PERSONALIZED LEARNING AND ASSESSMENT IN EDUCATION 5.0: A SYSTEMIC LITERATURE REVIEW

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Abstract

The adoption of Industry 5.0 technologies and practices in education raises the possibility of Education 5.0. It has paved the way for the widespread adoption of digital learning systems. These innovative platforms have the potential to provide personalized learning experiences, tailored to the unique needs and preferences of each student. This systematic review aims to get an overview of the implementation of personalized learning and assessment using educational technology in Education 5.0. The article searching method was carried out through two online databases: ScienceDirect and Taylor & Francis Online, and obtained 17 articles. The articles were extracted using PRISMA flow. As a result, the implementation of personalized learning in various countries can be described in the data results. The participants came from various educational backgrounds, such as elementary or high schools and universities. All studies in this systematic review have employed different approaches. The researchers also find that the implementation of personalized learning and assessment using educational technologies has experienced some challenges. This review does not cover all countries but the findings will be contributing to the literature expansion. From the results, there is an urge to consider the use of educational technology in implementing personalized learning and assessment.

Keywords – personalized learning, feedback, assessment, technology

Introduction

One of the most significant developments in humanity over the last 50 years has been tremendous technical advancement and growth, particularly with the emergence of the internet (Kamal et al., 2019). Nowadays, practically everyone utilizes the internet on their personal devices. Almost every student uses the internet for both information and learning purposes (Sudibjo et al., 2019). Our lives have changed dramatically during the past decade. Digital technology has transformed us from an industrial civilization focused on manufacturing to an information culture. Digital data and information technology pervade both our personal and professional lives, allowing us to generate and share ideas, resulting in the establishment of new businesses. However, Purnamasari et al. (2019) ask whether we are prepared to tackle the new digital era, not just in industry, but also in the transformation of society into Society 5.0.

Industry 5.0 is a new industrial paradigm that prioritizes sustainability, resilience, and a stronger focus on the needs of people (Breque et al., 2021; Dixson-Declève et al., 2022). It centers technological ecology around humans. In order to attain significant productivity, it sets up technologies and practices to accommodate human demands and circumstances. Müller (2020) presents technologies that support the concept of Industry 5.0 include: (a) human-centric solutions and human–machine-interaction technologies; (b) bio-inspired technologies and smart materials; (c) real-time-based digital twins and simulation; (d) cyber-safe data transmission, storage and analysis technologies; and (e) technologies for energy efficiency and trustworthy economy. These technologies expand the Industry 4.0 technology that already exists. For example, advanced generative AI technology is used in HMI tools such as ChatGPT to generate human-like, coherent, and contextually relevant

responses to input prompts such as queries, instructions, etc.

The adoption of Industry 5.0 technologies and practices in education raises the possibility of Education 5.0. Sydle (2022) defines it as the utilization of Industry 5.0 technologies and practices to create more humanized teaching, focusing on learner well-being, societal transformations, and environmental sustainability. It is a new educational paradigm based on the idea of Industry 5.0, with humans at the core of the learning process. It promotes the use of technology-enabled learning to foster cost-effectiveness, increased reach, scalability, flexibility, and other advantages. It utilizes Industry 5.0 technology (such as robotics/cobots, AI, big data, and so on) to personalize learning and education while minimizing health and environmental impacts.

The rapid advancements in technology have paved the way for the widespread adoption of digital learning systems. These innovative platforms have the potential to provide personalized learning experiences, tailored to the unique needs and preferences of each individual student (Xie et al., 2019). Personalized feedback, a key component of these systems, has emerged as a crucial factor in enhancing the effectiveness of digital learning (Lodge et al., 2018; Shaw et al., 2014).

Personalized learning prioritizes a clear understanding of the needs and goals of each student, and the tailoring of instruction to address those needs and goals (Ober et al., 2023). These needs and goals, as well as progress towards meeting them, are highly visible and easily accessible to teachers, students, and their families, and are frequently discussed and updated accordingly. The benefits of personalized learning have been widely recognized, even before the widespread use of modern technologies for personalized learning, with one-to-one tutoring being known to facilitate learning through the provision of personalized instruction.

The rapid development of information communication technology has enabled the personalization of learning through various methods, including the implementation of intelligent learning systems, the integration of learner preferences, and the analysis of individual learning data. One key difference between personalized learning and other similar terms is that the former is mostly used when classroom instruction involves learning technologies such as adaptive learning systems, intelligent tutoring systems, or even educational robots, which continuously collect data about students and adjust the learning experience accordingly. These learning technologies leverage algorithms and artificial intelligence to tailor the pace, instructional materials, and feedback to the individual needs and preferences of each student (Dumont & Ready, 2023; Xie et al., 2019). This personalization of the learning experience aims to optimize instruction for the needs of each learner, with objectives, approaches, and content varying based on individual requirements (Xie et al., 2019).

The shift towards technology-enabled personalized learning has been driven by the recognition that traditional classroom instruction often fails to address the diverse needs of students (Shaw et al., 2014). As Bloom's "Two Sigma Problem" demonstrated, one-to-one tutoring can significantly improve student performance, but providing such personalized instruction at scale is often challenging due to logistical and cost constraints. The integration of learning technologies offers a potential solution, allowing for the scalable implementation of personalized learning strategies (Ober et al., 2023). Previous studies have showed how technologies in Education 5.0 provide personalized learning with better strategies and implementation. From this

background, the researchers want to dig deeper into the implementation of personalized learning integrated with technologies in Education 5.0. The researchers assume that the integration of educational technologies can present unique results in personalized learning and assessment. It is hoped that this study can help related parties in any education contexts understand more about teaching and learning process in Education 5.0 and improve the quality of learning. Therefore, the researchers aim to know the overview of personalized learning and assessment and explore the implementation of personalized learning and assessment using educational technology in Education 5.0.

Methodology

The article selection process used in this systematic literature review was carried out based on the Preferred Items for Systematic Review and Meta-analysis (PRISMA) (Moher et al., 2009). PRISMA can be used as a guideline to ensure the completeness of studies when conducting and reporting systematic reviews and meta-analysis (Tam et al., 2019). The first step was articles searching in several journal databases, such as Taylor & Francis Online and ScienceDirect. To get the right articles, a keyword search process was carried out with the following combinations: 'personalized learning' AND/OR 'personalized assessment' AND/OR 'education 5.0'. Researchers also included the inclusion and exclusion criteria. The inclusion criteria include; First, the article must discuss personalized learning, personalized assessment/feedback, and self-assessment as the main variables. Second, the article should have been published in international journals, through a peer-review process, written in English, available in full-text, and published from January 2019 to June 2024. Third, the studies reviewed were empirical studies. Meanwhile, the exclusion criteria include; First, the article does not discuss personalized learning, personalized assessment/feedback, and self-assessment as the main variables. Second, articles that are not available in full text, are not written in English and were published before 2019. The flow of PRISMA can be seen in Figure 1.

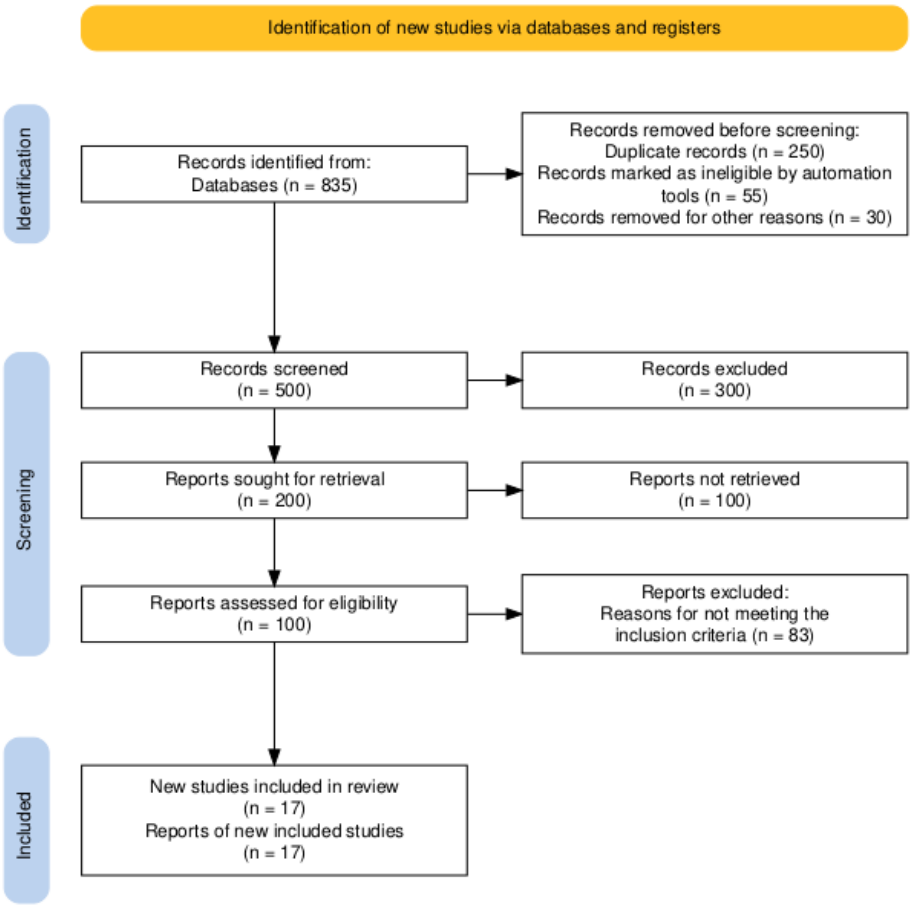

Figure 1. Flow Diagram of Study Selection Process (Haddaway, 2022)

Database	**Total Articles Identified**	**Total Articles that Do Not Meet Criteria**	**Total Articles that Meet Criteria**	**Article**
Taylor & Francis Online	465	460	5	Chen & Perez, (2023). Rico et al., (2022). Carroll (2020). Benraghda et al., (2022). Zheng et al., (2023).
ScienceDirect	570	558	12	Chaipidech et al., (2022). Yang et al., (2022). Shoaib et al., (2024). Lin & Chang, (2023). Huang et al., (2023). Alrawashdeh et al., (2023). Dan et al., (2024). Zhang et al., (2022). Bhutoria (2022).

	Gunawardena et al., (2024). Mötteli et al., (2023). Ingkavara et al., (2022).

Finding and Discussion

After the selection process of the studies, only seventeen were relevant to be included in this review. These came from various countries, namely Thailand (2), Japan, India (2), Canada, Taiwan, USA (3), Hongkong, Spain, Australia (2), Algeria, China, and Switzerland. The participants came from various educational backgrounds, such as elementary or high schools (Alrawashdeh et al., 2023; Chaipidech et al., 2022; Chen & Perez, 2023; Dan et al., 2024; Gunawardena et al., 2024; Ingkavara et al., 2022; Motteli et al., 2023) and university (Benraghda et al., 2022; Carroll, 2020; Huang et al., 2023; Juan et al., 2022; Shoaib et al., 2024; Yang et al., 2022; Zhang et al., 2022; Zheng et al., 2023).

All studies in this systematic review have employed different approaches, such as quantitative (Carroll, 2020; Chaipidech et al., 2022; Dan et al., 2024; Huang et al., 2023; Ingkavara et al., 2022; Juan et al., 2022; Motteli et al., 2023; Yang et al., 2022), qualitative (Chen & Perez, 2023; Gunawardena et al., 2024), mixed-methods (Benraghda et al., 2022; Zheng et al., 2023), systematic reviews (Bhutoria, 2022; Lin & Chang, 2023), meta-analysis (Alrawashdeh et al., 2023), design science research (Shoaib et al., 2024), and instrument development and content validation (Zhang et al., 2022). The overview of seventeen studies related to personalized learning and assessment can be seen in Table 2.

Building on the idea that self-assessment can improve student learning, Carroll (2020) investigates how well business students evaluate their own work. The study aims to see if clear criteria and feedback could enhance students' self-assessment accuracy, which is considered a key skill for self-regulated learning. Employing a quantitative, observational approach, the research examined changes in student accuracy across two tasks. Interestingly, students initially overestimated their performance, but accuracy improved after receiving feedback. Furthermore, the study reveals that different student characteristics and initial assessment tendencies (overestimation vs. underestimation) influence how accuracy changes over time. These findings suggest that self-assessment, when supported with clear criteria and feedback, can be a valuable tool for developing students' judgment and self-regulation skills.

Chaipidech et al. (2022) explore the use of a personalized learning system to support science teachers' development of Technological Pedagogical and Content Knowledge (TPACK). The research employed a quantitative approach, with 161 in-service teachers participating in a teacher professional development (TPD) program that utilized the personalized system. Founded in andragogy, the program aimed to improve teachers' TPACK through the intervention. The study measures teachers' TPACK levels before and after the program, demonstrating significant improvement due to the TPD program with the personalized learning system.

As stated by Dan et al. (2024), classroom relationships and self-regulation (SRL) influence EFL students' English proficiency in China. This study (436 4th-5th graders) finds girls reported higher use of SRL strategies but boys had slightly better English scores initially. Interestingly, the type of classroom relationship that mattered most differed by

gender. Peer relationships impacted girls' English proficiency more, while teacher-student relationships were more important for boys. These findings highlight the complex interplay between classroom dynamics, self-regulation, and EFL learning, suggesting teachers consider both gender and social context when tailoring instruction.

Huang et al. (2023) discuss how AI-powered recommendations in a flipped classroom setting impacted students' learning. The study involved 102 college students in a systems programming course, split between a control group and an experimental group receiving personalized video recommendations. Drawing on motivation theory, the research employed a quantitative approach with pre-tests, post-tests, and surveys to measure motivation, engagement, and learning outcomes. Interestingly, while AI recommendations didn't significantly improve overall motivation, they did increase the number of students with improved motivation, particularly those with moderate initial levels. Additionally, the research finds positive impacts on learning performance and engagement for students with moderate motivation. These findings suggest AI-powered recommendations hold promise for personalizing learning experiences and improving outcomes, particularly for students needing extra motivation.

Ingkavara et al. (2022) investigate integrating a personalized learning approach into self-regulated online learning for physics (292 secondary school students). Drawing on self-regulated learning and technology acceptance theories, the study used a quasi-experimental design with pre-tests, post-tests, and perception surveys. The results show that students who receive the personalized approach have significantly higher learning gains compared to the control group. The study also identifies factors influencing students' willingness to use this approach, suggesting its potential to improve learning outcomes and user adoption.

Juan et al. (2022) explore the influence of peer assessment on learning outcomes and self-assessment accuracy in higher education (82 computer engineering students). Drawing on Vygotsky's social learning theory, the study compared individual, pair, and group peer assessment modalities in a quasi-experimental design. Students completed tasks, self-assessed their work, and then peer-assessed each other through a digital platform. Interestingly, self-assessment accuracy improved significantly when students received feedback from groups of three, particularly after excluding the lowest-scoring member. Overall, peer assessment scores were more accurate than self-assessment, and accuracy increased with the number of assessments received. These findings suggest that collaborative peer assessment, particularly in well-functioning groups, can be a valuable tool for improving student learning and self-evaluation skills.

In the opinion of Motelli et al. (2023) about how enjoyment of learning changes between grades 8 and 9, and how personalized learning environments can influence this development. Drawing on stage-environment fit and control-value theories, the study analyzed data from 1241 Swiss students who participated in the perLen study on personalized learning. Students completed questionnaires in both grades, reporting on their enjoyment of learning, perceived control (choice and voice), and the degree of personalization in their schools (assessed through teacher questionnaires). The analysis revealed that both the level of personalization and students' feelings of choice and voice were positively linked to their enjoyment of learning. Furthermore, changes in students' perceived voice over time also impacted the development of their learning enjoyment. These findings suggest that

personalized learning environments that empower students with choice and voice can help sustain or even increase their enjoyment of learning during this critical transition period in early adolescence.

Yang et al. (2022) investigated the effectiveness of an adaptive learning system that combines computerized adaptive testing (CAT) with the learning memory cycle model. This quasi-experimental study involved three groups of first-year computer science students. The researchers compared a proposed system using CAT and the memory cycle to a system using only CAT and a conventional non-adaptive system. Data from pre-tests, post-tests, computer quizzes, and student usage logs revealed that students using the proposed system achieved better learning performance and showed greater engagement with practice tests and reading materials compared to the other two groups. These findings suggest that the combination of CAT and the learning memory cycle holds promise for enhancing student learning.

Chen and Perez (2023) discuss the potential of AI in enhancing assessment and personalized learning in education. They state that AI can support a whole-child perspective in assessments, focusing on collaborative problem-solving skills, digital measures of student engagement, and linguistic, social, and cultural backgrounds. AI algorithms can automate the assessment process, providing immediate feedback to students and analyzing their responses to offer personalized recommendations for instruction. This ensures that students receive targeted support and guidance tailored to their individual needs. Despite the potential benefits of AI, human involvement in the assessment process is crucial for maintaining connections and collaborative learning. Digital measures of engagement and collaboration should be supplemented with educator and peer input. However, implementing AI in education requires addressing privacy and data security concerns, ensuring equity and accessibility, and providing teacher training and support to effectively leverage AI tools.

Meanwhile, Gunawardena et al. (2024) explores the perspectives of Australian secondary school teachers on implementing personalized learning. The study employed complexity theory and NVivo coding to analyze the teachers' views on the practicality of personalized learning. From this study, it can be seen that teachers express both enthusiasm and wariness about implementing personalized learning, highlighting the need for a nuanced understanding of the complexities involved. The complexity exists with the strategies and their applications with all students in their classes. The sanctioned curriculum poses challenges for teachers as they attempt to address students' needs and interests. The study also highlights the practical challenges and issues that teachers face in implementing personalized learning, including concerns about data management, teacher workload, and student engagement. The study suggests that complexity theory can help teachers evolve and sustain their practices in managing the complexities of personalized learning, emphasizing the need for ongoing professional development and support.

Benraghda et al. (2022) explores the role of self-assessment in enhancing the learning outcomes of college students in English oral presentations. The study employed a mixed-methods approach, combining both quantitative and qualitative data to analyze the perceptions and choices of students regarding self-assessment. Students perceive self-assessment as an essential tool for improving their oral presentation skills, particularly in terms of content organization, language use, and delivery techniques. They employ several self-assessment strategies, such as peer review,

self-reflection, and video recordings, which help them refine their presentation skills. The study finds that students who engage in self-assessment report higher levels of confidence and motivation in their oral presentations, ultimately leading to improved learning outcomes. Meanwhile, teachers also play a crucial role in providing feedback and guidance, which help students develop their self-assessment skills. Thus, the study emphasizes the need for educators to incorporate self-assessment strategies into their teaching practices, particularly in English oral presentations. This approach can help students develop a more proactive and reflective approach to learning, leading to enhanced academic performance and lifelong learning skills.

Zheng et al. (2023) investigates the effects of different sequences of formative assessment practices on learners' English public speaking anxiety and performance. The study employed a mixed-methods approach, combining both quantitative and qualitative data to analyze the outcomes. The research finds that learners who engage in self-assessment first experience a significant reduction in public speaking anxiety and perform better in their English public speaking tasks compared to those who engage in peer-assessment first. The results suggest that the sequence of formative assessment practices matters. Self-assessment should be arranged first for learners with higher levels of anxiety, while peer-assessment should be conducted first for learners with lower levels of anxiety. The research emphasizes the importance of incorporating formative assessment practices into language learning, particularly in English public speaking courses. The results suggest that educators should consider the sequence of formative assessment practices and the use of video-based formative practice to support learners in reducing anxiety and improving performance.

Bhutoria (2022) explores how AI and big data are being used to personalize education in the US, China, and India. Drawing on the concept of personalized learning, the study reviewed research published between 2019-2021 to identify key themes using techniques like topic modeling. The analysis of over 2000 papers revealed how AI is being used to tailor learning content, identify student needs and learning difficulties, and optimize teaching approaches. These findings suggest that AI-powered personalized education holds promise for improving educational outcomes by catering to individual student needs.

Lin and Chang (2023) propose a framework (CHAT-ACTS) for integrating personalized chatbots in education to promote active learning and self-regulated learning (SRL). This conceptual paper examines the benefits of chatbots in education through a literature review, highlighting how personalized chatbots can provide feedback and guidance to support active learning and SRL strategies. The CHAT-ACTS framework offers a theoretical foundation for educators to leverage chatbots in enhancing student engagement and self-regulation in the learning process.

Alrawashdeh et al. (2023) conduct a meta-analysis to explore how personalized and adaptive learning technologies (PAL) impact K-12 students' reading literacy. Drawing on the Simple View of Reading model, the research examined the effectiveness of various PAL interventions on different reading skills (decoding, comprehension) and across different studies. The analysis involved statistically synthesizing data from multiple randomized controlled trials comparing PAL interventions to traditional reading instruction. The results revealed a moderate overall positive effect of PAL interventions on reading literacy (compared to traditional methods), with some variation in effectiveness influenced

by factors like language of instruction and device type. These findings suggest that PAL interventions hold promise for improving reading literacy skills in K-12 students, but their effectiveness can be influenced by specific implementation characteristics.

Shoaib et al. (2024) propose an AI-based student success predictor to personalize learning experiences in campus management systems. Drawing on learning analytics, the study developed an ensemble machine learning model by collecting and integrating student data from various databases. This model achieved high accuracy in predicting student grades (93%), identifying at-risk students (93%), and forecasting student retention/dropout (92%). These findings suggest that AI-powered student success predictors can be valuable tools for optimizing learning environments and supporting students at risk.

Zhang et al. (2022) focus on developing and validating a tool (PLSI) to measure student perceptions of personalized learning environments based on the Universal Design for Learning (UDL) framework. UDL promotes creating flexible learning experiences that reduce barriers for all learners. This study involved instrument development and content validation. Experts in UDL evaluated the PLSI's items for clarity and relevance using a rating scale. The results indicated a high level of content validity for the PLSI, suggesting it can be a valuable tool for measuring student perceptions of personalized learning environments designed with UDL principles in mind.

Table 2. Overview Matrix

No.	Author(s), Year	Title	Country	Theoretical Framework	Dependent Variable	Independent Variable	Method	Participants	Findings
1.	Pawat Chaipidech, Niwat Srisawasdi, Tanachai Kajornmanee, Kornchawal Chaipah (2022)	A personalized learning system-supported professional training model for teachers' TPACK development	Thailand	Andragogy	Teachers' TPACK	The TPD program design with an embedded personalized learning system.	Quantitative	161 in-service science teachers from 92 secondary schools located in the Northeastern region of Thailand that voluntarily participated in the proposed TPD program.	The in-service teachers significantly improved their TPACK after participating in the TPD program with the personalized learning system.

2.	Albert C.M. Yang, Brendan Flanagan, Hiroaki Ogata (2022)	Adaptive formative assessment system based on computerized adaptive testing and the learning memory cycle for personalized learning	Japan	Computerized adaptive testing (CAT) and learning memory cycle model.	Students' learning performance and engagement	Three different assessment systems - the proposed system combining CAT and memory cycle, the system using only CAT, and the conventional non-adaptive system.	Quasi-experimental design.	Three classes of first-year university students from the Department of Computer Science at a university in Taiwan, with one class designated as experimental group A, one as experimental group B, and one as the control group.	The students who used the proposed assessment system based on CAT and learning memory cycle outperformed those who used the other two systems in terms of learning performance and engagement in practice tests and reading materials.
3.	Muhammad Shoaib, Nasir Sayed , Jaiteg Singh, Jana Shafi, Shakir Khan, Farman Ali (2024)	AI student success predictor: Enhancing personalized learning in campus management systems	India	Learning analytics and educational data mining	Student grade, risk level, and retention/dropout	The student attributes and performance data collected from different databases and used as features for the machine learning models.	Design science research	Students whose data is collected and analyzed by the proposed AI student success predictor model.	The proposed AI student success predictor model which can predict student grades with 93% accuracy, identify at-risk students with 93% accuracy, and forecast student retention/ dropout

									with 92% accuracy when evaluated on test data.
4.	Michael Pin-Chuan Lin, Daniel Chang (2023)	CHAT-ACTS: A pedagogical framework for personalized chatbot to enhance active learning and self-regulated learning	Canada	the CHAT-ACTS framework proposed by the authors	There is no dependent variables clearly defined in this article as it presents a conceptual framework rather than empirical research with variables.	There is no independent variables clearly defined in this article as it presents a conceptual framework rather than empirical research with variables.	Literature review	There is no mention of research respondents in this article as it appears to be a conceptual paper proposing a theoretical framework rather than empirical research.	The proposal of the CHAT-ACTS theoretical framework to guide the integration of personalized chatbots to enhance active learning and SRL.
5.	Anna Y.Q. Huang, Owen H.T. Lu, Stephen J.H. Yang (2023)	Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom	Taiwan	learning motivation theory	Students' learning motivation, engagement and outcomes.	AI-enabled personalized video recommendations (whether students received recommendations or not).	Quantitative approach	102 college students enrolled in a systems programming course who were assigned to a control group and experimental group.	AI-enabled personalized recommendations did not significantly improve students' motivation but increased the proportion of students with improved motivation, especially

									those with moderate motivation level. It also improved learning performance and engagement of students with moderate motivation.
6.	Jennifer J. Chen & ChareMone' Perez (2023)	Enhancing Assessment and Personalized Learning Through Artificial Intelligence	USA	Learning theory that assessments inform responsive teaching. Vygotsky's zone of proximal development theory.	Students' language and literacy development and learning outcomes.	The use of Amira as an AI-powered assessment and instructional tool.	Qualitative case study approach	Ms. Perez's 2nd grade bilingual classroom of 28 low-income Hispanic students in New Jersey, US.	Amira enhances assessment, facilitates differentiated instruction, and generates comprehensive reports to inform teaching practice for bilingual learners. It makes teaching and learning more effective and efficient.
7.	Ghaida S. Alrawashdeh, Shea Fyffe, Renato F.L. Azevedo, Nathan M. Castillo	Exploring the impact of personalized and adaptive learning technologies on reading literacy: A global	USA	The Simple View of Reading (SVR) model	Reading literacy/achievement outcomes as measured post-intervention using standardized assessments.	The PAL interventions/ treatments implemented and their characteristics (e.g. type of PAL, language, device used etc.) that could potentially	Meta-analysi	K-12 students who participated in studies evaluating the effectiveness of PAL interventions on	PAL interventions had a moderate positive effect (g=0.29) on reading literacy outcomes compared to

	(2024)	meta-analysis				impact reading outcomes.		reading literacy outcomes	traditional instruction. Moderator analyses also revealed factors influencing intervention effectiveness such as language of instruction and device type.
8.	Qingyao Dan, Barry Bai, Qinhui Huang (2024)	Gender differences in the relations between EFL students' classroom relationships and English language proficiency: The mediating role of self-regulated learning strategy use	Hongkong	Sociocultural theory	English language proficiency	Classroom relationships (teacher-student relationships and peer relationships) and SRL strategy use (metacognitive strategies and social strategies). SRL strategy use also serves as a mediator.	Quantitative	436 4th-5th grade EFL students in mainland China.	1) Girls reported higher use of metacognitive and social SRL strategies than boys. Boys reported slightly higher English proficiency. 2) Classroom relationships influenced SRL strategy use and English proficiency differently between boys and girls. 3) Peer relationships predicted

									girls' English proficiency through SRL strategies, while teacher-student relationships predicted boys' English proficiency through SRL strategies.
9.	Juan Ramón Rico-Juan, Cristina Cachero a and Hermenegilda Macià (2022)	Influence of individual versus collaborative peer assessment on score accuracy and learning outcomes in higher education: an empirical study	Spain	Vygotsky's social development theory	Self-assessment accuracy and learning outcomes	The modality of peer assessment (individual, pairs, groups of three)	Quasi-experimental design	82 first-year computer engineering students from the University of Castilla-La Mancha in Spain.	Students' self-assessment accuracy significantly improved when peer assessment was done in groups of three, especially when excluding the lowest 20% performers. Peer assessment scores were generally more accurate than self-assessment and accuracy improved with more assessments received.
10.	Ling Zhang, James	Measuring personaliz	USA	Universal Design	The content validity of	The ratings of relevance and clarity	Instrument develo	7 experts in UDL	1) PLSI yielded an

	D. Basham, Richard Allen Carter Jr. (2022)	ed learning through the Lens of UDL: Development and content validation of a student self-report instrument		for Learning (UDL) framework	the PLSI instrument	provided by the UDL experts for each PLSI item. Higher ratings would indicate higher content validity of the instrument.	pment and content validation.	who were recruited to evaluate the content validity of the PLSI instrument.	excellent level of item-level content validity index (I-CVI) for relevance across all items. 2) PLSI yielded an average scale-level content validity index (S-CVI) of 0.97 for relevance and an average S-CVI of 0.99 for clarity across all constructs.
11.	Danny Carroll (2020)	Observations of student accuracy in criteria-based self-assessment	Australia	Developing evaluative judgement	student self-assessment accuracy, measured by the difference between student and instructor marks.	factors like student characteristics (course level, residency), self-assessment type, and task (Task 1 vs Task 2).	Quantitative	Students from two business courses - a first-year postgraduate commerce course and a second-year undergraduate management course in an Australian university.	Most students initially over-assessed, but accuracy generally improved from Task 1 to Task 2 after feedback. Different types of self-assessors (over, under, accurate) showed different patterns in marks and accuracy change.

12.	Aditi Bhutoria (2022)	Personalized education and Artificial Intelligence in the United States, China, and India: A systematic review using a Human-In-The-Loop model	India	The concept of personalized education	Outcomes/results of integrating AI for personalized education.	The use of AI and big data technologies for personalized education	Systematic literature review	Literature and research published between 2019-2021 on applications of AI in education from the IEEE Xplore database.	Identification of themes around how AI is successfully catering to individual student needs and customizing content. It also flags learning difficulties and optimizes teaching approaches.
13.	Maya Gunawardena, Penny Bishop, Kithmini Aviruppol (2024)	Personalized learning: The simple, the complicated, the complex and the chaotic	Australia	Complexity theory	Teachers' conceptualization and implementation of personalized learning	Complexity theory lens/classifications of simple, complicated, complex and chaotic	Qualitative case study approach	7 teachers from a K-10 school in the Australian Capital Territory who volunteered to participate in the study	1. Teachers' definitions of personalized learning were similar but their perspectives on implementation conflicted. 2. Data was classified into simple, complicated, complex and chaotic domains based on complexity theory to analyze

									teachers' views. 3. Teachers were enthusiastic about personalized learning in theory but wary of practical implementation issues.
14.	Abdelmadjid Benraghda, Noor Raha Mohd Radzuan2 and Fatima Ali Salah Lardhi (2022)	Self-assessment as a self-regulated learning approach in English oral presentations: College students' choices and perceptions	Algeria	Self-regulated learning framework	The engineering students' perceptions towards self-assessment strategy.	The self-assessment training received and its implementation in oral presentations.	Mixed-method approach	110 engineering students from the college of engineering, Department of Civil Engineering & Earth Resources of a public university in Malaysia	The engineering students had positive perceptions towards self-assessment both before and after its implementation in developing their oral presentation skills, with slightly higher scores in the post-questionnaire.
15.	Chunping Zhenga, Lili Wanga and Ching Sing Chai (2023)	Self-assessment first or peer-assessment first: effects of video-based formative	China	- Formative assessment theories and its positive effects	- Public speaking anxiety - Public speaking performance	Sequence of formative assessment (self-assessment first vs. peer assessment first).	Mixed-methods approach	51 undergraduate English majors enrolled in a 16-week English public	- Learners in the self-assessment first group showed significantly lower public

		practice on learners' English public speaking anxiety and performance		on learners' performance and reducing anxiety. - Theories regarding foreign language anxiety (FLA) and public speaking anxiety (PSA), their sources and ways to reduce them.				speaking course at a university in China.	speaking anxiety than those in the peer assessment first group. - Learners in the peer assessment first group showed significantly better public speaking performance.
16.	Christine Motteli, Urs Grob, Christine Pauli, Kurt Reusser, Rita Stebler (2023)	The influence of personalized learning on the development of learning enjoyment	Switzerland	The stage-environment fit theory and control-value theory	Learning enjoyment	Degree of personalization, choice, voice, and their development over time between grades 8 and 9.	Analyzing longitudinal data from the perLen study using latent change modeling.	35 secondary schools in Switzerland that participated in the perLen study on personalized learning. A total of 1241 grade 8 students completed questionnaires in 2014, of which 953 also complet	Both the extent of personalization in schools and students' perception of choice and voice are positively related to learning enjoyment. A change in students' perception of voice also affects the development of learning

								ed it in 2015 when they were in grade 9.	enjoyment.
17.	Thanyaluck Ingkavara, Patcharin Panjaburee, Niwat Srisawasdi, Suthiporn Sajjapanroj (2022)	The use of a personalized learning approach to implementing self-regulated online learning	Thailand	Self-regulated learning theory and technology acceptance theory.	1) Students' learning achievement 2) Students' behavioral intention to use the learning system	1) Type of learning approach - conventional self-regulated online learning vs self-regulated online learning with personalized learning approach. 2) Students' perceptions of various aspects like usefulness, ease of use, impacts on learning etc.	Quantitative approach through a quasi-experimental design	292 secondary school students who studied electric circuit topic in physics course	The experimental group who received self-regulated online learning guided by personalized learning approach had significantly higher post-test and learning gain scores than the control group. The study also identified various predictors that influenced students' behavioral intention to use this learning approach.

Conclusion

This study aims to provide an overview and predictors of the latest studies related to personalized learning and assessment. The researchers found and analyzed 17 studies that were selected based on inclusion and exclusion criteria. These came from various countries, namely Thailand (2), Japan, India (2), Canada, Taiwan, USA (3), Hongkong, Spain, Australia (2), Algeria, China, and Switzerland. All studies employ different research approaches. The researchers also find that the implementation of personalized learning and assessment using educational technologies has experienced many challenges. This review does not cover all countries but the

findings will be contributing to the literature expansion. From the results, there is an urge to consider the use of educational technology in implementing personalized learning and assessment.

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