Identifying Design Principles for an AI-enabled Adaptive Learning Systems

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Abstract

AI techniques have been used to develop systems that adapt to students' learning strategies and preferences. While research shows that AI-enabled Adaptive Learning Systems have potential, it remains unclear how the existing systems have been built and developed. The goal of this study is to come up with design principles for AI-enabled adaptive learning systems. In this paper, the first phase of the study is presented, where a systematic literature review of design principles and guidelines for AI-enabled Adaptive Learning Systems was performed. From a set of 224 retrieved articles, 16 papers published in the past five years were analysed. The findings of the paper present 5 design clusters that include a total of 24 design principles. This paper aims to contribute to the application of AI and adaptive learning systems in the field of education, by bringing awareness to the researchers and system designers.

Keywords: Design Principles, AI-enabled learning system, adaptive learning, adaptive learning systems

Introduction

Adaptive learning is personalizing the learning content for students in a learning system, in such a way that the system can deal with individual differences in aptitude (Almohammadi et al. 2017; de Bra et al. 2013; M Liu et al. 2017). This approach supports students to achieve the planned learning outcomes through a personalized way. The most common examples learning systems that enhance adaptive learning are adaptive learning systems. Adaptive learning systems (ALS) are platforms for personalized learning that adapt to learning strategies of students, altering and modifying the sequence and difficulty of the task based on their abilities (A T Bimba et al. 2017; Xie et al. 2019). These systems are integrated with AI, Machine Learning (ML) and new data analytical techniques. ALS were developed to help address several challenges affecting learning. These challenges include diversity of students' backgrounds, resource limitations, and variety in learning abilities of students (Xie et al. 2019). These learning systems motivate students to own their learning journey through automated feedback cycles in the systems. These automated cycles evoke students to make progress independently of their lecturer. The capability and capacity of ALS is to enable personalized learning of students while they progress through course content. This capability and capacity marks the potential of AI-enabled ALS and its enthusiasm to be used (Gros 2016). There are numerous benefits of ALS, such as faster student progression, improved learning experience, flexibility of time, redirection to needed knowledge and skills, multiple learning paths, and flexibility in managing their learning experience. Thus, the concept of adaptive learning and its systems is interesting especially for students and lecturers.

In the past few years, there has been acceleration of ALS enabled by AI. Recent ALS include Fishtree, Connect ™, ACTIVEMATH, QuizBot, Adaptive Mobile Learning System (AMLS), Personalized Adaptive Learning Dashboard (PALD), 'MostSaRT' system, Smart Sparrow, OPERA, LearnSmart, Personal Assistant for Life-Long Learning (PAL3), INSPIREus, ProSys, Student Diagnosis, Assistance, Evaluation System based on Artificial Intelligence (StuDiAsE), the LeaPTM system, and Adaptive Instructor Operating Systems (Kabudi et al. 2020a). The design of AI-enabled ALS is inspired and enabled by the advancement in cognitive theories, Big Data analytics, learning analytics, AI and educational data mining techniques. The fundamental design characteristics of these systems include: A customized user interface that handles the interaction between students and the learning system; track students' goals and progress; monitor and infer the internal state of students (e.g., cognitive, emotional, physical, behavioral, etc.); observe and deduce the external state of the learning environment; check and monitor feedback and adaptation (Hou and Fidopiastis 2017). Most of these systems developers and designers have integrated these design characteristics including design elements such as , adaptive instructional architecture, and the delivery platform that communicates learning concepts to students (Hou and Fidopiastis 2017; Ruan et al. 2019). However, while literature shows numerous ALS modelled by AI, the underlying design principles that guide the design, development, and implementation of AI-enabled ALS are not clearly known and sufficiently investigated. Not only are design issues of these systems still mentioned in literature (Kabudi et al. 2020a), but most of AI-enabled ALS are "restricted to research projects and a few commercial applications" despite their known potential (Essa 2016). Thus, this research aims to narrow the gap between experimental research and practice in the field, by providing practical design statements that can be implemented in an effective AI enabled ALS. Moreover, the study seeks to address the research gaps of communicating common and universal design guidelines of AI-enabled ALS.

On this account, the purpose of the study is to establish a set of empirically and theoretically grounded design principles (DPs) that guide the design, development and implementation of AI enabled learning systems, that would successfully serve certain purposes and contexts in a university. In this paper, the first phase of the study is presented, where a systematic literature review was performed. The author reviewed literature (academic publications) to establish theoretically grounded design principles. The main research question, thus, is: *What are the underlying DPs of AI enabled ALS that exist in academic literature*? The findings of this study may support designers and system developers, interested in creating effective ALS with meaningful learning and teaching experiences. The underlying DPs of AI-enabled ALS will provide practical guidance on how to solve various design problems within the context of the utilized learning system. Moreover, the proposed DPs helps the designers and developers understand the needs of students and lecturers (main users of the AI-enabled ALS), and break those needs to the important components of the system. DPs are more than just the visual aspects of a product; there are guiding sentences that help developers and designers make meaningful decisions to reach the purpose of the product i.e. AI-enabled ALS (Adnan and Ritzhaupt 2018)

State of the Art: Literature on AI-enabled ALS

New techniques are being developed to analyse data and build AI that supports educational systems. AI techniques have been used to develop systems that adapt to students' learning strategies and preferences. Contemporary learning environments are integrating with new technologies and machine learning techniques, creating more personalized educational settings (Mousavinasab et al. 2018). Students can thrive in a digital environment where current technology shapes students' expectations and their 'abilities to access, acquire, manipulate, construct, create and communicate information' (Green and Donovan 2018). The physical and virtual resources in contemporary learning environments are designed to deliver effective instruction by helping students construct knowledge. Good examples of contemporary learning environments are adaptive learning systems and recommender systems. Recommender systems are 'software tools based on machine learning and information retrieval techniques that provide suggestions for potential useful items to someone's interest' (Syed and Nair 2018). Adaptive learning systems are platforms for personalized learning that adapt to students' learning strategies, adjusting the sequence and difficulty of the task based on students' abilities, and preferences (Andrew Thomas Bimba et al. 2017; Xie et al. 2019). The development of new data analysis techniques has produced more successful educational systems. Most AI-enabled contemporary learning environments are in the form of systems, such as adaptive learning systems, intelligent mechanisms, and adaptive learning platforms.

In recent years, adaptive learning with AI-enabled ALS has drawn attention in the education sector. Studies indicate that such learning with such ALS is a promising approach for teaching and learning. AI-enabled ALS (adaptive learning system, intelligent mechanism and adaptive learning platform) are the most utilized AI - enabled adaptive learning interventions (Kabudi et al. 2020b). The use of AI - enabled ALS play an important role to improve learning experience of students, their learning outcomes, mitigating poor levels of motivation and engagement (Andrew Thomas Bimba et al. 2017; Janati and Maach 2017; Maravanyika et al. 2017; Padron-Rivera et al. 2018). Studies have shown several customized AI - enabled ALS developed to address learning and teaching challenges. A good example is an intelligent adaptive test system developed by (Tommy et al. 2016) to address existing systems' inefficiency in measuring student proficiency. Another example includes an affective tutoring system (ATS) called Tamaxtil; it identifies when students become irritated, discouraged and confused, and offers them help (Padron-Rivera et al. 2018). Other studies involved evaluating existing systems and improving them by adding data mining techniques, learning analytics, intelligent mechanisms, and plugins. For instance, Brightspace LeaP™, an adaptive technology, was utilized to create adaptive intervention modules i.e. Smart Adaptive Management for Flipped Learning (SAM-FL), that were embedded into an existing learning management system i.e. Canvas (Min Liu, McKelroy, et al. 2017). The researchers were examining the effect of adaptive learning in a university in USA. The recent recognition of the importance of AI enabled learning systems in solving more challenging problems in education has led to the increased attention.

Yet, there are few examples of identified AI enabled adaptive learning interventions implemented in real educational settings (Cavanagh et al. 2020; Wakelam et al. 2015). Most of these systems are described in literature, but rarely used in practice and in ordinary courses (Imhof et al. 2020; Verdú et al. 2015). AI techniques have been used to enable these systems to adapt to students' learning strategies, preferences, and the like, but not much has been done to accommodate learners' competencies and skills (Restrepo-Calle et al. 2018; Vijay 2017). Xie et al. noted that designers of ALS pay little attention to courses with prerequisite practical or technical skills (Xie et al. 2019); this research gap needs to be addressed. Literature also shows that the learning systems used are mainly limited in terms of "not possible to embed into the systems all the possibilities that cover the specific requirements and necessities of each learner in each part of the learning course" (Klašnja-Milićević et al. 2018). Moreover, issues such as design, assessing and low usage of ALS are still described as challenges (A T Bimba et al. 2017; Chen et al. 2018; Kabudi et al. 2020b; Tsarev et al. 2019).

Overall, the literature shows the potential of AI enabled adaptive learning system for students. At the same time there are still concerns and challenges that surround the implementation of these systems. These developments highlight that there are insufficient studies as to how AI-enabled ALS have been designed, i.e. in terms of underlying DPs. There is a need to address these limitations and research gaps by proposing DPs for an AI-enabled adaptive learning system. Thus, the main goal of this paper is to establish inherent DPs of AI enabled adaptive learning system targeted for students, that exist in literature. The author did not define a set of DPs beforehand, rather unpack DPs from the literature, that developers and designers apply consciously or not. It is important to establish and reveal the guiding DPs, as without them, evaluation and improvement of the systems is difficult.

Methodology

For this stage of study, a detailed critical analysis of existing literature in the form of systematic literature review is selected. The adoption of AI enabled ALS is still in its infancy, and thus there is a lot to discover. The author conducted a systematic review on the academic literature proposed by Petersen et al. (2015). This study was conducted from October to November 2020. EndNote X9 and Excel spreadsheets were used to extract publication outlets, find duplicates, and organize the information. The process of systematic literature review involves planning, conducting, and reporting the results phases. In the planning phase, the research objective for the review is identified. The research objective for the study is to obtain DPs of an AI adaptive learning system. After the plan, the next phase that followed was to conduct the review. A search strategy was formulated to reduce research bias. The search strategy was framed by expanding the research question. Next, search strings were created, and search keywords were identified, to reduce the number of articles. Substitute and synonyms were used.

The keywords used in the search string are *adaptive learning system' AND ('artificial intelligence' OR 'machine learning'), (("design guidelines" or "design principles") and ("learning systems" or "adaptive learning systems")), (framework and (design guidelines or design principles) and ("learning systems" or "adaptive learning systems")), (("design guidelines" or "design principles") and ("use" or "implement*" or "introduc*") and ("learning systems" or "adaptive learning systems")), (framework and ("design guidelines" or "design principles") and ("use" or "implement*" or "introduc*") and ("learning systems" or "adaptive learning systems")).* Both formal and informal searches were conducted to answer the research objective. The search was done on Web of Science, Scopus, and EBSCOhost. The search was based on selecting previous works published in the past five years to avoid outdated research. The initial search retrieved 363 articles. A total of 224 articles were then retrieved after removing duplicates. To narrow the scope of the articles, cross-checking was done. The following inclusion criteria were considered: 1) The article must be written in English 2) Should be published in conference proceedings and academic journals and 3) Should include DPs that are relevant to AI enabled ALS. Abstracts of papers were scanned to select the most relevant ones. The author also skimmed and read the articles to select the most relevant ones. At the end, 16 articles were selected from both formal and informal searches for detailed analysis. The publication selection process is outlined in the figure below.

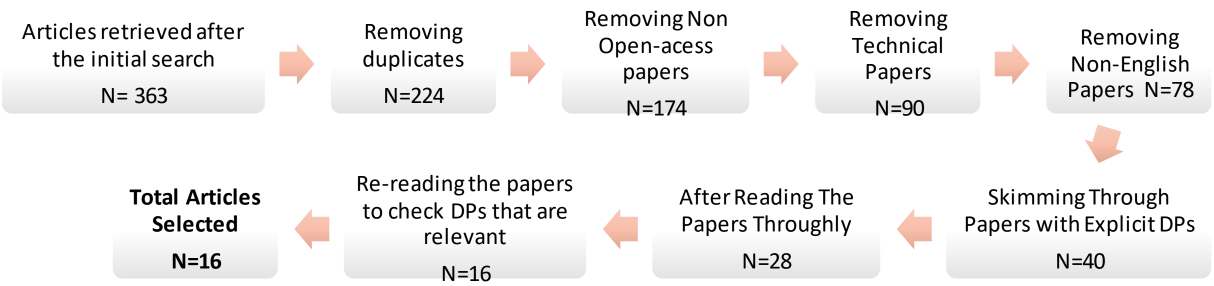

Figure 1 Systematic Literature Review Process

Results of Findings

This section presents findings based on the analysis of the 16 selected articles. The distribution of the articles per year is shown below.

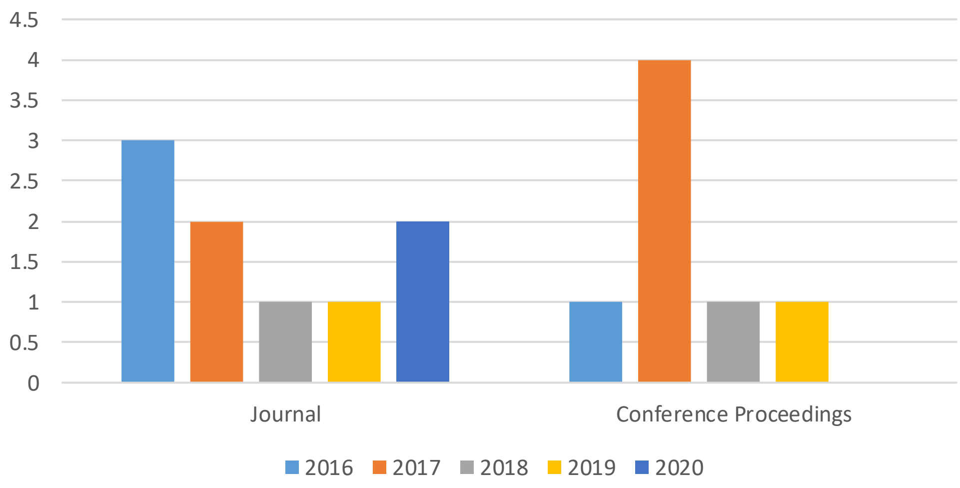

Figure 2 Distribution of the Articles per year

Among the sixteen papers, seven papers identified major design concerns in form of mitigation measures to address design problems, issues, and challenges that systems designers and developers face in the field of that AI-enabled ALS. Such design concerns are used as building blocks to come up with DPs, as seen in the next section. The design concerns that were identified in our findings are stipulated in the table below.

Table 1 List of Design Concerns (DCs)

DC	Major Design Concerns stated	Reference
DC1	There should be identification and measurement of skills, for attainment of skills	(Slater and Baker 2019)
DC2	There should be more of forecasting of students' knowledge	
DC3	The system should include learner preferences, experience, and knowledge	(Gavriushenko et al. 2017)
DC4	There should be a recent updated learner profile available. The process of personal learner profile creation should not be annoying for the student, should not be time consuming, should not demand significant efforts from students	(Gavriushenko et al. 2017)
DC5	Affective information (information on interests, attitudes, and motivations of students) should be used for adaptive instruction	(Keith W. Brawner and Gonzalez 2016)
DC6	Learner models in the systems should include information regarding the depth of knowledge desired and align expectations appropriately to the expertise level of the student.	(Vogel-Walcutt et al. 2016)
DC7	The system should have metrics (online computations) that can be computed effectively and regularly updated as students' progress through the course. This online capability would allow lecturers to receive feedback as the course progresses.	(Chen et al. 2018)
DC8	The expert model in the system must present the required learner proficiency within the particulars and specifics of the learning activities. In other words, the "what" that the students must do, should be presented to students, to successfully complete the learning task.	(Hou and Fidopiastis 2017)
DC9	In the expert model, there should be provision of feedback and assistance to students, in form of support and advice	
DC10	There should be a need to analyze and make sense of students' usages (such as logs) to understand their behavioral or learning patterns	(Min Liu, Kang, et al. 2017)

The remaining papers specifically present DPs for technology enhanced learning environments, such as adaptive learning. Sein et al. (2011) defines design principles as knowledge obtained through the development of an artifact. These DPs can be used to build other artifacts within the same area. The DPs highlighted in Table 3 are included as they are applicable to systems that promote adaptive learning. These principles consider monitoring and interpreting students' activities, understand preferences and needs of students, and dynamically adjust the learning process – all characteristics of adaptive learning. The DPs from the articles are presented in Table 2.

Table 2 List of DPs

Item No	**Reference**	**DPs addressed in the articles**
1	(Chin et al. 2016)	*DP:* Allow Flexible alterations to assignments based on learning goals and readiness
2	(Adnan and Ritzhaupt 2018)	*DPs:* Scalability i.e. The system should adapt well to the increasing of users and data Maintainability i.e., Instructional materials should easily be modified to add new features and be restored to explicit condition within a specified time frame
3	(Ocumpaugh et al. 2017)	*DPs:* Risk Communication Principles, Student Feedback Principles, Guidance Counselors' Design Priorities
4	(Palalas and Wark 2017)	*DPs:* Mobility i.e. Design for the mobile learner, Learner-determined i.e., Respond to the learner, Context i.e. Integrate environmental affordances into the design
5	(Hickey et al. 2016)	*DPs:* Productive forms of disciplinary engagement with resources, peers and instructors should be facilitated and rewarded., Give students authority over their disciplinary engagement and hold students accountable for their disciplinary engagement Let individuals assess their understanding privately, Measure aggregated achievement discreetly
6	(Rhyn and Blohm 2017)	*DPs:* The system should learn based collective and artificial intelligence
7	(Lee et al. 2019)	*DPs:* Unobtrusive Integration, Accurate Sensing, Protected Confidentiality, Protected Information Security, Engaging User Interface
8	(Altınpulluk et al. 2020)	*DPs:* Equitable Use, Simple and Intuitive Use, Perceptible Information, Tolerance for Error, Low Physical Effort, Size and Space for Approach and Use
9	(Piccoli et al. 2020)	*DPs:* Collect completion data for required and optional assignments, Reliably measure performance ensuring consistent evaluation of the same task over time and across learners, Produce valid measures of skill mastery (i.e., minimizing false positive and false negative evaluation errors Provide regular homework and practice assignments to learners to test their progress in skills acquisition. Provide feedback to learners for all the assignments learners voluntarily submit. Direct learners towards appropriate resources, online or physical, for specific skills that are not mastered. Provide feedback immediately after task completion. Enable learners to interpret the feedback by contextualizing it appropriately

	Create realistic practice exercises that learners view as instrumental to their future success.
	Create manageable practice exercises that fit easily within the schedule and habits of the learners.
	Create practice exercises that are limited in scope and enable learners to focus on specific skills and receive precise feedback.

Discussion and Implications of Findings

The results above show design principles and concerns that various scholars believe are necessary to include while designing and developing an AI-enabled ALS. These selected DPsare to address several challenges that student face, that have been overlooked while implementing AI enabled learning interventions (Kabudi et al. 2020b; Xie et al. 2019). Examples of such overlooked challenges include Difficulty of students attaining their necessary learner skills (Xie et al. 2019), Outdated and complex models in systems (Almohammadi et al. 2017; K W Brawner and Gonzalez 2016; Dargue and Biddle 2014), Background and learner profiles issues (Oliveira et al. 2017; Yang et al. 2019) and Engagement Issues (Afini Normadhi et al. 2019). The table below shows few major selected challenges that are addressed by the DPs from our findings.

Figure 3 Identified DPs mapped against overlooked Challenges

Another interesting insight that is revealed from this review is the relevance of learner analytics in an AI adaptive system. Min Liu, Kang, et al. (2017) and Piccoli et al. (2020) identify the need to analyse students' data that will help in understanding student's behaviour, learning patterns and help with their personalized learning. Moreover, in this review, Feedback is seen as a relevant DP (Chen et al. 2018; Hou and Fidopiastis 2017; Ocumpaugh et al. 2017; Piccoli et al. 2020). Other relevant principles, guidelines and requirements that were identified in this review are based on the type of information to be included (Keith W. Brawner and Gonzalez 2016; Lee et al. 2019; Vogel-Walcutt et al. 2016) and the kind of practical exercises and assignments (Chin et al. 2016; Piccoli et al. 2020).

To better understand the relevance of the different kinds of DPs found in the results, the author grouped the content of the 16 selected articles to five main clusters. These five clusters of DPs are *Design and Presentation; Learning Content; Learning Assessment; Adaptation and Personalization; and Data Processing using Learning Analytics and AI*. The findings were analysed based on their similarities, dependencies, and differences, and then grouped to avoid differences. These main clusters draws inspiration from Bradáč and Kostolányová (2017), Isaías (2018) and El Janati et al. (2018), who identify different design themes of an AI enabled learning system. Learning Assessment cluster reveals principles concerned with assessment of the learning experience. The DPs in this category monitors and tracks progress of students towards the learning objectives through learning activities. Design and Presentation cluster reveals principles connected to the visual presentation and interface according to the needs and preferences of students. The third cluster i.e., Adaptation and Personalization, includes DPs regarding dynamic adjustment of the learning process and personalization learning. The fouth cluster i.e., Data processing with Learning Analytics and AI cluster highlights principles on procession of data using learning analytics and AI. Lastly, learning content includes principles regarding selection of the right pedagogical content, which includes knowledge, preferences, and context. The 5clusters that include a total of 24 DPs are depicted in the table below.

Table 3 Proposed DPs for an AI adaptive Learning System

Learning Assessment	
DP1.1: The system should allow flexible alterations to assignments based on learning objectives	**DP1.6:** The system should have metrics (online computations) that can be computed effectively and regularly updated as students' progress through the course.
DP1.2: There should be identification and measurement of skills, for attainment of skills	**DP1.7:** The system should reliably measure performance, ensuring consistent evaluation of the learning tasks over time and across students
DP1.3: The system should produce valid measures of skill mastery (i.e., minimizing false positive and false negative evaluation errors)	**DP1.8:** The system should provide precise feedback immediately after task completion, and enable students to interpret the feedback by contextualizing it appropriately
DP1.4: The system should provide regular practice assignments to students to test their progress in skills acquisition.	**DP1.9:** The system should create realistic and manageable practice exercises that limited in scope and enable students to focus on specific skills.
DP1.5: The system should direct students towards appropriate resources, for specific skills that are not mastered.	**DP1.10:** The system should let students assess their understanding privately and measure aggregated achievement discreetly.

Design and Presentation	Adaptation and Personalization	Data Processing using Learning Analytics & AI	Learning Content
•**DP2.1:** The system should adapt well to the increasing number of users and data	•**DP3.1:** In the system, affective information (information on interests, attitudes, and motivations of students) should be used for adaptive instruction	•**DP4.1:** The system should learn based on artificial intelligence and machine learning	•**DP5.1:** The system should include learner preferences, experience, and knowledge
			•**DP5.2:** There should be a recent updated learner profile available on the system.
•**DP2.2**: The system should be context-sensitive i.e., integrate environmental affordances into the design		•**DP4.2:** The system should analyze and make sense of students' usages (such as logs) to understand their behavioral or learning patterns	• **DP5.3:** The process of personal learner profile creation should not be annoying for the student, should not be time consuming, should not demand significant efforts from students
			•**DP5.4:** The expert model in the system must present the required learner proficiency within the particulars and specifics of the learning activities
•**DP2.3:** The user interface of the system should be engaging. Productive forms of disciplinary engagement with resources, peers and instructors should be facilitated and rewarded	•**DP3.2**: Learner models in the systems should include information regarding the depth of knowledge desired and align expectations appropriately to the expertise level of the student.	•**DP4.3:** The system should collect completion data for required and optional assignments	•**DP5.5:** The system should give students authority over their disciplinary engagement and hold students accountable for their engagement
			•**DP5.6:** The system should include forecasting of students' knowledge

The above-mentioned DPs from the findings are believed to guide well the development and design of AI-enabled ALS that would successfully promote both adaptive and personalized learning in a university. The set of proposed DPs are not only theoretically grounded, but also empirically, as they have been applied to some degree on most of the AI enabled learning systems, such as QuizBot, Fishtree, Smart Sparrow and SmartU. However, the applicability of these DPs for the mentioned systems is different from principle to principle, and different from cluster to cluster. For instance, SmartU and QuizBot apply extensively DPs in the Learning Assessment cluster, while Fishtree and Smart Sparrow apply extensively DPs in the Adaptation and Personalization cluster. Thus, despite the empirical efforts on developing AI - enabled adaptive systems, little research and effort have been invested.

This study contributes to previous literature reviews studies and studies in the field of AI enabled ALS by identifying DPs. The study provides important insights and thus contributes to overcoming problems in AI enabled ALS field, such as design issues. One of future practical opportunities opened by this study include developers designing better AI-enabled ALS by conducting an empirical research that will design, validate, and examine the effectiveness of these DPs. An Action Design Research (ADR), can be used as the empirical research to design and validate, based on its characteristics, potential and stages. ADR deals with research area of concern that addresses technological issues (such as need of DPs for AI based ALS) together with its socio-technical setting (higher education institution setting), where technology is utilized. (Sein et al. 2011). Moreover, this study contributes to increasing the usage of AI enabled ALS in real settings by providing universal principles and guidelines that can be used to develop such systems (Kabudi et al. 2021) . This study also opens future research opportunities to design better AI enabled ALS that solve specific and overlooked learning problems such as issues relating to students' background and their learning profiles being integrated into the systems, and difficulty in attaining learners' skills (Kabudi et al. 2021).

Conclusion

This study investigated to establish theoretically and empirically grounded DPs from academic literature. These 24 DPs deal with various design areas such as design and Presentation; Learning Content; Learning Assessment; Adaptation and Personalization; and Data Processing using Learning Analytics and AI. The results indicate the need of underlying DPs of an AI adaptive learning system, that address several challenges such as difficulty in attaining learner skills. These principles will be further tested and evaluated in the next phases of this study. The study contributes to the application of AI in education and adaptive learning, by identifying the important DPs developers should consider while designing the system. This study extends the existing literature on design of AI based ALS, by proposing DPs that will develop systems that promote adaptive learning in universities. This study aims thus to bring awareness to researchers and system developers and designers. This study provides important insights for all interested in AI and adaptive learning system. Further studies should explore the extent to which these DPs are applied to the existing pool of . A further study that will validate the principles as an evaluation tool for AI-enabled ALS can be helpful in the field. Also, it will be valuable to study and examine the relationship between applying these DPs and learning outcomes. The author acknowledge that study was associated with several limitations. The search words, strings and chosen academic databases may have limited the review. Also, more ALS that have been used in educational settings could be part of this study.

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