Harnessing AI for Education 4.0: Drivers of Personalized Learning

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Abstract: Personalized learning, a pedagogical approach tailored to individual needs and capacities, has garnered considerable attention in the era of artificial intelligence (AI) and the fourth industrial revolution. This systematic literature review aims to identify key drivers of personalized learning and critically assess the role of AI in reinforcing these drivers. Following PRISMA guidelines, a thorough search was conducted across major peer-reviewed journal databases, resulting in the inclusion of 102 relevant studies published between 2013 and 2022. A combination of qualitative and quantitative analyses, employing categorization and frequency analysis techniques, was performed to discern patterns and insights from the literature. The findings of this review highlight several critical drivers that contribute to the effectiveness of personalized learning, both from a broad view of education and in the specific context of e-learning. Firstly, recognizing and accounting for individual student characteristics is foundational to tailoring educational experiences. Secondly, personalizing content delivery and instructional methods ensures that learning materials resonate with learners' preferences and aptitudes. Thirdly, customizing assessment and feedback mechanisms enables educators to provide timely and relevant guidance to learners. Additionally, tailoring user interfaces and learning environments fosters engagement and accessibility, catering to diverse learning styles and needs. Moreover, the integration of AI presents significant opportunities to enhance personalized learning. AI-driven solutions offer capabilities such as automated learner profiling, adaptive content recommendation, real-time assessment, and the development of intelligent user interfaces, thereby augmenting the personalization of learning experiences. However, the successful adoption of AI in personalized learning requires addressing various challenges, including the need to develop educators' competencies, refine theoretical frameworks, and navigate ethical considerations surrounding data privacy and bias. By providing a comprehensive understanding of the drivers and implications of AI-driven personalized learning, this review offers valuable insights for educators, researchers, and policymakers in the Education 4.0 era. Leveraging the transformative potential of AI while upholding robust pedagogical principles, personalized learning holds the promise of unlocking tailored educational experiences that maximize individual potential and relevance in the digital economy.

Keywords: Personalized learning, Artificial intelligence, Education 4.0, Individualized instruction, Systematic review, Adaptive learning

1. Introduction

Due to the fourth industrial revolution, the current world is marked by constant change, uncertainty, and ambiguity. In this context, education faces significant challenges in adapting to the complex dynamics of this new era (Sangole, Desai and Jain, 2022) As Aziz Hussin (2018) emphasizes, it is of paramount importance to bring learning processes closer to personalization. In this era of automation, artificial intelligence, the Internet of Things, robotics, and other exponential technological advances, personalized learning enables individuals to focus on specific areas of interest and need, maximizing their potential and relevance in the digital economy. Furthermore, by offering a teaching approach tailored to each student's abilities and aspirations, personalized learning empowers individuals to thrive in a society driven by innovation and digitalization, where adaptability and continuous skill acquisition are crucial for success (Khandelwal, Shankar and Siddiraju, 2022).

In this perspective, UNESCO (2017, p. 5) defines personalized learning (PL) as an “educational approach that places the learner at the centre, considering their prior knowledge, needs, and capacities”. Several authors, such as Parra (2016), Hwang et al. (2013), and Lee et al. (2018), underline the importance of considering individual differences when designing personalized learning. Schuwer & Kusters (2014) indicate that PL seeks to address these differences through differentiation and individualization. Differentiation focuses on adapting instruction to students' preferences, such as offering personalized options for setting goals and content. On the other hand,

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individualization aims to adjust instruction according to the needs and pace of each student's learning, such as modifying the level of difficulty and the rate of progress.

However, some researchers have pointed out the lack of clarity in interpretations of the term "personalized learning." For example, Shemshack & Spector (2020) identified the use of different terms like adaptive learning and individualized instruction to refer to this concept. In fact, Villegas-Ch and García-Ortiz (2023) and Nurcahyo and Agustina (2023) are some examples of an entire line of research that associates personalized learning with adaptation. In addition to the above, Schmid & Petko (2019) highlight the need for a precise definition due to the multifaceted and complex nature of personalized learning. This lack of consensus has resulted in multiple definitions and heterogeneous implementation of this educational approach.

Achieving personalized learning has not been an easy task. According to Cain (2022), for over a century, personalized learning has been a subject of discussion regarding its conceptualization and implementation. This has led to the consideration of various approaches and methods by researchers such as Montessori, Parkhurst, and Bloom, which have served as a foundation for developing strategies that address diverse learning modalities and educational objectives. Among these strategies are flipped instruction, project-based learning, effective group work, personalized questioning, and metacognitive guidance, among others. All of this is done to overcome the limitations inherent in conventional learning systems.

In the context of the use of digital technologies in education and more specifically related to e-learning, the personalization of learning has been addressed mainly associated with the adaptivity of learning management systems (LMS) (Ghallabi *et al.*, 2015; Aplugi and Santos, 2022; Nurcahyo and Agustina, 2023), to the adaptation of content through learning objects (Luna-Urquizo, 2019; Gan and Zhang, 2020) and to gamification processes and use of serious games (Kickmeier-Rust and Dietrich, 2009; Makarenya, Stash and Nikashina, 2020).

Furthermore, authors like Zheng (2018) and Vanbecelaere et al. (2020) have considered the use of digital technologies as an alternative to promote personalized learning. Some of these technologies currently stand out above others, such as artificial intelligence, which is generally understood, as Li and Wang (2020) state, as the capacity of machines to employ algorithms, acquire knowledge from data, and utilize this acquired knowledge in decision-making processes, mirroring human-like cognitive abilities.

With a tradition dating back several decades of continuous development, artificial intelligence tools have multiple facets. From early intelligent tutoring systems to personalized learning environments reported by Holmes et al. (2023), AI has begun to enable the provision of resources tailored to each student, considering their profile, learning style, and cognitive levels, as indicated by Dwivedi et al. (2018) and Murad et al. (2020). In this regard, biometric and contextual tracking technologies have also begun to be developed to detect emotions and learning preferences, allowing for more precise adjustments of learning systems to students' needs (Kaklauskas *et al.*, 2015; Thompson and McGill, 2017; Ennouamani, Mahani and Akharraz, 2020).

Despite the advancements reported in the literature, the implementation of personalized learning remains a challenge due to the lack of clarity regarding the practical aspects required to achieve it effectively (Schmid and Petko, 2019; Shemshack and Spector, 2020), and even more so, the knowledge is less for its application in intensely interconnected educational contexts or mediated by highly disruptive digital technologies.

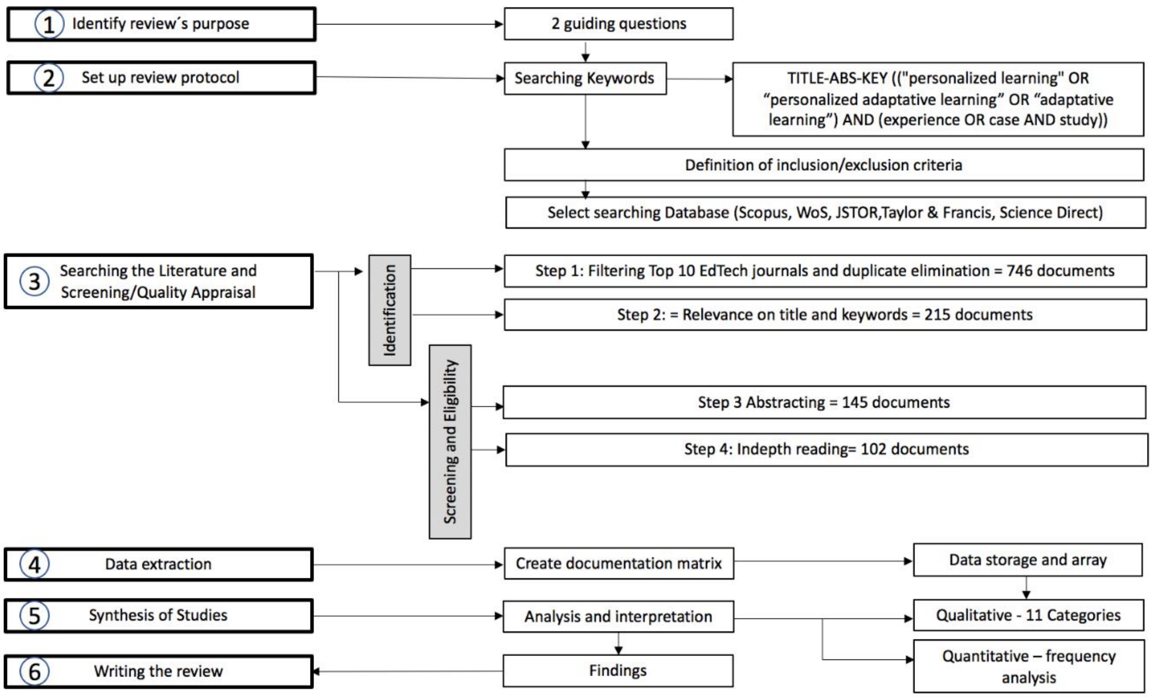
To address this concern, this study provides an extensive review of literature published in the past decade on personalized learning, aiming to identify its key drivers and subsequently offer a critical reflection on the role of artificial intelligence in enhancing them.

2. Method

Howell Smith and Shanahan Bazis (2021) mention that there is a diversity of studies classified as literature reviews, including meta-analyses, content analyses, mapping reviews, narrative reviews, scoping reviews, and systematic literature reviews, each with its methodological particularities. In particular, the methodological approach typically used in systematic literature reviews aligns best with the purpose of this review, which is why it has been chosen as the most relevant option.

For this systematic review of the literature, we considered the guidelines of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement and the recommendations and methodological structure proposed by Okoli (2010), whose application details are presented in Figure 1.

The PRISMA statement provides standardized guidelines for conducting systematic literature reviews, improving the quality and transparency of these studies. It helps researchers identify biases, ensure replicability, and facilitate the interpretation and comparison of results between studies. By following these guidelines, a rigorous process is established that includes clarification of inclusion criteria, an exhaustive search of relevant literature, and a critical evaluation of the methodological quality of the included studies.



Source: Own elaboration based on Okoli (2010)

Figure 1: Method diagram

2.1 Identify the Review´s Purpose

Considering the main objective of the review, two guiding questions were posed to analyze the reviewed studies:

- What drivers have been identified to achieve Personalized Learning?
- What aspects of personalization enhance learning?

Based on these questions, it is intended not only to identify pertinent elements related to the personalization of learning but also that such elements will become the basis for generating insights about the role of Artificial Intelligence in strengthening said personalization.

2.2 Setup Review Protocol

To address these questions, search keywords were defined and consolidated into a single search string: TITLE-ABS-KEY (("personalized learning" OR "personalized adaptive learning" OR "adaptive learning") AND (experience OR case AND study)). Next, inclusion criteria were established to select (or exclude) relevant articles, as follows:

- Articles published in the top 10 journals within Google Scholar Metrics (2022) with quality indicators and Scientific Journal Ranking (SJR) impact factors will be considered.
- Articles presenting research results, in English, published between 2013-2022 will be considered.

Subsequently, to strengthen the reliability of the information sources, the top 5 major databases of indexed journals with thematic coverage in "social sciences" and specifically in "educational technology" were selected: Scopus, Web of Science, JSTOR, Taylor & Francis Online, and Science Direct.

2.3 Searching the Literature, Screening/Quality Appraisal

The definition of the final set of documents for in-depth review was carried out in four steps, where the PRISMA guidelines were applied, specifically in the Identification, Screening and Eligibility processes:

- Step 1: The search string was applied in the databases, applying the previously determined selection criteria and eliminating duplicate records, resulting in an initial sample of 746 documents.

- Step 2: The 746 previously identified documents were reviewed, and relevance was assessed concerning the guiding question by reading titles and keywords, reducing the sample to 215 articles.
- Step 3: The sources identified in Step 2 were further reviewed, seeking a closer relationship with the keywords through abstract reading. This further reduced the sample to 145 relevant articles.
- Step 4: An in-depth reading of the articles identified in phase 3 was conducted, in which 102 definitive and relevant studies were identified for inclusion in the review. The results of this process are presented in detail in Table 1.

Table 1: # articles selected in steps 1-4

Journal	SJR Impact Factor 2022	Step 1	Step 2	Step 3	Step 4
Computers & Education	3.682	239	71	49	39
British Journal of Educational Technology	2.116	31	13	11	7
Internet and Higher Education	3.327	5	4	3	1
Journal of Educational Technology & Society	4.020 (JCR)	121	31	22	14
Education and Information Technologies	1.249	53	22	16	13
The International Review of Research in Open and Distance Learning	0.787	17	9	6	2
Educational Technology Research and Development	1.516	65	16	11	9
Interactive Learning Environments	1.170	155	40	19	13
Computer Assisted Language Learning	1.754	29	4	3	1
International Journal of Educational Technology in Higher Education	2.051	8	5	5	3
Total documents		746	215	145	102

2.4 Data Extraction

For the data extraction process aimed at identifying drivers of personalized learning, 11 categories of analysis were established:

- Teaching and learning strategies based on student needs.
- Identification of individual student characteristics.
- Customization of the curriculum content.
- Customization of learning assessment.
- Customization of the user-machine interface or environment.
- Development of adaptability technologies and/or the use of AI to provide different learning personalization systems.
- Literacy and other benefits for educators.
- Frameworks, theories, and/or models used in personalized learning.
- Public policies.
- Training domain.
- Level of training.

2.5 Synthesis of Studies

The reviewers conducted the synthesis of studies through qualitative data analysis obtained from the definitive articles using a categorization process. Additionally, basic quantitative analysis was performed through counting processes (n) and frequency analysis (f).

2.6 Writing the Review

Finally, based on the results found and related to the guiding questions of the review, the reviewers proceeded to write the review report following the IMRaD structure. They used the synthesis of the studies to develop the results section of the report.

3. Results

The results of the review are presented below based on the application of the methodological process shown in Figure 1 from the perspective of the guiding questions.

3.1 General Aspects of Personalization That Favour Learning

First, some personalization strategies (n=61, f=59.8%) were identified that demonstrated significant results in the learning of specific populations, explicitly validating the positive impact on learning. Some of these strategies include adaptive instructional sequences using badges (Bush, 2021), adaptability learning games (Pflaumer, Knorr and Berkling, 2021) and intelligent tutoring systems using robots (Chen, Park and Breazeal, 2020).

Second, the literature has frequently investigated strategies that favour non-cognitive characteristics of the student and their impact on learning. According to Yang et al. (2013) and Zou et al. (2021), motivation plays a crucial role in learning success, especially in complex e-learning environments, along with other elements such as meaningful activities for students. Several relevant characteristics were identified in this area, including motivation (n=35, f=34.3%), individual learning pace (n=20, f=19.6%), and eliminating time and place barriers (n= 17, f=16.7%). Some studies addressing these topics are El-Sabagh (2021), Kew & Tasir (2022) and Khan & Mustafa (2019).

Finally, several studies (n=53, f=52%) focus on positive perceptions about the usability and usefulness of personalized learning strategies. Both students and teachers found benefits in these strategies. According to Sahin and Uluyol (2016), perceived usefulness is important for evaluating users' ability to use a system and improve their performance, while usability concerns the system's ease of use. Some of the research includes the work of Aslan & Reigeluth (2016), Benmesbah et al. (2023) and Schuwer & Kusters (2014).

3.2 Main Drivers of Personalized Learning

How to drive personalized learning? The reviewed literature shows various ways to respond to this question. Some studies mention drivers that promote confidence, autonomy, initiative, and commitment of students in the teaching-learning process. In this regard, Scheiter et al. (2019) support the existence of a learning improvement opportunity when the adaptive mechanism contributes to increasing the learner's self-regulation control. The following are some relevant groups of drivers highlighted in the literature.

3.2.1 Driver #1: Identifying individual student characteristics

100% of studies highlight the importance of personalizing learning according to student characteristics. Each student must be individually recognized so that they can achieve the proposed learning objectives, thus offering an alternative to “one size fits all” schooling approaches (Schuwer and Kusters, 2014; Zhang *et al.*, 2023). The options used range from questionnaires to artificial intelligence techniques that aim to identify the unique characteristics and preferences of each learner, as a starting point to adjust other components of the teaching-learning process (Narciss *et al.*, 2014; Pliakos *et al.*, 2019). This driver highlights five subcategories: (1) Cognitive factors (n=83, f=81.3%), which mainly include prior knowledge levels and learning objectives; (2) Characteristics changing during learning (n=81, f=79.4%), among which learning pace, interest level, knowledge and skill progress stand out; (3) Stable characteristics (n=54, f=52.9%), such as learning styles and personal background; (4) Behavioral factors (n=18, f=17.6%), such as activity tracking, learning habits, engagement level and student behaviour in the system, and finally (5) Affective factors (n=13, f=12.7%), such as emotions, mood, self-esteem and feelings like stress, anxiety and neuroticism. Some research addressing the above includes Adewale et al., (2022); Barbagallo & Formica (2017) and Konijn & Hoorn (2020).

3.2.2 Driver #2: Content Personalization

This driver is frequently studied (n=87, f=85.3%), and refers to adapting the study content and its delivery according to the student profile, considering the selection, order, and structure of the material, as well as instructional mechanisms. More specifically, studies recommend generating learning paths (Feng and Yamada, 2021), courses with layers related to the student profile (Benton *et al.*, 2021) and incorporating student opinion in curriculum formulation (Lee *et al.*, 2018). In addition, student goals and motivations are linked to content (Hooshyar *et al.*, 2016), with up-to-date, quality resources to maintain interest and participation (Esteban-Millat *et al.*, 2014). This driver highlights five subcategories: (1) Delivery of content adapted to student characteristics (n=66, f=64.7%), whose most used techniques were recommending appropriate learning materials by intelligent analysis of the student profile, designing adaptive instructional sequences and module plans; (2) Instructional methods (n=40, f=39.2%), among which blended learning stands out, followed by asynchronous activities according to student profiling and context-aware ubiquitous learning (m-learning); (3) Use of serious games (n=11, f=10.85), which take into account the learner's mastery level, learning styles, gender and context; (4) Intelligent tutoring system [ITS] (n=9, f=8.8%), both to provide learning materials and explanations, exercises, examples, diagrams, images, movies, interactive and/or conversational tutorial material, as well as complement the normal school curriculum; and finally, (5) Use of robots (n=3, f=2.9%), linked to creating humanoid experiences with different behaviors, access to 24/7 tutoring or devices capable of changing roles to support learning. Some authors are Garcia-Cabot et al. (2015); Sampayo-Vargas et al. (2013) and Thompson & McGill (2017).

3.2.3 Driver #3: Assessment personalization

This driver (n=61, f=59.8%) focuses on providing continuous support to each student during their learning process, through assessment. It seeks to provide real-time feedback to motivate, identify difficulties, provide improvement opportunities, and encourage conscious self-assessment. These strategies go beyond a focus on student success or failure (Narciss *et al.*, 2014). Four subcategories were identified within this driver: (1) Handling student difficulties (n=50, f=49%), whose most reported strategies are suggestions for educational interventions (for example, elaborate comments, and support through an animated agent) and student performance diagnostics; (2) Quality feedback (n=49, f=48%), where the findings include real-time feedback, aligned with both the learning process and the products generated by the student, clearly described, assisted and supported by both technology and human peers; (3) Student progress (n=34, f=33.3%), through automated monitoring available to teachers and students and self-assessment processes and finally, (4) Assessment approaches (n=21, f=20.6%), where the most mentioned were formative assessment, flexible assessment approach, and competency-based learning. Some of the mentioned cases are found in Fırat et al. (2021), Gamrat et al. (2014) and McKenzie et al. (2013).

3.2.4 Driver #4: Personalization of the user-machine interface/environment

The literature shows different presentations and attributes of personalized learning environments (n=67, f=65.7%), mostly technology-mediated. This driver is based on the idea that learning environments should be attractive and support student retention in academic activities. The results related to this driver are presented grouped into six subcategories: (1) Structural design (n=49, f=48%), some of the key aspects are data interfaces, multimedia elements, collaborative environments, user customization, timely support and flexible learning environments; (2) Navigation (n=27, f=26.5%), which can improve the user's personal experience through adequate cognitive load and navigation panels on the home page; (3) Recommendations for customized educational games (n=12, f=11.8%), which mention the use of casual games and puzzles according to learning style, appropriate level of challenge, fun, role-playing games [RPG] with narrative elements, context-aware mobile role-playing games [CAMEG], high interactivity, learning objects [LO] associated with varied topics and formats; (4) Additional components (n=8, f=7.8%), such as attention regulation strategies, annotation module, stimuli, initial skill estimation and response prediction; (5) Use of language (n=7, f=6.9%), where the use of natural or conversational language, technologies such as robots, forums and chatbots replicating humanized conversations stand out and finally, (6) Human factors (n=6, f=5.9%), where collaborative work and humor in instruction were most relevant to promote social presence and trust. Some of the studies addressing the above are Chiu & Mok (2017); Ennouamani et al. (2020); Khenissi et al. (2016).

3.2.5 Driver #5: Use of Artificial Intelligence and other technological developments

Most of the analyzed articles (n=84, f=82.3%) highlight the technologies used, allowing the differentiation of at least two types of personalized learning systems: adaptive and intelligent systems. Adaptive systems adjust to student differences, although they are not necessarily intelligent since they can use simple algorithms to achieve such adaptation. On the other hand, intelligent systems use AI for data analysis and decision-making, thus offering more personalized learning support (Yang *et al.*, 2013). However, not all authors differentiate the underlying technology of the educational system. For example, the term "individualized learning environment" refers to the emergence and extension of Web-based Adaptive and Intelligent Educational Systems [AIWBES] (Özyurt *et al.*, 2014). In addition, the findings in this category allow for the identification of the elements that make up personalized learning systems, such as algorithms, architectures, and other tools used. This driver includes 5 subcategories: (1) AI techniques and algorithms (n=40, f=39.2%), which provide information on AI approaches used to analyze large volumes of data and provide personalized education. Techniques cited include data mining, analytics learning, and semantic recommendation systems. These techniques rely on algorithms like artificial neural networks, fuzzy logic, and item response theory; (2) Software, hardware, and other technical complements (n=27, f=26.5%), which present various tools and platforms used to implement personalized learning systems with different levels of complexity and sophistication. Some examples include Media Wiki, imoodle, JavaScript, Microsoft VB.NET, and Textit. Advanced technologies including activity trackers, Affective Tutoring Systems for Built Environment Management [ATEN], biometrics, adaptive multimedia systems, and educational chatbots [EC] are also mentioned; (3) Serious game developments (n=19, f=18.6%), which highlight sequences of data reorganized based on student needs. Games that make use of context-aware mobile devices and 3D game design, among others, are also mentioned; (4) System architectures (n=17, f=16.7%), corresponding to each of the components that allow organizing the structure of the personalized learning system. Common modules include the student profile, generation of appropriate teaching materials, interface customization, and evaluation, and finally, (5) Cold start difficulties (n=3, f=2.9%), where some authors address the difficulty of lack of initial data from new students, for example, combining item response theory (IRT) and a trained regression tree to estimate cognitive abilities predict future student performance. Some of these studies are Chaloupský et al. (2021); Kay & Kummerfeld (2019) and Lin et al. (2013).

3.2.6 Driver #6: Literacy and other benefits for teachers

This driver (n=16, f=15.7%) recognizes the need to train pre-service and in-service teachers on the different possibilities of personalized learning. Personalization environments are also presented as an alternative for the design and execution of teacher development programs. Some of the studies mentioned are Kong & Song (2015), Kunze & Rutherford (2018) and Lee et al. (2018).

3.2.7 Driver #7: Frameworks or models used in personalized learning

This driver provides information on proposed approaches to developing different levels of personalized learning. Various studies (n=60, f=58.8%) explore student-centred pedagogies and technological advances for implementing personalized learning, for example, McKenzie et al. (2013), Schmid & Petko (2019) and Wanner & Palmer(2015). The combination of these approaches guides the design and implementation of personalization as a learning technique in various disciplines (Zou *et al.*, 2021), in addition to enabling the monitoring of processes and verification of their effectiveness. This driver includes 4 subcategories: (1) Conceptual frameworks for personalized learning design (n=52, f=51%), which aim to facilitate user interaction and understanding, focusing on personalized learning. They include cognitive load theory [CLT], instructional design [ADDIE], and flipped and blended learning approaches; (2) Learning style and cognitive style models (n=23, f=22.5%), where the Felder-Silverman learning style models and VARK are the most used. As for cognitive styles, the literature explored the learning orientation model and the field dependent/independent model; (3) Theoretical frameworks for establishing learning profiles (n=10, f=9.8%), among these, artificial neural network stands out. Others, such as feature analysis techniques (TFA) and the involvement load hypothesis (ILH), are mentioned infrequently, and finally, (4) Models for assessing student knowledge (n=6, f=5.9%), referring to the variation associated with achievements and prior knowledge. The most frequently used are the Bayesian model and Bloom's taxonomy of educational objectives. Some of the authors who addressed this category are El Aissaoui et al. (2019); Ramos de Melo et al. (2014) and Yousaf et al. (2023).

3.2.8 Driver #8: Public policies

Some authors (n=3, f=2.9%) provide insight into public policies in their countries that promote personalized learning, especially linked to improving the student experience and academic performance. Some examples are found in Lee et al. (2018) and Schmid & Petko (2019).

3.2.9 Driver #9: Studies by domain

This driver shows the disciplines studied in the literature in order of frequency. Demonstrating the interest of researchers from various disciplines to include personalized learning systems in response to the different ways in which human beings learn and the versatility of this student-centred approach.

Computer science is the most studied discipline (n=34, f=33.3%), followed by mathematics (n=11, f=10.8%), linguistics and/or vocabulary (n=7, f=6.8%), natural sciences (n=7, f=6.8%), English as a foreign language (n=6, f=5.9%), higher-order skills (n=4, f=3.9%), health sciences (n=4, f=3.9%), social sciences (n=3, f=2.9%).

3.2.10 Driver #10: Studies by level

This driver presents the training levels reported in studies on personalized learning. Studies were found at all training levels. The most frequent were undergraduate (n=54, f=52.9%), followed by secondary school and graduate studies (n=17, f=16.7%), and in-service teachers (n=16, f=15.7%). Studies were also found at the primary education level and in free courses (n=11, f=10.8%) as well as in lifelong learners. However, it is striking that the preschool or early childhood level is the least explored, followed by pre-service teachers.

4. Discussion

The rapid advancement of artificial intelligence (AI) techniques presents intriguing possibilities to enhance personalized learning systems across multiple drivers identified in this review. As demonstrated by recent literature, AI-enabled solutions can play a pivotal role in the automated profiling of individual learners (Driver 1) by applying predictive analytics and machine learning algorithms to student interaction data (Tapalova and Zhiyenbayeva, 2022). The rich insights uncovered on knowledge levels, interests, and evolving needs can inform adaptive content sequencing and recommendation engines (Driver 2) to provide customized learning paths, intelligent tutoring, and conversational learning experiences (Castanha *et al.*, 2022).

For assessment personalization (Driver 3), AI shows promise in supplying real-time feedback, surfacing intervention needs, and tracking progress through analysis of students' work processes and responses (Feng, Magana and Kao, 2021). On the user interface front (Driver 4), AI-driven personalization can tailor navigation, structure, elements, and recommendations to enhance usability and engagement for each learner (Afini-Normadhi *et al.*, 2019). The aforementioned capabilities are enabled by employing advanced AI techniques such as machine learning, neural networks, natural language processing, and reinforcement learning that allow continuous improvement as more data is gathered (Driver 5) (Dhawan and Batra, 2020).

To fully harness the potential of AI in education, it is critical to develop teacher competencies (Driver 6) in interpreting analytics, implementing adaptive tools, and maintaining strong pedagogical foundations while protecting student privacy and preventing bias (Luckin and Holmes, 2016). Furthermore, human-centred design principles must be employed to develop intuitive interfaces and ensure transparency in AI systems' workings. Research is also needed to refine theoretical frameworks (Driver 7) underpinning personalized learning in light of the emerging affordances of AI (Bodily *et al.*, 2018). In summary, this discussion highlights the transformative yet balanced integration of AI to advance key drivers of personalized learning. More empirical studies are vital to unravel the full possibilities and pitfalls of this symbiosis.

This literature review shows that personalized learning holds vast potential across various disciplines and educational levels and modalities, including of course, e-learning. Furthermore, significant progress has been observed in the field of computer science, likely attributed to the rapid advancements in information technologies and artificial intelligence. These developments have drawn researchers' attention towards designing and implementing new computer-assisted learning strategies (Yang *et al.*, 2013).

It has been said that thoughtfully designed AI systems have immense potential to enhance data-driven, real-time personalization of instructional experiences to unlock the best in every student in the education 4.0 era. So, the next are some implications for education 4.0 and how AI can enhance the main drivers of personalized learning based on the literature review results.

Regarding the identification of learner characteristics, the ability of AI systems to rapidly process diverse student data opens new possibilities to build comprehensive learner profiles that capture academic abilities, conceptual misunderstandings, motivations, interests, and more. Also, advanced algorithms can identify patterns and relationships to model learner knowledge, skills, and needs in a sophisticated way. This enables the possibility of designing highly customized instructional strategies based on each student's profile (Liu, Primmer and Zhang, 2019).

Concerning personalizing content, with continually updated student models, AI systems can recommend the optimal content for each learner using machine learning techniques. As the system tracks their progress, the content can evolve in sync with the learner's demonstrated competencies, knowledge gaps, and interests. This creates a personalized content flow mapped to the learner's path that can be adjusted in terms of scope, complexity, modality, and pedagogical strategies based on the learner's evolving model (Ismail and Belkhouche, 2019).

Respecting personalizing assessments, AI has extensive potential to transform student assessment due to algorithms that can generate customized assessment items tailored to the skills and needs identified in each learner profile. Intelligent analysis of student responses and solution patterns can pinpoint knowledge gaps for targeted feedback and remediation, configuring on-demand assessments that can be tailored, enabling students to progress at their own pace.

Concerning personalizing interfaces, Mallik and Gangopadhyay (2023) indicate that with natural language processing and sentiment analysis capabilities, AI systems can interpret student voices, faces, and emotions to foster humanized interactions. In this sense, chatbots, virtual tutors, and gaming environments can dynamically adjust their interfaces, language, feedback, and motivational strategies to adapt to diverse learners and create connections, providing comfort and heightening engagement.

At last, but not least, it is interesting to consider leveraging emerging technologies, from smart devices to virtual reality, in which AI unlocks new modalities for personalized learning experiences.

Moving forward, further research is imperative, given that our comprehension of the optimal applications and consequences of AI in personalized learning is still evolving. Studies that encompass a diverse range of learner perspectives across various modalities, subjects, and extended durations are particularly significant.

One avenue for future research involves investigating AI techniques and algorithms. These studies should delve into identifying the most effective AI techniques and algorithms for modelling and responding to learner needs in real-time, aiming to enhance the intelligence and pedagogical effectiveness of AI adaptive systems.

Another vital area for exploration pertains to integration frameworks for AI and human instruction. It is crucial to explore frameworks that seamlessly integrate AI into personalization while preserving the roles of human educators, understanding how to harmonize AI and human instruction effectively is of utmost importance.

Besides the above, the development of a robust ethical framework is essential in the context of AI in education. Future research should delve into the ethics surrounding student data usage and privacy maintenance, especially with the increasing integration of AI in education. This issue has become a pressing challenge for educational policymakers and practitioners alike.

Another research approach that must be taken into consideration has to do with longitudinal studies comparing learning outcomes and engagement with AI-driven personalization versus traditional methods are essential. Concrete evidence gathered over an extended period is necessary to assess the true impact of AI in education.

Lastly, another valuable research branch to explore involves action research focused on effective change management strategies for the successful adoption of AI in educational institutions. Investigating how institutions can effectively implement AI-driven changes is crucial, and conducting comparative studies will help with this topic, assessing the limitations and best practices of human teacher personalization versus AI systems can provide valuable insights into the most effective approaches.

5. Conclusions

This systematic literature review thoroughly explores the fundamental drivers of personalized learning in the context of artificial intelligence (AI) and Education 4.0. The findings underscore critical factors such as identifying individual student characteristics, customizing content delivery and assessment methods, adapting user interfaces and learning environments, and harnessing advanced AI techniques and architectures. Significantly, AI emerges as a transformative catalyst, offering unprecedented capabilities in learner profiling, adaptive content delivery, real-time feedback, and intelligent interfaces. These AI-driven solutions hold great promise for enhancing personalized learning experiences, and addressing diverse learner needs, preferences, and competencies in a data-driven and dynamically responsive manner. This aligns with the vision of creating digital spaces or classrooms conducive to personalized learning, leveraging generative artificial intelligence to tailor instruction around core concepts, principles, and skills.

Regarding the above, achieving digital spaces (or even classrooms) that facilitate personalized learning has commonly been seen as an idealized and difficult scenario to attain. However, the rapid development of generative artificial intelligence may provide an appropriate response that allows for advancing opportunities for educators to carefully tailor instruction around the essential concepts, principles, and skills of each subject. This scenario provides a unique opportunity to advance the ideas promoted by Tomlinson (2017) regarding the design of differentiated classrooms. These classrooms are characterized by teachers who are attentive to student differences. In such settings, assessment and instruction are inseparable, and teachers can modify the content, process, and expected outcomes in the curriculum. Tomlinson's approach emphasizes the importance of adapting teaching strategies to meet the diverse needs of students, ensuring that each learner receives an education tailored to their abilities, interests, and learning levels.

Today’s classrooms are typically characterized by a diverse population of students. This diversity can be attributed to various factors such as increased access to education at all levels, immigration trends, deepening socioeconomic disparities within the general population, and the impact of the COVID-19 pandemic, which significantly affected student attendance at educational institutions. Addressing this scenario offers a unique opportunity to promote the creation of personalized learning programs. The current possibilities include utilizing different sources of information and developing new capacities for analyzing data with innovative strategies, such as data mining and machine learning, which can be enhanced by Artificial Intelligence (AI). These advancements prompt us to consider that we are at a juncture of transformation in our understanding of the teaching and learning processes. It is conceivable that future educators will need to be professionals who can adeptly interact with these new forms of information.

By way of closing these conclusions, it is worth mentioning that as the integration of AI in personalized learning continues to gain momentum, future research efforts must prioritize addressing the remaining challenges and unexplored opportunities. Longitudinal studies assessing the long-term impact of AI-driven personalization on learning outcomes, engagement, and skill development across diverse educational settings are crucial. Additionally, the development of robust ethical frameworks and governance models is imperative to ensure the responsible and equitable use of AI in education, safeguarding student privacy and mitigating potential biases. Furthermore, action research focused on effective change management strategies can provide valuable insights into the successful adoption of AI-enabled personalized learning systems within educational institutions. Ultimately, interdisciplinary collaboration among educators, technologists, policymakers, and stakeholders is vital to realizing the full transformative potential of AI in personalized learning and shaping the future of Education 4.0.

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Highlights

- AI systems holds vast potential to enhance data-driven, real-time personalization of learning.
- AI systems allow the creation of personalized content flow mapped to the learner's path
- AI has extensive potential to transform student customized assessment.
- Natural language processing facilitates the creation of connections, providing comfort and engagement.
- AI unlocks new modalities for personalized learning experiences

References

Adewale, O.S. *et al.* (2022) 'Design of a personalised adaptive ubiquitous learning system', *Interactive Learning Environments*, pp. 1–21. Available at: https://doi.org/10.1080/10494820.2022.2084114.

Afini-Normadhi, N.B. *et al.* (2019) 'Identification of personal traits in adaptive learning environment: Systematic literature review', *Computers & Education*, 130, pp. 168–190. Available at: https://doi.org/10.1016/j.compedu.2018.11.005.

Aplugi, G. and Santos, A. (2022) 'Adaptation and Personalization of Learning Management System, Oriented to Employees' Role in Enterprise Context - Literature Review', in A. Reis et al. (eds) *Technology and Innovation in Learning, Teaching and Education*. Cham: Springer Nature Switzerland (Communications in Computer and Information Science), pp. 15–30. Available at: https://doi.org/10.1007/978-3-031-22918-3_2.

Aslan, S. and Reigeluth, C.M. (2016) 'Investigating "The Coolest School in America": how technology is used in a learner-centered school', *Educational Technology Research and Development*, 64(6), pp. 1107–1133. Available at: https://doi.org/10.1007/s11423-016-9450-9.

Aziz Hussin, A. (2018) 'Education 4.0 Made Simple: Ideas For Teaching', *International Journal of Education and Literacy Studies*, 6(3), p. 92. Available at: https://doi.org/10.7575/aiac.ijels.v.6n.3p.92.

Barbagallo, A. and Formica, A. (2017) 'ELSE: an ontology-based system integrating semantic search and e-learning technologies', *Interactive Learning Environments*, 25(5), pp. 650–666. Available at: https://doi.org/10.1080/10494820.2016.1172240.

Benmesbah, O., Lamia, M. and Hafidi, M. (2023) 'An improved constrained learning path adaptation problem based on genetic algorithm', *Interactive Learning Environments*, 31(6), pp. 3595–3612. Available at: https://doi.org/10.1080/10494820.2021.1937659.

Benton, L. *et al.* (2021) 'Designing for "challenge" in a large-scale adaptive literacy game for primary school children', *British Journal of Educational Technology*, 52(5), pp. 1862–1880. Available at: https://doi.org/10.1111/bjet.13146.

Bodily, R. *et al.* (2018) 'Open learner models and learning analytics dashboards: a systematic review', in *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*. *LAK '18: International Conference on Learning Analytics and Knowledge*, Sydney New South Wales Australia: ACM, pp. 41–50. Available at: https://doi.org/10.1145/3170358.3170409.

Bush, J.B. (2021) 'Software-based intervention with digital manipulatives to support student conceptual understandings of fractions', *British Journal of Educational Technology*, 52(6), pp. 2299–2318. Available at: https://doi.org/10.1111/bjet.13139.

Cain, V. (2022) 'Teaching Machines: The History of Personalized Learning by Audrey Watters', *Technology and Culture*, 63(3), pp. 853–855. Available at: https://doi.org/10.1353/tech.2022.0112.

Castanha, J. *et al.* (2022) 'A Systematic Literature Review on Natural Language Processing (NLP)', in *2022 International Conference on Advanced Creative Networks and Intelligent Systems (ICACNIS)*. *2022 International Conference on Advanced Creative Networks and Intelligent Systems (ICACNIS)*, Bandung, Indonesia: IEEE, pp. 1–6. Available at: https://doi.org/10.1109/ICACNIS57039.2022.10055568.

Chaloupský, D., Chaloupská, P. and Hrušová, D. (2021) 'Use of fitness trackers in a blended learning model to personalize fitness running lessons', *Interactive Learning Environments*, 29(2), pp. 213–230. Available at: https://doi.org/10.1080/10494820.2020.1799027.

Chen, H., Park, H.W. and Breazeal, C. (2020) 'Teaching and learning with children: Impact of reciprocal peer learning with a social robot on children's learning and emotive engagement', *Computers & Education*, 150, p. 103836. Available at: https://doi.org/10.1016/j.compedu.2020.103836.

Chiu, T.K.F. and Mok, I.A.C. (2017) 'Learner expertise and mathematics different order thinking skills in multimedia learning', *Computers & Education*, 107, pp. 147–164. Available at: https://doi.org/10.1016/j.compedu.2017.01.008.

Dhawan, S. and Batra, G. (2020) 'Artificial intelligence in higher education: Promises, perils, and perspective', *Expanding Knowledge Horizon. OJAS*, 11(July-December), pp. 11–22.

Dwivedi, P., Kant, V. and Bharadwaj, K.K. (2018) 'Learning path recommendation based on modified variable length genetic algorithm', *Education and Information Technologies*, 23(2), pp. 819–836. Available at: https://doi.org/10.1007/s10639-017-9637-7.

El Aissaoui, O. *et al.* (2019) 'A fuzzy classification approach for learning style prediction based on web mining technique in e-learning environments', *Education and Information Technologies*, 24(3), pp. 1943–1959. Available at: https://doi.org/10.1007/s10639-018-9820-5.

El-Sabagh, H.A. (2021) 'Adaptive e-learning environment based on learning styles and its impact on development students' engagement', *International Journal of Educational Technology in Higher Education*, 18(1), p. 53. Available at: https://doi.org/10.1186/s41239-021-00289-4.

Ennouamani, S., Mahani, Z. and Akharraz, L. (2020) 'A context-aware mobile learning system for adapting learning content and format of presentation: design, validation and evaluation', *Education and Information Technologies*, 25(5), pp. 3919–3955. Available at: https://doi.org/10.1007/s10639-020-10149-9.

Esteban-Millat, I. *et al.* (2014) 'Modelling students' flow experiences in an online learning environment', *Computers & Education*, 71, pp. 111–123. Available at: https://doi.org/10.1016/j.compedu.2013.09.012.

Feng, S., Magana, A.J. and Kao, D. (2021) 'A Systematic Review of Literature on the Effectiveness of Intelligent Tutoring Systems in STEM', in *2021 IEEE Frontiers in Education Conference (FIE)*. *2021 IEEE Frontiers in Education Conference (FIE)*, Lincoln, NE, USA: IEEE, pp. 1–9. Available at: https://doi.org/10.1109/FIE49875.2021.9637240.

Feng, X. and Yamada, M. (2021) 'An analytical approach for detecting and explaining the learning path patterns of an informal learning game', *Educational Technology & Society*, 24(1), pp. 176–190.

Fırat, E.A., Köksal, M.S. and Bahşi, A. (2021) 'Effects of technology-enhanced constructivist learning on science achievement of students with different cognitive styles', *Education and Information Technologies*, 26(4), pp. 3659–3676. Available at: https://doi.org/10.1007/s10639-021-10427-0.

Gamrat, C. *et al.* (2014) 'Personalized workplace learning: An exploratory study on digital badging within a teacher professional development program', *British Journal of Educational Technology*, 45(6), pp. 1136–1148. Available at: https://doi.org/10.1111/bjet.12200.

Gan, B. and Zhang, C. (2020) 'Research on Design of Personalized Learning Experience Based on Intelligent Internet Technology', in *2020 International Conference on E-Commerce and Internet Technology (ECIT)*. *2020 International Conference on E-Commerce and Internet Technology (ECIT)*, Zhangjiajie, China: IEEE, pp. 306–309. Available at: https://doi.org/10.1109/ECIT50008.2020.00077.

Ghallabi, S. *et al.* (2015) 'Optimal composition of e-leaming personalization parameters', in *2015 5th International Conference on Information & Communication Technology and Accessibility (ICTA)*. *2015 5th International Conference on Information & Communication Technology and Accessibility (ICTA)*, Marrakech: IEEE, pp. 1–4. Available at: https://doi.org/10.1109/ICTA.2015.7426921.

Holmes, W., Bialik, M. and Fadel, C. (2023) 'Artificial intelligence in education', in C. Stückelberger and P. Duggal (eds) *Data ethics : building trust : how digital technologies can serve humanity*. Geneva: Globethics Publications, pp. 621–653. Available at: https://doi.org/10.58863/20.500.12424/4276068.

Hooshyar, D. *et al.* (2016) 'Applying an online game-based formative assessment in a flowchart-based intelligent tutoring system for improving problem-solving skills', *Computers & Education*, 94, pp. 18–36. Available at: https://doi.org/10.1016/j.compedu.2015.10.013.

Howell Smith, M.C. and Shanahan Bazis, P. (2021) 'Conducting Mixed Methods Research Systematic Methodological Reviews: A Review of Practice and Recommendations', *Journal of Mixed Methods Research*, 15(4), pp. 546–566. Available at: https://doi.org/10.1177/1558689820967626.

Hwang, G.-J. *et al.* (2013) 'A learning style perspective to investigate the necessity of developing adaptive learning systems', *Journal of Educational Technology & Society*, 16(2), pp. 188–197.

Ismail, H. and Belkhouche, B. (2019) 'Evaluating the Impact of Personalized Content Recommendations on Informal Learning from Wikipedia', in *2019 IEEE Global Engineering Education Conference (EDUCON)*. *2019 IEEE Global Engineering Education Conference (EDUCON)*, Dubai, United Arab Emirates: IEEE, pp. 943–952. Available at: https://doi.org/10.1109/EDUCON.2019.8725052.

Kaklauskas, A. *et al.* (2015) 'Affective Tutoring System for Built Environment Management', *Computers & Education*, 82, pp. 202–216. Available at: https://doi.org/10.1016/j.compedu.2014.11.016.

Kay, J. and Kummerfeld, B. (2019) 'From data to personal user models for life-long, life-wide learners', *British Journal of Educational Technology*, 50(6), pp. 2871–2884. Available at: https://doi.org/10.1111/bjet.12878.

Kew, S.N. and Tasir, Z. (2022) 'Developing a Learning Analytics Intervention in E-learning to Enhance Students' Learning Performance: A Case Study', *Education and Information Technologies*, 27(5), pp. 7099–7134. Available at: https://doi.org/10.1007/s10639-022-10904-0.

Khan, M.J. and Mustafa, K. (2019) 'Adaptive hypermedia instructional system (AHIS): A model', *Education and Information Technologies*, 24(6), pp. 3329–3392. Available at: https://doi.org/10.1007/s10639-019-09927-x.

Khandelwal, P., Shankar, P. and Siddiraju, U.R. (2022) 'Skillsets and attributes for enhanced teaching–learning outcomes at higher educational institutions in disruptive times', in *Academic Voices*. Elsevier, pp. 227–238. Available at: https://doi.org/10.1016/B978-0-323-91185-6.00032-X.

Khenissi, M.A. *et al.* (2016) 'Relationship between learning styles and genres of games', *Computers & Education*, 101, pp. 1–14. Available at: https://doi.org/10.1016/j.compedu.2016.05.005.

Kickmeier-Rust, M. and Dietrich, A. (2009) 'Emergence in digital educational games: A world of incidents in a universe of rules', in. *Proceedings of the European Conference on Games-based Learning*, Graz: Dechema e.V., pp. 220–226.

Kong, S.C. and Song, Y. (2015) 'An experience of personalized learning hub initiative embedding BYOD for reflective engagement in higher education', *Computers & Education*, 88, pp. 227–240. Available at: https://doi.org/10.1016/j.compedu.2015.06.003.

Konijn, E.A. and Hoorn, J.F. (2020) 'Robot tutor and pupils' educational ability: Teaching the times tables', *Computers & Education*, 157, p. 103970. Available at: https://doi.org/10.1016/j.compedu.2020.103970.

Kunze, A. and Rutherford, T. (2018) 'Blood from a stone: Where teachers report finding time for computer-based instruction', *Computers & Education*, 127, pp. 165–177. Available at: https://doi.org/10.1016/j.compedu.2018.08.022.

Lee, D. *et al.* (2018) 'Technology functions for personalized learning in learner-centered schools', *Educational Technology Research and Development*, 66(5), pp. 1269–1302. Available at: https://doi.org/10.1007/s11423-018-9615-9.

Li, H. and Wang, H. (2020) 'Research on the Application of Artificial Intelligence in Education', in *2020 15th International Conference on Computer Science & Education (ICCSE)*. *2020 15th International Conference on Computer Science & Education (ICCSE)*, Delft, Netherlands: IEEE, pp. 589–591. Available at: https://doi.org/10.1109/ICCSE49874.2020.9201743.

Lin, C.F. *et al.* (2013) 'Data mining for providing a personalized learning path in creativity: An application of decision trees', *Computers & Education*, 68, pp. 199–210. Available at: https://doi.org/10.1016/j.compedu.2013.05.009.

Liu, G., Primmer, J. and Zhang, Z. (2019) 'Rapid Generation of High-Quality RISC-V Processors from Functional Instruction Set Specifications', in *Proceedings of the 56th Annual Design Automation Conference 2019*. *DAC '19: The 56th Annual Design Automation Conference 2019*, Las Vegas NV USA: ACM, pp. 1–6. Available at: https://doi.org/10.1145/3316781.3317890.

Luckin, R. and Holmes, W. (2016) *Intelligence unleashed: An argument for AI in education*. London: Pearson Education. Available at: https://discovery.ucl.ac.uk/id/eprint/1475756/ (Accessed: 28 January 2024).

Luna-Urquizo, J. (2019) 'Learning Management System Personalization based on Multi-Attribute Decision Making Techniques and Intuitionistic Fuzzy Numbers', *International Journal of Advanced Computer Science and Applications*, 10(11). Available at: https://doi.org/10.14569/IJACSA.2019.0101188.

Makarenya, T.A., Stash, S.V. and Nikashina, P.O. (2020) 'Modern educational technologies in the context of distance learning', *Journal of Physics: Conference Series*, 1691(1), p. 012117. Available at: https://doi.org/10.1088/1742-6596/1691/1/012117.

Mallik, S. and Gangopadhyay, A. (2023) 'Proactive and reactive engagement of artificial intelligence methods for education: a review', *Frontiers in Artificial Intelligence*, 6, p. 1151391. Available at: https://doi.org/10.3389/frai.2023.1151391.

McKenzie, W.A. *et al.* (2013) 'A blended learning lecture delivery model for large and diverse undergraduate cohorts', *Computers & Education*, 64, pp. 116–126. Available at: https://doi.org/10.1016/j.compedu.2013.01.009.

Murad, D.F. *et al.* (2020) 'Personalization of study material based on predicted final grades using multi-criteria user-collaborative filtering recommender system', *Education and Information Technologies*, 25(6), pp. 5655–5668. Available at: https://doi.org/10.1007/s10639-020-10238-9.

Narciss, S. *et al.* (2014) 'Exploring feedback and student characteristics relevant for personalizing feedback strategies', *Computers & Education*, 71, pp. 56–76. Available at: https://doi.org/10.1016/j.compedu.2013.09.011.

Nurcahyo, W. and Agustina, Y. (2023) 'Framework for personalized learning with smart E-learning system using macro and micro adaptive approach', in. *COMPUTATIONAL INTELLIGENCE AND NETWORK SECURITY*, Raipur (C.G), India, p. 100007. Available at: https://doi.org/10.1063/5.0122540.

Okoli, C. and Schabram, K. (2010) 'A guide to conducting a systematic literature review of information systems research', *Sprouts: Working Papers on Information Systems*, 10(26), pp. 1–51.

Özyurt, Ö. *et al.* (2014) 'The effects of UZWEBMAT on the probability unit achievement of Turkish eleventh grade students and the reasons for such effects', *Computers & Education*, 75, pp. 1–18. Available at: https://doi.org/10.1016/j.compedu.2014.02.005.

Parra, B.J. (2016) 'Learning strategies and styles as a basis for building personal learning environments', *International Journal of Educational Technology in Higher Education*, 13(1), p. 4. Available at: https://doi.org/10.1186/s41239-016-0008-z.

Pflaumer, N., Knorr, N. and Berkling, K. (2021) 'Appropriation of adaptive literacy games into the German elementary school classroom', *British Journal of Educational Technology*, 52(5), pp. 1917–1934. Available at: https://doi.org/10.1111/bjet.13149.

Pliakos, K. *et al.* (2019) 'Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems', *Computers & Education*, 137, pp. 91–103. Available at: https://doi.org/10.1016/j.compedu.2019.04.009.

Ramos De Melo, F. *et al.* (2014) 'Computational organization of didactic contents for personalized virtual learning environments', *Computers & Education*, 79, pp. 126–137. Available at: https://doi.org/10.1016/j.compedu.2014.07.012.

Şahin, S. and Uluyol, Ç. (2016) 'Preservice Teachers' Perception and Use of Personal Learning Environments (PLEs)', *The International Review of Research in Open and Distributed Learning*, 17(2). Available at: https://doi.org/10.19173/irrodl.v17i2.2284.

Sampayo-Vargas, S. *et al.* (2013) 'The effectiveness of adaptive difficulty adjustments on students' motivation and learning in an educational computer game', *Computers & Education*, 69, pp. 452–462. Available at: https://doi.org/10.1016/j.compedu.2013.07.004.

Sangole, R., Desai, D. and Jain, A. (2022) 'Education 4.0: Case Study on Selection of Digital Learning Platform and Communication Tools for Future Education 4.0 in India', in *2022 IEEE Pune Section International Conference (PuneCon)*. *2022 IEEE Pune Section International Conference (PuneCon)*, Pune, India: IEEE, pp. 1–7. Available at: https://doi.org/10.1109/PuneCon55413.2022.10014956.

Scheiter, K. *et al.* (2019) 'Adaptive multimedia: Using gaze-contingent instructional guidance to provide personalized processing support', *Computers & Education*, 139, pp. 31–47. Available at: https://doi.org/10.1016/j.compedu.2019.05.005.

Schmid, R. and Petko, D. (2019) 'Does the use of educational technology in personalized learning environments correlate with self-reported digital skills and beliefs of secondary-school students?', *Computers & Education*, 136, pp. 75–86. Available at: https://doi.org/10.1016/j.compedu.2019.03.006.

Schuwer, R. and Kusters, R. (2014) 'Mass customization of education by an institution of HE: What can we learn from industry?', *The International Review of Research in Open and Distributed Learning*, 15(2). Available at: https://doi.org/10.19173/irrodl.v15i2.1704.

Shemshack, A. and Spector, J.M. (2020) 'A systematic literature review of personalized learning terms', *Smart Learning Environments*, 7(1), p. 33. Available at: https://doi.org/10.1186/s40561-020-00140-9.

Tapalova, O. and Zhiyenbayeva, N. (2022) 'Artificial Intelligence in Education: AIEd for Personalised Learning Pathways.', *Electronic Journal of e-Learning*, 20(5), pp. 639–653.

Thompson, N. and McGill, T.J. (2017) 'Genetics with Jean: the design, development and evaluation of an affective tutoring system', *Educational Technology Research and Development*, 65(2), pp. 279–299. Available at: https://doi.org/10.1007/s11423-016-9470-5.

Tomlinson, C.A. (2017) *How to differentiate instruction in academically diverse classrooms*. Alexandria: ASCD. Available at: https://books.google.com/books?hl=es&lr=&id=DYzgEAAAQBAJ&oi=fnd&pg=PP4&dq=How+to+differentiate+instruction+in+academically+diverse+classrooms&ots=C9LotaEh1v&sig=GbGGvklEnN1Uc_wmWi2xyZA3QBc (Accessed: 28 January 2024).

UNESCO (2017) 'Herramientas de Formación Curricular: Aprendizaje Personalizado', in *Herramientas de Formación para el Desarrollo Curricular*. Ginebra: OEI-UNESCO, pp. 1–63. Available at: https://unesdoc.unesco.org/ark:/48223/pf0000250057_spa.

Vanbecelaere, S. *et al.* (2020) 'Technology-mediated personalised learning for younger learners: concepts, design, methods and practice', in *Proceedings of the 2020 ACM Interaction Design and Children Conference: Extended Abstracts*. *IDC '20: Interaction Design and Children*, London United Kingdom: ACM, pp. 126–134. Available at: https://doi.org/10.1145/3397617.3398059.

Villegas-Ch, W. and García-Ortiz, J. (2023) 'Enhancing Learning Personalization in Educational Environments through Ontology-Based Knowledge Representation', *Computers*, 12(10), p. 199. Available at: https://doi.org/10.3390/computers12100199.

Wanner, T. and Palmer, E. (2015) 'Personalising learning: Exploring student and teacher perceptions about flexible learning and assessment in a flipped university course', *Computers & Education*, 88, pp. 354–369. Available at: https://doi.org/10.1016/j.compedu.2015.07.008.

Yang, Y. *et al.* (2013) 'Generating a two-phase lesson for guiding beginners to learn basic dance movements', *Computers & Education*, 61, pp. 1–20. Available at: https://doi.org/10.1016/j.compedu.2012.09.006.

Yousaf, Y. *et al.* (2023) 'An intelligent content provider based on students learning style to increase their engagement level and performance', *Interactive Learning Environments*, 31(5), pp. 2737–2750. Available at: https://doi.org/10.1080/10494820.2021.1900875.

Zhang, L. *et al.* (2023) 'Evaluation of a student-centered online one-to-one tutoring system', *Interactive Learning Environments*, 31(7), pp. 4251–4269. Available at: https://doi.org/10.1080/10494820.2021.1958234

Zheng, R. (ed.) (2018) *Digital Technologies and Instructional Design for Personalized Learning:* IGI Global (Advances in Educational Technologies and Instructional Design). Available at: https://doi.org/10.4018/978-1-5225-3940-7.

Zou, D. *et al.* (2021) 'A comparative study on linguistic theories for modeling EFL learners: facilitating personalized vocabulary learning via task recommendations', *Interactive Learning Environments*, 29(2), pp. 270–282. Available at: https://doi.org/10.1080/10494820.2020.1789178