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RESEARCH ARTICLE

Development and Efficacy of Adaptive Personalised Learning Environments: A Systematic Review and Meta-analysis

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ABSTRACT

Several previous research elaborates that the individual learning approach is quite superior to the traditional "one-size-fits-all" approach which mainly focuses upon singular teaching methods for all learners. The concept of e-learning has evolved significantly, and the advancement brings us towards adaptivity based inventions that are more advanced learning systems. These adaptive personalised learning environments (ALE) that integrates a generalized adaptive content presentational approach to address varying characteristics of learners has become an utmost need of the time for improving learning among the learners of the 21st century. This review is aimed to identify, appraise and synthesize the literature on the development of ALE originating from the studies published from 2019 - 2023. The main focus of this review was to holistically delve deep into the advancement in defining, designing, implementing and evaluating ALE through the lens of the activity theory integrated with the personalised learning design framework (PLDF). Following the PRISMA framework, data sources were extracted from JSTOR, Web of Science and ERIC databases. The review revealed that there have been tremendous advances in the implementation of ALE. The development ranges from determining student learning styles using self-reported questionnaires to integrating advanced technology such as machine learning and Artificial Intelligence (AI) to auto-deliver personalised learning paths that define learner profiles. A meta-analysis revealed that ALE that support varying needs, goals, backgrounds, knowledge levels and learning capabilities of the learners are effective in improving learner's academic achievement and satisfaction.

INTRODUCTION

Recent advancements in educational research have led to the abandonment of the long-standing notion of "one size fits all," as numerous students encounter challenges in adhering to lessons that are not tailored to their individual needs. Several studies (Alshammari & Qtaish, 2019; Yalcinalp & Avc, 2019) [5][57] suggest a lack of consideration for the specific needs and preferences of each learner, resulting in a uniform approach to instruction for all students. This shift has prompted a move towards personalised learning (Katsaris & Vidakis, 2021) [33].

Personalised learning entails tailoring the pace of learning, instructional methods, and learning materials to align with the unique needs of each learner (Raj & Renumol, 2019) [49]. This approach emphasizes delivering an effective, tailored, and efficient learning pathway to ensure every student's active engagement in the learning process (Hussein & Al-Chalabi, 2020) [29]. The evolution of personalised learning underscores the idea that students learn most effectively when instruction is personalised to their individual needs, acknowledging the diversity among learners (Taylor, Yeung, & Bashet, 2021; Dockterman, 2018) [55]. This paradigm shift is reshaping higher education from traditional instructor-centered approaches to student-centered ones. Personalization within learning environments occurs when these environments are aligned with learners' profiles, thereby enhancing their performance and the quality of their learning experience (Hussein & Al-Chalabi, 2020) [29].

For students to be more motivated to learn, it's crucial for any learning environment with a specific goal to maintain consistency in the content delivery (Ilić, Mikić, Kopanja & Vesin, 2023) [32], ensuring that students receive personalised content tailored to their specific needs, rather than generic, one-size-fits-all material (Arsovic & Stefanovic, 2020) [6]. Such environments can foster a culture of self-learning, drawing in students and enhancing their engagement in the learning process (El-Sabagh, 2021) [18]. Additionally, recent research highlights that learning environments capable of adjusting to the individual needs, requirements, and competencies of students facilitate the learning process, resulting in enhanced learning outcomes and achievements (Arsovic & Stefanovic, 2020) [6]. Hence, environments incorporating an adaptive learning approach yield valuable outcomes for learners. For instance, students gain awareness of their individual learning speed in ALE (Dry et al., 2018) [17], enabling them to advance at their own pace and narrow the learning gap with peers (Feng et al., 2018). Additionally, they cultivate independent learning skills (Knight & Buckingham-Shum, 2018) [35]. Fakoya, Adewale, and Agbonifo (2020) [21] emphasize the positive impact of utilizing ALE, regarding enhanced teaching quality and students' heightened awareness of their learning strengths and areas for improvement. Therefore, the notion of personalised learning enables a shift in learning design from a 'one size fits all' model to an adaptive and student-centered approach, enhancing the customization of student learning (Hidayat, Afuan, 2021) [27]. Consequently, learning is optimized, aiding learners in efficiently achieving course objectives in a shorter time frame and at reduced costs (Raj & Renumol, 2022) [50], thus offering education that caters to the needs of learners across all age groups (Burak & Gultekin, 2022) [9].

While personalised learning holds the potential to greatly support teachers during the educational process, traditional methodologies often present challenges in delivering personalised and tailored lessons that cater to the unique preferences and needs of each student (Katsaris & Vidakis, 2021) [33]. However, advances in educational technology have greatly simplified the process of offering personalised learning across diverse settings and to students with varying attributes, including skills, knowledge, and motivation (McCarthy, Watanabe, Dai, & McNamara, 2020) [37]. Adaptive computer-based learning enables learners to engage with educational content tailored to their individual learning preferences (El-Sabagh, 2021) [18].

Numerous studies have underscored the efficacy of adaptive e-learning in delivering electronic content tailored to learners' individual needs. This approach aids in enhancing students' acquisition of knowledge, experiences, and the development of higher-order thinking skills (Ali, Eassa, & Hamed, 2019; Daines, Troka, & Santiago, 2016; Dominic, Xavier, & Francis, 2015; Wu, Chen, & Chen, 2017) [4][13][15][56]. Nevertheless, higher educational institutions continue to employ uniform learning materials that overlook students' learning styles, disparities in knowledge levels, required depth of study, and timeframes for course completion. Consequently, the integration of adaptive learning stands out as a current imperative for HEIs (Morze, Varchenko-Trotsenko, Terletska, & Smyrnova-Trybulska, 2021) [41]. The failure to tailor content to individual needs and abilities, coupled with an inability to address the diverse needs, goals, backgrounds, knowledge levels, and learning capabilities of students, still represents a major challenge within most e-learning environments (Aeiad & Meziane, 2019) [2].

The field of adaptive e-learning environment (ALE) is rapidly growing, aiming to customize the learning experience to match each student's unique learning needs. This entails modifying the learning environment to revolutionize how e-content is delivered. Adaptive e-learning involves a dynamic learning process where the content is either taught or adjusted according to students' responses, learning styles, or preferences (Nor-madhi et al., 2019; Oxman & Wong, 2014) [45][47]. However, the integration of adaptive learning into teaching and learning practices to provide a personalised learning experience is still irregular, and there is a lack of clarity on the most effective methods for designing and delivering adaptive learning courses within higher education contexts (Cavanagh, Chen, Lahcen, & Paradiso, 2020) [11]. Additionally, it seems that there's a dearth of understanding regarding how dynamic approaches can be effectively incorporated into designs to maximize the efficacy of ALE (Burak & Gultekin, 2022) [9]. Consequently, future research should aim to provide clearer insights into the design and adaptivity processes of ALEs, as suggested by Fontaine, et al., (2019) [25] to facilitate enhanced comprehension and utilization of dynamic approaches, ultimately leading to improved outcomes.

Rationale and Purpose

In order to improve and further develop something, it is very useful and important to look at the ways in which it has been done in the past and the efforts made to do it. A Systematic Literature Review (SLR) is a comprehensive and rigorous approach to synthesizing existing research on a particular topic (Johnson, 2019) [31]. The study of PL has developed rapidly in recent years. This can be seen in the number of studies and publications in this field since 2017 (Fariani, Junus & Santoso, 2023) [22]. To gain an understanding of the development of PL studies, several literature reviews have been carried out. For example, a review conducted by Fariani, Junus and Santoso (2023) [20] focused on summarising research in the field of PL on a broader aspect, from the component to the impact of PL implementation in higher education context. Similarly, Bernacki, Greene and Lobczowski (2021) [8] reported the result of a review of PL within the context of higher education based on who studies personalised learning; with whom and in what contexts; and with focus on what learner characteristics, instructional design approaches, and learning outcomes. These studies mainly address the concept of PL and do not emphasize on the adaptive techniques used to derive the personalisation.

The other main trend observed with regard to the previous reviews related to PL is that they focus on one aspect or component within the implementation of PL environments. For example, the review of Essa, Celik, and Hendricks (2023) [20] addressed the Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles; the review of Murtaza, Ahmed, Shamsi, Sherwani, And Usman (2022) [43] focused on AI-Based Personalisedd E-Learning Systems. Some reviews focused on a specific field like the review by Fontaine, Cossette, Cadotte et al. (2019) [25] which contextualised the review for efficacy of adaptive e-learning for health professionals and students.

These SLRs have not considered and delved deeply into the design, implementation, integration and application of ALEs holistically addressing each of the components involved within the process. Moreover, most of the reviews do not rely on a strong basis to appraise based on indicators. The current review therefore is aimed to conduct a thorough review on ALEs through the lens of Activity Theory (AT). According to Schmidt and Tawfik (2022) [51], understanding learners' experiences when engaged in technology-mediated learning could benefit from a more holistic perspective of Human Computer Interaction (HCI) and AT is found to be a theory that is resonance in HCI. Moreover, the review integrates the personalised learning design framework (PLDF) as a benchmark to appraise the studies on the design and development of ALEs along with AT. In addition, the review presented here differs as it covers the period from 2019 to 2023 covering the recent advancement and includes a meta-analysis on the effectiveness of ALE.

METHODS

Systematic reviews frequently lack awareness of established guidelines that ensure their replicability and scientific adequacy (Abelha, et al., 2020) [1]. Therefore, the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines were strictly followed which provides a standard peer accepted methodology that uses a guideline checklist, contributing to the quality assurance of the revision process and to its replicability.

A review protocol was formulated (as shown in Figure 1), outlining the criteria for article selection, the approach for conducting searches, the methods for data extraction, and the procedures for data analysis.

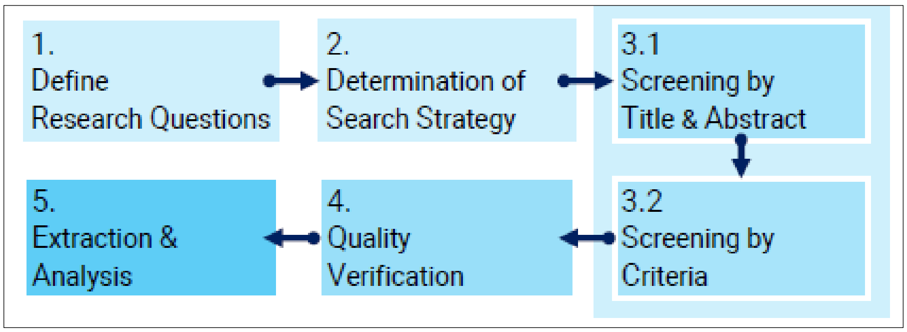

Figure 1: Steps in the formulated PRISMA protocol

Research Questions

This SLR is conducted to specifically answer the following research questions (RQ):

- RQ1: Through the lens of AT along with PLDF, what are the components and considerations that can be identified concerning the design, development, implementation and evaluation of ALEs?
- RQ2: What is the efficacy of ALEs in enhancing the measure of learning of the learners?

Search Strategy

The search strategy outlined was implemented to seek primary studies, incorporating specific search terms and constructing search strings for exploration. Reviewers pinpointed keywords, meticulously selecting terms to address the research inquiries. The primary keywords employed to locate articles encompassed 'personalized learning' or 'personalised learning', 'adaptive learning', and 'e-learning'. To maximize the identification of eligible studies, we expanded our search terms and strategies. Search terms were combined using Boolean operators as follows:

> ("Adaptive learning" OR "personalized learning" OR "adaptive e-learning" OR "personalised e-learning" OR "adaptive personalised e-learning" OR "adaptive personalized e-learning" OR "personalised learning") AND ("Higher Education" OR "University" OR "Tertiary Education")

The SLR was conducted, encompassing papers published in peer reviewed journals, accessible through three specified electronic databases: ERIC, JSTOR, and Web of Science (WoS). In order to ensure the research was up to date, the literature search spanned contributions from 2019 to 2023.

Screening and Selection of Studies

The initial search from the databases resulted a total of 1212 articles: ERIC (685), JSTOR (362), WoS (165). After removing the duplicates, 1209 articles were carried forward for the next step of screening the articles for the final inclusion in the review. The literature screening conducted for the selection process identified the most suitable papers for the mapping study based on the inclusion and exclusion criteria outlined in the Table 1.

Table 1: Inclusion and exclusion criteria of articles.

Inclusion criteria	Exclusion criteria
Empirical studies focusing on adaptive personalised learning	Review papers, theoretical studies, Reports and white papers
Papers that implement ALE as intervention to enhance learning	Papers that do not implement ALE and compare with older methods
Focus on higher education setting	Do not focus on higher education
Involve learners as participants	Do not include learners as participants
Measure efficacy based on enhancement of learning	Do not measure efficacy based on learning performance
Full text available	Full text unavailable
Written in English	Written in another language other than English
Published between 2019 - 2023	Published before 2019 and after 2023
Reports the mean and standard deviation for two groups [only for meta-analysis]	Do not report mean and standard deviation for both groups [only for meta-analysis]

Two types of screening were carried out. At first, titles and abstracts were reviewed, and 1104 articles were removed. The 105 remaining papers underwent full-text consideration and assessment which is the second round of screening. It was found that 88 of them did not meet the inclusion criteria. Therefore, only 17 studies that specifically satisfied the inclusion criteria were deemed suitable for the final analysis.

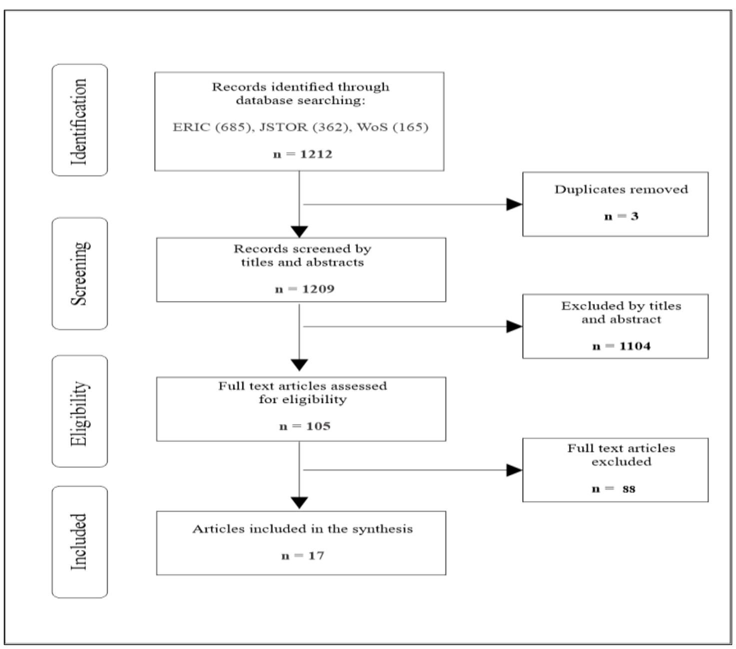

Figure 2: PRISMA flowchart of study selection process.

Most of the papers were published during the years 2021 and 2023 (Figure 3). Papers ranged from multiple journals (Table 2), but it was found that 4 papers were published in the "Educational Technology & Society" journal.

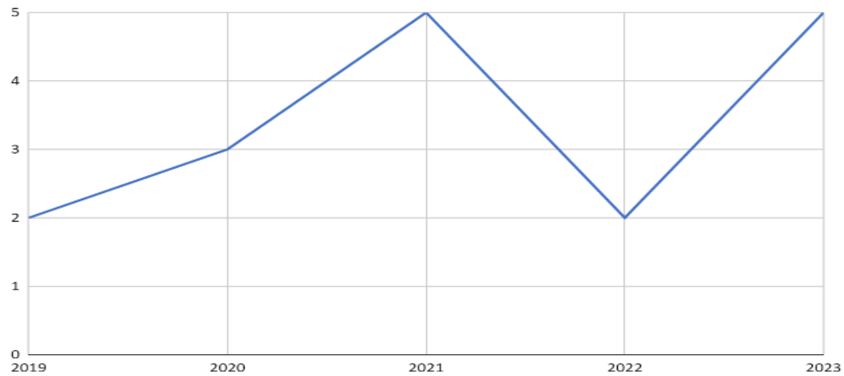

Figure 3: Number of articles published by year.

Table 2: Journals and number of selected papers.

Journal	No. of paper
International Journal of Educational Technology in Higher Education	1
IEEE Transactions on Learning Technologies	1
Australasian Journal of Educational Technology	2
Online Learning Journal	2
Journal on Efficiency and Responsibility in Education and Science	1
Contemporary Educational Technology	1
Journal of the Scholarship of Teaching and Learning	1
Journal of Information Literacy	1
LEARN Journal: Language Education and Acquisition Research Network	1
Journal of Education for Business	1
Educational Technology & Society	4
British Journal of Educational Technology	1

Quality Verification

This SLR downloaded the search results from each database in BibTex format, and we performed the selection process by a single person using the Mendeley tool. All authors double-checked the results of the sorting to confirm the quality, appraising the evidence based on its relevance, reliability, validity, and applicability as presented in Table 3.

Table 3: Quality verification measures of evidence.

Measure of evidence	Quality indicator
Relevance	• Is the research method/study design appropriate for answering the research question? • Are specific inclusion / exclusion criteria used?

Reliability	● Can the results be reproduced when the research is repeated under the same conditions.?
Validity	● Were there enough subjects in the study to establish that the findings did not occur by chance? ● Were subjects randomly allocated? Were the groups comparable? If not, could this have introduced bias? ● Are the measurements/ tools validated by other studies? ● Could there be confounding factors?
Applicability	● Can the results be applied to other similar settings?

Extraction and Analysis

To analyse the data, significant details from the 17 papers were extracted, encompassing authors, publication year, title, journal, adaptive technique, technology, theory/ Instructional model or strategy, how personalisation is achieved, method, implementation, field/ subject area, outcome measured and principal findings (see APPENDIX).

This review adopted Activity Theory (AT) framework to perform final analysis on the interplay of various components and actors involved in research on adaptive personalised learning from multiple perspectives. According to Kim (2010) [34], AT defines an activity as a system of purposeful behaviours leading to recognisable changes in human practises. The theory outlines the roles and interconnected relationships among stakeholders involved in an activity, influenced by additional individual and social factors (Engeström, 2001) [19] [. As shown in Figure 4, it centres on six key components within an activity: subject, object, technology, rules, community, and division of labour (Engeström, 2001) [19].

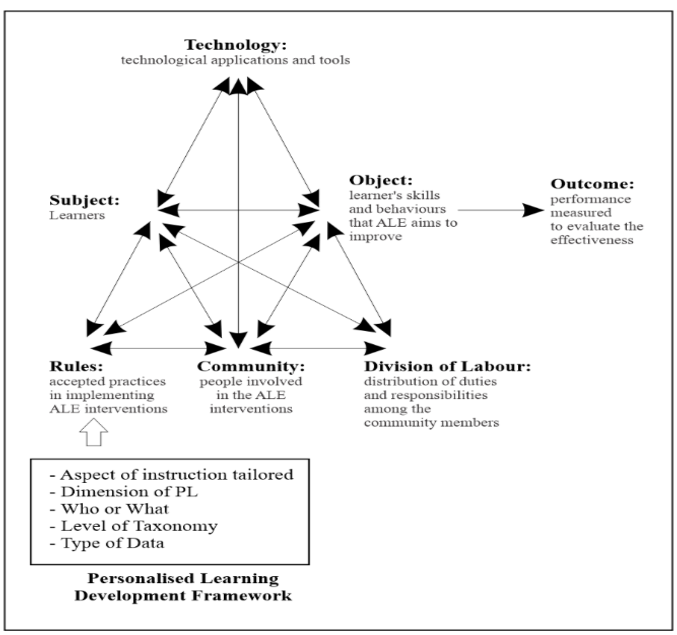

Figure 4: Integrated framework of AT and PLDF.

For the purpose of the review, subjects are referred to the learners; technology is considered as the technological applications and tools used to implement adaptive personalised learning environments; objects include learner's skills and behaviours that ALE aims to improve (e.g. academic performance, satisfaction, and engagement); rules are the accepted practices in implementing ALE interventions; community is referred to the people involved in the ALE interventions (e.g. instructional designers, subject matter experts, multimedia experts, and programmers); division of labour is referred to the distribution of duties and responsibilities among the community members and outcome is considered as the performance measured to evaluate the effectiveness of ALE. Each of these components were critically analysed and the results are presented in the coming section.

RESULT AND DISCUSSIONS

To address RQ1, each component of AT individually is reviewed with special focus on Rules component with relevant to PLDF. For RQ2, meta-analysis was carried out for the outcome measures that supports the meta-analysis calculations. Results are presented with discussions with relevant literature.

Subject

Based on the analysis conducted on the gathered studies, Figure 5 illustrates the distribution of studies according to education levels of the learners.

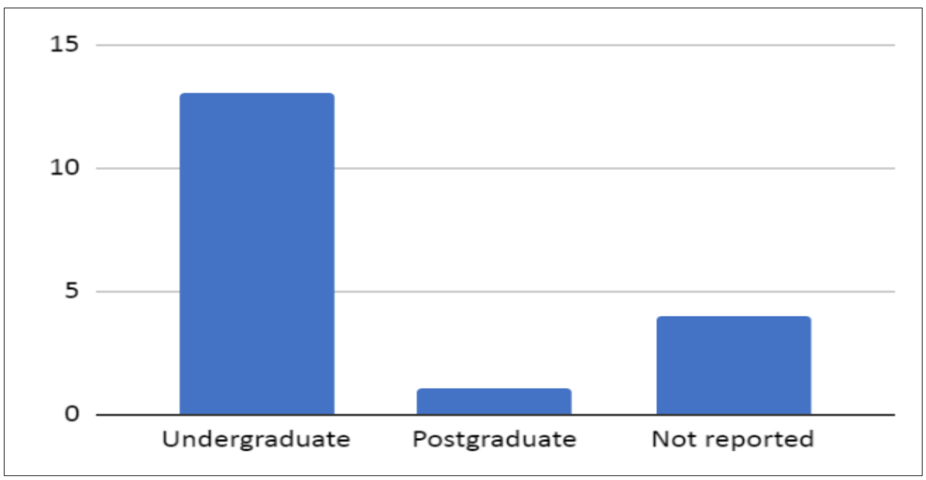

Figure 5: Study level of learners.

Among these, 13 studies concentrated on undergraduate learners (for example, Dixon and Packwood, 2023; El-Sabagh, 2021) [14][18] and only one of the studies were observed to be targeted for postgraduate learners. It is worth noting that this study of Jitpaisarnwattana, Reinders and Pornapit Darasawang (2021) [30] also involved undergraduate learners. A total of 4 studies did not report about the study level of learners.

When we look into the field or subject area of studies among the learners, a wide range of areas were observed. As illustrated in Figure 6, the majority of 35.3% were in IT/computer science field. Medicine/health sciences and English language are the second highest with 11.8%.

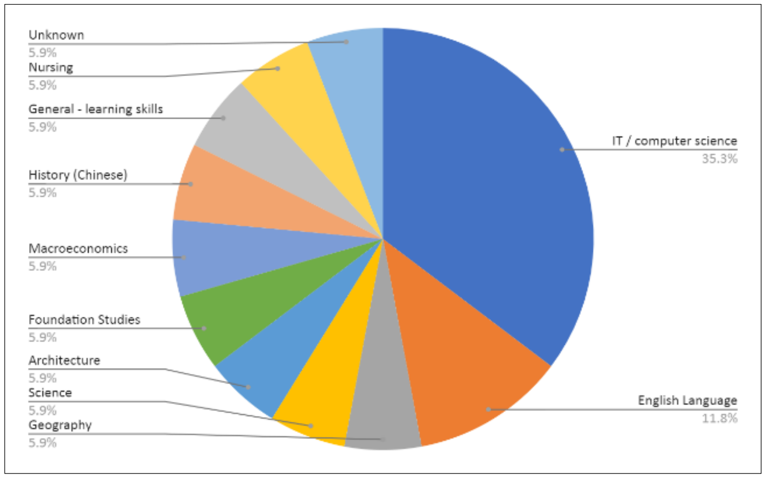

Figure 6: Field of study of learners.

The other areas include geography, science, architecture, foundation studies, macroeconomics, history (Chinese), general – learning skills and nursing. Even though most of the studies focus on single field, the study of Lim, Dawson, Gašević, Joksimović, Fudge, Pardo and Gentili (2020) [37] combined learners from Health Science, Architecture, Computer Engineering and Foundation Studies.

Technology

As Nan Cenka, Santoso and Junus (2022) [44] stated, technology is the key enabler in assembling a meaningful ALE. Figure 7 depicts the result of the analysis on the major type of technology and tools that the reviewed studies used to implement the adaptivity.

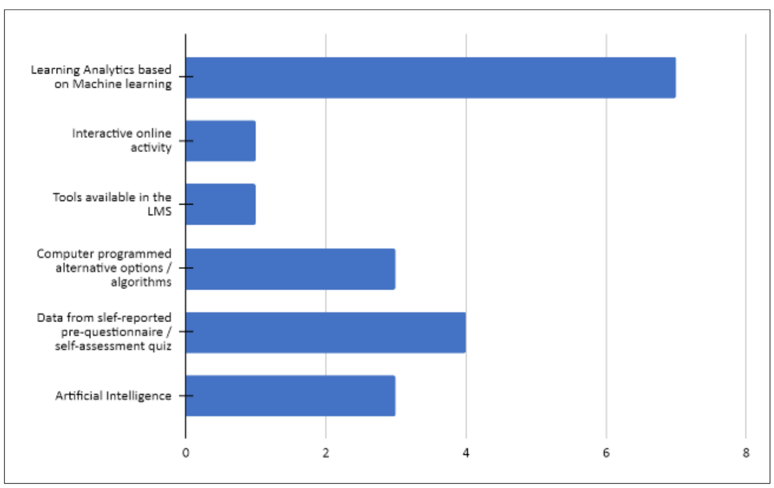

Figure 7: Major type of technology and tools used to implement the adaptivity.

A total of seven studies (e.g. Okubo, Shiino, Minematsu, Taniguchi and Shimada, 2023; Pardo, Jovanovic, Dawson, Gasevic´ and Mirriahi, 2019) [46][48] used machine learning to generate learning analytics and four studies (e.g. Miller, Asartab and Schmidta, 2019; El-Sabagh, 2021) [40][18] used self-reported questionnaires or quizzes as a tool to generate adaptivity for the learners. However, filling in questionnaires is considered as traditional methods (Essa, Celik and Human-Hendricks, 2023) [20] and is criticised for its drawbacks (Aissaoui, Madani, Oughdir and Allioui, 2019) [3]. Major criticism includes time consumption for filling the questionnaire, students' unconsciousness providing uninformed answers, and it results obtained from questionnaires are static but learning of learners continually change during the learning process. It is important to note that even though some of the studies used self-reported questionnaires, they have combined learning analytics (e.g. Millera, Asartab and Schmidta, 2019) and classifying algorithms (e.g. El-Sabagh, 2021) [18] rather than simply relying on learning style models like VARK model or FSLSM.

The current development of Artificial Intelligence (AI) is considered a promising technology that could overcome the limitations of self-reported questionnaires in implementing ALE. Among the studies, 3 has been reported (e.g. Zheng, Zhong, Niu, Long and Zhao, 2021; Huang, Chang, Yang, Ogata, Li, Yen, and Yang, 2023) [58][28] that they have used AI as the main technology for the adaptation.

Object

As illustrated in Figure 8, the Objects of the reviewed studies were to enhance learners' 1) academic achievement or performance, 2) engagement and motivational factors, 3) self-regulated learning and learning performance, 4) learning features and learning activity, 5) satisfaction, 6) course completion rate, 7) student's perception towards the learning environment and 8) collaborative knowledge building, group performance, socially shared metacognitive regulation, and cognitive load.

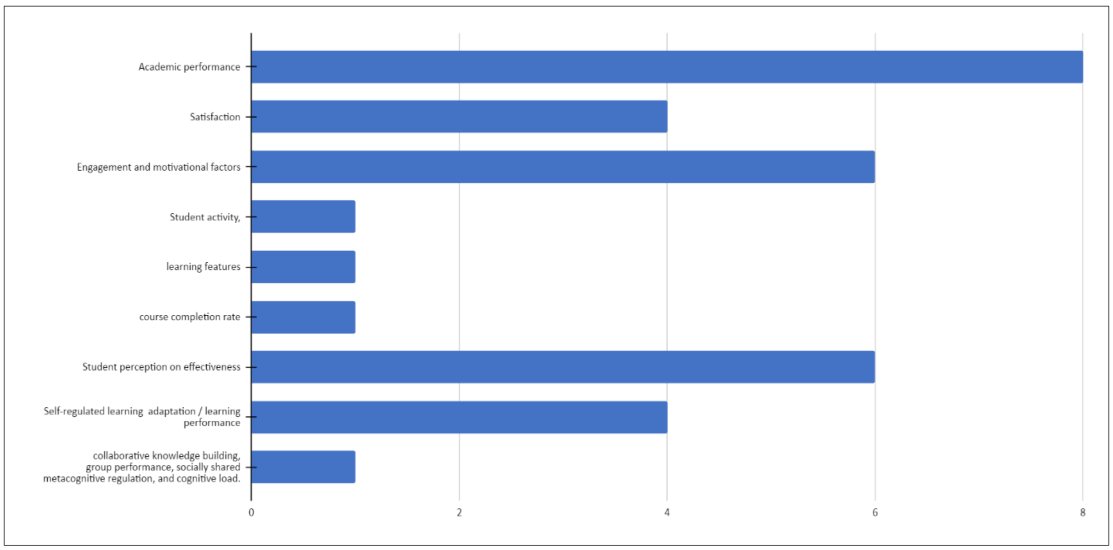

Figure 8: Objects of the reviewed studies.

A total of eight studies focused on enhancing academic performance, six studies were aimed in enhancing learner engagement and motivational factors. For example, the study of Suppasetseree, Kumdee and Minh (2023) [54] investigated engagement in three dimensions; behavioural, cognitive and emotional. Ha and Im (2020) [26] in their study investigated the enhancement of Student's flow (control, attention focus, curiosity, intrinsic interest), hedonic value (enjoyment), utilitarian value (usefulness) which directs toward their motivation. With regards to object also, many studies combined different enhancement measures.

Rules

The effectiveness of ALE relies on the method employed to categorise and gather information about learners' learning preferences based on their individual needs and characteristics, as well as how this information is utilised to create an adaptive and intelligent learning environment (Bajaj and Sharma, 2018) [7]. Consequently, through more precise classification of learners' learning preferences, ALE can leverage this information to offer precise personalisation (Essa, Celik, and Hendricks, 2023) [20]. Therefore, to effectively personalise instruction, it's essential to have a clear vision outlining how instruction can be tailored, what factors inform personalisation, and who or what is responsible for customising instruction (Short, 2022) [52]. These are determined by the rules and/or procedures for defining, designing, and evaluating PL. This review based the ruled on the Personalised Learning Design Framework (PLDF) presented by Short (2022) [52] which tries to address five factors. The result of the review based on each of the PLDF factors is presented in Table 4.

Table 4: The result of review of Rues component based on PLDF.

Aspect of instruction tailored	**no.**	**%**
Learning Objectives	1	5.88
Learning Activities	0	0.00
Assessments	10	58.82
Other	8	47.06
Unclear	2	11.76
Dimensions of PL tailored	**no.**	**%**
Time	16	94.12
Pace	16	94.12
Place	16	94.12
Path	12	70.59
Goals	1	5.88
N/A	1	5.88
Who or what is tailoring the instruction	**no.**	**%**
Educator	4	23.53
Learner	3	17.65
System	10	58.82
Level of the Taxonomy of Learner Agency	**no.**	**%**
Level 2	4	23.53
Level 3	9	52.94
Level 4	4	23.53
Type of data used for tailoring	**no.**	**%**
Performance	11	64.71
Activity	10	58.82
Learner Profile	5	29.41

As illustrated in Table 4, 58.8% of the studies reviewed, assessment aspect of the instruction is tailored to the learner. It is also worth highlighting that a reasonable number of studies (47%) used different aspects other than aspects mentioned in the PLDF. For example, Mudrák, Turčáni and Reichel, 2020; Jitpaisarnwattana, Reinders and Darasawang, 2021; Suppasetseree, Kumdee and Minh, 2023; Chang, Kuo and Hwang, 2022 [30][12] have used content or learning material tailored to the learner. Content recommendation systems are frequently mentioned as a type of adaptive learning systems.

Time, pace, and place can be considered as the frequently used dimensions of PL that is being tailored to the learner as 94% of the studies observed applying those. These are the main considerations to provide flexible learning through PL. Also, a reasonable number of studies (70%) were accountable for providing a customised learning path for the learners.

Regarding whom or what is tailoring the instruction, 58% of the studies relied on a system which automatically tailor the instruction for the learner based on data. But few (17%) allowed learners to tailor the instruction for themselves. These could be ALE where self-reported questionnaires were used. Also, 23% of the studies were found where educator tailors instructions by themselves for the learners. These were observed in studies like Lim, Dawson, Gašević, Joksimović, Fudge, Pardo, and

Gentili, 2020 [37] which provided instructor – based personalised feedback, and Chang, Kuo, and Hwang, 2022 which focused on using chatbot to retrieve prompts from the learners. Even though all the studies did not rely completely on system to tailor instruction, all the studies have used some kind of a system to implement the ALE. As displayed in Figure 9, 47% of the studies used a Learning Management System (LMS) and 23% developed either online web-based platform or a separately developed ALE.

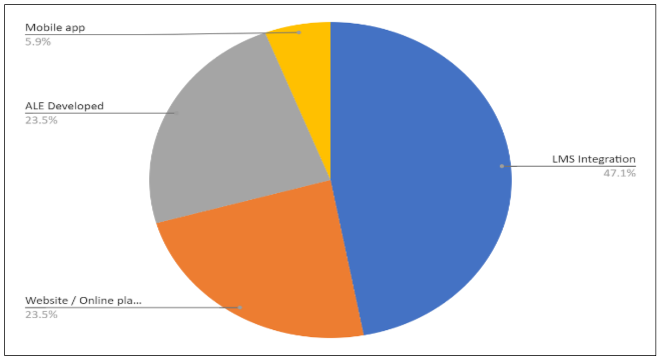

Figure 9: Type of ALE systems implemented.

According to Short (2022) [52], educators should prioritise understanding the learner's role in customising instruction. While PL often emphasises empowering learners, it could be imprudent to expect all learners to independently make learning choices without first equipping them with the necessary skills. Therefore, to address this, in his PLDF, he created the Taxonomy of Learner Agency (refer to Figure 10) to guide learners in managing the decisions associated with increased control over their learning journey.

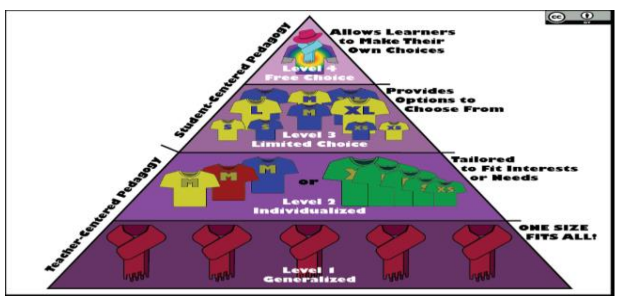

Figure 10: Levels of Taxonomy of Learner Agency.

With respect to the studies reviewed, 52% fall under Level 3 within the taxonomy where learners were given learning options to select from. For example, studies by Spinney (2023) [53] and Majuddin, Khambari, Wong, Ghazali and Norowi (2022) [38] provided choices for assessments, and study of Okubo, Shiino, Minematsu, Taniguchi and Shimada (2023) [46] suggested choices for learning materials. It is quite fascinating that 23% of the studies provided Level 4 control of learner agency where learners were allowed to make their own learning options. In the study of Jitpaisarnwattana, Reinders and Darasawang (2021) [30], learners were given opportunity to self-evaluate themselves on the presentation type and their needs along with discussions with peers. System then recommends a customised learning plan based on their responses. Studies that use self-reported questionnaires to determine learning preferences of learners (e.g. El-Sabagh, 2021) [18] also tailors the instruction relying on learner responses.

As mentioned earlier, the precision of personalisation depends highly on the effectiveness of the classifications of learning preferences. This highly depends on the data collected regarding the learner which would determine the adaptation or the tailoring of instruction for the learner. Regarding the type of data with respect to PLDF, 64% of the analysed studies used performance data (learner's knowledge or ability measurements) (e.g. Majuddin, Khambari, Wong and Norowi, 2022 [38] used knowledge level to differentiate alternative assessments), 58% used activity data (learner's learning behaviours and habits) (e.g. Zheng, Zhong, Niu, Long and Zhao, 2021 [58] used automatic classifications of online discussion to provide customised feedback based on learner behaviour in online discussions) and 29% relied on learner profile data (learner's interests and background) (e.g. Cardenas, Castano, Guzman and Alvarez, 2021) [10]. It is important to highlight that reasonable number of studies relied on both performance and activity data.

Community and Division of Labour

Community is referred to the people involved in the ALE interventions (e.g. instructional designers, subject matter experts, multimedia experts, and programmers); division of labour is referred to the distribution of duties and responsibilities among the community members. However, none of the studies analysed reported the details of the community and division of responsibilities during the design, development and implementation of ALEs.

Outcome

The outcome component included the performance measure of the effectiveness of ALE. These measures were based on learner's performance as well as perceptions. The results are illustrated in Figure 11.

Based on the distribution of the outcome, 88% of the reviewed studies concluded that ALE have a significant effect on enhancing learning measures of learners; academic achievement (e.g. Cardenas, Castano, Guzman and Alvarez, 2021; Chang, Kuo, and Hwang, 2022) [10], satisfaction (e.g. Chang, Kuo and Hwang, 2022) [12], motivation and engagement factors (e.g. El-Sabagh, 2021; Pardo, Jovanovic, Dawson, Gasevic´ and Mirriahi, 2019) [18][48], perception (e.g. Okubo, Shiino, Minematsu, Taniguchi and Shimada, 2023) [46] etc.

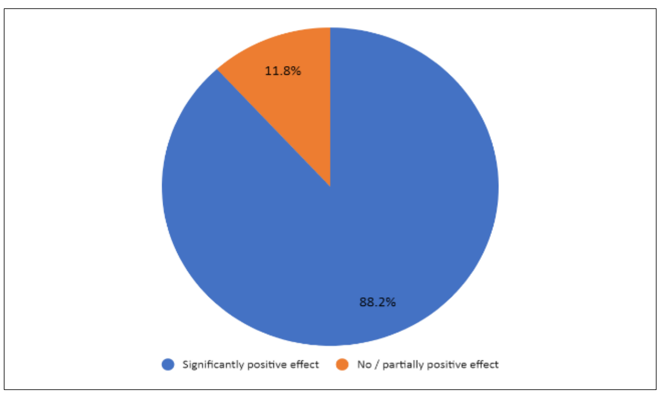

Figure 11: Result of outcome component.

These findings support major literatures available within the field. For instance, Hussein & Al-Chalabi (2020) [29] stated that ALE helps to ensure student's active engagement in the learning process. El-Sabagh (2021) [18] and Arsovic & Stefanovic (2020) [6] support the argument of ALE encourages motivation and self-learning among learners. Furthermore, Lim, Lim, & Lim (2022) [36] considers learner satisfaction as a measure of quality of learning environments as it plays a significant role due to the relationship between users and the learning environment.

The methods followed by the studies to measure the outcomes basically involve 1) Quasi-experimental with pre-test and post-test, 2) Experimental with a control and experimental group, 3)

Focus group interviews for qualitative data 4) quantitative data analysis based on learning analytics data, 5) c and 6) Mixed methods.

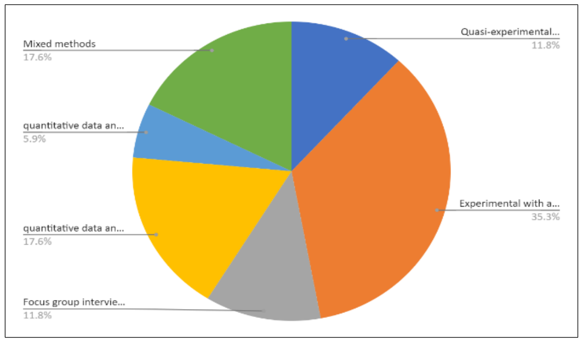

Figure 12: Methods used to measure outcomes.

As per Figure 12, 35% of the studies used experimental methods with a control group and experiment group to measure the effectiveness of the ALE.

Meta-analysis on the efficacy of ALEs on enhancing student learning

Among the selected studies, four studies reported complete data on the mean and standard deviation of one-size-fit-all approaches and ALE intervention. Out of these five studies, five measured student achievement and two measured satisfactions. Therefor meta-analysis based on standard mean difference (SMD) was conducted on both measures separately to determine the effectiveness of ALEs on enhancing leaners' academic achievement and satisfaction.

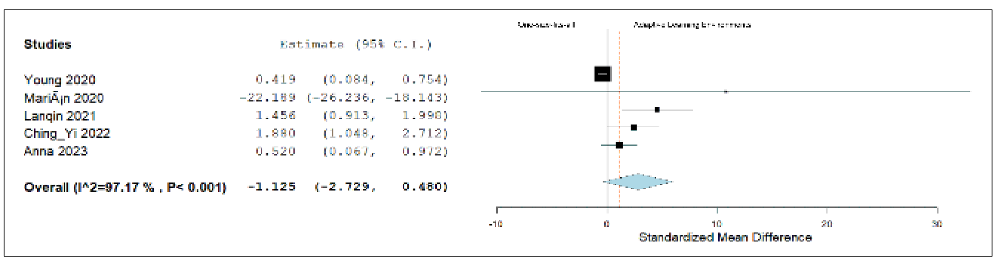

Figure 13: Forest plot result of learner's academic performance.

Figure 13 displays the forest plot from the result of the meta-analysis on learner's academic performance. As per the plot, the overall Effect Size (ES) of ALEs compared with one-size-fit-all approaches in enhancing academic performance favours the ALEs and is significant as $p<0.05$.

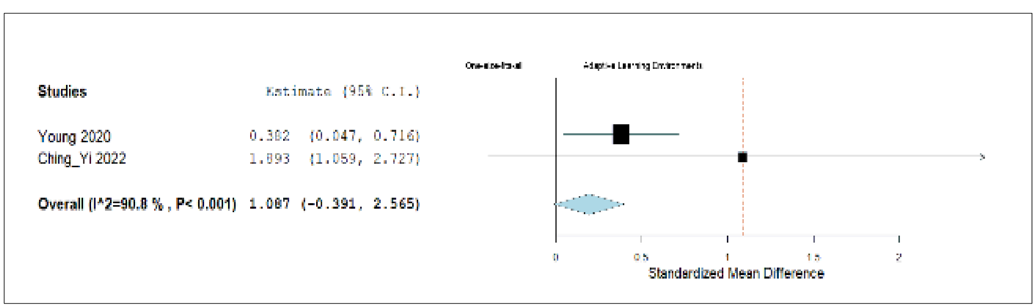

Figure 14: Forest plot result of learner's satisfaction.

Figure 14 displays the forest plot from the result of the meta-analysis on learner's level of satisfaction. As per the plot, the overall Effect Size (ES) of ALEs compared with one-size-fit-all approaches in enhancing academic performance favours the ALEs and is significant as $p<0.05$.

CONCLUSIONS AND FUTURE DIRECTIONS

This study conducted a systematic review of 17 empirical studies focusing on Adaptive Personalised Learning Environments (ALEs). It specifically investigated the design, execution, and results of game-based learning within the realm of higher education context, employing an Activity Theory (AT) framework. The study analysed key components of ALE activity systems, including the learners, technology (technological applications and tools used), learner's skills and behaviours that ALE aims to improve (object), accepted practices in implementing ALE interventions (rules), the involved community (individuals involved in the ALE interventions), the distribution of tasks the individuals, and the outcomes (performance measured to evaluate the effectiveness of ALE). Furthermore, the rules are guided by the Personal Learning Design Framework (PLDF) which considers the aspect of instructions, dimensions of PL, who or what is tailoring, level of taxonomy of learner agency and type of data.

Results showed that majority targeted for undergraduate learners and the development of ALEs have advanced from self-reported questionnaires to use of Artificial intelligence (AI) technologies to provide more dynamic and accurate methods to determine the learning preference of learners that would help for efficiency in the personalisation. In addition, most of the studies utilise performance data of learners on assessments to provide personalisation choices for learners. Most of the ALEs are implemented within Learning Management Systems (LMS) which assists in customising the instruction automatically. The outcomes measured usually involved enhancing different aspects of measure of students' learning including academic achievements, satisfaction and engagement. The meta-analysis on the academic achievement and satisfaction favoured for the efficacy of ALEs.

From the findings, it is noticed that the articles do not report on the community and the roles and responsibilities of individuals involved in implementing ALEs. It is obvious that the whole process would involve different stakeholders, and it is important to understand their roles for the successful establishment of ALEs. The search keywords and electronic databases might be limiting the studies that report the details. Hence, for future studies a thorough review targeting the community and division of labour component of AT can be performed. Also, the number of databases can be increased to increase the probability as well as the effectiveness of the result of the meta-analysis as well. In addition, while developing ALEs, we could consider multiple means of adaptation or tailoring methods and check the effectiveness as part of future research in the area.

Despite a few limitations, this study has laid a strong foundation for comprehending the design and impacts of ALEs. In particular, this study serves as a valuable reference for educators, instructional designers, and policymakers seeking insights into the effective design and implementation of ALEs tailored to learners with different learning preferences.

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APPENDIX

No.	Author	Year	Title	Journal	Adaptive Technique	Technology	Theory/ Instructional model or strategy	How personalisation is achieved?	Method	Implementation	Field/ subject Area	Target Group	Measure of Learning	Outcome
1	Lizette Susana Hernandez Cardenas, Leticia Castano, Cristina Cruz Guzman, Juan Pablo Nigenda Alvarez	2021	Personalised learning model for academic leveling and improvement in higher education	Australasian Journal of Educational Technology	Personalised learning paths based on learner profile	Machine learning based on learning analytics	learning style preferences, knowledge levelling		Pre-test / Post-test	LMS integration	Medicie / Health Science		Student's knowledge (academic performance) and satisfaction	Academic performance and satisfaction improved
2	Young Ha, Hyunjoo Im	2020	The Role of an Interactive Visual Learning Tool and its Personalizability in Online Learning: Flow Experience Online Learning	Online Learning Journal	Personalised Level of difficulty	Interactive online activity	knoweldge levelling		Experimental; control group and experimental group	Website	IT/computer science	Undergraduate Students	Student's flow (control, attention focus, curiosity, intrinsic interet), hedonic value (enjoyment), utilitarian value (usefullness), Academic performance and satisfaction	curisosity, interest, enjoyment, satisfaction shown significant effect but control, focus and usefullness did nto show significant effect
3	Marián Mudrák, Milan Turčáni, Jaroslav Reichel	2020	Impact of Using Personalized E-Course in Computer Science Education	Journal on Efficiency and Responsibility in Education and Science	Personalised content based on learning styles and adaptive navigation + Data related to motivation and previous knowledge	Tools available in the LMS	Felder-Silverman learning styles model + instructional strategies supported by the tools in LMS	LS, motivation and prior knowledge determined by self-reported questionnaires. Content recommended based on the data and additional resources recommneded	Post/pre-test Experimental; control and experimental group	LMS - Moodle	computer science	First year Students	Student activity, motivation and level of knowledge	Positive impact on level of student's output knowledge as well as overall learning efficiency
4	Napat Jitpaisarnwattana, Hayo Reinders, Pornapit Darasawang	2021	Understanding the roles of personalization and social learning in a language MOOC through learning analytics	Online Learning Journal	Personalised learning path with content recommendation	Learning analytics based on machine learning	Group/social learning, peer feedback and assessment	Learners self-evaluate themselves on the presentation type and their needs along with discussions with peers. System recommends a customised learning plan	Qunatitative analysis based on the learning analytics data in relation to learning factor and course completion	LMS Integration (Moodle)	English Language	undergraduate, post graduate and working professionals	learning features and course completion	Working in groups and creating an individual learning plan were important factors associated with course completion.
5	Christye Majuddin, Mas Nida Md. Khambari, Su Luan Wong, Norliza Ghazali, Noris Mohd. Norowi	2022	Students' Perspectives on the Use of Differentiated Assessment Tool: Results from an Explanatory Sequential Mixed-Method Pilot Study	Contemporary Educational Technology	Differentiated alternative assessments based on the knowledge level / personalised navigation	Computer programmed alternative options	Multiple Intelligence by Gardner (1983). Vygotsky's (1999) theory of Zone of Proximal Development (ZPD), Unified Theory of Acceptance and Use of Technology (UTAUT), differentiated alternative assessment	Alternative assessments were provided based on the performances of the learner (easy, medium, hard) which are restricted to move forward unless correctly answered.	Mixed-method on student perceptions based on UTAUT concepts	Developed web-based tool	Computer science / IT	Undergraduate students	Student perception	Most learners perceived the tools has a positive effect on their learning
6	Jamie E. L. Spinney	2023	Students' Perceptions of Choice-based Assessment: A Case Study	Journal of the Scholarship of Teaching and Learning	Choice-based assessment	Computer programmed alternative options	Choice-based assessment / differentiated Instructions	Students were given choice to select from different types of assessments based on their preferences	Quantiative analysis using questionnaire	Choice-based assessment system developed	Geography	Undergraduate	Student engagement and satisfaction	most students expressed strong support for this choice-based assessment strategy
7	Neil Dixon, Andrea Packwood	2023	Personalised learning paths for information literacy using Canvas MasteryPaths	Journal of Information Literacy	Personalise navigation to enrichment contents based on knowledge level	Data from a prior self-assessment quiz	knoweldge levelling	Students were allowed to attend series of quizzes to assess their knowledge and based on their score, they were directed to enrichment	Qualitative Analysis (Focus group interviews)	LMS integration (Canvas)	Science	Undergraduate	Perception on the effectiveness	Student viewed the approach positively improving their learning
8	Suksan Suppasetseree, Sorarut Kumdee, Thang Ho Minh	2023	Supporting Student Engagement with Technology: Findings from a Study of an Online Personal Learning Environment for Extensive Listening	LEARN Journal: Language Education and Acquisition Research Network	Personalised learning materials based on preferences	Data from slef-repored pre-questionnaire		Students were given pre-questionnaire to find out about their preference on the learning materials. Moodle was developed with the preferred learning materials	Mixed method - self-reported questionnaire and interviews	LMS (Moodle)	English Language	Undergraduate	Student engagement and perception	high levels of student engagement in all three dimensions; behavioral, cognitive, and emotional. Students had positive opinions towards the online PLE because they found it enjoyable.

No.	Author	Year	Title	Journal	Adaptive Technique	Technology	Theory/ Instructional model or strategy	How personalisation is achieved?	Method	Implementation	Field/ subject Area	Target Group	Measure of Learning	Outcome
9	Lisa-Angelique Lim Shane Dawson, Dragan Gašević, Srećko Joksimović, Anthea Fudge, Abelardo Pardo, Sheridan Gentili	2020	Students' sense-making of personalised feedback based on learning analytics	Australasian Journal of Educational Technology	Personalised feedback based on LA	Learning Analytics	Zimmerman's (2000) SRL model Winstone et al.'s (2017) perceptions of the interpersonal communication factors of feedback	Instructors use LA-based software to personalise feedback to all students. The software collets learner data from various sources (e.g., learning management system activity and engagement, assessment and attendance) to enable instructors to generate and send personalised feedback to all students in their course.	Focus group interviews, thematic analysis and epistemic network analysis	LA software integrated with LMS and other systems	Health Science, Architecture, Computer Engineering, Foundation Studies	Undergraduate	Self-regulated learning adaptation and perception of feedback	Results from a combination of thematic analysis and epistemic network analysis show an association between student perceptions of their personalised feedback and how these map to subsequent self-described self-regulated learning processes. Most notably, the results indicate that personalised feedback, elaborated by personal messages from course instructors, helps students refine or strengthen important forethought processes of goal-
10	Laurie A. Millera, Carlos J. Asarta, and James R. Schmidta	2019	Completion deadlines, adaptive learning assignments, and student performance	JOURNAL OF EDUCATION FOR BUSINESS	personalised assessment based on confidence level and knowledge leve	Self-reported answers + Learning Analytics	Scaffolding / Knowledge levelling	Students are allowed to complete adaptive learning assignments - one with strict deadlines and other with control for students based	Quantitative analysis Experimental with control and experimental group	adaptive learning tool	macroeconomics		Student academic performance	the presence of rigid deadlines detracted from student participation with the adaptive learning assignments
11	Lanqin Zheng, Lu Zhong, Jiayu Niu, Miaolang Long and Jiayi Zhao	2021	Effects of Personalized Intervention on Collaborative Knowledge Building, Group Performance, Socially Shared Metacognitive Regulation, and Cognitive Load in Computer-Supported Collaborative Learning.	Educational Technology & Society	Personalised feedback and recommendation	Artificial Intelligence (deep neural network model, Bidirectional Encoder Representations from Transformers (BERT)	Scaffolding / Knowledge levelling IIS-map analysis method proposed by Zheng, Yang, and Huang (2012). Collabortaive learning	BERT automatically classif online discussion transcripts and provide classification results. Personalized feedback and recommendations were automatically generated from the classification results	Mixed - quasi-Experimental pre-test-post test, focus group	Online platform	Computer Science		collaborative knowledge building, group performance, socially shared metacognitive regulation, and cognitive load.	significant differences in the le of collaborative knowledge building and group performance between the experimental and control groups. Furthermore, the experimental group demonstrated more socially shared metacognitive regulatio than the control group. There was no significant difference ir cognitive load between the experimental and control
12	Xuanqi Feng and Masanori Yamada	2021	An Analytical Approach for Detecting and Explaining the Learnin Path Patterns of an Informal Learning Game	Educational Technology & Society	personalised learnin path based on learning pattern - game-based assessment	Learning Analytics Levenshtein distance and hierarchical cluster analysis	game-based learning, concept maps	Learning sequence of the players were determined by the distance then learning content path patterns were recommended	Qunatitative analysis on LA based data	educational game developed	History (Chinese)	graduated students, Middle school	learning results	help us understand learners' knowledge acquisition and provide evidence for enhancing the accuracy of precision education and improving the quality of the educational game
13	Abelardo Pardo, Jelena Jovanovic, Shane Dawson, Dragan Gašević and Negin Mirriahi	2019	Using learning analytic to scale the provision of personalised feedback	British Journal of Educational Technology	Personalised feedback	Learning Analytics	scaffolding	tudents engage in activities organised into cycles with an identical curriculum structure. Algorithm colects tsudents data and selects an	Quantitative based on LA and Student feedback survey	LMS integration	Computer Science	Undergraduate	Student perception on feedback, student engagement and academic achievement	a positive impact on student perception of feedback quality and on academic achievement.
14	Hassan A. El-Sabagh	2021	Adaptive e-learning environment based on learning styles and its impact on development students' engagement	Int J Educ Technol High Educ	Peronalised content recommendations based on learning styles	Self-reported data from student questionnaire - classifying algorithms - program	VARK learning styles model Dixson scale of studer engagement	Student answer questionnaire and their learning style is identified. Content is then presented based on the learning style	Quantitative experimental	ALE develped	General - learning skills	Undergraduate	Student engagement	The student engagement scale i experimental group is statistically significantly higher than those in the control group

No.	Author	Year	Title	Journal	Adaptive Technique	Technology	Theory/ Instructional model or strategy	How personalisation is achieved?	Method	Implementation	Field/ subject Area	Target Group	Measure of Learning	Outcome
15	Ching-Yi Chang, Shu-Yu Kuo and Gwo-Haur Hwang	2022	Chatbot-facilitated Nursing Education: Incorporating a Knowledge-Based Chatbot System into a Nursing Training Program	Educational Technology & Society	Personalised content presentation based on user prompt	Knowledge-Based Chatbot System	Knowledge levelling	Students ask questions using prompts, chatbot present content based on the prompt.	Quasi-experimental pre-test and post-test, quantiative	Mobile based app	Nursing	Undergraduate	academic performance, critical thinking, and learnin satisfaction	the knowledge-based chatbot system effectively enhanced students' academic performance, critical thinking, and learning satisfaction.
16	Anna Y. Q. Huang1, Jei Wei Chang1, Albert C. M. Yang2,4, Hiroaki Ogata3, Shun Ting Li1, Ruo Xuan Yen1 and Stephen J. H. Yang1*	2023	Personalized Intervention based on the Early Prediction of At-risk Students to Improve Their Learning Performance	Educational Technology & Society	Personalised tutoring by recommending remidial material	AI (text-processing artificial intelligence technologies)	Knowledge levelling MSLQ	Students were provided with remidial materials and based on their performance further content suggested by identifying their learning ty and assessed	Experimental pretest and post test, quantittive	Python integrated learning environment	Computer Science	Undergraduate	self-regulated learning and learning performance	Compared with the traditional class tutoring, the personalized intervention review activity not only helped students obtain higher learning performance bu also prompted greater improvements in the following learning strategies: rehearsal, critical thinking, metacognitive self-regulation, effort regulation, and peer learning - indirectly affected
17	Fumiya Okubo , Tetsuya Shiino, Tsubasa Minematsu, Yuta Taniguchi, and Atsushi Shimada	2023	Adaptive Learning Support System Based on Automatic Recommendation of Personalized Review Materials	IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES	Personalised content recommendation / navigation	Learning Analytics		Students are presented with suggestions for materials to review based on their performance on quizzes	Experimental control and experimental group qunatitative data analysis	Moodle Integration			Students perception on the usefullness	at least half of the participants found it useful for most types o feedback.