	You have a classroom with varying levels of ability and need to use different methods to reach all students.	Group work, tiered assignments, varied instructional strategies.
Individualisation **Teacher-driven.** Customizing instruction to meet specific needs of an individual student.	**Monitors unique paces for each student. High flexilibity**	**Follows taylored teacher's suggestions**	A student has specific learning needs that require a tailored approach, such as in special education.	Individualized Education Programs (IEPs), one-on-one tutoring.
Adaptive Learning **Tech-driven.** Using technology to adjust the learning experience based on real-time student data.	**Uses data to adjust learning paths automatically. High flexilibity**	**Follow data-driven system suggestions (tasks, resources, etc.)**	You want to leverage ICT to provide a personalised learning experience adjusting to each student's progress & needs.	Intelligent tutoring systems, adaptive learning platforms.

Personalised learning, individualised learning, differentiated learning, and adaptive learning share foundational pedagogical principles that collectively reimagine education as a dynamic, learner-centred process. All four approaches reject the 'one-size-fits-all' model, instead prioritising constructivist theories that position learners as active participants in knowledge construction. They also align with mastery-based progression, ensuring learners demonstrate competency before advancing, and self-regulation frameworks, which emphasise goal-setting and metacognitive awareness. These models further intersect in their use of data—whether from learner profiles, formative assessments, or AI algorithms—to tailor experiences. For instance, differentiated and adaptive learning both respond to cognitive diversity, though the former relies on teacher expertise to adjust content, while the latter automates adaptations via predictive analytics. Similarly, personalised and individualised learning foster autonomy but diverge in structure: the former offers flexible pathways, while the latter enforces sequential mastery. These frameworks complement one another by addressing distinct layers of the learning ecosystem.

Differentiated learning provides a teacher-driven strategy for managing diverse classrooms, adapting content and assessments to neurodiverse needs. Adaptive learning supplements this by offering real-time, technology-mediated scaffolding, optimising cognitive load through iterative feedback loops. Meanwhile, personalised learning bridges socioemotional and academic growth by aligning instruction with learners' interests and aspirations, while individualised learning ensures rigour through self-paced, competency-gated progression. Together, they create a synergy where human intuition and technological precision coexists: educators curate inclusive environments, while AI handles granular adjustments. This interplay empowers systems to support learner variability without sacrificing scalability, ultimately fostering equitable access to tailored education.

1.4 Personalised learning and artificial intelligence

AI-powered educational technologies—such as adaptive learning systems, intelligent tutoring systems, and mobile learning devices—can support the implementation of PL by providing accessibility, interactivity, and tailored resources, content, or materials that promote diverse learning experiences (Zhang et al., 2020). Some key features for integrating AI into adaptive learning systems are outlined by Shete et al. (2024):

- The collection and analysis of large amounts of data on how students interact with course materials, their performance, and other variables enables AI-powered personalised learning systems to generate learner profiles that guide the selection of content and learning pathways.
- These AI systems continuously assess student progress and modify content and activities in real time.
- AI-driven adjustments allow for dynamic modifications to content structure, difficulty levels, and presentation to match the learner's level and preferences.
- Adaptive learning systems provide immediate feedback, helping students identify weaknesses and areas for improvement.
- AI-powered systems can design distinct learning routes for each student, allowing them to progress at their own pace.

- Learning analytics offer insights into performance trends and academic development, supporting informed decision-making.

Studies such as Jiali et al. (2024) demonstrate the significant impact of artificial intelligence (AI) on PL and its related technologies, including intelligent tutoring systems, predictive analytics, and automated assessment and feedback systems. These technologies contribute to the optimisation of learning experiences, thereby enhancing student engagement and learning outcomes. According to Gligorea et al. (2023), AI in adaptive learning continuously improves system performance by detecting patterns, identifying learners' strengths and weaknesses, and generating personalised recommendations and interventions. It also enables the collection of relevant data on the effectiveness of learning materials and instructional strategies.

Thus, among the benefits of AI-driven personalisation are improved learning outcomes, greater student engagement, enhanced differentiation and flexibility, time optimisation, and the continuous improvement of curriculum design, teaching methods, and instructional strategies (Shete et al., 2024).

Recent research also highlights the advantages offered by both machine learning (ML) and deep learning (DL) algorithms. While both are subfields of AI designed to analyse data, detect patterns, and make predictions or classifications, ML is a more general tool used for a wide range of simple to moderately complex problems. In contrast, DL is a more advanced branch of ML, typically applied to complex and unstructured tasks through the use of deep neural networks to model intricate data.

In adaptive learning systems, ML algorithms collect, analyse, and interpret large volumes of data generated by students (Gligorea et al., 2023). These algorithms allow the systems to create detailed learner profiles and identify strengths and weaknesses, enabling dynamic adjustments to the learning experience. As a result, students receive personalised content and activities that align with their capabilities and goals. According to Gligorea et al. (2023), the benefits of ML in adaptive learning include:

- Personalised learning experiences and pathways.
- Dynamic recommendations of supplementary materials.
- Optimisation of learning objects and pathways.
- Rapid adaptation of learning models.
- Improved recommendation systems and delivery of targeted materials.
- Efficient student grouping for tailored strategies.
- Identification of learning styles to improve predictive accuracy.
- Enhanced learning outcomes.
- Increased motivation and student engagement.

Nevertheless, several implementation challenges have also been reported. These include the complexity of integrating multiple techniques, ensuring data privacy and security, compatibility with existing platforms, the need for constant updates and maintenance of AI models and systems, and a general dependence on technological infrastructure.

Additionally, Naseer et al. (2024) highlight that deep learning is particularly valuable for designing and implementing personalised strategies in higher education due to the diversity of its student population. Their findings suggest that integrating deep learning models to personalise and adapt learning pathways leads to enriched learning experiences, due to the interactive nature of the technology, its ability to adjust and personalise content according to specific learner needs, and the provision of immediate feedback. Furthermore, instructors observed improvements in students' understanding of complex concepts, attributed to the use of adaptive learning algorithms integrated into the learning platform.

1.5 Personalised Learning and Learning Analytics

The field of learning analytics encompasses the measurement, collection, analysis and reporting of data concerning learners and their contexts, with the objective of enhancing comprehension and optimisation of learning processes (Lang et al., 2022). Cheng and Wang (2020) highlight the potential of learning analytics (LA) in the implementation of PL, opening up new opportunities for analysis. Similarly, Shemshack and Spector (2020) argue that the use of LA facilitates the identification of student characteristics and the personalisation of content. Jeremic, Kumar & Graf (2017) enforce the provision of personalised feedback and recommendations for learning activities, strategies or pathways as a benefit to learners. For example, visualisations of learning processes promote reflection on one's own learning and facilitate the identification of undesirable learning behaviours and difficulties. Teachers gain insights into students' individual progress and their interactions with learning materials. This enables the adaptation, scaling and optimisation of learning opportunities for heterogeneous students. The implementation of learning analytics processes poses considerable challenges for universities in terms of technological, didactic, legal, organisational, cultural and financial aspects (Jeremic, Kumar & Graf, 2017). Khor and Mutthulakshmi (2024), for their part, point out that there are two ways in which analytics support personalised learning: extracted analytics and embedded analytics. In the first case, extracted analytics involve the collection and visualisation of data to enable teachers to make informed decisions.

Table 2: *Purpose and applications of extracted analytics at the individual, group, and structural levels.*

Level	Purpose	Applications
Individual	Analyse the characteristics, progress, and behaviours of each student.	• Real-time tracking of individual progress. • Identification of specific issues for each student. • Provides teachers with feedback based on performance. • Monitoring student behaviour during problem-solving (quantity and sequence of actions). • Classification of students by skill level and support needs.
Class/Group	Understand and optimise collective dynamics, engagement, and performance.	• Analyse classroom statistics (e.g., task completion rates). • Identify activities that generate higher participation. • Supervise group projects and track individual contributions. • Detect group dynamics such as interaction and participation among students.
Structural	Understand and optimise structural elements of the educational context.	• Use data to improve lessons and schedules based on student performance. • Analyse tools and learning methods for effectiveness. • Implement improvement plans based on identified challenges.

In the second case, *embedded analytics* automate the personalisation process by recommending tasks and educational resources in real time based on the student's level (Khor & Mutthulakshmi, 2024). This reduces the need for teacher intervention. Some functions of this type of analytics include:

- collecting data on students' skills and learning styles;
- automatically grouping students based on similar profiles;
- recommending personalised educational resources;
- using students' responses to continuously adjust learning materials and activities;
- and suggesting successful activities and strategies to students with similar profiles.

Additionally, they can also automatically generate personalised dashboards for learners.

Thus, various studies—such as those by Peng et al. (2021), Walkinton and Bernacki (2020), Gligorea et al. (2020), and Jiali et al. (2024)—highlight the role of analytics in personalised learning, specifically their impact on analysing data related to student performance and individual characteristics. This analysis enables informed decision-making, the creation of PL pathways, and the adaptation of content, sequencing, and presentation of learning materials, among other applications.

The aggregation of large amounts of data and the integration of analysis tools into existing learning environments are prerequisites for the implementation of learning analytics processes. Drachsler (2023) points out that these processes have to be embedded in didactic concepts and learning designs in a scientifically sound manner. It is imperative that a diverse range of stakeholders, including teachers, students, faculties and data management centres, are engaged in this process. The integration of these analytics processes necessitates the implementation of an overarching organisational strategy, complemented by subject-specific change management initiatives.

Conclusion

Personalised learning (PL) is gaining traction in online and distance higher education (ODHE) as a way to address learner diversity, boost engagement, and improve outcomes. By tailoring pathways, content, and assessment to individual needs, PL can advance inclusion for students with disabilities, part-time learners, and those balancing work and family commitments. Institutions should view it as part of a broader equity agenda, not just a teaching innovation.

Clear definitions are essential: confusion between personalised, adaptive, differentiated, and individualised learning can hinder progress. PL should be grounded in pedagogy, with technology—AI, analytics, adaptive platforms—serving educational goals rather than dictating them.

Effective implementation also requires capacity-building. Educators need training to design personalised experiences, use data ethically, and foster learner autonomy. Institutions must invest in infrastructure, policy, and collaboration to embed PL into curricula and support systems.

At its core, PL aims to empower learners by offering flexible pathways, timely feedback, and opportunities for self-regulation—skills vital for lifelong learning. Ethical concerns must also be addressed, including transparency in data use, informed consent, and bias mitigation in AI tools.

Further discussion of technology, capacity-building, and ethics can also be found in the remaining chapters. Before moving on, consider the following reflective questions:

Questions for reflection

How can institutions ensure that personalisation strategies genuinely promote inclusion rather than reinforce existing inequalities?

What balance should be struck between learner autonomy and system-driven adaptivity in personalised learning environments?

In what ways can educators be supported to design and facilitate meaningful, personalised learning experiences in increasingly digital contexts? And what structures and supports are needed to scale personalisation sustainably?

How can ethical data practices be established and maintained in the implementation of personalisation technologies?

What areas of PL remain under-researched or poorly understood, and how can future studies contribute to building a more cohesive and inclusive field?

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2. Strategies, Models, and Frameworks for Personalisation

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Introduction

As online and distance higher education (ODHE) continues to evolve in response to societal, technological, and (ped)agogical developments, the need for personalisation is increasingly recognised across institutions in Europe and beyond. Building on the conceptual foundations laid in Chapter 1, this chapter investigates how distance teaching universities develop and implement institutional strategies, frameworks, and operational models for personalisation. Drawing from various national and institutional sources, including strategy papers, (ped)agogical models, and policy frameworks, this chapter illustrates that personalisation is a shared priority across European ODHE institutions. By showcasing a range of models and practices, it aims to support a nuanced understanding of how personalisation can be structurally embedded within ODHE institutions.

The concept of personalisation in ODHE extends beyond technological adaptations. It encompasses (ped)agogical, organisational, and ethical considerations to meet the needs of increasingly diverse learners. Institutions such as the Open University (OU UK), FernUniversität in Hagen, Universitat Oberta de Catalunya (UOC), University of Jyväskylä, the Open Universiteit and Université TÉLUQ have developed distinct but comparable strategies to promote flexible, inclusive, and learner-centred educational environments. These strategies aim to balance the affordances of digital tools with educational principles such as autonomy, equity, accessibility, and academic success.

This chapter is structured as follows: Section 1 provides an overview of strategies for implementing personalisation adopted by European distance teaching universities. Section 2 presents key institutional frameworks and models that guide personalisation efforts. Section 3 proposes a maturity model for institutional readiness, synthesising characteristics from the reviewed practices. Section 4 addresses challenges including scalability, staff readiness, and data privacy. Section 5 showcases a variety of good practices across institutions. The final sections provide implications for practice and policy, followed by reflective questions aimed at guiding future research and innovation.

2.1 Overview of Strategies for Implementing Personalisation

Across (European) open and distance teaching universities, the implementation of personalisation strategies reveals a shared commitment to tailoring education to diverse student needs, preferences, and life situations. These strategies are deeply intertwined with the missions of these institutions, which prioritise accessibility, flexibility, and inclusivity. While specific implementations vary, several overarching patterns emerge that reflect a common trajectory toward personalisation as a driver of both (ped)agogical innovation and equity.

At the core of many institutional strategies is the recognition that personalisation must be integrated into the overall educational model rather than treated as an isolated initiative. For example, the UOC embeds personalisation into its digital transformation plan and pedagogical model, emphasising flexible, learner-centred approaches that use learning analytics and adaptive systems to scaffold learning pathways. Similarly, the Open University foregrounds personalised support and flexible study options in its strategic framework 'Learn and Live', which positions personalisation as a means of widening participation and supporting lifelong learning.

The University of Jyväskylä incorporates personalisation through its human-centric digitalisation strategy, which prioritises individual learner development, wellbeing, and inclusion within a digitally transforming educational system. This aligns with its institutional values of openness, trust, and sustainability (University of Jyväskylä, n.d.). Similarly, TÉLUQ embeds personalisation by offering all its courses online and promoting access to quality education. It allows students to register and begin studying whenever they want, at their own pace (there are no group sessions). Furthermore, students are granted a degree of flexibility in selecting their required and elective courses. In some courses, they may also be given the opportunity to choose among different types of assignments or to focus on a topic of particular interest to them. The university facilitates student success through pedagogical methods, digital tools, and personalised support, thereby placing a strong emphasis on accessibility, equity and diversity.

The FernUniversität in Hagen outlines quality goals that explicitly reference personalisation as a quality criterion, committing to individualised support and modularisation of study programmes to accommodate varying learner profiles. Likewise, the Universidade Aberta connects personalisation directly to its pedagogical model, focusing on asynchronous and student-centred design that accommodates different rhythms of study and forms of participation.

Common strategic components include:

- **Personalised learning pathways**, where learners can progress through content at their own pace, choose from elective modules, or follow different sequences based on their goals and background.

- **Flexible learning modes**, enabling combinations of synchronous and asynchronous learning, part-time and full-time study, and varied assessment options.
- **Targeted student support**, such as individual tutoring, mentoring, or coaching services that are triggered based on learner data or self-reported needs.
- **Technology-enhanced personalisation**, with learning analytics, AI-powered tools, and adaptive systems used to guide content delivery, feedback, and progress monitoring.
- **Inclusive and accessible design**, ensuring that personalisation strategies accommodate students with disabilities, learners from diverse backgrounds, and non-traditional students.

Several institutions have aligned personalisation strategies with broader national or institutional inclusion policies. For instance, the Open Universiteit incorporates personalisation into its diversity and accessibility strategy, offering accommodations for students with functional impairments and promoting inclusive design in both its digital learning environment and study centres. These efforts are also informed by national frameworks such as the Dutch national action plan for diversity and inclusion, which encourages higher education institutions to address structural barriers and expand learner-centric approaches.

Finally, collaboration and co-design with learners and staff are emerging as key mechanisms for shaping effective personalisation strategies. As shown in examples from the SHIFT pilot project at Université Grenoble Alpes and the EADTU's own pilot cases, involving students in the design of personalisation practices increases relevance and fosters a culture of shared responsibility for learning.

In sum, the strategic landscape across European distance teaching universities demonstrates a clear convergence: personalisation is viewed as a structural necessity for inclusive, flexible, and effective education. Institutions are not merely experimenting with personalisation; they are embedding it as a cross-cutting principle into curriculum design, student support systems, and digital infrastructures.

2.2 Frameworks for Implementation

A coherent and strategic implementation of personalisation in online and distance higher education (ODHE) depends on the availability of (ped)agogical, technological, and institutional frameworks that can guide decision-making across all levels of the organisation. These frameworks help to align institutional goals with educational practices, ensuring consistency, scalability, and equity in personalisation efforts.

Several distance teaching universities across Europe have formalised their approaches to personalisation through comprehensive educational models and strategic frameworks.

The UOC has embedded personalisation within its educational model through a student-centred framework that prioritises flexibility, learner agency, and continuous assessment. The model is structured around three core elements: (1) personalised academic support provided by a team of tutors and teachers, (2) customisable learning paths enabled by modular curricula, and (3) the use of learning analytics to inform decisions and anticipate learner needs. The UOC's 'Digital Transformation Strategy' supports this model by ensuring technological infrastructure aligns with pedagogical objectives, promoting automation and data-driven personalisation while maintaining pedagogical integrity (UOC, 2023).

The Open University implements personalisation through a strategic framework that merges inclusive education principles with digital innovation. The OU UK's "Learn and Live" strategy (2022–2027) presents personalisation as a core pillar, focusing on designing flexible learning journeys that respect diverse learner contexts. Their implementation framework emphasises co-creation with learners, inclusive design, and continuous evaluation of learner engagement and outcomes (OU UK, 2022). This is supported by a university-wide digital learning ecosystem that integrates adaptive platforms and data-informed support interventions.

At Universidade Aberta (UAb), the personalisation strategy is grounded in its pedagogical model (Modelo Pedagógico Virtual – MPV), which promotes autonomy, flexibility, and individualised learning trajectories. The MPV outlines four key dimensions—student-centredness, flexibility, interaction, and digital inclusion—which guide the development of PL environments. The university's "Plan for Equality and Diversity" (2023–2026) reinforces this pedagogical vision by incorporating personalisation as a mechanism to promote accessibility and inclusion for students with diverse needs and backgrounds (UAb, 2024).

FernUniversität in Hagen operates under a strategic framework that connects personalisation with institutional quality objectives. Their "Qualitätsziele" (quality goals) emphasise learner orientation, flexibility, and competence-based education. These goals are operationalised through cross-cutting measures such as modularised programmes, diverse learning resources, and embedded student support mechanisms tailored to individual progression paths (FernUniversität, 2024).

The Open Universiteit of the Netherlands integrates personalisation into its institutional frameworks for educational innovation and digital transformation. While its implementation is distributed across multiple strategic documents—including the Digital Learning & Working Environment (DLWO) strategy, the university's diversity policy (2024–2026), and the ECO domain year plans—the common thread is a systemic commitment to inclusive, flexible, and data-informed personalisation. A range of frameworks support these efforts, including PDCA-cycles for quality assurance, institutional guidelines for accessibility, and tailored provisions for students with disabilities (OU NL, 2024).

Collectively, these frameworks underscore the importance of aligning technological tools, pedagogical practices, and organisational processes to enable sustainable personalisation in ODHE. They also demonstrate that institutional frameworks must remain adaptable to local contexts while supporting interoperability and exchange across the European distance education landscape.

2.3 Maturity Model for Institutional Readiness

As institutions of online and distance higher education (ODHE) increasingly embrace personalisation as a strategic priority, it becomes vital to assess and scaffold their readiness to implement such initiatives. A maturity model provides a structured framework to evaluate an institution's capabilities and progress in embedding PL into its educational practices, technologies, and organisational culture. Based on an analysis of institutional strategies and evidence gathered from various European distance teaching universities, this section proposes a five-level maturity model that institutions can use to assess and advance their readiness for personalisation.

Level 1 – Awareness and Exploration
At this initial stage, institutions recognise the importance of PL but have yet to integrate it into formal strategies. Individual staff members or departments may experiment with pilot initiatives, often supported by research or (external) funding. However, there is limited alignment with institutional policies, and efforts are fragmented. For instance, early-stage experimentation with AI-driven feedback tools or basic accessibility services (as observed in preliminary actions at FernUniversität Hagen or UAb and TÉLUQ) characterises this level.

Level 2 – Strategic Intent and Planning
Institutions at this level begin formulating institutional strategies that include personalisation, equity, and student support. Examples include the Open Universiteit's multi-year plans prioritising inclusive digital learning environments, or the UOC's commitment to transforming its pedagogical model to respond to learner variability. Dedicated working groups or task forces (e.g., the Diversity Office at OU NL or UAb's Equality and Diversity Plan) are created to initiate planning and policy development. However, implementation remains in planning stages, and organisational structures are still being adapted.

Level 3 – Initial Integration and Capacity Building
At this stage, personalisation is embedded in curriculum design, digital tools, and staff development programmes. The OU UK, for example, incorporates personalisation into its 'Learn and Live' strategy by emphasising inclusivity, lifelong learning, and tailored student journeys. The UOC integrates personalisation within its educational model and professional development offerings. Institutions at this stage actively invest in staff training, deploy adaptive technologies, and use learning analytics to inform pedagogical decisions. Pilot studies evolve into scaled programmes across faculties.

Level 4 – Institutionalisation and Cross-Functional Collaboration
Personalisation becomes institutionalised across governance, quality assurance, technology, and educational design. Universities such as the UOC and the Open University show advanced integration where cross-functional teams—comprising instructional designers, IT specialists, data analysts, and academic staff—collaborate to deliver adaptive, accessible learning experiences. Institutional strategies clearly align (ped)agogical and technological visions, and continuous improvement cycles (e.g., quality assurance (QA) at FernUni Hagen or Learning Analytics (LA) integration at OU NL) are used to refine personalisation initiatives.

Level 5 – Continuous Innovation and Systemic Responsiveness
At this highest maturity level, personalisation is not just a goal but a dynamic, data-informed and learner-centred practice embedded in all institutional functions. Institutions continuously iterate based on stakeholder feedback, ethical evaluations, and strategic foresight. Practices from leading institutions such as UOC and the Open University indicate that mature institutions harness AI and learning analytics to drive lifelong personalised learning, inclusion, and educational equity at scale. Ethical considerations are operationalised via data governance, transparency mechanisms, and participatory approaches to educational design.

This maturity model serves both diagnostic and developmental purposes. Institutions can use it to map their current position, identify strategic gaps, and plan coherent interventions. It also supports alignment with national or European frameworks on diversity, accessibility, and innovation in education, ensuring that personalisation is implemented in a sustainable and ethically responsible manner.

Table 1: *Maturity Model for Institutional Readiness for Personalisation*

Maturity Level	Characteristics	Examples
Level 1 – Awareness and Exploration	Recognition of importance; fragmented pilot initiatives; limited policy alignment.	• Early-stage pilots at FernUniversität Hagen, UAb and TÉLUQ.
Level 2 – Strategic Intent and Planning	Strategic plans formulated; creation of working groups; still in planning phase.	• Strategic plans at OU NL, UOC • Diversity Office at OU NL • UAb's Equality Plan • Equity, diversity, and inclusion policy at TÉLUQ.
Level 3 – Initial Integration and Capacity Building	Embedded in curriculum, tools, staff training; pilot scaling across faculties.	• OU UK's 'Learn and Live' • UOC's integrated model and training programmes.
Level 4 – Institutionalisation and Cross-Functional Collaboration	Institution-wide integration; collaboration across departments; quality cycles in place.	• Cross-functional teams at OU UK and UOC; • QA at FernUni Hagen • LA at OU NL.
Level 5 – Continuous Innovation and Systemic Responsiveness	Fully embedded; continuous innovation and feedback loops; ethical governance operationalised.	• AI-driven lifelong learning at UOC and OU UK • Systemic data governance.

2.4 Challenges (scalability, data privacy, staff resistance)

The implementation of personalisation strategies in online and distance higher education (ODHE) offers significant potential but also presents a range of complex challenges. These issues must be addressed strategically to ensure sustainable, equitable, and ethically sound deployment of personalised learning approaches.

One of the primary challenges relates to scalability. While many pilot projects and institutional innovations have shown promising results, scaling PL across entire institutions or systems can prove difficult. Adaptive technologies and learning analytics require substantial technological infrastructure, continuous updates, and technical support, which can place a strain on institutional resources (Shete et al., 2024). Furthermore, designing personalised pathways across diverse programmes and course offerings demands considerable instructional design expertise, as well as robust collaboration between faculty, technologists, and educational developers.

Another challenge is the cost. For example, an experiment at Université TÉLUQ revealed that an approach emphasising learning support rather than relying primarily on accommodations was more effective in fostering the academic success of students with disabilities. Indeed, students with disabilities do not always take the initiative to seek out the information or support they need, and maintaining a staff dedicated to providing constant, proactive assistance would be too costly. Therefore, an automated system was developed to deliver context-specific information and tools at key moments during the course. The overarching goal was to complement human support and online resources with a form of just-in-time assistance that is seamlessly delivered to students, without necessitating any prior request or action on their part (Plante et al., 2024). Moreover, in this fully asynchronous course environment, where tutors and instructors respond promptly but not instantaneously, a portal was created to provide access to peer communication spaces. This platform enables all students who wish to do so to exchange ideas or study together, while also allowing some trained students to take on the role of moderators. In addition, a conversational agent is currently being tested in certain courses. The guiding idea is not to replace tutors and instructors, who provide essential support, but rather to add opportunities for assistance that are available 24/7.

Another key challenge involves data privacy and the ethical use of learner data. Personalisation in ODHE relies heavily on collecting, analysing, and acting upon data related to learner behaviour, preferences, goals, and performance. As demonstrated by the Open University and the UOC, data-driven personalisation must be embedded in a strong data governance framework. This includes ensuring transparency, securing informed consent, and adhering to data protection regulations such as the General Data Protection Regulation (GDPR). The risk of algorithmic bias also looms large; poorly trained AI systems may reproduce or amplify inequalities rather than mitigate them (Gligorea et al., 2023). Institutions must establish ethical standards and continuous monitoring mechanisms to safeguard against such outcomes.

Staff resistance and capacity issues further complicate implementation. Faculty members may be sceptical of data-driven educational models or uncertain about their role in technology-mediated environments. As evidenced by several institutions (e.g., FernUni Hagen, Open Universiteit), professional development and change management are critical for fostering acceptance and building digital competencies among educators. Without sufficient training and institutional support, staff may struggle to design, implement and facilitate meaningful personalised learning experiences.

Institutional alignment also poses a barrier. In some cases, personalisation initiatives remain fragmented or isolated within specific departments or pilot programmes. To ensure long-term success, a whole-institution approach is required—one that integrates personalisation into broader educational strategies, quality frameworks, and resource planning. The Fernuniversität in Hagen and the UOC both underscore the importance of connecting personalisation with institutional missions, values, and strategic goals.

Finally, the digital divide and student access to technology cannot be overlooked. Effective personalisation assumes that all learners have access to stable internet connections, appropriate devices, and digital literacy. This is not always the case, particularly for students from disadvantaged backgrounds, those with disabilities, or those studying in remote areas. Institutions like the Open Universiteit and UOC have responded with targeted support measures, but digital inclusion remains a broader societal challenge requiring cross-sector collaboration.

Addressing these challenges calls for a multi-faceted and inclusive strategy. While personalisation offers transformative possibilities, its implementation must be thoughtful, context-sensitive, and ethically guided.

2.5 Good Practices

In this section, we highlight good practices from various (European) distance teaching universities that illustrate how personalisation strategies can be effectively integrated into institutional frameworks. These cases demonstrate diverse approaches in embedding personalisation through educational models, technology, learner support, and organisational strategy—showing that while implementation differs across contexts, a shared commitment to learner-centred design and equity is evident.

Universitat Oberta de Catalunya

UOC integrates personalisation deeply into its digital transformation and educational model. The institution's Educational Model promotes continuous, flexible, and adaptive learning, supported by a strong infrastructure of learning analytics and intelligent systems. Personalisation is operationalised through a pedagogical approach that allows each student to follow a PL path, supported by tutors and digital resources tailored to individual needs. UOC's strategic focus on inclusion and digital innovation (UOC, n.d.-1; n.d.-2) demonstrates how a holistic model can support scalable and sustainable personalisation.

The Open University

The OU UK has embedded personalisation into its institutional strategy through the "Learn and Live" initiative (OU UK, 2022). This five-year strategy explicitly prioritises flexibility and personal relevance in the learning experience, combining technology-enhanced feedback, personalised study plans, and targeted student support services. The OU UK's large-scale use of learning analytics to proactively identify at-risk students and recommend tailored interventions is a notable example of data-informed personalisation at scale.

FernUniversität in Hagen

FernUniversität's quality goals include a strong emphasis on "lifelong learning" and supporting heterogeneous learner groups through flexible learning paths and differentiated didactic concepts (FernUni Hagen, n.d.). The institution integrates personalisation through its strategic objectives for quality development and learner-centred design. FernUni's personalised support structures include targeted academic counselling and differentiated pathways for part-time learners and working professionals.

Open Universiteit

The OU NL promotes personalisation through inclusive learning design and support structures for students with disabilities or chronic conditions. This is evident in the university's regulations for accessibility, such as tailored facilities at study centres and individual adjustments during assessments (OU NL, 2025a; 2025b). Furthermore, its Diversity Office's multi-year strategy (2024–2026) prioritises educational equity through support structures and flexible learning design, reflecting a personalised approach embedded in institutional diversity policy (OU NL, 2024).

Université Grenoble Alpes (UGA)

As part of the SHIFT pilot project, UGA explored personalised support in hybrid and distance learning. The project included co-design of learning paths between students and instructors, adaptive resource curation, and self-reflective learning dashboards. This example showcases how personalisation can be introduced not only through technology but also through pedagogical innovation and learner empowerment (UGA, 2023).

University of Jyväskylä

The University of Jyväskylä exemplifies a holistic approach to personalisation by embedding it in its human-centric digitalisation strategy. Its educational development policies emphasise student wellbeing, learner agency, and personalised support across diverse educational pathways. These efforts are guided by institutional values such as openness, responsibility, and trust, which are foundational to its inclusion-oriented pedagogical vision.

Université TÉLUQ

TÉLUQ offers a fully distance-based educational model and has adopted a university-wide policy for equity, diversity, and inclusion (EDI). This includes personalised accommodations, inclusive curriculum design, and institutional structures such as EDI committees. TÉLUQ's example highlights how personalisation in distance education can be embedded in institutional strategy to serve underrepresented and non-traditional learners while ensuring accessibility and inclusion.

Conclusion

This chapter has demonstrated that personalisation in online and distance higher education (ODHE) is no longer a peripheral innovation but a central strategic priority. Through the contributions of multiple institutions—ranging from UOC, OU UK, and UAb to FernUni Hagen, OU NL, UGA, TÉLUQ, and the University of Jyväskylä—it is evident that personalisation is broadly recognised as critical to addressing the needs of diverse student populations, enhancing learner engagement, and fostering educational equity.

The reviewed strategies reveal a shared commitment to flexibility, student autonomy, and inclusive design. While implementation differs across national and institutional contexts, the convergence lies in the growing integration of personalisation into broader institutional strategies, (ped)agogical models, and digital infrastructures. This shared orientation supports collaborative development of sector-wide benchmarks, frameworks, and ethical standards.

The maturity model introduced in this chapter provides a practical guide to support institutions at various stages of readiness. It highlights that personalisation is not a binary state but a continuum of development, requiring coordinated investment in strategy, governance, technology, and staff development. Institutions like OU UK, UOC, and the University of Jyväskylä exemplify more mature stages, whereas others are actively building capacity through pilot initiatives and strategic alignment.

Many ethical themes raised here—such as data privacy, bias in automation, and equitable access—will be further explored in Chapter 5. Chapter 7 will build on the recommendations outlined here, translating institutional strategies into actionable guidance for policymakers and practitioners.

Questions for reflection

How can personalisation strategies ensure equity and inclusion for diverse learner populations across digital contexts?

What are the long-term effects of AI-driven personalisation on learner autonomy, motivation, and academic integrity?

How can institutions evaluate the impact of personalisation on student outcomes in a valid and continuous way?

In what ways can staff and students be co-creators of personalised learning models within distance education?

What collective actions can European distance teaching universities take to shape ethical, inclusive frameworks for personalisation?

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3. Technology and Tools supporting Personalised Learning

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Introduction

Personalised learning (PL) has emerged as a transformative paradigm in contemporary higher education, driven by the imperative to address student diversity, adapt to individual learning preferences, and harness the potential of advanced technologies such as artificial intelligence (AI) (Nguyen & Nguyen, 2023; Xie et al., 2019). This educational approach has demonstrated significant effectiveness in improving academic performance, enhancing student engagement and motivation, while simultaneously narrowing educational gaps and promoting more equitable learning experiences (Bayly-Castaneda et al., 2024; Walkington & Bernacki, 2021).

The conceptualisation of personalised learning (PL) draws from the influential definition provided by the U.S. Department of Education's Office of Educational Technology (2016), which characterises personalisation as a student-centred approach that adapts instruction to individual needs, preferences, and interests through strategic adjustments to learning goals, content, methods, pace, and pathways, supported by strategic technology integration (Bernacki et al., 2021). This foundational understanding has evolved to encompass what Zhang et al. (2020) describe as a systematic design focused on tailoring teaching to students' strengths, preferences, needs, and goals, emphasising flexibility in what is learned, how it is learned, and how learning progress is demonstrated.

Technology has emerged as the critical enabler that transforms PL from a theoretical ideal into practical reality. AI's capacity to process vast amounts of data and adapt in real-time has made individualised instruction increasingly attainable, promising education that is more effective, engaging, and equitable. The integration of AI-driven learning analytics enables measurement, collection, analysis, and reporting of learner data to create truly personalised learning environments (Shemshack & Spector, 2020). These technological advances support Peng et al.'s (2019) term "adaptive personalised learning," which combines pedagogical strategies with advanced technology to dynamically adjust teaching methods based on individual differences, performance, and developmental needs.

The technological landscape supporting PL encompasses a diverse ecosystem of tools and platforms. Intelligent Tutoring Systems (ITS) simulate human tutors by providing adaptive support and instruction tailored to individual learning needs. Learning Management Systems (LMS) have evolved to incorporate personalisation features such as conditional content release, adaptive quizzing, and competency-based learning pathways. Virtual Learning Environments (VLEs), enhanced by immersive technologies such as virtual and augmented reality, create engaging and adaptive learning experiences. Next Generation Digital Learning Environments (NGDLEs) represent the evolution toward interoperable, component-based architectures that prioritise personalisation as a core functional domain. Emerging technologies, including generative AI and conversational agents, offer unprecedented opportunities for real-time, contextually responsive personalised support throughout the learning process.

The remainder of this chapter is organised as follows. We begin by examining AI's foundational role in PL and learning analytics applications. We then explore monitoring and feedback mechanisms, adaptive content pathways, and predictive insights for early intervention. The chapter addresses Intelligent Tutoring Systems and AI-driven competency mapping, followed by an analysis of Learning Management Systems and Virtual Learning Environments, including immersive technologies. We examine Next Generation Digital Learning Environments and emerging tools, including generative AI and conversational agents. Throughout, practical examples illustrate real-world applications. The chapter concludes with key takeaways for educational practice and policy, and reflective questions for future research and implementation.

3.1 AI and personalised learning

AI has emerged as a powerful enabler of PL, offering sophisticated mechanisms to create truly adaptive educational experiences. AI can support learners by finding the best content for them. It can also link concepts to content and adjust the content based on students' success. AI's capacity to process vast amounts of data and adapt in real time is making this once aspirational goal increasingly attainable, promising a future where education is more effective, engaging, and equitable.

The advent of AI has been pivotal in translating the theoretical ideal of personalised learning into a practical reality. Historically, the ability to deeply personalise learning for large cohorts of students was a significant challenge for educators working with limited resources and tools (Laak and Aru, 2025). AI is not merely an add-on to existing educational practices but a catalyst that makes learning inherently more responsive, proactive, and intricately aligned with individual student needs (Merino-Campos, 2025).

AI-Driven Learning Analytics

AI-driven learning analytics (LA) have the potential to support personalised learning environments by measuring, collecting, analysing, and reporting on data relating to learners' performance, achievement, and engagement in learning activities (Barth et al., 2025; Ning et al., 2025). These technologies can provide a deeper understanding of meaningful learner data and enable timely adjustments to learning experiences (Kew & Tasir, 2022).

AI-driven learning analytics tools are used for a variety of purposes. One of the primary uses is to monitor learners' behavior, progress and interaction with the learning ecosystem, and provide personalised feedback accordingly. This can assist instructors to identify learning patterns and issues when designing future learning activities, curricula, and assessments (EADTU, 2025; Johar et al., 2023). Providing learners with meaningful data metrics about their learning progress can also give them the autonomy to take an active part in their learning, helping them identify their strengths and weaknesses (Macfadyen, 2022). By analysing and evaluating educational data, these technologies also enable real-time adaptation of learning content, pace, and teaching methods to meet the individual needs of learners (Gligorea et al., 2023). Based on learners' performance, interests, and learning progress, these systems can offer learners unique learning pathways and facilitate timely interventions, thereby enhancing learner motivation and retention.

Also, predictive systems that use machine learning algorithms and learning analytics data are employed as an early warning system for learners at risk of failing or dropping out (Macfadyen, 2022). These technologies use learners' historical and current academic data to predict their future performance and offer personalised, proactive intervention to those who might struggle. By analysing learners' needs, strengths, and weaknesses, these systems can provide access to customised content, personalised feedback and timely targeted support, potentially leading to a more effective and efficient learning experience.

Intelligent Tutoring Systems

According to Koedinger et al (2013), director of the Learn Lab at Carnegie Mellon University, an intelligent tutorial system: "Is software designed to simulate the behaviour and guidance of a human tutor. It can help students study various subjects by asking questions, analysing answers and offering personalised instructions and feedback. It can interpret complex student responses and learn as it goes along. It establishes a profile for each student and estimates their degree of mastery. It can modify its tutoring behaviour in real time, tracking differences in individual student strategies or adjusting its knowledge base for more effective interaction with all students." As John Self points out, ITS are "computer-based learning systems that attempt to adapt to learners' needs and are therefore the only systems that attempt to 'care' about learners in this sense" (Self, 1999, p. 350). An ITS can communicate with the learner to provide personalised pedagogical feedback on errors made during the learning process. An ITS is therefore associated with the paradigm of intelligent adaptive learning, personalised learning, self-management and autonomy in learning.

An ITS is an environment structured around four components: 1. the domain or expert model (representing the subject being taught), 2. the learner model (representing the learning profile), 3. the tutor model (representing the pedagogical strategies for learning, assessment and support) and 4. the interface model (representing communication and interaction between the system and the learner). It's an environment that can adapt and interact with the learner in real-time. It does so because it understands the subject being taught and the learner's cognitive state, but also because it can guide and advise the learner pedagogically by making a cognitive diagnosis using artificial intelligence techniques, notably its inference engine or other machine learning techniques (Luckin et al., 2016).

From a learner-centred perspective of inclusive pedagogy, intelligent tutors can play an important role in learner inclusion since their main characteristic is to adjust to learners' learning pace, which could be particularly favourable to those with learning or adaptation difficulties or disabilities (Gaudreau and Lemieux, 2020).

AI and Competency Mapping

AI can also play a key role in the competencies and skills development process of students. AI enables accurate diagnosis of individual student abilities, which supports the development of specific skills and fosters personalised learning while preparing students for a dynamic labor market (Celik et al., 2024; Delcker et al., 2024).

AI tools can be used to collect and analyse academic activities through courses, projects, and extracurricular engagements. Based on the analysis of this collected data, the skills a student has developed during academic and extracurricular activities can be identified. For example, platforms such as Artemis integrate competency-based education into interactive systems, enabling students to track their progress and receive personalised recommendations for further learning tailored to their unique needs. In the context of higher education, AI supports the creation of personalised educational feedback, enabling the development of individualised learning pathways that help students strengthen areas where skills are lacking.

Benefits and Challenges

AI-driven personalised learning has several benefits. Research indicates that tailoring content to individual learning needs has a significant impact on both student motivation and academic performance (Silva et al., 2024; Singh et al., 2024). Furthermore, studies show that such personalisation contributes to increased learning efficiency, allowing students to master concepts more rapidly. It also leads to better comprehension of complex information and, ultimately, improved academic outcomes, as measured by grades and project performance (Du Boulay et al., 2025; Merino-Campos, 2025).

Besides benefits, there are also some challenges, such as ethical concerns. These concerns encompass issues such as the privacy and security of sensitive student data, the potential for algorithmic bias to perpetuate or exacerbate existing inequalities, and the maintenance of academic integrity in an environment where AI tools can generate sophisticated content (e.g., Mennella et al., 2024; Schiff, 2022). Furthermore, ensuring equitable access to AI-powered educational tools and resources for all students, regardless of their socioeconomic background or technological proficiency, remains a realistic hurdle (Du Boulay et al., 2025; Merino-Campos, 2025).

3.2 Learning Management Systems

Technology plays an essential role in enabling PL, particularly in distance learning environments. While AI and learning analytics advance personalisation possibilities, practical implementation relies on robust educational infrastructure. A central tool within this landscape is the Learning Management System (LMS) - a software application designed to manage, deliver, and evaluate educational courses and training programs. It provides a centralised digital environment for creating educational content, facilitating learner-educator interactions, administering assessments, and tracking learning progress.

Key functionalities

In LMS contexts, personalisation refers to adaptive provision of educational content, experiences, and feedback aligned to individual learners' needs, interests, abilities, and goals. LMS personalisation leverages data-driven insights and intelligent algorithms to create differentiated learning pathways, personalised resources, and tailored interactions, enhancing learner engagement, motivation, and achievement (Bhatia et al., 2024). Heng et al. (2021) demonstrate how personalisation is achieved by providing diverse learning materials matching learners' preferences and needs, showcasing improved student performance. Enabling learners to select preferred material types or providing recommendation-based pre-assessments leads to improved engagement, enhanced comprehension, and knowledge retention. Tlili et al. (2019) show that LMS systems with advanced analytics can model learners' personality based on interactions and performance, informing teaching strategies to enhance satisfaction.

Johnson (2024) provides empirical evidence for using conditional release functionality to better connect with learners, providing personalised support at scale. Conditional release allows educators to sequence and control content access based on predefined conditions including activity completion, grade achievement, learner characteristics, or specific timeframes. This facilitates personalised learning paths, ensuring learners engage with material suited to their progression and readiness. In addition, adaptive quizzing can also amplify personalisation. Adaptive quizzes dynamically adjust questions across difficulty levels to accurately assess knowledge, provide immediate feedback, and promote deeper engagement (Morze et al., 2023). To facilitate adaptive assessment, a microlearning approach can be utilised by educators to divide the learning material based on difficulty levels and successfully construct the relevant assessments

Mihnev et al. (2021) discuss how LMS platforms promote competency-based courses. Competency-based learning enhances personalisation by aligning content, assessments, and activities with clearly defined competencies or outcomes. This enables educators to create tailored learning paths based on competence frameworks, allowing learners to build upon existing skills, target knowledge gaps, and engage in upskilling aligned with personal, professional, or academic goals. As described before, AI can play a key role in this process. Especially, integration with external AI-driven tutoring systems can significantly extend LMS capacity for sophisticated, personalised support (Bayly-Castaneda et al., 2024).

Benefits and Challenges

LMS personalisation offers significant benefits (Heng et al., 2021; Veluvali & Surisetti, 2021). It increases learner engagement by aligning content with individual interests, competencies, and goals, making activities more relevant and meaningful. Adaptive functionalities improve learning outcomes by identifying strengths and weaknesses, dynamically adjusting content difficulty and pacing. These features support efficient concept mastery, promoting deeper understanding and retention while fostering learner autonomy through competency-based progression.

However, personalisation also introduces challenges (Veluvali & Surisetti, 2021; Oudat & Othman, 2024). Implementation complexity requires substantial technical expertise, resources, and ongoing support. Integrating advanced functionalities requires robust infrastructure and institutional readiness. This integration can be particularly challenging for institutions with limited budgets or technological capacity. Extensive reliance on learner data raises concerns regarding privacy, security, and the ethical use of this data. Ultimately, the effectiveness of PL depends heavily on the quality of content and pedagogical approaches. Technological infrastructure alone doesn't guarantee success; it requires thoughtful, intentional design of learning experiences that cater to individual needs.

Virtual Learning Environments

Virtual learning environments (VLEs) are digital platforms designed to support and manage educational processes, enabling both synchronous and asynchronous interactions between students and teachers. At their core, VLEs provide access to educational resources, facilitate communication, and enable the administration, documentation, tracking, and assessment of learning activities (Caprara & Caprara, 2022). Unlike traditional classrooms bound by physical and temporal constraints, VLEs transcend these barriers, allowing learners to engage with content and peers from virtually anywhere at any time. These platforms deliver course materials through diverse digital formats, including video presentations, audio recordings, and interactive virtual classes. Advanced VLEs incorporate real-time elements such as live video conferencing and interactive whiteboards, while integrating with institutional Management Information Systems.

It is crucial to distinguish VLEs from Learning Management Systems (LMS), terms often used interchangeably. An LMS primarily concentrates on the administrative aspects of learning—managing student enrolment, tracking progress, and administering assessments. VLEs also incorporate these functionalities, yet they offer a holistic educational environment, emphasising interaction, collaboration, and rich learning experiences, effectively serving as the broader pedagogical space within (Dobozy, 2011; Karvelas, 2015).

Adaptive Learning Integration

Traditional VLEs typically present assignments sequentially. However, adaptive learning offers a personalised approach, with VLEs reacting to user actions and providing various learning paths. As described by Zhao and Wang (2019), this personalisation involves developing learning strategies tailored to each student's unique characteristics and preferences. Despotovic-Zrakic (2012) notes that adaptive learning encompasses learner-oriented platforms, adaptive environments, and personalised systems.

As described previously, AI and intelligent agents significantly advance personalisation by recognising individual learning paces, offering tailored advice and instant support, and dynamically modifying learning plans, materials, and assessments (Xu and Wang, 2006). However, careful balance must be maintained to ensure AI-driven pathways foster student agency and self-directed learning, preventing over-reliance on system-directed instruction that might limit independent exploration and metacognitive skill development.

Immersive Technologies

VR and AR integration offer engaging educational experiences. VR creates fully immersive, computer-generated environments accessed via special headsets, allowing learners to simulate real-world or hypothetical scenarios—from exploring historical sites to practicing complex surgical procedures. AR overlays digital information onto users' real-world view through smartphones, tablets, or specialised glasses, enhancing physical materials with interactive digital features.

Benefits and Challenges

VLEs provide increased accessibility, flexibility, personalisation, and collaboration opportunities. They remove geographical and temporal barriers, enabling global participation at convenient times. Personalised learning journeys, enabled by data analytics and adaptive technologies, allow students to focus on areas of need, progress individually, and receive targeted feedback. VLEs facilitate diverse interactions, ranging from peer collaboration in discussion forums to real-time instructor communication, thereby building virtual communities that support social learning and professional networking.

Despite the benefits, VLE implementation also faces significant challenges. Technological and infrastructural barriers are prominent, particularly the digital divide—unequal access to stable internet connectivity, suitable devices, and necessary software (Peña-López, 2010). This challenge is acute for VR/AR's higher bandwidth and processing demands. Technical issues, including platform glitches, software incompatibilities, and the need for robust technical support, can disrupt learning. VR and AR introduce additional complexities related to hardware maintenance and specialised peripheral requirements.

3.3 Next Generation Digital Learning Environments

Next Generation Digital Learning Environments (NGDLEs) represent a significant paradigm shift in how we conceptualise digital learning infrastructures. The NGDLE concept was introduced by EDUCAUSE in a 2015 white paper authored by Brown et al. (2015) and represents a fundamental reimagining of digital learning environments. Unlike the conventional Learning Management System (LMS) approach or even the Virtual Learning Environment (VLE), NGDLEs are defined as "a digital learning architecture encompassing a confederation of learning applications, tools, and resources woven together by means of open standards" (Brown et al., 2015). This approach acknowledges that learning is far too diverse to be adequately enabled by a single application or platform.

What distinguishes NGDLEs from traditional systems is their component-agnostic architecture. As noted in the EDUCAUSE research, "such a confederation may or may not include an LMS; in this regard the NGDLE concept is agnostic" (Brown et al., 2015). This represents a significant departure from the LMS-centric approach that has dominated educational technology for decades. Among the five core principles underpinning NGDLEs—interoperability, personalisation, analytics, collaboration, and accessibility—personalisation stands out as one of the most critical user-facing principles. Personalisation within NGDLEs encompasses two distinct aspects. The first involves "the outfitting and configuration of the learning environment, which is then used to construct pathways to accomplish learning tasks and attain learning goals"(Brown et al., 2015). The second aspect focuses on adaptive learning, where an automated system provides learners with coaching and suggestions tailored to each learner's specific needs.

Empirical Evidence for Effectiveness

Recent research demonstrates the effectiveness of PL approaches. A study by Sanceon et al. (2022) on a web-based personalised learning system for Singapore primary and secondary education demonstrated significant improvements in student performance. The system used adaptive recommendation algorithms to generate customised assessment worksheets based on individual proficiency levels. Their randomised controlled trial showed that students receiving personalised content performed better academically than those using non-adaptive materials.

Additionally, a meta-analysis examined the effectiveness of technology-supported personalised learning in low- and middle-income countries, revealing that PL technologies had a statistically significant positive effect on learning outcomes, particularly when these approaches adapted to the learners' proficiency levels. This suggests that PL can play an important role in improving educational access and quality in resource-constrained settings

Building block approach

A defining characteristic of NGDLEs is their "Lego" or 'building block's' approach to educational technology infrastructure. As described in the EDUCAUSE research, this involves NGDLE-conforming components that enable individuals and institutions to construct learning environments tailored to their specific requirements and goals (Brown et al., 2015). This component-agnostic architecture enables an environment or ecosystem of interconnected learning tools built on common standards.

Benefits and Challenges

NGDLEs offer substantial benefits including enhanced flexibility through modular architecture, improved personalisation capabilities addressing diverse learning needs, and increased interoperability between educational tools. However, significant challenges exist, including technical complexity that requires substantial IT infrastructure and expertise, integration difficulties when connecting diverse platforms, cost considerations for implementation and maintenance, the need for faculty training on new technological paradigms, and increased data privacy and security concerns across interconnected systems.

The future of PL lies not in monolithic systems but in flexible, component-agnostic environments that can evolve alongside our understanding of effective learning and teaching practices. This approach promises to deliver more responsive, adaptive, and ultimately more effective educational experiences for learners across diverse contexts and disciplines.

3.4 Emerging tools for personalised learning

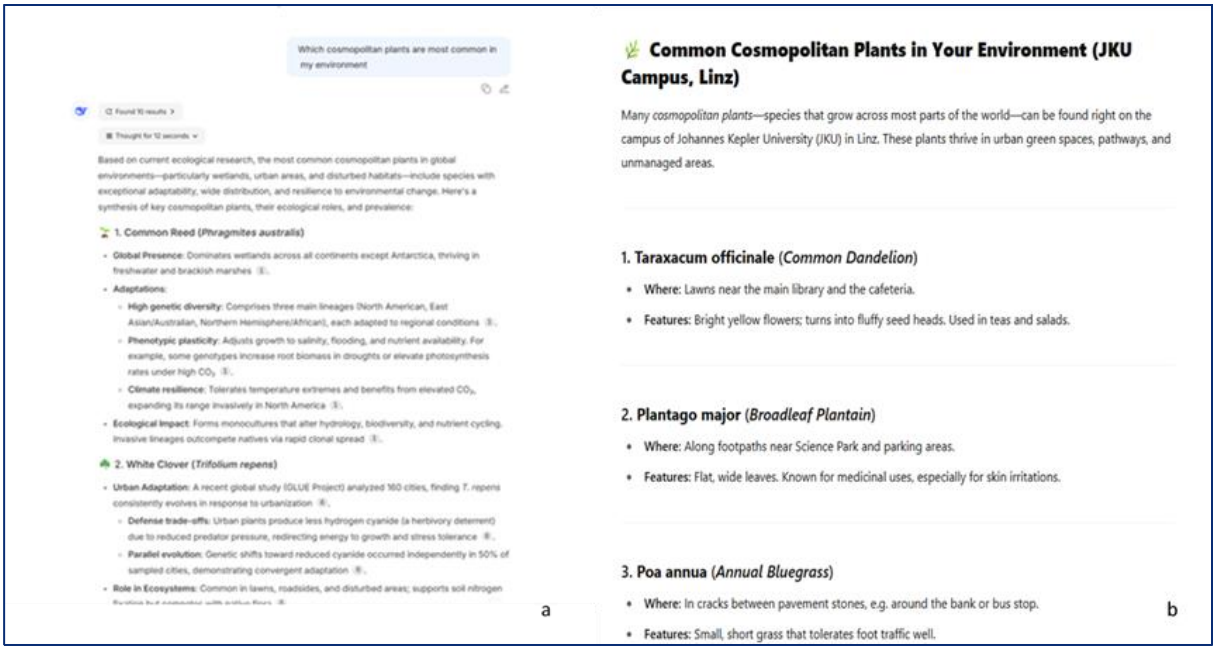
Generative Artificial Intelligence (GenAI) and Conversational Agents (AI Chatbots) represent one of the newest and most dynamic directions in the development of tools for personalised learning (Milana et al., 2024). These systems, based on advanced language models such as GPT or Gemini, enable the generation of customised content in real time, the creation of dialogue with students, and continuous support throughout the learning process (Labadze et al., 2023; Tlili et al., 2023). The ability of conversational agents to simulate human communication, adapt to users, and support self-directed learning makes them particularly relevant in higher education contexts.

GenAI tools and chatbots are increasingly integrated into digital educational platforms, where they create content (summaries, quizzes, essays, assignments) tailored to individual students' knowledge, interests, and learning pace. This approach enables micro-adaptive learning, which continuously adjusts based on users' performance and system interactions. Theoretically, such personalisation relies on principles from Self-Determination Theory (Deci & Ryan, 1985) and Vygotsky's zone of proximal development concept (Moll, 1990), as GenAI allows timely support and encourages learner autonomy.

Conversational agents further enhance these possibilities through dialogic support for learners. Modern AI conversational agents retain conversation flow and learn from context, enabling meaningful, interactive, and personalised communication. The support model shifts from reactive to proactive, giving students guided support throughout the learning process. These tools are especially helpful in structuring complex tasks. For example, students struggling with seminar papers can use ChatGPT to create outlines, formulate theses, or receive language feedback. In natural and technical sciences, GenAI can explain mathematical problem-solving steps or assist in simulating experimental procedures, promoting active and constructive learning.

Arun et al. (2024) emphasise the great potential of customised AI chatbots in educational personalisation. Popular chatbots like ChatGPT and Google Gemini now offer customisation options. When customising chatbots for educational purposes, teachers can define instructional content, communication style, interaction tone, and pedagogical approach. By specifying instructional content, conversational agent creators can adapt material to students' needs and knowledge levels. Through communication style and pedagogical approaches, teachers can encourage specific tones, prompt information verification, and facilitate follow-up questions.

Figure 1. *A – Response from an open chatbot; B – Personalised response from a customised chatbot.*



Teachers can fully tailor instructional content within conversational agents to meet the needs of students and their individual characteristics. However, when developing conversational agents for PL, teachers must carefully consider information availability and reliability, as well as student privacy and platform safety.

Emerging personalised learning tools predominantly leverage artificial intelligence to create adaptive and responsive educational experiences. Key among these are sophisticated Adaptive Learning Systems (ALS) that tailor instructional content, pace, and pathways in real-time based on individual student performance and needs (Hennekeuser et al., 2024; Laak and Aru, 2025). Furthermore, intelligent Tutoring Systems (ITS) are evolving to simulate human-like one-on-one tutoring, offering personalised guidance, instant feedback, and support. These tools often work with AI-powered learning analytics dashboards, providing actionable student progress insights, while some systems explore immersive VR/AR technologies to enhance engagement and understanding (Vorobyeva et al., 2025). .

3.5 Good practice

PL has become essential for making professional development more focused, efficient, and impactful. In cybersecurity, there is an urgent need to increase the supply of competent professionals to address the tremendous skills gap in the domain. Aspiring professionals must invest considerable amounts of time researching and navigating the complexity of the cybersecurity domain to identify entry points and progressive advancement pathways. Cybersecurity experts also struggle to effectively manage lifelong learning and stay ahead of rapid technological advancements. While mentoring is acknowledged as a prominent solution in cybersecurity professional development, it faces notable scalability challenges as it requires substantial human resources and broad domain expertise. This highlights the need for designing innovative interventions that promote PL while fostering individual attention and support within a scalable framework.

Within the context of the MSc in Computer and Network Security at the Open University of Cyprus, generative AI is leveraged to promote career-driven personalisation in cybersecurity at scale, addressing the challenges in professional development. A novel intervention was designed (Kallonas et al., 2024) that leverages generative AI to create effective and personalised, career role-oriented study plans. The objective was to provide guidance for learners to navigate the complexities of professional development in cybersecurity while adapting to individual needs and empowering learners to control their learning trajectories.

To achieve this goal, a new curriculum was designed to enhance learners' understanding of the professional aspects essential in cybersecurity and cultivate forward-thinking planning for career progression. The curriculum was intentionally designed to enhance a set of skills crucial for lifelong learning and career progression, including research, analytical, synthesis, self-efficacy, and critical thinking skills. The curriculum was integrated as part of an existing module, with learning materials prepared to assist learners in investigating career roles based on ENISA's European Cybersecurity Skills Framework (ECSF), identifying their career goals and learning objectives, recognising their learning style and pace, and developing prompt engineering skills tailored for professional development in cybersecurity.

In one of the delivered learning activities, learners had the opportunity to utilise ChatGPT to explore what they need to master in cybersecurity to achieve their short- or long-term career goals, identify learning materials and resources they should utilise, and create their professional development plan powered by generative AI. Prior to the curriculum design, investigations were conducted to confirm that the tool could suggest appropriate learning topics to learners, indicate where they could find learning resources, and assist them in structuring their professional development plans to promote sustainable learning routines. It was also confirmed that suggestions included credible resources, which is crucial when empowering learners to take control of their own learning.

A challenging aspect was that the tool demonstrated moderate realism in suggesting completion timeframes for activities listed in the plan. Reasonable completion timeframes were suggested for theoretical activities such as reading articles and listening to podcasts; however, insufficient time was allocated for practical activities such as laboratory exercises. This indicates that human supervision is essential to validate and adjust AI-generated plans, ensuring alignment with the learner's context, capacity, and practical demands of the subject matter. Combining AI-generated recommendations with expert oversight enables more realistic and effective learning pathways, striking a balance between automation, personalisation, and pedagogical soundness. The professional development plans created by learners were submitted to the module tutor, who provided appropriate feedback to help learners improve their plans. Learners reported satisfaction and confirmed that such interventions can empower them to take ownership of their learning, maintain engagement, and make more informed decisions about their academic and professional journeys.

The approach taken in this intervention is applicable across disciplines to support learner autonomy and bridge the gap between self-directed learning and structured mentoring. By combining AI-driven guidance with expert feedback, the intervention replicated key aspects of mentorship—such as career goal setting, resource curation, and progress monitoring—at scale. The intervention demonstrates how technology-enhanced learning can empower individuals to take control of their growth while still benefiting from targeted, expert-informed feedback, ultimately fostering more resilient and proactive lifelong learners.

Conclusion

This chapter presented an overview of how artificial intelligence is transforming personalised learning and offered insights into approaches to adaptive, learner-centred educational experiences. AI-driven analytics, intelligent tutoring systems, and adaptive assessments can shift teaching from a reactive model to a proactive one, helping educators identify at-risk students earlier and tailor interventions more precisely. Generative AI and conversational agents enable scalable creation of customised content and feedback, redefining the educator's role as a designer of learning experiences rather than just a content deliverer.

Technological infrastructure alone doesn't guarantee success, yet thoughtful, intentional design of learning experiences that truly cater to individual needs is essential. Success depends on balancing technological capabilities with sound pedagogical principles and ethical considerations. Overall, the future of personalised learning lies not in replacing human educators but in augmenting their capabilities through intelligent systems that adapt to learners rather than forcing learners to adapt to static systems. This requires institutional commitment to both technological innovation and pedagogical excellence. Such a comprehensive approach to AI-driven personalized learning represents a fundamental shift toward more responsive, adaptive, and ultimately more effective educational experiences.

Ethical issues—such as privacy, algorithmic bias, and the digital divide—must remain central to implementation efforts to avoid perpetuating inequalities. These themes are explored in greater depth in chapter 5. For institutions and policymakers, the chapter highlighted the importance of strategic infrastructure investment, faculty development, and policy frameworks that support interoperable systems and equitable access. More on this can be found in Chapter 6.

Before moving on, reflect on the following questions to examine the use of technology in PL:

Questions for reflection

As AI systems become increasingly sophisticated at predicting student behaviour and academic outcomes, where should we draw the line between helpful intervention and invasive surveillance? How do we balance personalised support with student privacy and autonomy?

If AI can adapt learning pathways in real-time and provide instant feedback, what unique value do human educators bring that cannot be replicated? How do we ensure AI enhances rather than diminishes critical thinking and creativity?

Given that AI-powered PL requires substantial technological infrastructure, how can institutions ensure these tools don't exacerbate existing educational inequalities? What strategies can bridge the digital divide?

As students become accustomed to AI-adapted learning experiences, how might this affect their ability to learn in non-personalised, traditional settings or develop self-regulation skills?

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4. Curriculum design for Personalisation

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Introduction

Personalised learning has emerged as a central principle in reimagining higher education to meet the demands of increasingly diverse learners, evolving labour markets, and the imperative of lifelong learning. Central to this shift is the design of curriculum—both at the macro (programme-level) and micro (course or learning experience-level)—which forms the backbone of educational provision and learner engagement. This chapter explores how curriculum design can serve as a strategic lever for embedding personalisation, enhancing learner agency, and aligning education with future-oriented competencies.

Understanding curriculum: From structure to experience

Curriculum can be understood on two interrelated levels. At the macro level, it refers to the formal, structured programme or institutional offering, including degrees, qualifications, and predefined learning pathways. These are shaped by national policies, institutional frameworks, accreditation requirements, and disciplinary conventions. The macro curriculum defines the scope, sequence, and coherence of educational provision at scale.

At the micro level, curriculum encompasses the design and delivery of individual courses, modules, or learning experiences. This includes content, pedagogical strategies, assessment methods, and the interaction between teacher and learner. While macro curriculum sets the structure, the micro level shapes how learners experience, interpret, and engage with their education.

In both cases, the curriculum is not merely a static set of contents but a dynamic interface between institutional intentions and learner aspirations. It reflects choices—what to include or exclude, who decides, how flexibility is enabled or constrained—and these choices critically impact the extent to which learners can personalise their educational journeys.

Institutional vs. individual perspectives on Curriculum Design

Curriculum design traditionally reflects an institutional perspective, rooted in regulatory compliance, disciplinary coherence, and efficiency in delivery. Programmes are typically developed by academic teams and validated through institutional and national quality assurance bodies. From this angle, personalisation may appear secondary to the standardisation and comparability of qualifications.

In contrast, the individual perspective on curriculum foregrounds the learner's unique needs, aspirations, prior knowledge, and life contexts. This view advocates for customisation, flexibility, and co-construction—recognising students as active agents in shaping their learning pathways rather than passive recipients of predetermined content.

Balancing these two perspectives—upholding academic standards while enabling learner agency—is a key challenge and opportunity in curriculum design for personalisation. It requires rethinking not only the structure of programmes but also the processes of curriculum governance, pedagogical design, and assessment strategies.

Why personalisation matters

The call for personalisation is driven by multiple, intersecting factors. First, learners are increasingly diverse in terms of age, background, motivation, and prior experiences. Traditional one-size-fits-all curricula risk marginalising those who do not fit the 'typical' learner profile. Personalisation allows for more inclusive approaches, where pathways and pedagogies respond to individual starting points and trajectories.

Second, the accelerating pace of technological, economic, and social change requires curricula that foster future-readiness. This includes equipping learners with transversal competencies—such as critical thinking, adaptability, and digital fluency—as well as domain-specific knowledge. A personalised curriculum enables learners to pursue relevant, timely, and interdisciplinary combinations of content that align with emerging roles and lifelong learning needs.

Third, there is growing recognition of the importance of student agency in learning. Personalisation empowers learners to set their own goals, make meaningful choices, and engage in self-directed learning. This not only enhances motivation and persistence but also cultivates meta-cognitive skills that are essential in complex, rapidly evolving environments.

A transformative approach to Curriculum Design

Embedding personalisation in curriculum design entails more than adding flexible options or technological tools. It requires a paradigm shift in how curriculum is conceptualised, developed, and enacted. At the macro level, this may involve modularisation, stackable credentials, and cross-disciplinary pathways. At the micro level, it includes adaptive learning environments, learner-driven assessments, and hybrid delivery models. Across both levels, the role of educators, students, institutional policies, and learning technologies must be aligned to support personalisation meaningfully and sustainably.

This chapter unpacks these dynamics by addressing personalisation at the programme level (4.1), at the course and experience level (4.2), through student agency and co-design (4.3), and within assessment (4.4). Each section is grounded in concrete cases and examples that illustrate how these principles are being put into practice across Europe and beyond. Together, these perspectives show how curriculum design can evolve to centre the learner, enhance flexibility, and promote equity—while maintaining rigour and coherence in higher education. The chapter concludes with a good practice example from the Open University (4.5), highlighting how personalised feedback can be supported through innovative approaches.

4.1 Personalisation at the Programme Level (macro-level)

This section focuses on personalisation at the macro level, that is, at the level of study programmes shaped by national frameworks and supported by regulatory bodies. To illustrate how this is enacted in practice, we look at the Netherlands, where the Dutch government and the accreditation agency (NVAO) facilitated and supported the "National Experiment on Flexible Learning Design" (often called the FlexScan experiments or the experiment on flexible higher education). The experiment involved 21 universities of applied sciences to make higher education more accessible to adult and working learners by focusing on learning outcomes, tailor-made learning paths, and blended (including work-based) learning (Leushuis, Coppiëns & Ponds, 2022). The experiment took place between 2016 and 2024 (Bazen, 2024).

FlexScan was part of the Acceleration Plan (Versnellingsplan). The experiment was initiated due to a sharp decline—approximately 50% since 2001—in the number of adults enrolling in part-time higher education programs. The primary objective was to boost the enrolment of working adults by making programs more flexible and easier to access, which would in turn lead to the official recognition of their learning and the awarding of degrees. The experiment was founded on the concept of 'learning outcomes', which outlines the specific knowledge, skills, and professional competencies students should acquire upon completing a program. This approach applied to adult students in part-time and work-based programs at universities of applied sciences and research universities. The experiment included various programs, such as associate degree/short cycle, bachelor's, and master's degrees (Leushuis, Coppiëns & Ponds, 2022).

To maintain the structure and coherence of the learning outcomes, the study units were capped at a maximum of 30 ECTS credit points. This ensured that the units collectively built toward the final qualifications of the program (Leushuis, Coppiëns & Ponds, 2022).

How FlexScan Was Designed

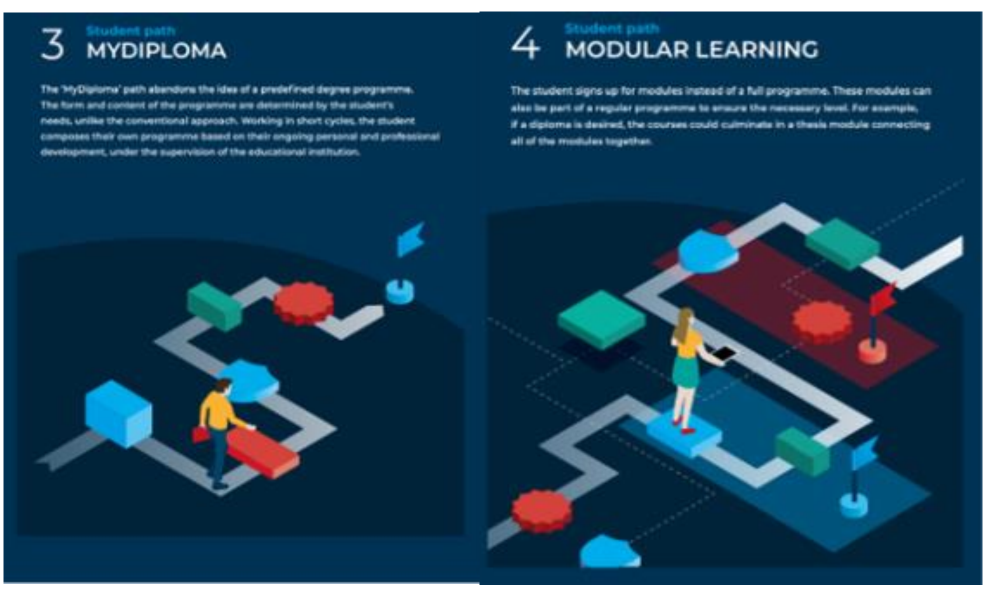
Several features were central to the design of the FlexScan experiment. A cornerstone was the use of individual learning agreements that recognised prior learning. Each student developed a personalised study plan in dialogue with a coach, which served as a dynamic document, reviewed and adjusted over time to reflect evolving goals and circumstances. Flexibility was also built into the pace and mode of study. Although students enrolled in a specific programme at a university of applied sciences, they could progress at their own speed and choose from different delivery modes, including full-time, part-time, dual study formats, or blended and distance learning. In addition, institutional mobility further expanded opportunities for personalisation, allowing students to take courses at other institutions and compose a more individualised programme of study.

Images 1 and 2: *Illustrations showing flexible study paths—either progressing at one's own pace or moving across institutions and disciplines (Versnellingsplan, 2021).*

MyDiploma Paths

Another innovative element of the experiment was the introduction of *MyDiploma Paths*. Instead of committing to a predefined degree structure, students could compose their own study programmes in shorter cycles, aligning them with their personal and professional development needs. The emphasis on modular learning meant that students registered for individual modules rather than entire programmes. These modules could then be combined into a diploma, giving learners more control over both the pace and the direction of their studies.

Images 3 and 4: *Illustrations showing personalised qualification routes—either through self-designed diploma paths or modular learning options (Versnellingsplan, 2021).*



Blended learning
A further cornerstone of the FlexScan approach was the integration of blended and work-based learning. Programmes combined synchronous and asynchronous online activities with face-to-face sessions, allowing students to tailor their engagement to their professional and personal schedules. Work-based learning was particularly important, ensuring that students could directly apply academic knowledge to their professional contexts. To support institutions in designing such flexible provision, the *FlexScan* tool was developed to assess and benchmark programme flexibility from the perspectives of students, teachers, and the professional field.

Outcomes of FlexScan
An output-oriented educational concept was found to be effective in promoting student self-management and encouraging them to think more critically about their own learning paths. The key was shifting from a fixed curriculum to a flexible structure based on learning outcomes (Leushuis, Coppiëns & Ponds, 2022).

Enrollment in part-time and dual higher professional education programs grew by about 50% compared to 2015, with the experimental programs showing greater growth than other similar programs. The impact on graduation rates is still unclear, but all students indicated they plan to complete their degrees (Bazen, 2024).

Most employers were satisfied with the experimental programs, noting that students developed a more proactive learning attitude, enjoyed greater customization, and formed a stronger link to their professional field. The majority of students were also satisfied with the program and its flexible options. Programs that incorporated a mix of online, in-class, and workplace learning were especially well received, with 55–59% of respondents expressing satisfaction with this blended approach (Leushuis, Coppiëns & Ponds, 2022).

At the same time, a minority of students (18%) were critical of the programs and would not recommend them. Their dissatisfaction stemmed either from expectations of more flexibility than was provided or from a desire for more structure. These findings underline that flexible curriculum design must be carefully balanced and accompanied by clear communication to align with diverse learner needs (Leushuis, Coppiëns and Ponds, 2022).

A focus group study (Huyer et al., 2024) conducted with nursing programs, which participated in FlexScan investigate the flexible assessment format. The majority of students and teachers felt that this approach gave them an opportunity to present evidence of learning in various ways.

Students and teachers shared several common concerns regarding flexible assessment. Both groups highlighted the need for closer alignment between assessment formats, learning outcomes, and rubrics, particularly given the wide range of evidence and methods being used. They also struggled with defining assessment criteria for cognitive skills at the bachelor’s level and with establishing clear processes for granting exemptions based on prior evidence of learning.

At the same time, their perspectives diverged in important ways. Students were generally more critical than teachers of the breadth and specificity of learning outcomes and rubrics, often finding them overly restrictive or unclear. Teachers, by contrast, tended to view the criteria as transparent and felt confident in their ability to evaluate diverse evidence. Students also noted inconsistencies in grading practices across instructors and reported a lack of sufficient guidance to make informed decisions about their assessment options, while teachers did not perceive these issues as strongly.

These similarities and differences highlight the complexity of implementing flexible assessment in practice, underscoring the need for careful design and shared understanding among both students and teachers. The study concluded that the success of flexible assessments depends on a delicate balance in their design and on a clear understanding of them by both teachers and students. This balance is essential for matching the level of assessment flexibility with diverse types of evidence and a suitable grading methodology, which can improve the educational experience in nursing and other fields.

Personalisation at the program level is about giving students more control over their study paths to meet their individual and professional needs. It moves away from the traditional, rigid curriculum where all students follow the same courses in a predefined order. Instead, a personalized approach allows for tailor-made learning paths, which can include composing a student's own program based on their personal and professional development goals. This is often achieved by focusing on learning outcomes—the specific knowledge, skills, and competencies a student should have at the end of a program—rather than on the number of hours spent in a classroom. This approach supports a variety of learning methods, such as blended learning, which combines online, in-class, and work-based learning. Students can choose different modules or units, and their progress is measured by their ability to demonstrate mastery of the required outcomes, regardless of how they acquired the knowledge. This allows students to study at their own pace and even pursue part of their program at another institution, fostering mobility and flexibility.

This example illustrates how programme-level curriculum reform, supported by macro-level policy frameworks, can expand opportunities for adult learners while maintaining coherence and quality assurance.

Challenges of programme-level personalisation

Despite its benefits, the case also presents several challenges for programme-level personalisation.

Difficulty with self-direction: Many students struggled to take charge of their own study programmes and required more guidance than anticipated. This highlights the need for strong coaching and support structures.

Mismatched expectations: Flexible learning does not suit all learners. Some students expected greater freedom than was provided, while others preferred more structure. Both situations led to dissatisfaction.

Institutional and communication barriers: Institutions noted that students adapting to self-directed learning needed clearer information and closer supervision. Transparent guidance is crucial so prospective learners can make informed choices about whether a flexible programme matches their preferences and needs.

These challenges underline that structural flexibility at the programme level is only one part of the picture. For personalisation to succeed, it must also be embedded in the design of courses and day-to-day learning experiences. The next section turns to personalisation at the micro level.

4.2 Personalisation at the Course and Experience Level (micro-level)

At micro-level - that is, within individual courses and learning pathways - personalisation enables greater flexibility, responsiveness, and relevance. Through adaptive technologies, multimodal content delivery, learner choice, and real-time feedback, educators can create pathways that align with students' interests, goals, and prior knowledge or prior skills.

Personalisation in online learning enables flexibility in how content is delivered - accommodating varying learner preferences through multiple formats such as text, video, and audio. This multimodal approach allows students to engage with material in ways that best suit their cognitive styles and accessibility needs (Bernacki et al., 2021). Flexibility also extends to learning pace, with self-paced modules allowing learners to progress according to their prior knowledge and availability - particularly important for adult learners balancing education with work or caregiving (Nguyen & Nguyen, 2023).

Adaptive content sequencing further supports differentiated pathways, letting students revisit foundational concepts or skip redundant material. This individualised progression fosters sustained engagement and deeper understanding. Evidence suggests that learners value delivery formats aligned with their preferences, which enhances perceived learning effectiveness (Ismail et al., 2023).

A learner-centered practice is key to motivation and involvement. Jacques Lévine (2004) highlights the importance of learning environments that respect learners' subjectivity and experience, where adults learn based on their own motivations rather than imposed goals. PL can be further enhanced by embedding decision points where students select topics, case studies, or paths that align with their personal interests or skill gaps. This approach ensures learners can engage with content that resonates with their goals and fosters intrinsic motivation. An example of this is the Making your learning count course from the Open University (UK). In this course, students can compile credits from a variety of courses / modules of their choice to build a personalised qualification. This flexibility allows learners to tailor their education to their specific needs and interests, ensuring that their learning journey is both relevant and rewarding. By providing these choices, the course promotes a deeper sense of ownership over the learning process, leading to greater learner satisfaction and engagement. Learners accumulate credits from a range of learning experiences, both formal and informal, across formats. Such autonomy is made possible by an assessment of the skills developed and not on the content.

Hybrid delivery combines online and in-person learning with both synchronous and asynchronous formats, offering flexibility and accessibility greater than traditional presential courses for diverse learners. This multimodal approach supports students in managing time, balancing commitments, and engaging with content through the format that best suits their needs. The SHIFT project, at Université Grenoble Alpes, in France, exemplifies how hybrid personalisation can increase participation and motivation across varied educational environments (Université Grenoble Alpes, 2023). In this case, the synchronous part of the course takes place in online videoconferencing sessions, "remote face-to-face". This hybrid model fosters deeper learner autonomy while maintaining structured academic support, bridging accessibility with personalisation. It was first created to answer the need of high-level athletes with complicated agendas.

Adaptive Systems and Learning Analytics

Learner profiling and learning analytics allow educational platforms to gather and interpret data on student interactions, progress, and performance. By monitoring behaviours like time spent on tasks, assessment results, and content engagement, these systems personalise the learning experience—adjusting content, pacing, and support in real time. This adaptive approach enhances learner engagement and outcomes by aligning instruction with individual needs. Transparency about data use is important to build trust and empower learners. Chapter 3, of this report, explores how AI and emerging technologies further refine personalisation through advanced analytics, adaptive systems, and intelligent tutoring.

Personalised feedback systems dynamically respond to learner inputs—such as quiz results, activity patterns, and time spent on tasks—to tailor the learning experience. These systems offer immediate, targeted feedback, redirect learners to additional resources, or adjust task difficulty in real time. For instance, the University of Santiago de Compostela (Spain) has implemented an adaptive learning pedagogical strategy supported by learning analytics for the personalised training of pre-service teachers. This system assesses students' progress and adjusts content and feedback accordingly. The collected data is centralised in a Learning Record Store (LRS), enabling collaboration among mentors and contributing to PL based on each student's progress.

Challenges and Opportunities at the Course Level

While personalised learning offers significant benefits, its implementation at the micro-level often faces constraints due to regulatory frameworks in higher education. Degree programs must adhere to structured credit systems, accreditation standards, and prescribed learning outcomes, which limit how much flexibility is available in tailoring courses to individual needs. At the bachelor's level, curricula are typically more rigid, with fewer opportunities for electives and a focus on broad foundational knowledge. This structure leaves limited room for personalisation. In contrast, master's programs tend to offer more flexibility, including specialisations and research-based components, allowing for greater adaptation to individual learner needs.

Despite these differences, personalisation can be improved at both levels by leveraging adaptive learning technologies and data analytics. For example, incorporating formative assessments and personalised feedback systems within the constraints of required learning outcomes can better support learners without sacrificing academic rigour. While bachelor programs often face more prescriptive structures, adaptive systems can still offer personalised pacing, targeted resources, and real-time feedback, allowing students to engage with the material at their own pace. Master's programs, with their greater flexibility, can more easily incorporate fully individualised learning pathways, but still must align with accreditation and regulatory standards.

As suggested by Papamitsiou and Economides (2014), learning analytics and adaptive learning systems provide promising tools for personalising learning within the regulatory frameworks of both bachelor's and master's programs, ensuring that educational quality and compliance are maintained.
Personalisation at the micro-level enhances learner engagement by offering adaptive pathways that cater to individual needs and preferences, despite regulatory constraints. By integrating technologies such as learning analytics, adaptive feedback systems, and multimodal content delivery, institutions can create flexible learning environments that align with both academic standards and students' unique learning journeys. This balance supports deeper learner autonomy and satisfaction, ultimately leading to more effective and engaging educational experiences.

Beyond institutional design, personalisation also depends on the role of the learner. Section 4.3 therefore examines how student agency and co-design bring the curriculum to life.

4.3 Student Agency and Co-design

In chapter 1 (table 1), personalisation is described as "student-driven, tailoring learning to each student's strengths, needs and interests". Achieving this requires student agency and co-design, both central to personalisation and student-centred learning (Stenalt & Lassesen, 2022; Torres Castro & Pineda-Báez, 2023). In this context, student agency refers to the student's own will and intentional actions combined with the institutional opportunities provided to contribute to the design and experience of their own learning environments and pathways (Klemenčič, 2017; Stenalt, 2021; Torres Castro & Pineda-Báez, 2023). Agency shifts the focus from students being solely the recipients of curriculum to also being active participants (Nieminen et al., 2025; Williams & Ingle, 2025). With agency, students can influence how curriculum is personalised through structure, delivery and assessment. This involves three dimensions: voice, choice and ownership (Walkington & Bernacki, 2020). For example, students could be given the opportunity to articulate their study motivations, learning needs or preferences and views and have these inform their curriculum and assessment experiences (voice). Students could choose their own pathways, content or pace (choice). Ownership comes from the extent to which students are involved in co-designing curriculum and related learning activities (Fouché, 2025; Lubicz-Nawrocka, 2023; Omland et al., 2025; Walkington & Bernacki, 2020).

Opportunities for personalised learning

By placing student agency at the core and moving beyond student engagement, co-design of curriculum offers significant opportunities for personalised learning, building in meaningful choice and flexibility (Klemenčič, 2017). Personalisation is not about tailoring learning through technology alone, rather enabling students to co-design the structure, pace, mode and content of their curriculum to reflect their goals, needs and interests (Salehian Kia et al., 2023; Walkington & Bernacki, 2020).

Explicit choice can be offered at different levels. At programme level, students could be offered a choice of modules or different pathways or choice of the pace or timing at which they study and are assessed

(Bovill et al., 2011; Walkington & Bernacki, 2020). Choice in delivery mode could extend across group tutorials, one-to-one sessions, asynchronous study such as empty room recordings, or blended learning in a way that best fits a students' circumstances (Billett & Martin, 2018; Zhou et al., 2023). Personalisation can also occur through content delivery where students engage in a variety of media such as text, audio, video, or images. Delivery of media could range from voice-over slide presentations, animated video lectures or traditional methods, enabling students to align their learning with preferred styles and accessibility needs. Students can also be given contextual choice, for example in which topics they would like to cover, case studies they would like to explore, or a choice of real-life application related to the curriculum (Billett & Martin, 2018; Zhou et al., 2023). Project based learning and learning opportunities tailored to students' career goals can provide engaging personalised learning opportunities (Walkington & Bernacki, 2020). Contextual choice incorporates lived or living experiences and cultural identity, personalising curriculum for inclusion and a sense of belonging by centring students in their own learning experience (Fouché, 2025).

Examples from the European distance learning community illustrate how student agency and co-design can be put into practice in diverse ways. At the Open University of Catalonia, students participate in virtual learning communities where they not only access resources but also co-create them, strengthening collaboration and ownership. Similarly, the Open University (UK) has established a *Curriculum Design Student Panel* in which students and staff work together to shape engaging learning experiences. Beyond this, the OU also offers the *Open Degree*, a multidisciplinary programme that enables students to combine modules across disciplines, tailoring a qualification to their own professional and personal interests.

Other institutions provide personalisation through distinctive forms of flexible provision. UNED (Spain) combines online teaching with on-site support delivered through its network of local centres, complemented by adaptive digital platforms that respond to individual student needs. Meanwhile, Università Telematica (Italy) offers fully online programmes designed for maximum scheduling flexibility, allowing learners to adapt their pace of study to align with professional or personal responsibilities. Together, these examples highlight the different institutional strategies through which distance learning providers across Europe embed student agency and co-design into the heart of curriculum personalisation.

Beyond curriculum and delivery, co-design extends into assessment, offering new possibilities and raising important questions—an issue explored in the next section.

Challenges of student agency and co-design

While student agency and co-design provide opportunities for personalisation, several challenges limit full realisation.

Rigidity remains a significant barrier. Professional, statutory and regulatory bodies may set rigid standards and may also accredit and approve course programmes within prescribed frameworks. Internal and external quality assurance mechanisms may limit the ways in which co-design can be applied in practice along with inflexible or less flexible governance processes and requirements and in some cases, curriculum must follow pre-determined or fixed structures (Billett & Martin, 2018). Finally, institutional leadership and managerial ways of working may not be conducive to actively engaging with students to co-design curriculum, let alone for students to have agency over their own learning (Carey, 2013; Cossham & Irvine, 2021).

Timing poses another constraint. Often distance learning virtual environments require all materials, curriculum, tuition and assessment to be fully prepared in advance of course start, which is challenging if a module team wants to co-design with existing students rather than prior students. This also limits co-production when the module is live and makes full co-design unfeasible (Cossham & Irvine, 2021).

Resources are also a limiting factor. It takes time and money to fully co-design with students. Students will need upskilling, guidance and ongoing support, for example to learn about module design, understand institutional and external requirements, and break through technical jargon (Bovill et al., 2011; Woods & Homer, 2022). Students are notoriously time poor and often financially constrained, thus it is not appropriate to expect students to co-design without compensation. Compensation could be payment, fee reduction, academic credit, co-authorship of any publications, or digital badges recognising the skills developed through this extra-curricular work (Bovill et al., 2011; Mackelprang et al., 2025; Woods & Homer, 2022).

Accessibility, digital barriers and inclusivity also present challenges. Often in distance learning institutions, co-design takes place online. Technical difficulties or digital barriers must be well managed (Nieminen et al., 2025). Student co-designers should represent the wider student body including students from traditionally minoritised backgrounds. Online collaboration risks reinforcing power imbalances, so careful onboarding, staff preparation and expectation setting are crucial (Jones et al., 2020). Students must feel like equal contributors rather than tokenistic recipients, with facilitators, who can be students, fostering trust, community and genuine partnership. All members should see themselves as part of a single curriculum production team (Lubicz-Nawrocka, 2023).

Benefits of student agency and personalisation

The evidence demonstrates that student agency and co-design can make personalisation meaningful by connecting curriculum, delivery, and assessment to students' strengths, needs, and aspirations (Nieminen & Tuohilampi, 2020). Co-designed approaches foster critical reflection, motivation, confidence, and self-efficacy, while also supporting employability through personalised pathways and skills development (Billett & Martin, 2018; Fouché, 2025; King et al., 2024). Crucially, agency builds autonomy and cultivates academic citizens who feel a sense of belonging and contribution within their learning community (Zhou et al., 2023).

Personalisation cannot be reduced to a technological fix (Salehian Kia et al., 2023; Walkington & Bernacki, 2020). It is a negotiated and relational process that depends on equitable structures of participation, recognition of power dynamics, and careful attention to inclusivity (Jones et al., 2020). By embedding student agency and co-design, institutions can move beyond designing for inclusion toward designing *with* students for belonging. This shift reframes personalisation not simply as an institutional offering, but as a shared practice of partnership.

A central dimension of curriculum design is assessment. Section 4.4 considers how assessment can be reimagined to support personalisation and student ownership of learning.

4.4 Personalisation in Assessment

How can you personalise assessment in a system where curriculum, learning and assessment are traditionally designed for the average student? By adapting content, format, delivery, and feedback, assessment can be personalised to meet students' study motivations, diverse characteristics and needs (El-Hmoudova & Milkova, 2016; Rodrigues et al., 2024). Beghetto (2019) proposes that we allow for a different *what* - students define their own questions, problems and criteria for success, and a different *how* - different ways of solving problems. Therefore, key to effective personalised assessment is moving from assessment *of* learning to assessment *for* learning, where student learning is centred and tailored, and the assessment itself focuses on the process, not just a predetermined result (Beghetto, 2019; Black & Wiliam, 2012; Pramjeeth & Till, 2023). Ultimately, if we can produce personalised assessment where students can exercise autonomy and are motivated to engage, we can improve learning outcomes and students will become strong academic citizens (Nieminen et al., 2025; Shen, 2024).

Adapting content and format

Allowing different *what* and *how* allows for different pathways and different outcomes, providing a high level of personalised assessment (Beghetto, 2019). In order to maximise engagement and motivation, student characteristics such as prior educational qualifications, lived experience, cultural identity or preference for mode of assessment should be incorporated directly into assessment design (Gonsalves, 2025; Sinharay et al., 2025). Assessment that is highly contextualised, for example for specific professional contexts, living experiences, or local communities or cultures can allow for the different *what* (Beghetto, 2019) and can promote positive academic conduct (Gonsalves, 2025; Kofinas et al., 2025; Hardie et al., 2024; Reimer, 2024). In true co-design, students could determine their own or shared criteria for success (Beghetto, 2019).

Assessment format can also be tailored to individual students' abilities and interests, maximising their opportunity to demonstrate learning and allowing for a different *how* (Beghetto, 2019). A rich variety of formats should be provided for the students both within an assignment and across their entire student experience. Formats are many and include essays, reports, oral presentations, portfolios, demonstrations, performance, professionals practice assessment, posters, videos, blogs, vlogs, websites, group projects, debates or panel discussions, hackathons, simulation or role play, reflective journals, personal development plans and more (Hardie et al., 2024; Shen, 2024; Walkington & Bernacki, 2020).

Leveraging technology for assessment delivery

Often linked to learning analytics and artificial intelligence tools, adaptive assessment makes continuous and dynamic adjustments to the evaluation process to match the student's needs (Halkiopoulos & Gkintoni, 2024). Computerised adaptive testing is a method where the test dynamically shifts adjusting the difficulty based on the previous answer, thus allowing personalisation for large cohorts (El-Hmoudova & Milkova, 2016). Computerised formative assessment tailored to the individual student can create reliable, scalable rapid formative assessment that providers personalised tasks and instant feedback (Mustapha et al., 2024; Pellas, 2023; Shin & Bulut, 2022; Tharapos et al., 2025). Visualisation tools can be used to create individual student profiles that show the student what they already know and how well, and what they still need to learn (Ho & Jeon, 2023). Recommender systems can be used to determine when a student is ready to be assessed, to what extent and how often (Shin & Bulut, 2022).

Feedback and reflection

Assessment can be personalised by incorporating opportunities for self-reflection and self-assessment and for integrated peer assessment, providing students the opportunity to develop reflective and critical thinking skills (Shen, 2024; Zheng et al., 2022). Large language models, including the use of learning analytics, can be used to auto-generate and personalise continuous feedback at scale which could include prompts and early alerts to students based on their engagement of formative assessment for learning (Tsai et al., 2020). In addition, autogenerated personalised messages, can highlight the achievement of skills based on correct answers and provide review materials for content based on incorrect answers for both formative and summative assessment (Beluzzi et al., 2025).

Agency and ownership

To develop student agency and ownership, assessment should be designed with choice and flexibility built in (Sinharay et al., 2025; Walkington & Bernacki, 2020) and should value originality and creativity (Khlaif et al., 2025; Hardie et al., 2024). This also pertains to assessment that values process over outcome or product (Beghetto, 2019; Kofinas et al., 2025). Students should be given the opportunity to document their learning process including decision making and critical reflection, particularly regarding higher-order thinking (Binh Nguyen Thanh et al., 2023; Khlaif et al., 2025; Nieminen et al., 2025; Shen, 2024). It is also beneficial for students to be given the transparency to own their learning data and understand adaptive content and format (Lindbäck et al., 2025; Nieminen et al., 2025).

Assessment aligned to real-world relevance

The term authentic assessment is complex and increasingly debated. To avoid confusion, in this section, the phrase *assessment aligned to real-world relevance* will be used instead of authentic assessment. This is assessment that bridges learning with the student's real-world and requires higher order thinking such as critical thinking, evaluative judgement and problem-solving skills (Binh Nguyen Thanh et al., 2023; Gonsalves, 2025; Reimer, 2024).

Assessment aligned to real-world relevance provides mechanisms that facilitate personalisation by anchoring assessment in personal experience or lived context (Moorhouse et al., 2023). A level of authenticity is required for the student to apply theory to their own real-world context (Gil-Jaurena et al., 2022). As above, content, context and experience can be tailored to the student's study motivation, the why the student is studying. Format can be tailored to the student's abilities and interests and should focus on higher order thinking and multi-modal formats are recommended (Binh Nguyen Thanh et al., 2023; Moorhouse et al., 2023). Assessment aligned to real-world relevance methods may include individual digital portfolios, reflection assignments and critical self-reflection, or process focused assignments and more (Khlaif et al., 2025; Marinho et al., 2021; Moorhouse et al., 2023). All elements of the assessment should be directly relatable for the student.

Challenges and opportunities of personalised assessment in distance education

While personalised assessment in distance education offers significant promise, its implementation also presents distinct challenges. One major concern is the digital divide and inequitable access to artificial intelligence tools, which can create barriers both for designing fair personalised assessments and for students in achieving equitable outcomes (De La Torre et al., 2025; Khlaif et al., 2025). Safeguarding academic integrity is another persistent issue, particularly around identity verification and the vulnerability of certain assessment formats (Binh Nguyen Thanh et al., 2023; Guadelupe et al., 2021; Hardie et al., 2024). Institutions must also contend with logistical, scalability, and resource challenges, which make it difficult to implement personalised assessment reliably and sustainably at scale (Bulut et al., 2022; De La Torre et al., 2025; Kolluru et al., 2018; Shen, 2024).

Despite these concerns, personalised assessment has the potential to transform learning for distance education students. Many students in this context balance full-time jobs, caring responsibilities, and other commitments alongside their studies. Assessments that are flexible in delivery and directly relevant to learners' contexts can better engage students and reduce the time needed to complete tasks to a high standard, thereby demonstrating true learning (Beluzzi et al., 2025; De La Torre et al., 2025). Socio-cultural factors can also disadvantage students when only traditional evaluation methods are used; offering diverse formats enables learners to demonstrate their knowledge and skills to the fullest extent (Shen, 2024; Sinharay et al., 2025; Zheng et al., 2022).

Well-designed personalised assessment is not only robust but also appealing to students. It encourages positive engagement and the development of academic skills rather than contributing to academic misconduct (Hardie et al., 2024). Importantly, the strategic reimagining of personalised assessment should emphasise higher cognitive skills that all students—regardless of previous qualifications or study level—are capable of developing (Arce Espinoza & Monge Nájera, 2015; Binh Nguyen Thanh et al., 2023; Gonsalves, 2025; Reimer, 2024).

To achieve high quality personalised assessment, staff must be upskilled, students must possess critical digital literacy skills and leadership must provide financial, temporal and colleague resource (De La Torre et al., 2025; Kolluru et al., 2018; Shen, 2024).

To conclude this section on assessment, we highlight a good practice from the Open University (presented in 4.5), which demonstrates how the principles outlined above can be enacted in practice through AI-supported feedback.

4.5 Good Practice: AI-Supported Feedback for Student Success

The Open University has long been recognised for its commitment to personalised feedback, particularly through its practice of providing detailed commentary on every Tutor Marked Assignment (TMA). This feedback tradition reflects a pedagogical ethos that values both formative and summative assessment as a driver of learning. Effective feedback, as Sadler (1989) argues, must clarify goals, criteria, and standards in unambiguous terms, enabling students to understand their current position within a learning trajectory and what instructional experiences might follow. Yet, the challenge of delivering feedback that is both cognitively rigorous and socioemotionally supportive remains a persistent concern in higher education (Carless, 2006; Nicol & Macfarlane-Dick, 2006).

In response to this challenge, Whitelock and Watt (2007) developed Open Mentor (OM), an early AI-enabled system designed to support tutors in the feedback process. Built as a production system its design was grounded in Bales' (1950) interaction process analysis, which categorised tutor comments into four types: positive reactions, negative reactions, questions, and answers. This taxonomy provided a structured framework for evaluating the balance and tone of tutor feedback, offering a lens through which both cognitive and socioemotive dimensions could be assessed.

The pedagogical rationale underpinning OM was further elaborated by Whitelock (2009), who emphasised that technology-enabled assessment should be embedded within the learning model of a course, rather than treated as an add-on activity. She advocated for a dialogic framework in which e-assessment and e-feedback are integrated holistically, encouraging students to reflect and take control of their own learning. OM operationalised this vision by extracting tutor comments from marked assignments, classifying them according to Bales' categories, and comparing the actual distribution of feedback types against predetermined benchmarks. This process enabled tutors to reflect on the appropriateness and balance of their feedback, particularly in relation to the grade awarded.

One of the key insights from the implementation of OM was the recognition that tutors often assumed high-achieving students did not require socio-emotive reinforcement. The rationale was that a high mark spoke for itself. However, when these students were questioned, many expressed uncertainty about the quality of their work, particularly in the absence of contextual information such as the mean score for the assignment. This finding underscored the importance of positive reinforcement even for high performers, and OM helped tutors recalibrate their feedback to address this need. By guiding tutors to provide clearer affirmations and actionable advice, OM contributed to a more equitable and supportive feedback culture (Hounsell, 2007).

The OMTetra project represented a significant phase in the evolution and dissemination of Open Mentor. Funded by JISC, the initiative aimed to refine the system's functionality and explore its adaptability across diverse institutional contexts. In addition to the Open University, the project involved two further UK universities which were; Southampton and King's College London. Both of which contributed to the evaluation and implementation of Open Mentor within their own assessment practices. This multi-institutional collaboration enabled comparative insights into feedback cultures and highlighted the system's potential to support tutor development at scale. The project's findings informed enhancements to Open Mentor's interface, classification algorithms, and reporting mechanisms, ensuring its relevance across varied pedagogical environments (Recio-Saucedo et al., 2013).

The reach of OM extended beyond tutor development. In fact, it shaped the feedback students ultimately received through encouraging tutors to tailor their comments to the emotional and cognitive needs of each learner, OM contributed to a more responsive and student-centred assessment culture. Yet, as Buhagiar (2012) notes, even high-quality feedback may be ineffective if students lack the skills to interpret it. This insight prompted further innovation in AI-supported assessment, shifting the focus from tutor-facing tools to student-facing systems.

OpenEssayist (Whitelock et al 2015) represents a significant advance in this direction. It was developed to support students directly, particularly in contexts where tutor support is limited or unavailable, OpenEssayist offers automated, personalised feedback on draft essays. The rationale for its development was grounded in the recognition that university students often find essay writing to be a cognitively demanding and emotionally fraught task. In such cases, immediate feedback, in the form of "advice for action" can assist students to move forward in their studies by using the information obtained from the immediate analysis of their writing.

Unlike traditional automated essay scoring systems, which focus primarily on summative assessment and grading, OpenEssayist was designed to support formative learning processes .As Whitelock argues, automated essay evaluation technologies can be repurposed not just for efficiency in scoring, but to provide students with feedback tailored to their developmental needs. This shift in emphasis aligns with broader pedagogical goals: to increase the volume and immediacy of feedback available to learners, and to scaffold their understanding of academic writing conventions (Williams 2024).

OpenEssayist operates through two core components: the EssayAnalyser engine, which performs linguistic summarisation, and the OpenEssayist interface, which presents feedback in an accessible format. The system uses key phrase extraction to identify salient concepts and extractive summarisation to highlight pivotal sentences (Whitelock, Twiner, Richardson, Field, & Pulman, 2015). Each essay is pre-processed using modules from the Natural Language Processing Toolkit (Bird, Klein, & Loper, 2009), drawing on large linguistic corpora to analyse textual features.

The feedback provided by OpenEssayist is multifaceted. It highlights structural elements of the essay, tracks the dispersion of key terms, and generates a summary of the content for student reflection. Importantly, it does not assign marks or grades. Instead, it invites students to engage with their own writing, encouraging iterative revision and deeper understanding of academic expectations. This approach reflects the principle of personalisation through formative feedback which empowers students to take ownership of their learning and develop as reflective writers .

Student experiences with OpenEssayist have highlighted both its potential and its complexity. While many learners appreciated the immediacy and clarity of the system's responses, others found it challenging to interpret the feedback or integrate it meaningfully into their revisions. These observations underscore the importance of designing interfaces that not only deliver feedback but also support metacognitive engagement with it. As Ras, Whitelock, and Kalz (2015) suggest, the promise of e-assessment lies not merely in automation, but in its capacity to visualise learning and provoke reflection.

Subsequent research has explored the types of feedback that most effectively influence student implementation. Whitelock et al. (2017) found that feedback addressing both structure and content was more likely to prompt meaningful revision than feedback focused solely on structural features. This insight reinforces the pedagogical imperative to design systems that attend to the holistic demands of academic writing, including argumentation, coherence, and disciplinary conventions.

Together, Open Mentor and OpenEssayist illustrate how AI can support personalisation across the assessment landscape. Ranging from tutor development to student empowerment. These systems contribute to a more nuanced and effective feedback culture by fostering reflective practice, promoting socioemotive balance, and enabling student-tutor dialogue. Their evolution from prototypes to transferable tools demonstrates the potential of AI to scaffold both teaching and learning in meaningful, personalised ways.

More broadly, as discussed in Section 4.4 and 4.5, personalisation in assessment should be understood as a pedagogical strategy that goes far beyond adaptive questioning or intelligent tutoring systems that simply adjust content based on correctness. True personalisation involves interpreting the learner's cognitive position, emotional state, and disciplinary context to offer feedback that is timely, resonant, and actionable. It is not merely about changing the next question, but about transforming the learner's relationship to their own learning. Systems like Open Mentor and OpenEssayist exemplify this deeper form of personalisation, where feedback becomes a reflective mirror, a motivational scaffold, and a strategic guide toward academic success, embedded within the assessment process.

Conclusion

Curriculum is the backbone of personalisation. As this chapter has illustrated, personalisation cannot be achieved at a single level of curriculum design but must be woven through the system as a whole. At the macro level, programme structures and national frameworks can create the enabling conditions for flexible pathways, as seen in experiments such as the Dutch FlexScan initiative. At the micro level, courses and learning experiences bring personalisation to life through adaptive technologies, hybrid models, multimodal content, and individualised feedback. Yet structures and tools alone are not enough. Personalisation depends equally on the role of learners themselves, whose agency, voice, and co-design are essential to shaping learning that is meaningful, motivating, and equitable.

Assessment emerges as a particularly powerful lever for personalisation. Moving from assessment *of* learning to assessment *for* learning requires formats, processes, and feedback that recognise students' diverse needs, contexts, and aspirations. The Open University examples demonstrate how AI-supported systems can extend and deepen these principles, offering personalised feedback at scale while maintaining a human-centred ethos. Together, Sections 4.4 and 4.5 show how assessment can shift from being a static measure of performance to becoming a catalyst for reflection, growth, and learner ownership.

Across these perspectives, a consistent theme emerges: personalisation is not a technological quick fix but a systemic and relational practice. It involves aligning policy and institutional structures with pedagogical innovation, recognising the diverse realities of learners, and fostering genuine partnership between educators and students. When macro-level policy frameworks, programme-level structures, micro-level teaching practices, and assessment strategies are all directed toward flexibility, agency, and coherence, personalisation can move from rhetoric to reality.

Use the reflective questions below to consider how your own curriculum addresses these different levels and dimensions, and look ahead to the final chapter for practical recommendations on enhancing personalisation in higher education.

Questions for reflection

How can flexibility be achieved while remaining compliant with regulatory and administrative requirements?

How can institutions ensure that colleagues who design modules are designing assessment for learning and not assessment of learning? What systems and resources are necessary to support learning designers and academic colleagues?

In what ways can institutions leverage learning analytics and AI-driven adaptive assessment to provide equitable, scalable and personalised support for all students?

How can institutions actively foster students' digital AI literacy through assessment design, ensure that technology enhances human interaction rather than replaces it?

What strategies can be employed to reconcile the tensions between regulatory/quality assurance frameworks and the flexibility required for authentic and meaningful student co-design?

How can institutional leadership and learning design staff foster curriculum co-design practices that advance the student experience from inclusion toward a genuine sense of belonging?

What forms of evidence are most useful for evaluating whether personalisation through student agency and co-design enhances student motivation, employability and their sense of belonging within the learning community?

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5. Ethical considerations in Personalisation

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Introduction

The accelerated development of emerging technologies, such as artificial intelligence (AI), has significantly transformed the ways in which students acquire knowledge. The traditional learning process, which positions the teacher as the primary source of information, has been increasingly replaced by e-learning systems that support remote and learner-centred education tailored to individual characteristics. Digital technologies have enabled the personalisation of learning activities, the provision of real-time feedback, and the adaptation of instruction, allowing students to progress at their own pace (Alamri et al., 2021; Schmidt, 2025; Qin et al., 2025). To deliver such personalised learning experiences, educational technologies and e-learning systems rely heavily on data collection, data processing, and data presentation. The tools and software used for personalisation of education collect and process student data, which necessitates ethical and societal reflection on their use. In selecting appropriate personalisation strategies, it is important to consider several critical issues: data privacy, surveillance, equity, and the digital divide.

Data privacy refers to regulations, rights, and practices that ensure individuals' personal and sensitive data are collected, stored, used, and shared only with their informed consent, in a manner that protects their privacy. With the increased use of emerging technologies, the collection of personal data has become more pervasive, sometimes reaching surveillance levels. Surveillance involves monitoring, following, observing, and collecting information about individuals, locations, or activities, often for control, security, or data-gathering purposes. While surveillance is commonly used to prevent online abuse and misconduct, its application in personalised learning demands heightened ethical scrutiny.

Furthermore, the implementation of large-scale personalised learning systems requires extensive data infrastructures, as well as their processing, development, and maintenance. These requirements often drive-up costs and, consequently, raise concerns about equal access. This necessitates ethical consideration of the affordability and accessibility of such tools for all learners which is about equity. Equity refers to fair and needs-based access to education, ensuring that all individuals have equal opportunities to succeed regardless of their starting conditions, challenges, or personal circumstances. However, achieving equity becomes increasingly difficult in the context of rapid technological advancement. Meanwhile the digital divide, unequal access to digital technologies and internet connectivity, continues to widen. This divide exacerbates social and economic inequalities and may lead to the exclusion of certain groups.

In the age of artificial intelligence, data privacy and surveillance become particularly critical, as AI-powered personalised learning systems collect and analyse vast amounts of personal data, increasing the risk of misuse, privacy violations, and social exclusion. At the same time, equity and the digital divide have to be addressed to ensure that all students regardless of their resources, digital skills, or access to technology can equitably participate in and benefit from AI-enhanced education.

The remainder of this chapter explores in more detail the ethical and societal challenges related to the use of digital tools and software for personalised learning. It is structured around four key themes: (1) Data Privacy, Surveillance, and the Ethics of Student Profiling, (2) The Digital Divide: Ensuring Equitable Access to Personalised Learning, (3) Addressing the Risks of Over-Personalisation, (4) Good Practices for Ethical Personalisation.

5.1 Data Privacy, Surveillance, and the Ethics of Student Profiling

Personalised Learning (PL) is a pedagogical approach that aims to customise the educational experience to the individual needs, interests, and strengths of each student (Bernacki et al., 2021). PL is predicated on the creation of a student profile, which is constructed from a set of personal data (Cingil et al., 2000). In this context, profiling refers to the collection and analysis of student data to create an individualised learning profile. Such profiles typically include information about students' knowledge and skills, learning styles and preferences, motivational factors, goals, interests, online behaviour, and performance on assessments and quizzes (Eke et al., 2019; Purificato et al., 2024). Based on these profiles, educational systems, particularly those powered by AI, adapt learning content, recommend suitable delivery media, assign tasks, and adjust the pace and mode of instruction to increase the relevance and efficiency of learning. The manner in which collected data is anonymised, stored, and used determines the boundary between learning support and surveillance (Viberg et al., 2022). With informed consent, personalised learning systems can monitor student behaviour and progress to provide tailored support. In such cases, students should be clearly informed about what data is collected, how it is stored, processed, and utilised (Jones, 2015; Rubel et al., 2016). However, similar mechanisms can easily cross into surveillance if student activities are continuously monitored without clear consent or understanding of the purpose. This practice may compromise students' privacy, autonomy, and sense of security (Corrin et al., 2019; Tsai et al., 2020).

One of the fundamental ethical requirements for effective personalised learning is the protection of user privacy and the prevention of data misuse or manipulation. In the European Union, the collection and processing of personal data are regulated under the GDPR) (European Union, 2016). According to GDPR, the processing of personal data has to be lawful, fair, and transparent. Educational institutions implementing personalised learning systems are therefore obligated to clearly inform students about what data is being collected, for what purposes, how it is stored, who has access and make sure that only the minimum and essential data are utilised. Educational institutions face the challenge of striking a balance between data collection for personalised learning and protecting learners' right to privacy. It should therefore be ensured that the systems used meet the highest security standards, for example through measures such as encryption, pseudonymisation, and access restrictions. Data protection should be integrated into the system design from the outset ("privacy by design"), and regular security checks are essential to minimise risks and ensure the protection of personal data (UNESCO, 2022). Consent to data processing should be voluntary, explicit, and revocable at any time in order to comply with the requirements of the GDPR. It is essential that educational institutions communicate the rights of students to view, correct, and revoke their data processing at any time (GDPR) in a comprehensible manner, for example through information events or written guidelines for students and their legal guardians.

However, Mathrani et al. (2021) highlight that learning systems in practice often provide only general and insufficiently transparent information regarding data collection and usage. This lack of clarity presents both ethical and security risks, potentially leading to data misuse, discrimination, and the reinforcement of bias. Discrimination may occur when algorithms unintentionally favour certain groups based on gender, ethnicity, or socio-economic status. Bias reinforcement happens when systems rely on historical data that reflect existing inequalities, thereby perpetuating them. Privacy violations are also a concern when personal data is collected without clear consent or shared with third parties without proper oversight.

It is essential to implement ethical guidelines, ensure transparency, and embed data protection into the design of personalised learning systems. The Ethical Guidelines on the Use of Artificial Intelligence (AI) and Data in Teaching and Learning for Educators (2022) issued by the European Commission emphasise the need for caution in the use of personalisation. AI systems should support, not replace, human decision-making and are expected to safeguard the autonomy of both students and teachers. Moreover, under the new EU Artificial Intelligence Act (2024), educational AI systems are classified as high-risk systems. This classification entails strict requirements related to transparency, explainability, human oversight, and safety. Personalised learning tools and software's should clearly communicate how they function, what data they rely on to make recommendations, and must grant users the right to explanation and the ability to contest system-generated decisions.

5.2 The Digital Divide: Ensuring Equitable Access to Personalised Learning

What is the 'digital divide'?
Personalisation in education often depends on internet access, modern devices, and adequate digital literacy. However, not all learners have equal access to these resources, which highlights the issue of the "digital divide." The term "digital divide" describes the inequality in access to computers, the internet, and digital resources, affecting individuals, communities, and nations alike. Initially, the concept centred on physical access, such as whether households had a computer or an internet connection. Over time, however, its scope has broadened to include the competencies and knowledge required to effectively engage with digital technologies and information (Warschauer, 2010).

To better understand the digital divide and the associated inequalities, DiMaggio and Hargittai (2001) identified five dimensions of inequality that demonstrate how different access to and use of digital technologies can be.

Five dimensions of inequality
DiMaggio and Hargittai (2001) distinguish between five dimensions of inequality to understand the digital divide: 1) inequality in technical equipment, 2) inequality in the autonomy of use, 3) inequality in skill, 4) inequality in the availability of social support and 5) inequality in the adequacy of hardware, software and connections.

The first dimension addresses inequality in access to technical equipment and its impact on Internet use. Suitable hardware, software, and Internet connections are important because users with outdated or slow technology cannot access certain content (e.g., Java applications, streaming) and, therefore, have fewer opportunities to benefit from the Internet. This leads them using the Internet less frequently, acquiring fewer skills, and thus becoming indirectly disadvantaged. It should also be noted here that digital content should be made accessible to people with different physical or cognitive limitations. To ensure digital accessibility in accordance with the Web Content Accessibility Guidelines (WCAG 2.2, 2025), information or functions should be presented in such a way that they can be perceived through multiple sensory channels. This means, for example, that content that is perceived through hearing should also be made visible, such as offering videos with subtitles.

The second dimension, referring to the inequality in the autonomy of use, describes how much control people have over their Internet use, particularly where they access it, such as at home, at work, at school, or in public facilities such as libraries. Studies show a clear correlation between educational attainment, income, ethnicity, and the likelihood of having Internet access at home. In addition, it is hypothesised that autonomy in Internet use at work depends on job position and function. Finally, it is assumed that greater autonomy in Internet use is associated with greater benefits for users.

The third dimension, addressing inequality in skill, describes the inequality in users' abilities to use the Internet effectively. Technical know-how, cognitive abilities, and specific knowledge are essential for finding and evaluating information. Users with fewer skills encounter barriers such as complex websites or inadequate search technologies. Studies show that Internet literacy is directly related to the ability to use the Internet in a targeted manner and that it influences satisfaction, stress, and willingness to continue using it.

The fourth dimension, which is about inequality of availability of social support, describes inequality in access to social support for Internet use. Although there are differences in competence among users, most new users become more competent over time, often because of the support from more experienced users. This social support can take three forms: formal technical assistance (e.g., from IT staff, teachers, or librarians), technical assistance from friends and family, and emotional support, such as encouragement or joint discovery. Such support motivates users to continue using the internet and develop their digital skills. Differences in access to social support also influence how much users benefit from the internet.

Lastly, the fifth dimension, referring to inequality in the adequacy of hardware, software and connections, examines how factors (income, education) influence the way people use the internet. A distinction is made between productive uses (e.g., education, job search, political participation) and purely consumption-oriented activities (e.g. entertainment). Studies show that lower-income and less educated users use the internet more often for job search and education, which could have potentially positive effects on their social and economic status. However, it remains unclear to what extent these uses improve access to better opportunities in the long term. It is assumed that productive uses are associated with more positive life outcomes than purely consumption-oriented activities.

Personalisation in education, which aims to promote individual learning paths and actively involve students in the learning process, can unintentionally reinforce existing digital inequalities. Since personalised approaches often rely on the use of digital technologies, students from lower-income families or disadvantaged regions who do not have access to high-speed internet or modern hardware may fall behind. Although official measures such as the expansion of broadband infrastructure, subsidised devices, or public internet access points exist, these are often insufficient to provide all students with equal opportunities. Critics also emphasise that mere access to technology is not enough to create equal opportunities. Without targeted promotion of digital skills and a deeper understanding of the digital world, students who are already disadvantaged could fall further behind, widening the digital divide even more (Hofmann, 2023; Keefe, 2007).

Digital inclusion as an approach to overcoming the digital divide

Digital inclusion refers to the state in which all people have access to online technologies, can afford them, and have the necessary digital skills to use them effectively. It is based on the principle that everyone should have the opportunity to use digital technologies comprehensively, whether to promote health and well-being, access education and services, organise finances, or maintain social and global connections (Thomas et al., 2018).

Digital inclusion can help bridge the digital divide by specifically promoting the skills of students. Fisk et al (2023) identified six key competencies that are crucial for digital inclusion:

- **Technological skills**: The ability to use digital devices and learning platforms safely and effectively.
- **Digital problem-solving skills**: The ability to independently overcome technical challenges.
- **Career-enhancing skills**: Competencies that prepare students for the demands of the world of work.
- **Coping skills**: Strategies for dealing with setbacks and changes in the digital learning environment.
- **Well-being management skills**: The ability to use digital tools to promote one's own well-being and organise learning.
- **Social interaction and networking skills**: The ability to use digital platforms to connect and collaborate with classmates, teachers, and the community.

These competencies go beyond mere access to digital technologies and aim to develop digital skills and strengthen students' social participation. These competencies can be promoted through various approaches in the school environment, including:

- **Role models**: Teachers show students how digital tasks and tools can be used effectively.
- **Coaching**: Individual support from teachers or educational staff to strengthen students' confidence and competence in using digital technologies.
- **Student-to-student mentoring**: Older or more experienced students support their peers in acquiring digital skills.
- **Network expansion**: Building social and digital networks that promote exchange between students and with external partners and create new learning opportunities.

These approaches make digital inclusion a central element in closing the digital divide and the associated inequalities mentioned above. They empower students, enable them to use digital technologies with confidence, and prepare them for an increasingly digital world (Fisk et al., 2023).

5.3 Addressing the Risks of Over-Personalisation

Personalised learning in higher education generally brings positive effects; however, it is essential that designers of such systems remain aware of the various risks that the over-personalisation of the learning process could entail. The negative consequences of over-personalisation can adversely affect the quality of the educational process, the academic community, students' rights and knowledge, and may hinder the development of social skills (Xu et al., 2024; Lim & Newby, 2020; Chen et al., 2021).

Selwyn (2019) points out that one of the most significant risks of over-personalisation in learning is the erosion of social interaction, collaborative learning, and peer engagement—core components of the educational process. Personalised learning is most often driven by algorithms that generate individualised learning pathways, potentially reducing interaction among students, the exchange of ideas, and collective problem-solving. According to Selwyn (2019), algorithmic over-personalisation may lead to student isolation and weaken the academic community, which is essential for the development of critical thinking and academic identity. Knox (2020) argues that such systems may treat students as passive recipients of learning content rather than active participants in the learning process. According to this researcher, AI tools for personalised learning may automatically decide which learning materials and media are best suited for a student, potentially excluding students from participating in such decisions. This learning environment may discourage independent decision making, reduce the sense of responsibility, and slow the development of metacognitive skills.

To manage the risks associated with over-personalisation in learning, personalised systems should offer recommendations as optional rather than mandatory, allowing students to make decisions about their learning pathways. Additionally, integrating opportunities for collaborative activities and peer engagement within personalised systems can also help maintain the social aspects of learning while benefiting from tailored support.

The European Commission, in its *Ethical Guidelines for Trustworthy Artificial Intelligence* (2021), highlights the importance of transparency and data minimisation, especially in the context of education and student data collection. Williamson and Eynon (2020) emphasise that algorithm-based personalised learning systems may rely excessively on students' initial data (such as prior knowledge, demographic information, or previous experience) and propose over personalised educational pathways that do not allow for sufficient student progression. If the initial data used to develop these pathways reflect existing inequalities or stereotypes, algorithms may reinforce those biases instead of overcoming them. This may result in students from underrepresented groups being denied access to advanced opportunities because the system predicts lower success.

Over-personalisation of learning supported by AI may negatively impact creativity, innovation, and academic critical thinking because educational environments can emerge that steer students' learning along narrowly defined, algorithmically determined content paths. In its publication *Bespoke or Prescribed? The Myth of Personalised Learning* (2025), UNESCO warns of the danger that AI could guide education through limited algorithmic recommendations. The report states that learning should not be overly prescriptive and narrowly personalised, but instead open to discovery and diverse perspectives. Emphasis should be placed on encouraging freedom, creativity, and intellectual curiosity, not merely on efficiency and optimisation. This message highlights the importance of education retaining its openness and its ability to expand intellectual horizons and encourage critical thinking.

In summary, the reviewed literature highlights that over-personalisation of learning can undermine key aspects of education, including academic freedom, equal access to opportunities, collaborative learning, and the development of critical thinking. To address these challenges, it is crucial for educational institutions to balance the advantages of personalisation with its risks, implement ethical guidelines to ensure fairness and transparency, and prioritise human agency and creativity over purely algorithmic decision-making in the learning process.

5.4 Good Practices for Ethical Personalisation

In practical educational contexts, the successful implementation of personalised adaptive learning requires the careful alignment of technology and pedagogy, alongside strict adherence to ethical regulations and guidelines. Empirical research and examples of best practice demonstrate that adaptive platforms and strategies can generate significant educational benefits, yet also highlight the need to systematically address their limitations. A review of the literature Du Plooy, E., Casteleijn, D., & Franzsen, D. (2024) indicates that in higher education, digital platforms such as Moodle Learning Management System, McGraw-Hill's Connect LearnSmart, Smart Sparrow, Realizeit, and Blackboard Learning Management System are most frequently applied. However, an equally important dimension of personalisation concerns the protection of data privacy and the ethical use of information, which necessitates specific regulations and monitoring.

The development of artificial intelligence has influenced not only the practice of personalised learning in higher education but also the legal frameworks governing this field. Since 2020, universities and state institutions across the EU have established guidelines and initiatives to ensure the responsible implementation of innovations in personalised learning. These efforts are embedded within broader European Union strategies, such as the *Digital Education Action Plan 2021–2027*, which promotes "high-quality and inclusive digital education" while simultaneously addressing challenges such as data protection and the digital divide. Building on these recommendations, numerous higher education institutions have developed their own policies and regulations for the use of AI in education, particularly within the context of personalisation. For example, the University of Vienna and the Vienna University of Technology (TU Wien) emphasise that AI tools may only be used in accordance with the GDPR, with transparent student communication, and under the supervision and approval of instructors.

In addition to institutional regulations, data governance models are being developed to ensure the ethical sustainability of personalisation. A prominent example is the Eindhoven University of Technology, which in 2023 adopted a *Code of Practice for Learning Analytics*. This document clearly states that the primary purpose of using student data is to provide personalised learning support, such as identifying students in need of additional help or recommending courses aligned with their interests. The use of analytics for surveillance or disciplinary purposes is explicitly prohibited, while students retain the right to access their profiles and decide how personalised recommendations are applied. In this way, personalisation becomes a process in which students remain active agents and maintain control over their learning trajectories.

For technology enhanced personalisation to be genuinely inclusive, it is essential to ensure equal access to digital tools. The COVID-19 pandemic further underscored the importance of digital infrastructure and technological accessibility, prompting European countries to launch initiatives supporting students from disadvantaged backgrounds. In Ireland, for example, a program implemented in 2020 distributed more than 16,700 laptops, enabling students without adequate resources to participate in personalised online learning. Similar initiatives were carried out in France, where laptops and 4G devices were distributed to students, and in Catalonia, where EU funds were allocated to provide devices and internet connectivity for both students and teachers. These examples confirm that technology enhanced personalisation in education cannot be realised without basic digital infrastructure and equal access to technology for all learners.

Conclusion

This chapter showed that personalisation, while promising enhanced learning outcomes, operates within a complex ethical framework that demands careful consideration of privacy, fairness, and educational values. It demonstrates that effective personalisation extends beyond technological implementation; it requires a change in how educational stakeholders approach student data, algorithmic decision-making, and the balance between individual learning needs and collective educational values.

Educators must balance pedagogical authority with the use of technology, acting as ethical guardians who evaluate algorithmic recommendations while fostering authentic student relationships. This requires strong digital literacy, awareness of biases, protection of student privacy, and ongoing professional development in data ethics. Policymakers, under the GDPR and the EU AI Act (2024), face the task of creating regulatory frameworks that safeguard student rights while enabling innovation. Key issues include consent, data minimisation, algorithmic accountability, and preventing the digital divide. Institutions, meanwhile, must align technological innovation with ethical responsibility by establishing governance structures for data stewardship, ensuring transparent communication, and supporting inclusive decision-making processes that preserve academic freedom.

A big challenge lies in distinguishing between legitimate learning support and intrusive surveillance. Student profiling, based on extensive personal data collection that includes learning behaviours, preferences, and performance metrics, raises a delicate issue between educational enhancement and privacy violation. The lack of transparency in many existing systems enlarges this issue, as students are often uninformed about the purposes of data collection.

A significant concern involves algorithmic systems that may perpetuate existing inequalities through biased recommendations. When systems rely on historical data reflecting societal disparities, they risk reinforcing discrimination based on gender, ethnicity, or socioeconomic status rather than promoting equitable learning opportunities. Personalisation systems that depend heavily on digital technologies may unintentionally widen existing educational gaps. Students from disadvantaged backgrounds with limited access to high-speed internet or modern devices face barriers that could further impact their educational experiences.

Another important concern in the context of personalised and adaptive learning is the risk of excessive individualisation. While tailoring learning paths to each student’s needs can be highly effective, it may unintentionally reduce opportunities for peer interaction and collaborative learning. Interaction with peers and exposure to diverse perspectives are essential elements of quality education, as they promote not only the development of critical thinking but also social and emotional growth. Without these dimensions, education risks becoming a purely individual process, where students primarily engage with adaptive systems rather than with each other. This can weaken the sense of community and limit the ability to develop communication, teamwork, and intercultural skills, competences that are increasingly important in contemporary societies. Therefore, when implementing personalised adaptive learning, it is necessary to carefully balance individual support with opportunities for collaboration and shared learning experience.

To conclude, while PL offers significant potential for educational enhancement, its implementation requires a carefully balanced approach that prioritises both ethical considerations and technological capabilities. The risk of over-personalisation threatening academic freedom and equality necessitates ongoing vigilance and human oversight.

Ultimately, the promise of personalised learning lies not only in efficiency or adaptability but in preserving the humanistic values of education—equity, autonomy, and community. The reflective questions that follow invite you to consider how these tensions and opportunities play out in your own context, while the final chapter provides concrete recommendations for educators, policymakers and institutions.

Questions for reflection

How will students be given real choice, override/appeal options, and support to build metacognitive skills, rather than passively following algorithmic paths?

What data are strictly necessary for personalisation, and how will privacy-by-design, data minimisation, and independent audits prevent drift into surveillance?

Which learner groups are most at risk from device/connectivity/skills gaps, and what funded interventions (access, training, social support) and metrics will close these gaps?

Where does educational authority reside when AI recommendations conflict with professional judgment, and how will staff be prepared to exercise accountable oversight?

How will collaborative work, peer interaction, and exposure to diverse perspectives be designed into personalised pathways, and how will we measure that they occur?

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6. Conclusions

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With this report, the EADTU Task Force set out to explore how universities can advance personalisation in higher education. The report demonstrates that personalisation is not merely a theoretical ambition but a transformative approach, offering practical ways to respond to learner diversity, strengthen engagement, and improve outcomes.

The work of the Task Force highlights that personalisation is both a pedagogical ambition and an institutional responsibility. It is not a single innovation but a multidimensional endeavour that depends on the alignment of pedagogy, strategy, technology, and ethics. When these dimensions are brought together, personalisation can move beyond isolated initiatives to become a coherent transformation across higher education.

This conclusion synthesises the key insights developed throughout the report and underlines the Task Force's role in shaping a shared vision for the future. It affirms that the personalisation of education is a pathway to inclusion, engagement, and success, guiding institutions, educators, and policymakers toward more equitable and impactful learning models. Personalisation of education emerges as a means of enhancing equity, strengthening learner agency, and promoting academic success — the ambitions that have guided the work throughout.

Personalisation as a Driver of Inclusion

Personalisation has significant potential to foster inclusion. By adapting learning pathways, content, pace, and assessment to individual learners' characteristics, PL supports students with diverse backgrounds, abilities, and life circumstances. This includes students with disabilities, learners from marginalised communities, part-time students, and working adults requiring flexible and responsive learning environments. Personalisation is thus not only a mechanism for academic improvement but also a strategy to advance educational equity and social justice. In this way, personalisation emerges as part of a broader (institutional) inclusion strategy, supporting all learners in accessing and benefiting from high-quality education.

Conceptual Clarity and Pedagogical Foundations

Despite its popularity, PL remains inconsistently defined and applied across disciplines, creating implementation challenges and missed opportunities. Shared conceptual clarity is needed to distinguish between personalised, adaptive, differentiated, and individualised learning while recognising their overlaps. As discussed in Chapter 1, the analyses show that effective personalisation is grounded in sound pedagogy, where technologies and practices are aligned with clear learning goals and learner characteristics.

Curriculum as the Backbone of Personalisation

As highlighted in Chapter 4, curriculum design is central to making personalisation a reality. At the macro level, modularisation, stackable credentials, and flexible pathways allow learners to build qualifications that reflect their professional and personal goals. At the micro level, course design, co-created learning activities, and personalised assessment strategies give students agency, voice, and ownership. By embedding co-design and flexibility into curriculum structures and assessment, institutions can balance academic rigour with learner choice, moving from inclusion to a genuine sense of belonging.

Technology, AI and Human Oversight

The role of technology in enabling PL was a central theme in Chapter 3. Technology plays a key role in enabling PL, especially in ODHE. AI-driven learning analytics can shift teaching from reactive to proactive by identifying at-risk students early. Intelligent Tutoring Systems (ITS) dynamically adjust content and pacing, supporting diverse learners, including those with learning difficulties. Generative AI and conversational agents enable customised content, assessment, and feedback at scale, shifting educators' roles from content delivery to learning experience design. Adaptive assessment tools and competency mapping further support targeted interventions. While technology enables powerful forms of personalisation, it complements rather than replaces human teaching.

Digital Inclusion and Infrastructure

As argued in Chapters 2 and 3, Personalisation cannot be achieved without robust digital infrastructure and equal access to technology. Institutions must address the digital divide, particularly for bandwidth-intensive applications like VR/AR. A transition to Next Generation Digital Learning Environments (NGDLEs) is recommended, moving from monolithic systems toward modular, interoperable architectures that allow institutions to integrate tools flexibly. Implementation should be phased: begin with learning analytics, pilot adaptive assessments, and gradually transition to NGDLE components as capacity grows. Students lacking high-speed internet or modern devices face additional barriers; providing devices, connectivity, and comprehensive digital literacy programs is essential to prevent personalisation from exacerbating inequalities.

Ethics, Data Governance and Academic Freedom

As discussed in Chapter 5, the reliance of PL on learner data makes ethical considerations central to implementation. The chapter highlighted ethics-by-design approaches and robust data protection measures, such as anonymisation, encryption, and strict access controls, as key elements in building trust. The collection and analysis of learning data raise questions of privacy rights, data ownership, and security. Policies on data collection, storage, and usage were shown to require transparency and clear communication in order to be effective. Consent processes were presented as needing to be voluntary, explicit, and revocable, with mechanisms for students to contest or override algorithmic decisions.

The discussion further pointed to the challenge of balancing legitimate learning support with the risk of intrusive surveillance, emphasising the importance of keeping students informed about how their data is used. Continuous monitoring of algorithmic systems was described as essential to avoid reinforcing social inequalities, while safeguarding academic freedom and engaging stakeholders in inclusive decision-making were highlighted as critical institutional strategies. Finally, transparent communication with both staff and students consistently emerged as a condition for maintaining trust in the responsible use of personalisation.

Learner Agency and Risk of Over-Personalisation

A central goal of PL, emphasised in Chapters 1 and 4 is to empower students to actively shape their learning journeys. PL is seen as a way to cultivate learner agency, goal-setting, and self-regulation. However, excessive individualisation can limit opportunities for peer interaction and exposure to diverse perspectives, which are vital for critical thinking, social growth, and community building. Effective PL balances tailored support with collaborative learning opportunities, ensuring students engage with peers as well as adaptive systems.

From Pilots to Maturity

The maturity model discussed in Chapter 2 provides a guide for institutions at different readiness levels, showing that PL is a continuum rather than a binary state. Institutions are encouraged to position themselves on this maturity continuum as a self-assessment exercise, using it to identify strengths, gaps, and priority actions. Implementation should be phased, beginning with analytics and pilots, then scaling to systemic integration. Technological infrastructure alone is insufficient: success depends on thoughtful, intentional design of learning experiences and investment in both infrastructure and ethical frameworks. Personalisation must be understood as a multi-dimensional, evolving practice that combines technology, pedagogy, human support, and ethical reflection. Institutions that embed PL across their systems—not just in isolated pilots—are best positioned to meet the demands of lifelong, inclusive, and learner-driven education.

As highlighted throughout the chapters, recurring priorities include the embedding of inclusive, learner-centred values in strategic planning and curriculum design; the centrality of ethical governance and transparency in data-driven and AI-enabled systems; the importance of professional development and co-design opportunities for staff; the role of student agency and feedback in shaping meaningful learning pathways; and the value of inter-institutional collaboration for sharing models and supporting policy-informed innovation.

Taken together, these insights reaffirm that personalisation is not a technological quick fix but a systemic and relational practice. It rests on curriculum as the connective tissue linking pedagogy, assessment, and institutional structures. When macro-level frameworks, programme-level modularity, micro-level practices, and ethical governance are aligned, personalisation can move from isolated pilots to a coherent transformation across higher education.

Responsibilities across the institution

As noted across Chapters 2, 4, and 5, the implementation of personalisation involves responsibilities shared across the entire institution. The chapters emphasised that collaboration between educators, instructional designers, and technology specialists strengthens legitimacy and fosters a sense of shared ownership. Students also appeared as active partners in this process, developing self-regulation, goal-setting, and reflective learning skills.

Educators were portrayed as maintaining pedagogical authority while drawing on technological tools and critically evaluating algorithmic recommendations. Professional development in data ethics and human-centred strategies was repeatedly underscored as essential. At the management level, personalisation was shown to be most effective when integrated into curriculum design, support services, and quality assurance frameworks, balancing innovation with ethical responsibility.

The discussions further highlighted the role of support services in providing coherent guidance and accessibility measures, and of technical teams in ensuring secure, interoperable systems that protect learner data. Finally, external partnerships were identified as valuable for linking personalisation with labour market needs, for instance through competency mapping and micro-credentials. Taken together, these contributions point to personalisation as an institution-wide endeavour that relies on the coordinated efforts of multiple actors.

Future Research and Practice Directions

Looking ahead, the chapters point to several directions for future research and practice. Longitudinal studies could deepen understanding of how AI-driven personalisation affects diverse learner populations, while further exploration of human–AI collaboration models and bias-detection in educational systems would help clarify both opportunities and risks. Key questions emerging from the discussion include how AI-enabled personalisation might strengthen rather than constrain learner autonomy, and how systems can be designed to promote inclusion rather than widen the digital divide.

The report also drew attention to the importance of revisiting accreditation and credit frameworks to accommodate more flexible, learner-driven pathways. Ultimately, the future of PL hinges on its capacity to promote inclusivity, protect autonomy, and ensure equitable access, while remaining anchored in the humanistic values that underpin meaningful education.

7. Guidelines and Recommendations

The reflections and analyses presented in this report have led to guidelines and recommendations, formulated by the Task Force in the final chapter. These guidelines are the distilled outcome of our collective work: they bring together lessons learned into a coherent set of priorities that can support institutions in moving from aspiration to implementation.

For Educators

For educators, personalisation means designing flexible, learner-centred environments while safeguarding equity and agency. Their role is to use new tools responsibly, but also to preserve (ped)agogical judgment and foster collaboration. They are advised to ground PL strategies in (ped)agogical theory, ensuring that technologies and practices are aligned with learning goals and learner characteristics. Teachers remain at the centre: designers of meaningful experiences, not just facilitators of automated systems.

The recommendations below build on insights and conclusions (chapter 6) developed throughout this report, translating them into practical steps for educators:

- Start small with pilots, evaluate results, and scale based on evidence.

- Design flexible learning pathways with multiple entry and exit points, opportunities to re-engage, varied pacing options, and clear success criteria.

- Foster student agency by engaging them as partners in learning—providing choice, supporting self-regulation and goal-setting, and embedding reflective practice within assessment.

- Use learning analytics responsibly, ensuring transparency, privacy, and ethical handling of data.

- Apply predictive analytics, not only to identify and support students at risk, but also to help all learners reach their full potential. Ensure that insights are transparent and accessible for students (e.g. through dashboards), while complying with GDPR requirements regarding consent and privacy.

- Use Intelligent Tutoring Systems to provide adaptive support and scaffolding.

- Leverage generative AI and conversational agents for customised content and feedback, while maintaining oversight.

- Preserve pedagogical leadership and human judgment

- Balance PL with peer interaction and collaborative opportunities.

- Experiment with personalised assessment formats and feedback approaches, aligning them with students' diverse needs, motivations, and contexts while maintaining fairness and rigour.

- Participate in ongoing professional development focused on data ethics and AI literacy.

For Policymakers

For policymakers, personalisation means creating the enabling environment that allows institutions and educators to innovate responsibly. This includes funding, regulation, and accreditation systems that support flexibility, transparency, and inclusion. Policymakers are key in bridging the gap between institutional ambition and systemic adoption, ensuring that personalisation contributes to social justice, lifelong learning, and labour market relevance. In particular, updating accreditation and credit systems to allow modular, stackable qualifications and more flexible academic calendars will be essential for enabling institutions to scale personalisation in sustainable ways.

The recommendations below build on insights and conclusions (chapter 6) developed throughout this report, translating them into practical steps for policy makers:

- Adopt a learner-centred approach that integrates PL into the wider mission of inclusion and equity.

- Support workforce development through competency mapping aligned with labour market needs.

- Establish shared definitions and frameworks to guide institutional strategies.

- Support the development of Next Generation Digital Learning Environments (NGDLEs) with policies and funding that encourage modular, interoperable systems.

- Update accreditation and credit systems to allow modular, stackable qualifications and flexible calendars.

- Promote policies that encourage student participation in curriculum co-design, ensuring that personalisation strengthens both agency and belonging

- Strive to bridge the digital divide, by addressing affordability, connectivity speed, device access, and support for bandwidth-intensive applications such as VR/AR.

- Establish ethical and legal guidelines for AI in education, aligned with GDPR and the EU AI Act, focusing on consent, data minimisation and algorithmic accountability.

- Facilitate collaborative projects across European and global institutions, supported by strong leadership and sustainable funding, to share innovation and evidence.

For Institutions and leaders

For institutions and their leaders, personalisation means embedding inclusion, technology, and ethics into a coherent organisational strategy. As seen in Chapters 2, 3, and 5, leaders must coordinate across (ped)agogical, technological, and governance domains, integrating PL into curriculum design, learning support service, and quality assurance processes. Their role is to move personalisation from pilot projects towards systemic integration, while protecting academic freedom, ensuring transparency, and building trust with staff and students. Personalisation at this level is about culture change, capacity-building, and long-term sustainability.

The recommendations below build on insights and conclusions (chapter 6) developed throughout this report, translating them into practical steps for institutional leadership:

- Develop a comprehensive organisational strategy for PL and involve all relevant stakeholders.

- Make use of maturity models to progress from pilots to full institutional adoption.

- Embed flexibility into curriculum structures by supporting modularisation, stackable credentials, and interdisciplinary pathways.

- Implement systematic evaluation frameworks to monitor effectiveness

- Keep communication channels open with stakeholders to build trust.

- Integrate ethics-by-design in all personalisation initiatives, with strong data protection and security measures

- Ensure that consent to data collection and processing for personalisation is voluntary, explicit, and revocable, with transparent information on data use and clear mechanisms for students to view, correct, and contest algorithmic decisions

- Avoid intrusive surveillance and communicate clearly about data use.

- Maintain human oversight of AI recommendations through regular audits.

- Balance technological innovation with safeguarding academic freedom.

- Provide digital literacy training, mentoring, and peer-to-peer support for staff and students.

Contributing Institutions

Universitat Oberta de Catalunya (UOC) | Spain
Open Universiteit | The Netherlands
Fédération Interuniversitaire de l'Enseignement à Distance (FIED) | France
Johannes Kepler Universität Linz (JKU) | Austria
The Open University | United Kingdom
Télé-université du Québec (TÉLUQ) | Canada
Anadolu University | Turkey
FernUniversität in Hagen | Germany
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