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Personalisation of learning through artificial intelligence in higher education in the United Kingdom

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Abstract. Artificial intelligence in higher education allows adapting the content to the individual needs of students, but it is necessary to evaluate the effectiveness, consider the issue of algorithmic bias and provide the appropriate development of staff. The purpose of the study was to investigate the influence of artificial intelligence integration on the personalisation of learning in higher education in terms of academic achievement, motivation and engagement. By comparing the functional possibilities of adaptive platforms, it was found that personalisation through intelligent algorithms allows for an individual approach to learning, dynamic adjustment of tasks and timely feedback, while the traditional model is limited in flexibility and is aimed at a nominal average student with a typical level of prior knowledge, a standard rate of content assimilation and conventional educational needs without regard for individual peculiarities. An analysis of educational platforms showed that learning management systems with integrated artificial intelligence tools (Moodle, Blackboard, Canvas, Brightspace, FutureLearn) make it possible to construct individual learning pathways, predict the risk of academic underperformance, and adapt materials in line with student progress, thereby reducing dropout rates and increasing module completion and system activity. The case study method indicated that the use of generative artificial intelligence at the University of Glasgow, the Open University, and the University of Manchester is regarded as a promising tool for supporting the learning process, developing digital competences, and enhancing the flexibility of interaction between students and academic staff, without detailed specification of particular pedagogical interventions, quantitative effectiveness indicators, or structural changes to curricula. An analysis of the role of the lecturer demonstrated that the integration of artificial intelligence transforms professional functions from those of a traditional lecturer to those of a coordinator and mentor who employs analytics to adapt content, adjust learning pathways, and provide personalised support, thereby creating a hybrid model of pedagogical guidance and enhancing the effectiveness of the educational process. The results show that personalisation of learning through artificial intelligence has a holistic positive impact: academic resilience, student engagement and the general effectiveness of the educational process in higher education in the United Kingdom are enhanced. The results of the study can be of use for lecturers, university managers and developers of educational platforms in the implementation of effective artificial intelligence solutions within the teaching and learning process

Keywords: adaptive learning; motivation; digital literacy; distance learning; information technologies

INTRODUCTION

The rapid growth of digital technologies and the increasing role of artificial intelligence (AI) in higher education open up new opportunities for the individualisation of the educational process. AIpersonalisation of learning allows adapting educational trajectories to the individual needs of students, enhancing motivation, increasing the effectiveness of knowledge assimilation and retaining students in the context of distance and blended learning. However, the introduction of innovative technologies is accompanied by a number of challenges, including ethical issues, the digital literacy of academic staff and students and the risk of algorithmic bias. Therefore, the research into AI-based practices for the personalisation of learning in British universities is of particular relevance

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as it enables evaluating the potential benefits and limitations of these technologies, developing recommendations for their effective implementation and contributing to enhancing the quality of the educational process in modern conditions.

In contemporary British academic discourse, studies devoted to the implementation of artificial intelligence in higher education increasingly focus on issues of learning personalisation and the enhancement of students' academic achievement. Thus, K. Sunmboye *et al.* (2025) carried out a large-scale cross-sectional survey of students of medical faculties in the United Kingdom, which assessed the effect of integrating intelligent systems into the process of personalisation of learning. The authors showed that adaptive learning systems allow constructing individual educational trajectories, taking into account the pace of content assimilation of each student and automatically selecting additional resources to eliminate knowledge gaps. The study notes that this approach enhances student engagement, reduces cognitive load and improves academic performance compared to traditional teaching methods. In response, H. Rahiman & R. Kodikal (2024) further developed the discussion of the practical utility of AI in higher education, this time focusing on the impact of incorporating adaptive systems and generative tools in distance and face-to-face classes. The authors report that the use of machine intelligence not only supports automated individual student care but also opens new avenues for the work of academic staff, namely in the realm of progress tracking and real-time curriculum revision. According to F. Dervishi & A. Vrapi (2022), computer technology for educational use has seen extraordinary growth. The authors stress the significance of the digital competences of lecturers, since the performance of AI-enhanced support systems relies on the degree to which educators appropriately use advice and data for the tasks of teaching and learning.

AI in the studies A. Vrapi *et al.* (2023) focus on the assessment and reassessment of personal skills and achievements, as well as on the conscious monitoring of the results of professional activities and the analysis of real-life situations. Another approach to evaluating the influence of AI on the personalisation of learning is presented in the study by C. Merino-Campos (2025), who carried out a systematic literature review on the use of intelligent systems in higher education. The author demonstrated that adaptive platforms and Learning Analytics tools allow optimising educational trajectories of students, enhancing their cognitive effectiveness and reducing the number of dropouts. The study by R. Sajja *et al.* (2024) describes the application of AI-based intelligent assistants for the personalisation and adaptation of learning in various disciplines. The authors prove that the systems that include modules for prediction, recommendation and adaptation allow monitoring of the students' learning process, provide an individual educational trajectory, and optimise the involvement of students in the educational process. Particular attention is paid to the potential of these platforms to diagnose knowledge gaps of the students and automatically offer the resources to overcome them, thus contributing to the acquisition of knowledge and the development of competence.

Simultaneously, K. Kaswan *et al.* (2024) note in their research that AI in personalised learning is capable of dynamically adjusting the educational trajectory of students by algorithmic prediction of knowledge gaps and recommendation of resources, which, in turn, increases the cognitive efficiency and reduces the lag in learning. The authors highlight that the efficiency of machine learning systems directly depends on their embedding in the overall didactic and methodological design and pedagogical practice, which testifies to the need for a systematic approach to their implementation. In the study of L. Mulaudzi & J. Hamilton (2025), the emphasis is put on the role of the lecturer in the process of AI-supported personalised learning. The researchers prove that the success of AI integration largely depends on the lecturer's active participation in the analytics, interpretation of the system recommendations, and adjustment of the educational process. Alongside this, ethical issues are raised, primarily related to the transparency of algorithms and the security of students' personal data. The authors argue that the lecturer's methodological competence in the field of AI is a key factor in increasing the efficiency of personalised education.

S. Hashim *et al.* (2022) conducted a systematic review of the trends in the application of machine learning technologies in the context of personalised education. The researchers identify the following areas of use of machine learning technologies: adaptive diagnostics, recommendation algorithms, learning behaviour analytics, and intelligent assistants. The integration of these systems is observed in different disciplines and levels of education, from distance courses to face-to-face education, which provides flexibility of educational trajectories and increases students' motivation. In turn, N. Alifah & A. Hidayat (2025) investigate the effectiveness of AI-based Learning Analytics tools in supporting personalised learning. The results of the study show that the use of analytics dashboards and adaptive recommendations makes it possible to effectively predict knowledge gaps in students and offer appropriate educational resources, which contributes to knowledge acquisition and student retention. Referring to the processes and results of the previously discussed studies, S. Pahmi *et al.* (2024) the implementation of virtual reality technology has become an increasingly intriguing topic. However, as noted by the authors, the most efficient way to use these tools would be to combine them with methodological techniques.

Previous studies have primarily focused on assessing the influence of adaptive systems, Learning Analytics, and generative AI assistants on students' academic performance, motivation, and engagement have been mainly investigated. However, the majority of the existing studies have been conducted within the scope of a single subject and distance learning courses, whereas the integral influence of machine learning systems, lecturers, and Learning Management System (LMS) on traditional and blended learning has not been investigated yet. Another research gap is identified in exploring the effect of personalisation on the lecturers' methodological activity, the inclusion of analytics into educational trajectory planning, and methods to minimise algorithmic bias. This study aimed to identify how adaptive systems and learning behaviour analytics influence academic achievement, student motivation, and engagement, as well as to reveal the role of the lecturer in the process of personalisation. The objectives of the study were to analyse research articles and case studies on the use of smart systems in the educational process, in particular to consider the pros and cons of adaptive systems and generative AI assistants, and the interconnection between students, lecturers, and the learning management system to identify best practices and the risks of algorithmic bias.

MATERIALS AND METHODS

The methodological framework of the study involved structural-functional analysis, content analysis, a comparative approach, the case study method, and institutional-comparative analysis. The application of these methods provided a multidimensional insight into the processes of implementing intelligent systems in higher education and enabled consideration of learning personalisation from technological, organisational, and methodological perspectives. The content analysis embraced adaptive LMS, AI-based tutoring tools, algorithms for predicting students' learning behaviour, and feedback mechanisms. Within the framework of the analysis, the key functional characteristics of these tools, principles of adaptivity, and approaches to personalising educational trajectories applied in modern educational platforms were synthesised.

The case study method in this research was applied as an approach to the in-depth analysis of individual educational institutions and practices, with the aim of examining in detail the mechanisms for integrating machine intelligence solutions into the teaching and learning process. Its selection was justified by the need to examine real-world examples of the implementation of intelligent technologies in higher education in the United Kingdom and to trace the interrelationships between technological solutions, organisational strategies, and pedagogical practices. In the framework of the case study, official documents, the digitalisation of the universities, and educational policies at the University of Glasgow (n.d.), the Open University (n.d.), and the University of Manchester (n.d.), as examples of British universities with a systematic policy in the implementation of digital and AIbased educational strategies, were analysed. Particular attention was paid to new solutions such as the Early Alert Indicators (EAI) system, which was implemented at the Open University, and the TeachMateAI (TMAI) (n.d.) used in the practice of the Manchester Institute of Education.

The analysis of the integration of adaptive platforms and AI-based tutoring systems was conducted in order to assess their use in programmes aimed at enhancing learning effectiveness at the University of Glasgow, particularly in the context of applying Learning Analytics and Learning Design tools (n.d.) to personalise educational pathways. At the same time, a limitation of the study was the lack of detailed information on the platforms, analytical systems, and tools actually used in the university. A comparative analysis of the functionality, opportunities, and subject orientation of adaptive platforms, including Knewton Alta (n.d.), Synap (n.d.), Edumentors (n.d.), and the main LMS with embedded AI modules – Moodle (n.d.), Blackboard (n.d.), Canvas (n.d.), Brightspace (n.d.), and FutureLearn (n.d.) was carried out. The comparative method was used to systematise the differences between the identified platforms in terms of the degree of integration of machine intelligence solutions, types of predictive models, depth of content personalisation, forms of feedback, and tools for real-time student support. In addition, a structural and functional analysis was used to assess the role of these tools in the construction of an individual educational trajectory and the prevention of academic risks. The final stage of the study consisted of an institutional and comparative analysis aimed at comparing the approaches of British universities to integrate AI into the educational process and synthesising the strategy for the implementation of intelligent technologies in educational practice.

RESULTS

Theoretical foundations of learning personalisation through artificial intelligence. Learning personalisation in the higher education system is understood as an educational approach focused on the individual needs, learning style, and academic potential of university students. The main goal of this approach is to form a variable educational process that allows each student to learn at an individual pace and master the content as efficiently as possible. First and foremost, adaptive learning trajectories (Fig. 1) are used, which make it possible to adjust the trajectory in real time depending on the student's fulfilment of learning tasks and their initial preparation. The students who demonstrate high academic results are offered more complex tasks aimed at further academic development, while the students who face learning difficulties are provided with the possibility of repeated explanations or revision of the material. Such step-by-step adjustment of the learning trajectory increases students' motivation and academic effectiveness. Another component is the individual learning plan (ILP), which structures the adaptive educational trajectory and includes students' personalised learning goals, a list of mandatory and elective disciplines, recommendations for additional educational resources and methods of assessing academic achievements, as well as a distribution between independent and group work. Due to ILP, students can clearly articulate their educational goals and ways to achieve them, which increases their involvement in the educational process. For example, an ILP may include core disciplines and additional online educational resources such as the Knewton Alta (n.d.) or Coursera (n.d.) platforms to support the mastery of a discipline. Differentiated learning tasks also play an important role as they allow changing the complexity, form, and type of learning activity in accordance with the individual educational needs of the students. Learning tasks may be extensive for students with a high initial level of preparation, basic for students who need academic support, and repetitive for mastering and revising educational material. Using differentiated tasks, it is possible to find a balance between the need to provide high-achieving students with more complex tasks and the need to provide lowachieving students with academic support, which ultimately increases the effectiveness of the learning process.

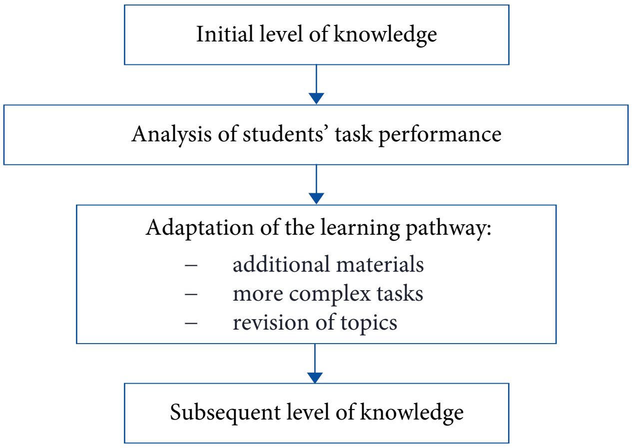

Figure 1. Principle of the adaptive learning pathway
Source: developed by the authors based on the study by S. Zhao *et al.* (2024)

The effectiveness of personalised learning at the university is determined by the ability of AI systems to analyse and adjust the educational process based on the analysis of students' behavioural data. The main tools for conducting such an evaluation are Learning Analytics and Learning Design (n.d.), which provide possibilities for the collection and analysis of digital footprints of students' activity on educational platforms. On the basis of these data, it is not only possible to estimate the actual knowledge level, but also to forecast the risk of academic failure, detect weaknesses and create adaptive advice. It is even possible to identify the course modules that are the most challenging for the student, as well as to estimate the success of AI personalisation algorithms that are built in the system.

Another tool for assessing the effectiveness of individualised learning is adaptive educational platforms. These platforms combine testing, recommendation, and learning analytics modules that allow obtaining an objective view of students' achievements in real-time. They allow both individual and generalised analyses to identify general trends and evaluate the effectiveness of the personalised approach at the group level. Moreover, they provide an opportunity to compare traditional teaching methods with AI-personalised approaches, which allows for identifying the advantages and disadvantages of new technologies based on evidence. Different approaches, indicators, and their impact on learning outcomes are presented in Table 1.

Table 1. Comparative analysis of approaches to evaluating the effectiveness of AI-personalised learning

Evaluation model	Core functions	Performance indicators	Potential impact on learning
Learning Analytics	Collection and analysis of data on student behaviour	Number of completed tasks, time spent on modules, assessment performance	Prediction of learning gaps, support for individual learning
Adaptive platforms	Integration of testing, recommendation, and analytics	Course progress, level of content mastery, student engagement	Adjustment of learning pathways, increased effectiveness of knowledge acquisition

Source: developed by the authors based on the study by D. Iqbal *et al.* (2025)

Table 1 summarises the two main approaches to evaluating the effectiveness of personalised learning that differ functionally and methodologically. Learning Analytics is aimed at collecting and analysing big data about students' learning behaviour that allows identifying hidden gaps in knowledge, predicting the risk of underperformance, and providing support. Adaptive platforms play a more applied role: they use the results of analytics to directly influence the learning trajectory by adjusting the level of difficulty, depth, and speed of the delivery of learning content. Thus, the first model has a diagnostic function, while the second model is a means of applying a personalised intervention. They form an integrated system that contributes to improving learning effectiveness.

It is necessary to note that the effectiveness of these models is not evaluated by academic achievement but also by the level of motivation, engagement, and satisfaction of students with the learning process. Therefore, the combination of Learning Analytics with adaptive platforms forms a complex framework for evaluating personalised learning, which allows evaluating both an individual student and the whole system on the level of outcomes. A comparative analysis of traditional learning models with models that involve AI-personalisation allows identifying both benefits and drawbacks of the application of contemporary technologies in higher education. Traditional learning is usually based on a standardised curriculum and assessment that are targeted at the average student and imply the same amount of learning materials, tasks, and speed of studying for all students. Within this system, a lecturer is not always able to respond to the needs of each student in a timely manner, which can lead to a gap in the acquisition of knowledge and, as a result, lower motivation and engagement of students. In contrast to traditional models, AI-personalised learning involves adaptive technologies and algorithms that allow creating an individual learning trajectory optimised for each student. Moreover, not only enhances motivation and engagement but also provides flexibility in the learning process that is targeted at the needs of each student. Personalisation based on intelligent systems allows students to study at an individual speed, receive tasks that correspond to their level of readiness, and provide feedback in a timely manner that contributes to a better understanding and mastery of subject material (Maphosa & Maphosa, 2023).

At the same time, the application of machine learning-based personalisation is not devoid of disadvantages. The technical difficulties related to the embedding of adaptive systems into existing digital learning platforms, as well as the low level of digital literacy of lecturers and students, can dramatically decrease the effectiveness of technologies. Moreover, the application of personalisation algorithms can lead to bias when systems incorrectly interpret data or provide recommendations that enhance existing inequality in education. To systematise the comparison, the main differences between traditional and AI-personalised learning are presented in Table 2.

Table 2. Comparative analysis of traditional and AI-personalised learning

Analysis parameter	Traditional learning	AI-personalised learning
Approach to students	Standardised, oriented towards the average level of preparation and learning pace, without accounting for individual differences	Individualised, adapted to each student
Motivation and engagement	Dependent on personal student factors	Enhanced through personalised tasks and timely feedback
Flexibility of the educational process	Limited, standard pace	High, with the ability to adapt pace and task complexity
Technical requirements	Minimal; the lecturer does not require specialised tools	High: requires AI integration and platform configuration
Risks	Limited, mainly human factor	Present: algorithmic bias, errors in personalisation

Source: developed by the authors based on the study by K. Amoako *et al.* (2024)

The comparative data presented in Table 2 illustrate the fundamental differences between the traditional pedagogical model and an approach based on artificial intelligence and personalisation. Traditional learning is built on a standardised logic of organising the educational process, in which educational interventions are largely uniform and oriented towards the "average" student, inevitably limiting pedagogical flexibility and the variation of learning pace. By contrast, AI-personalisation creates a highly dynamic learning environment in which adaptive and predictive algorithms enable individual adjustment of tasks, complexity, and pace. This stimulates motivation, increases cognitive engagement, and enhances progress in knowledge acquisition. Simultaneously, the technological complexity of the educational environment dramatically increases: in contrast to the traditional approach, personalised systems require more advanced technical opportunities, effective embedding into LMS, and lecturers' readiness to work with analytical tools. Another aspect here is the appearance of new challenges, first of all, algorithmic bias and recommendation errors, which necessitate the controlled and methodologically competent introduction of machine learning technologies in the educational process. In this sense, AI-personalisation creates a synergetic effect, which consists of the sum of the advantages of individualised and learning-behavioural approaches to knowledge acquisition. Simultaneously, the effective introduction of these technologies requires consideration of technological, organisational and ethical factors, which can affect the results of the educational process.

Review of AI application practices in British universities. The application practice of AI technologies in the United Kingdom's higher education institutions involves a variety of platforms for the creation of individualised educational trajectories and the increase of learning efficiency. For example, the Knewton Alta system (n.d.) specialises in adaptive learning of students in Mathematics and Science, Technology, Engineering, and Mathematics (STEM) fields. Alta uses algorithms to diagnose the current level of knowledge of the students, and, accordingly, changes the complexity of tasks and offers an individual educational trajectory. A peculiar feature of this system is the inclusion of assessment tools in educational content, which enables the assessment of the current level of knowledge of the students and learning activities, and, thus, more accurately identifies gaps in their academic and professional training. Another example is the Synap platform (n.d.), which specialises in adaptive assessment and revision of educational content. The system analyses the responses of the students and identifies knowledge gaps, and generates individual blocks of practice tasks to address these gaps. The system also uses spaced repetition algorithms and reduces the time of mastering key concepts, which enables students to achieve better retention of the material. In other words, Synap not only assesses the students' knowledge but also supports individualised construction of the learning process by automating educational content. The Edumentors platform (n.d.) realises the AItutor model and offers students individual educational trajectories and recommendations. The system combines adaptive assessment tools, learning-behavioural analytics and individualised support to learning activities, which enable students to receive educational content in accordance with their academic strengths and weaknesses, pace and goals of learning. One of the key functionalities of the tool is its interactivity, which allows immediate feedback and further understanding of the material. To further organise the functionalities and characteristics of these tools, Table 3 is presented.

Table 3. Functional and personalisation characteristics of leading AI tools used in British universities

Platform	Core functions	Target disciplines	Personalisation capabilities
Knewton Alta (n.d.)	Adaptive learning, integration of testing and content	Mathematics, STEM	Dynamic task adaptation, individual learning pathways
Synap (n.d.)	Adaptive tests, spaced repetition	General courses, STEM	Personalised revision blocks, identification of weak areas
Edumentors (n.d.)	AI tutoring, individual learning plans	Various disciplines	Personalised plans and recommendations, interactive feedback

Source: developed by the authors based on analysis

As can be inferred from the comparison of tool functionalities, each tool serves different learning purposes and personalisation strategies. Knewton Alta is most effective in Mathematics and STEM disciplines due to structured adaptive educational trajectories, which enable more precise identification of knowledge gaps and quick adjustment of the complexity of tasks. As a result, the accuracy of learning grows, and the risks of underperformance of students are minimised. The system Synap focuses on spaced repetition and adaptive assessment, which ensures the durability of knowledge acquisition and development of cognitive skills, due to which students demonstrating better retention and stability of academic achievements. The Edumentors system is characterised by interdisciplinarity and interactivity of AI-tutoring, which stimulates the development of metacognitive competencies and supports self-regulated learning, which, in turn, contributes to the academic engagement of students and their autonomy. In general, the differences in the functional orientations of the systems cause differences in their application focus and models of learning interaction, which resulted in three models of individualisation: structured adaptivity, cognitive consolidation and interactive support of learning activities. Overall, the table suggests that these platforms are not only an opportunity to extend the potential of personalisation but to make it multidimensional, i.e. to include content, pace, feedback, and cognitive support all at once.

LMS is essential in the provision of personalised learning to higher education students, especially if linked with AI tools. LMS tools used by British universities are mostly Moodle (n.d.) and Blackboard (n.d.). Both tools can be linked with AI tools to support adaptive learning in the provision of individual learning pathways and creation of an individual learning plan (Badaru & Adu, 2022). Recommendation algorithms, adaptive testing modules, and learning analytics are embedded in the platforms, which provide the ground for real-time support of students. For instance, adaptive quizzes and completion tracking modules are employed in Moodle. They not only control the knowledge of the students but can also adapt the complexity of the tasks according to the students' progress. In addition, the system can be linked with machine intelligence tools such as the Learning Analytics Toolkit, which helps lecturers to predict at-risk students, trace the progress and make individualised recommendations. The system allows for the construction of personalised learning trajectories that are tailored to the student's current level of knowledge and the rate at which they learn in order to maximise both challenge and motivation. Blackboard offers the possibility to use more sophisticated analytical tools, such as Blackboard Predict, that traces the student activity, estimates the chance of success and allows automated tuning of the individual learning pathway. The tool allows the insertion of additional learning materials, individualised assignments, and interactive tools for students who need additional support, which reduces the rate of drop-outs and increases academic achievement.

Along with Moodle and Blackboard, British universities mostly use Canvas (n.d.), Brightspace (D2L) (n.d.) and FutureLearn (n.d.). All of them demonstrate a wide range of personalisation potential. Canvas can be linked with Canvas Analytics and third-party AI plugins to trace the engagement of the students and provide individualised recommendations. Brightspace employs Predictive Learning Analytics, which predicts the risks and triggers the automated intervention with some corrective tasks. FutureLearn can also be linked with a machine intelligence tool to provide adaptive learning opportunities through Massive Open Online Courses (MOOCs). The content can be adapted to the individual students according to the students' interaction with the content and assessment results. The integration of intelligent tools into LMS tools allows for the creation of an individual learning pathway for each student who receives individualised tasks, materials and traceability. This approach promotes greater student engagement, reduces the risk of falling behind, and fosters deeper learning. In addition, the role of a lecturer changes from the lecturer to the facilitator who monitors the process and traceability and provides additional support if needed. Table 4 presents a systematic overview of functions and contributions of LMS tools linked with AI tools.

Table 4. Comparative analysis of LMS tools with integrated AI tools used in British universities

LMS platform	Integrated AI tools	Core functions	Impact on personalisation of learning
Moodle (n.d.)	Adaptive Quiz, Learning Analytics Toolkit	Adaptive testing, progress monitoring	Individual learning pathways, risk prediction
Blackboard (n.d.)	Blackboard Predict, IIII Recommendation Engine	Success forecasting, personalised resources	Creation of individual pathways, increased engagement
Canvas (n.d.)	Canvas Analytics, third-party AI plugins	Activity monitoring, adaptive learning	Personalised resources, recommendations, integration of external AI
Brightspace (D2L) (n.d.)	Predictive Learning Analytics	Corrective assignments, adaptive planning	Support for mixed-ability groups, forecasting and personalisation
FutureLearn (n.d.)	AI content recommendations	Personalisation of MOOC pathways	Adaptive learning, increased motivation and student retention

Source: developed by the authors based on research

Comparative analysis of the LMS tools with integrated AI tools demonstrated the different models of support for personalised learning in British universities. Firstly, the Moodle tool, through the adaptive testing and Learning Analytics Toolkit, demonstrates the rapid monitoring of student learning and risk prediction, which allows for the creation of individual learning pathways. Blackboard and Canvas provide the possibility to personalise the resources and assignments, which allows for increasing the engagement of the students and the opportunity to dynamically adjust the learning process to the needs of the learner. Brightspace stands out with support for mixed-ability groups and corrective assignments, which enables planning adapted to the needs of heterogeneous classes. FutureLearn specialises in MOOCs and provides AI-driven content recommendations aimed at enhancing student motivation and retention in online courses. In general, the differences in functional approaches of the above-mentioned platforms can be explained by the specificity of educational settings and target audience, from individual learning pathways and adaptive testing to support of massive online courses and behaviour analytics. The incorporation of machine learning solutions leads to the creation of a holistic ecosystem for individualised learning consisting of analytics, adaptive tasks and recommendations to improve the acquisition of learning material and the overall academic achievement of students.

Critical discussion of AI adoption in British universities and its influence on student academic achievement. The adoption of artificial intelligence in higher education in the United Kingdom is a complex and multi-faceted process, including technological, pedagogical and organisational dimensions. AI tools capable of modelling individual learning trajectories and adjusting learning materials to meet individual students' needs are gradually changing the classical educational paradigm, increasing engagement and motivation, but also raising new challenges in terms of ethical use, data management and academic staff professional development. University practices demonstrate the potential of artificial intelligence not only as a technological tool, but also as a driver of strategic innovation in the educational process and in the development of competences of future professionals in the conditions of rapid digitalisation.

The University of Glasgow (n.d.) demonstrates a pro-active and well-balanced approach to the incorporation of GenAI into the learning process. In particular, the official university policy highlights the importance of ethical, critical and transparent use of GenAI: instead of a ban, the University is willing to teach students to work with these tools in an effective and responsible manner, acknowledging their potential role as an innovation driver in future professional activity. In the area of learning support, the Student Learning Development service offers students resources, workshops and one-to-one tutorials to develop digital literacy in the sphere of AI, acquire skills of critical thinking in the analysis of AI-generated content and proper integration of the tools into the learning process. In terms of assessment policy, the University works on the redesign of assessments: academic staff is encouraged to rethink the assessment structure to ensure that the GenAI use is not punished, but understood as a learning tool, for instance, through reflection, analysis or explanation of AI-generated results. Another valuable practice is the creation of spaces for student participation and discussion. The University organises AI student panels, surveys (in which the majority of students admit that they regularly use ChatGPT (n.d.) or other similar tools), and a series of educational activities aimed at raising a collective understanding of the opportunities and challenges provided by the machine-intelligent solutions. It is also worth mentioning that the University of Glasgow provides students with explicit guidelines on the responsible use of GenAI, particularly in Life Sciences, where relevant documents clarify that AI can and should be used as a facilitating tool and not as a replacement for the independent academic work (Hough *et al*., 2023). This example illustrates a systemic approach: the University not only elaborates a policy, but also develops practical programmes of digital skills acquisition, assessment support, as well as community involvement. This experience shows that AI-based personalisation in universities can grow not only as a technological prototype but also as a part of a long-term approach towards preparing students to live and work in a world in which GenAI will be widely used.

Similarly, the Open University (OU) (n.d.) is one of the most forward-looking British universities in terms of Learning Analytics and machine-based technologies. In the Institute of Educational Technology (IET) at OU, the research group on Learning Analytics and Learning Design (n.d.) collects the "digital traces" of student behaviour in the virtual learning environment and analyses them in order to boost engagement, satisfaction and success. OU also applies predictive analytics via the EAI, which sends a notification to associated lecturers (ALs) if the student is possibly experiencing problems. However, some research reveals that not all staff engage with this tool: in an EdD dissertation, A. Gillespie (2022) explored barriers to the use of predictive learning analytics (PLA) among ALs. They include, in particular, scepticism, lack of experience, and unwillingness to change the teaching practices. Another area of machine-intelligent technology is explored at OU: researchers examine the possibility of using generative AI for creating and adapting content. For example, an exploratory study was conducted on how ChatGPT and similar models could assist with the creation of distance learning materials for more efficient curriculum development. The OU developed a policy for responsible use of generative AI in teaching and assessment, which covers ethical issues, academic integrity, and inclusion. In general, the OU's journey proves that the adoption of AI tools in a large-scale distance teaching university has promising prospects, yet also encounters a range of organisational difficulties, such as staff uptake of analytics, professional development and development of responsible AI-use policies.

The University of Manchester (n.d.) offers several examples of good practice for incorporating AI into the teaching process. L. Birchinall *et al*. (2025) have recently found that the adoption of generative AI, in particular through the TeachMateAI tool (n.d.), in teacher education can assist in the development of future educators. The results of the first year of the study have revealed that trainee teachers engaged with AI in a critical, creative and contextual way: they did not simply follow AI recommendations but rather developed professional judgment, creativity, and situational sensitivity. The University of Manchester is also exploring how machine-intelligent solutions can contribute to the development of teaching competencies. This example shows that AI-driven personalisation in British universities can be extended from student learning to the development of teaching practices.

A critical overview of these three universities reveals a variety of practices in the integration of AI and analytics into the educational process (Table 5). The OU, with its background in distance education, is the most advanced in the application of Learning Analytics for risk prediction and generative AI for content generation. However, at the same time, lecturers face barriers related to the use of analytics dashboards and the development of a policy on responsible use of intelligent technologies. In Manchester, the TMAI case shows that AI can also be used as a tool for lecturer development, expanding the scope of personalisation: it is not only learning paths that can be personalised through AI but also pedagogical practices.

Table 5. Comparison of AI implementation practices in British universities

University	Main AI/analytics strategy	Tools and approaches	Key outcomes and challenges
University of Glasgow	Integration of generative AI in teaching and digital literacy development; emphasis on ethical and critical use	Generative AI (ChatGPT), student panels, learning workshops, policies on responsible AI use	Enhanced digital literacy and critical thinking regarding AI; challenges – need for development of teaching competencies and alignment of AI-use policies
Open University	Predictive analytics (Predictive Learning Analytics) and integration of generative AI for adaptive distance learning	Early-Alert Dashboard, ChatGPT for content creation, Learning Analytics Toolkit	Increased student engagement and retention, personalised learning pathways; challenges – low uptake of analytics tools among some lecturers, need for staff training
University of Manchester	Pedagogical integration of AI to develop teaching skills; support for critical and creative use of AI	TMAI (generative AI for Postgraduate Certificate in Education programmes), integrated workshops, modular cases for student-lecturers	Positive impact on professional judgment and creativity of future lecturers; challenges – limited scalability of tools and need for adaptation to different disciplines

Source: compiled by the authors based on studies University of Glasgow (n.d.), Open University (n.d.), University of Manchester (n.d.), ChatGPT (n.d.), TeachMateAI (n.d.), A. Atkinson-Toal & C. Guo (2024)

Table 5 provides an overview of the ways in which these three British universities are adopting machine-intelligent echnologies to support learning. University of Glasgow prioritises the critical and ethical use of generative intelligence and digital literacy development for all students, but acknowledges that staff competences need to be strengthened. The Open University uses predictive analytics and generative tools to support the personalisation of distance learning, but not all academic staff are using the analytic systems to their full potential. University of Manchester highlights the use of AI in pedagogical contexts to support the development of critical and creative thinking in student-lecturers, but points out that there are challenges for scaling and transferring the practice to other subjects.

Predicted impact on students' academic achievement. The introduction of individualised study trajectories with the help of AI in higher education modifies the traditional models of student motivation and engagement. In a traditional educational setting with the same academic content and tasks for all group members, individual motivation is quite low and negatively affects student activity and the efficiency of student engagement with the course. Personalisation of learning content and tasks using intelligent systems, responding to each student's current academic achievement and learning style, ensures more effective participation in the learning process.

Firstly, one of the key advantages of machine-intelligent systems is that they provide immediate differentiated feedback that allows students to rectify mistakes immediately and gain more profound knowledge of the subject. Such feedback mechanisms not only support the acquisition of cognitive knowledge but also cause a positive psychological effect: students feel more in control of their learning and immediately perceive evidence of their academic progress that significantly improves intrinsic motivation. From the perspective of self-determination theory (Vallerand, 2000), such a level of personalisation contributes to the development of autonomy, competence, and engagement, which are the basic determinants of learning motivation. Learning behaviour analytics supported by AI systems enables tracing students' interaction with learning content that helps assess the frequency and quality of activities, time spent on tasks, and the level of students' independent mastery. This lays the basis for constructing individualised trajectories responding to the academic needs of concrete students, primarily students with a low level of initial preparation or those prone to lagging behind. In its turn, this individualisation not only encourages motivation but also improves academic engagement and reduces passivity and the propensity to coast that is often observed in large group lectures.

Moreover, the empirical evidence from the experience of British universities proves the positive effect of these systems on students' motivation. Thus, in the Open University (n.d.), OU Analyse, a Learning Analytics system, is currently being used to identify students who are at risk of falling behind and intervene in a timely manner. In the study by B. Rienties (2021) as part of the OU Analyse initiative, it is proven that three module teams made changes to course design based on real-time analytics, with a positive effect on student retention. Besides, it was found that the frequency of lecturers' access to the OU Analyse dashboard was positively correlated with higher student completion rates, lecturers who made regular use of the analytics reported higher levels of module completion among their students. Additionally, Open University guidance mentions that data are used for monitoring, early identification of vulnerable students, and adjustments to course design. It proves that analytics is used not only as a technical tool but also as part of a proactive strategy for student support. Therefore, the introduction of machine-intelligent solutions in the process of individualised learning causes a synergy between the acquisition of cognitive knowledge and students' motivational involvement, leading to more effective and holistic engagement in the learning process.

It has already been proven in a number of studies that personalisation in terms of adapting the learning route depending on the learning analytics improves both the quality and speed of acquiring knowledge. For example, such tools as Knewton Alta (n.d.) and Synap (n.d.) use a combination of adaptive testing and spaced repetition algorithms that help to allocate additional exercises to students in their weak knowledge spots. Thus, there is a kind of closed cycle where students receive immediate feedback for the correct answers, or an indication that a student should repeat a piece of knowledge, which contributes to increasing the effectiveness of the time spent on learning and deepening the knowledge gained. Figure 2 presents a scheme that illustrates how an intelligent system processes learning analytics data and individual learning paths of students.

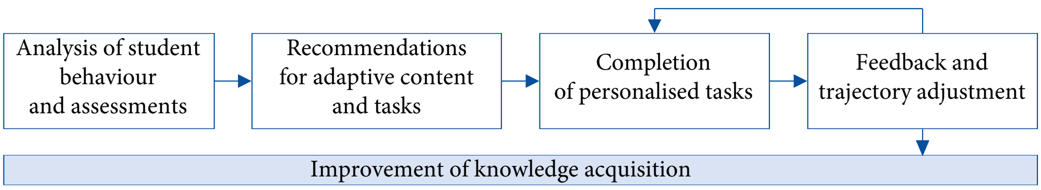

Figure 2. Learning-path adaptation through AI
Source: developed by the authors based on the study by M. Penmetsa (2025)

Besides, empirical evidence from the Open University (n.d.) suggests that applying an adaptive approach improves the quality of the learning process, especially in massive distance education courses where a conventional undifferentiated curriculum does not take into account the characteristics of individual students. In the study by B. Rienties (2021), it was found that students whose learning paths were adjusted using analytics showed a higher level of possession of key competencies and knowledge than students in a control group where this technology was not used. Table 6 shows the results of a comparative analysis of the quality of learning outcomes in the framework of conventional and AI-based personalised learning.

Table 6. Efficiency of adaptive and analytical technologies in improving learning outcomes in British universities

Parameter/category	Description/methodology	Type of impact on the learning process
Learning design structure	Analysis of 87 modules using Learning Analytics to assess the impact of student activities (communication, task completion) on outcomes	Indirect improvement of learning through module and activity adjustments
Interventions based on the OU analysis	Use of predictive models to identify students at risk of low performance and provide tutoring support	Direct enhancement of learning through personalised guidance and resources
Adjustment of learning trajectories	Application of analytics to modify tasks and course content in real time according to student behaviour	Increased cognitive efficiency and depth of knowledge acquisition
Prediction and feedback	Integration of predictive systems within LMS (e.g. Moodle, OU Analyse) to identify weak knowledge areas and recommend supplementary materials	Optimisation of individual learning pathways and improved accuracy of knowledge acquisition

Source: developed by the authors based on studies Open University (n.d.), P. Joseph-Richard *et al.* (2021), and B. Rienties (2021)

As seen from the data in Table 6, applying Learning Analytics and differentiating pedagogical influence contribute to an improvement in the effectiveness of learning. The results of the analysis of the structure of modules make it possible to differentiate students' activities, which indirectly has a positive effect on acquiring knowledge. Using tools such as OU Analyse and predictive analytics makes it possible to identify risk groups of students, which directly affects the quality of learning outcomes. Using real-time analytics to adjust individual learning trajectories leads to an optimisation of the educational route and a deepening of the acquisition of knowledge. All these instruments, in sum, form an effective ecosystem of personalised learning.

Personalised learning as a result of AI integration in higher education institutions in the United Kingdom has not only a cognitive but also a socio-pedagogical effect, in terms of which the integration of artificial intelligence affects students' retention and contributes to the reduction of the dropout rate. Indeed, in the case of distance education on a mass scale, which is practised, for example, by the Open University, conventional forms of pedagogical support of students cannot be adjusted to meet the individual needs of each student and, accordingly, the risk of students dropping out of the discipline or completely withdrawing from their studies is rather high. Using analytical and adaptive technologies integrated into LMS, it is possible to identify at an early stage signs of difficulties in mastering the discipline on the part of students and take prompt measures to eliminate the problems through the efforts of the lecturer or using automatic notifications.

According to the empirical data, the use of Learning Analytics for personalisation of learning contributes to an improvement in the retention rate. Thus, in the framework of the above-mentioned study by B. Rienties (2021), it was found that students whose individual learning paths were adjusted using real-time analytics had a 15-20 % lower risk of dropping out compared to students in a control group where the technology of personalisation was not used. The use of such an analytical tool as OU Analyse makes it possible to identify students who are at risk of failing a discipline and take relevant measures in the form of individual recommendations, reminders, and adaptive tasks to level the students' academic achievement. Table 7 presents the main differences in retention and dropout rates in the context of conventional and AI-based distance learning.

Table 7. Impact of AI-based personalisation on students' retention and dropout

Parameter	Traditional learning	AI-personalised learning
Student dropout (%)	22-25	15-20
On-time module completion (%)	75	85-88
LMS activity (logins and completed tasks)	60-65	75-80

Source: developed by the authors based on studies Open University (n.d.), B. Rienties (2021)

As can be seen in Table 7, the use of intelligent technologies makes it possible to monitor students at risk and organise relevant and timely measures of individual support, which contributes to the growth of passing and completion rates and reduces student dropout. In addition, the use of analytical data makes it possible to improve the design of the course and make more efficient decisions about the distribution of teachers' time, which contributes to the growth of academic stability in the student body. In terms of the personalisation of learning through the use of AI, the lecturer's role changes from a lecturer or mentor to a coordinator, analyst and adaptive tutor. Analytical systems embedded in LMS systems such as OU Analyse, Moodle (n.d.) or Blackboard (n.d.) enable the lecturer to monitor the current progress of students, identify areas of potential difficulties, and take timely measures to optimise the students' individual trajectory. This is especially relevant in distance or blended learning formats, where the absence of direct face-to-face communication increases the likelihood of truancy or a decrease in student activity.

The lecturer has access to a wide range of indicators of student activity and progress, such as frequency of logging into the system, completion of tasks, results of adaptive tests, and work with educational content. Based on the results of the analysis, the lecturer can change the learning task, provide additional resources, adjust the level of difficulty of the material, or organise an individual consultation. According to the results of scientific research by B. Rienties (2021), the use of analytics in support of the educational process helps reduce the differentiation between students with different levels of readiness, thereby contributing to a more efficient distribution of attention and educational resources, which has a direct impact on academic achievement and student retention. The lecturer's role in the process of personalisation of learning is presented in Figure 3.

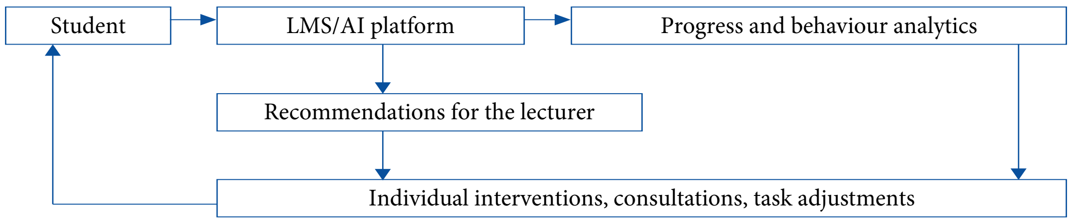

Figure 3. Lecturer's interaction with the AI system in personalisation of learning
Source: developed by the authors based on the study by Y. Copur-Gencturk *et al.* (2024)

The figure shows a conceptual model of cyclical interaction of the student, lecturer and intelligent system, in the process of which machine learning algorithms constantly monitor student progress, cognitive features and behavioural actions. The data obtained is translated into pedagogical recommendations that are sent to the lecturer and serve as the basis for the introduction of individual educational interventions, such as changes in tasks, pace of study, or individual consultations. Due to this, with each new student interaction with the AI system, a new analytical data set is formed, which not only allows the lecturer to respond to the challenges but also to predict and prevent them. This strengthens the personalisation of the educational process and contributes to academic resilience and student engagement. A comparative analysis of the lecturer's role in the traditional and AI-based personalised educational process is presented in Table 8.

Table 8. Comparative analysis of the lecturer's role in traditional and AI-personalised learning

Role aspect	Traditional learning	AI-personalised learning
Monitoring student progress	Visual/manual observation, periodic assessments	Real-time tracking via analytic dashboards, automatic risk detection
Individual support	Limited by time and resources	Personalised interventions, material adaptation, AIgenerated recommendations
Task planning and assessment	General tasks, identical for all students	Dynamic adaptation of task difficulty, content selection tailored to student needs

Source: developed by the authors based on studies M. Pratama *et al.* (2023), A. Bhatia *et al.* (2024)

As can be seen in Table 8, the introduction of intelligent technologies changes the functionalrole structure of the lecturer in the educational process. While in the traditional format, the monitoring of progress is limited to carrying out periodic assessments and visual control, and individual support is limited by the time and resources of the lecturer, in AI-personalised learning, the use of analytical dashboards allows the lecturer to monitor the current progress of students in real time and automatically identify students who are at risk of falling behind. Personalised interventions, adaptive educational content and AI-generated recommendations allow for more accurate and timely support of students. Dynamic adaptation of the level of difficulty and content contributes to the optimisation of the educational process for each student. This indicates a qualitative improvement in the efficiency of educational activity and the accuracy of the individualisation of the educational services provided with the use of AI technologies. A lecturer who successfully incorporates analytics received from intelligent systems into their pedagogical activities not only increases the effectiveness of their work with students but also optimises it, devoting more time to those students who need it and delegating routine tasks of control and monitoring to intelligent systems. Thus, AI technologies do not crowd out the lecturer but rather intensify their activities, and a new model of pedagogical assistance emerges in the form of synergy of actions of technologies and the professional potential of the lecturer, which together increase the effectiveness of the educational services provided.

Inclusion of intelligent systems in the system of individualised learning in the higher educational institutions of the United Kingdom has a positive effect on the motivation and involvement of students in the educational process, increases the effectiveness of individualised learning, reduces the time of its implementation, improves the accuracy of performing tasks due to adaptive learning paths, immediate feedback, and AI technologies' predictive analytics. In this case, the lecturer performs the function of a coordinator and a lecturer whose task is to promptly respond to the analytics received and adjust the individualised educational content, and provide students with necessary support. The use of AI systems for the individualisation of the educational process gives a synergistic effect, enhances the pedagogical influence, and generally improves the quality of the educational process.

DISCUSSION

In recent years (2021-2025), publications have appeared that consider the problem of changes in the lecturer's role and the student's experience, and the evolution of the educational ecosystem under the influence of AI technologies. The results of the studies of other researchers do not contradict the results obtained in the present study, which indicates an increase in the efficiency, flexibility, and individualisation of educational services in the system of higher education in the United Kingdom as a result of the implementation of machine-intelligent systems. Thus, in their conceptual article, X. O'Dea & M. O'Dea (2023) note that AI in higher education is often positioned as "the next big technological innovation" while universities and colleges are not yet ready to implement it. The authors paid attention to the danger of the formal implementation of AI without a pedagogical strategy. Compared to the results obtained, these researchers emphasised a strategic and cultural perspective, while the conducted study focused more on the effect of individualisation and analytical opportunities of the platform. Concurrently, S. Maghsudi *et al.* (2021) discuss the concept of personalised learning with respect to machine learning, in which AI serves as an engine for knowledge gap prediction, recommendation and content adaptation. The findings are consistent with the results of the current study and suggest the importance of adaptive learning paths and adaptive educational models.

The study by A. Klašnja-Milićević & M. Ivanović (2021) focused on e-learning personalisation systems for sustainable education. The article focused on adaptive interfaces, recommender systems and cognitive models of users. While the conducted research highlights LMS systems with AI tools in addressing dropout rate and student engagement, this article, instead, puts the emphasis on the learning ecosystem and sustainability in the narrative. Likewise, A. Al-Badi *et al.* (2022) examine the attitudes towards AI of students and lecturers. The results showed that the students had high levels of expectation with respect to personalisation and a decrease in the workload, but they presented doubts with respect to the reliability of the algorithm and the objectivity of the evaluation. However, these results do not totally match the presented study: risk management and ethics governance in British universities in this study are better, which reduces the worry about intelligent technology application. The discrepancies may stem from the different environments that A. Al-Badi *et al.* investigated in Gulf Countries' universities, which may be at different levels of regulations and technologies. According to V. Kuleto *et al.* (2021), in the article, the main benefits of AI in higher education include flexible learning, data analytics, and decision support, while the most significant drawbacks are ethical concerns and inequalities. Their results are consistent with those of the current study, underlining the importance of institutional policies and lecturers' digital literacy. While V. Kuleto *et al.* discuss the macro-level issues (management and strategy), this study addresses the micro-level (the models of personalisation itself), in the United Kingdom context. According to C. Zhou (2023), the universities that are most effective are those that infuse AI into content, course management, and student support at the same time, resulting in an "ecosystem" model of digital learning. The outcomes of this study are in line with the current observations of the broader picture of the overall ecosystem of personalised learning in the University of Glasgow, the Open University and the University of Manchester. Meanwhile, C. Zhou emphasises a variety of technologies (VR/AR, big data, AI). In addition, according to the study conducted by J. Hutson *et al.* (2022), when successfully implemented, the role of the lecturer using intelligent machine-based innovations becomes one of a facilitator, mentor, and moderator of technology. These findings are fully consistent with the results of the current study concerning the hybrid model of pedagogical support in the United Kingdom universities. However, the authors pay more attention to inter-disciplinary applications of AI, while the current study offers a more in-depth analysis of the use of adaptive algorithms within particular platforms (Knewton Alta, Synap, Edumentors).

The most recent bibliometric review study published by V. Maphosa & M. Maphosa (2023) suggested that the most prevalent keywords in the global research articles include personalised learning, AI ethics, and learning analytics, which proves that the theoretical framework of the current research is not outdated. However, the authors acknowledged the theoretical bias in the current literature and the absence of empirical studies, which offer in-depth discussions about practical personalisation models. For this reason, some of their conclusions (e.g. the insufficiency of empirical evidence for assessing AI effectivity in actual classes) partially diverge from the conclusions of the current study. The current research provides more empirical evidence from the British university cases with more practical granularity. This contradiction may be due to the level of evidence: bibliometric review research provides a macro-level view, while the current research provides microlevel views. This systematic review, done by H. Crompton & D. Burke (2023), demonstrates the situation of higher education and its utilisation of machine-intelligent software. The authors of the review discuss that personal learning is one of the emerging trends. Their findings on the efficiency of intelligent systems in the form of interactive prompts, adaptive modules, and a decrease in cognitive load are in line with the current results, which point to the improvement in motivation and engagement. However, H. Crompton & D. Burke state that the improvement of academic performance through AI-enabled systems is not yet "empirically validated", which contrasts with the present results on the improvement of academic performance in British universities. This disparity may be attributed to the authors' use of international data, whereas this study is using local data where AI use is more standardised and technologically advanced. On the other hand, K. Nikolopoulou (2024) studied the effect of generative AI, ChatGPT in particular, on the pedagogical practices and highlighted the need to develop the critical thinking of the students. The results are in line with the results obtained by K. Nikolopoulou about the potential of AI-assisted tutoring to facilitate creative learning and foster digital literacy skills. At the same time, the author points to the potential dangers of addiction to AI, whereas in the current research, such problems were not observed in the British due to the active role of the lecturer.

The review of O. Ayeni *et al.* (2024) systematises the studies on individualised learning and shows that AI contributes to better learning outcomes due to individualised pathways and continuous feedback. These results fully coincide with the current study in terms of the functionality of platforms such as Knewton Alta and Canvas. At the same time, the authors state that in the majority of countries, teachers have low levels of preparedness to work with intelligent systems, whereas in British universities, they are highly digitalised. This difference, therefore, can be explained by the difference in lecturers' training and support provided by universities. In the systematic review, S. Essa *et al.* (2023) discussed the adaptive learning technologies, which detect the learning style of the student using machine learning techniques. The results support the current hypothesis about the role of data collection and analysis in individualised learning. At the same time, S. Essa *et al.* are critical of the "learning style" concept, pointing to the low empirical validity of the theory. In the current research, the UK-based system does not rely on learning style but rather on dynamic performance metrics, avoiding, thus, controversial concepts. On the whole, the literature overview shows that there is a global tendency toward shifting from the uniform approach toward more flexible and individualised models of learning, which supports the results of the current research. The discrepancies between the studies can be explained by the contextual differences, digital infrastructure, and the differences in platforms used in the countries.

CONCLUSIONS

The study showed that individualised learning in higher education leads to the creation of a flexible educational process that can be adapted to the individual needs of the students, their learning style, and academic abilities. The application of individualised trajectories, learning plans and differentiated assignments allows for dynamic adaptation of the educational trajectory in accordance with the students' academic performance and level of preparation, which in turn has a positive effect both on motivation and learning outcomes. Learning Analytics systems and adaptive educational platforms make it possible to quickly collect and process data about the educational activity of students, identify gaps in their knowledge and skills, and provide recommendations for further education. This allows creating a full-fledged ecosystem of individualised learning, which in turn has a positive effect on students' engagement and effectiveness of mastering the material.

This difference between the traditional approach and AI-personalised learning (when the traditional approach is not very flexible and based on the "average" student, and AI personalisation is more individualised, based on real-time task automatic adjustment and real-time feedback) also shows that the effectiveness of AI personalised learning depends on technological infrastructure, lecturer training and minimising the risks of algorithmic bias. In British universities, integration of intelligent systems in learning platforms (such as Knewton Alta, Synap, Edumentors) has allowed for the implementation of different adaptive learning models: structured learning pathways for teaching STEM disciplines; interval-based quizzing to reinforce learning, and AI-powered tutoring coupled with individualised learning pathways. LMS platforms (Moodle, Blackboard, Canvas, Brightspace, FutureLearn) provide functionalities to individualise learning pathways, predict student underperformance risk and adjust learning content based on the student learning outcomes. This results in lower dropout rates and higher completion rates of modules and students' engagement within the systems.

The use of generative intelligence for education in the University of Glasgow, the Open University and the University of Manchester contributes to fostering the digital literacy, critical thinking and creativity of both students and lecturers. Intelligent systems allow real-time adaptation of the learning material, provide immediate, individualised feedback, increase cognitive gains, and increase motivation and engagement. Integration of intelligent systems has changed the lecturer's role from lecturer to coordinator and mentor, using analytics to adjust learning content and learning pathways and provide individualised support. A combination of lecturers' professional teaching competences and intelligent systems has created the new "hybrid" model of pedagogical support, enhancing both the process and quality of education. Thus, personalisation via AI-powered learning systems produces an all-encompassing positive effect: it enhances academic resilience, student engagement and learning outcomes in the United Kingdom higher education. This study is limited to the analysis of practices of integration of intelligent systems in the United Kingdom higher education and has not covered international comparative perspectives. Future research might focus on scaling up personalised AI-driven solutions to different countries and their effect on academic performance and teaching competences, as well as risks associated with this process (e.g. algorithmic bias, predictive inaccuracy, violation of students' data security, over-dependence on automated systems and decrease of the lecturer's role in the learning process).

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CONFLICT OF INTEREST

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