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Deriving Design Principles for AI-Adaptive Learning Systems: Findings from Interviews with Experts

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Abstract. AI applications are increasing in the field of education, from laboratory set-ups to contemporary and complex learning systems. A great example of such systems is AI-enabled adaptive learning systems (AI-ALS) that promote adaptive learning. Despite its promised potential, there are challenges such as design issues, highly complex models, and lack of evidence-based guidelines and design principles that hinder the large-scale adoption and implementation of AI-ALS. The goal of this paper thus is to establish a set of empirically grounded design principles (DPs) of AI-ALS, that would serve well in a university context. 22 interviews were con-ducted with experts knowledgeable about the design and development of AI-ALS. Several rounds of coding and deep analysis of the expert interviews revealed features and functionalities of AI-ALS; purposes for designing and using AI-ALS; and recommended improvements for AI-ALS as requirements. These requirements were translated to 13 preliminary DPs. The findings of this study serve as a guide on how to better design AI-ALS, that will improve the learning experiences of students.

Keywords: AI · AIEd · Design principles · Adaptive learning systems · Adaptive learning

1 Introduction

The application of AI in Education (AIEd) has increased due to its promising potential to provide personalized and adaptive learning, provide instant and correct feedback, facilitate meaningful interactions, improve students' engagement and learning outcomes [1]. Thus, AI has been transforming the ways of teaching and learning in education and has contributed to maintaining high quality teaching learning during global crisis like the pandemic [2]. AI in the education field has evolved, from idealized laboratory set-ups to learning contexts with more complexity. These more complex and advanced learning systems are gaining traction in to be used in real learning settings. Examples of such

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systems include Adaptive Learning systems that are enabled by AI, intelligent tutoring systems, and recommender systems. AI enabled adaptive learning systems (AI-ALS) are platforms that adapt to the learning strategies of students, changing and modifying the order and the difficulty level of learning tasks, based on the abilities of students [3, 4].

The potential and importance of such systems is well established, however, AI enabled learning interventions and applications, especially AI-ALS remain largely at an experimental stage [5, 6]. A recent literature review in the area noted a critical gap between what AI-ALS could be and can do, and what the current systems do, that is how they are implemented in real educational environments [7]. Moreover, few studies in the AIEd field have addressed design issues and highly complex models of these contemporary learning systems [8–10]. In addition, there is still gap in the research of AIEd to provide evidence-based guidelines and support for AI-ALS, as AI technology advances rapidly [9]. Thus, lack of evidence-based guidelines and de-sign principles for AI-ALS applications affect its large-scale implementation and adoption [7, 11]. Most of these AI-ALS are still "restricted to research projects and a few commercial applications" despite their known potential [12]. With AI evolving rapidly in the education field, issues such as the integration of AI-ALS systems within real education contexts need to be addressed.

To further advance AI-ALS in education, this article narrows the gap between experimental research and practice by establishing a set of empirically grounded design principles (DPs) of AI-ALS. These DPs are formulated based on the design, development, and implementation of AI-ALS, that would serve well in a university context. The main research question (RQ) that guided this empirical research is: *What fundamental design principles for developing and implementing an AI-ALS can be dis-tilled from practice?*

To address our RQ we conducted in-depth interviews with AIEd technological experts, who are knowledgeable with the design and development of AI-ALS. Our findings contribute to the ongoing research on the digitalisation of education and show how IS research can lead the way in designing the learning systems of the future. The paper will help the AI in Education (AIEd) community, including developers, designers, lecturers, researchers, and other stakeholders to build better understanding on AI-ALS research from different perspectives such as design, development, implementation, and evaluation.

2 Theoretical Background

With AI technology thriving in recent years, its applications in the form of AI-ALS have increased [1, 4]. AI-ALS generally are digital learning tools enabled by AI, that "adapts, as well as possible, to the learner, so that the learning process is optimized, and/or the student performance improve" [13]. Most recent AI-ALS include Smart Sparrow, Knewton, Fishtree, INSPIREus, ProSys, QuizBot, OPERA, LearnSmart, Connect ™, ACTIVEMATH, and Student Diagnosis, Assistance, Evaluation System based on Artificial Intelligence (StuDiAsE) [7]. AI-ALS were developed to help address most challenges that occurred in technology enhanced learning environments. These included resource limitations, difficulty in students attaining and mastering their learning skills, variety in learning abilities of students, and diversity of students' backgrounds [9, 14]. AI-ALS motivates students to embark on their own learning journey through automated feedback cycles in these systems. The capability of AI-ALS to enable personalized learning of students sparks interest in the field of education, and thus marks its enthusiasm to be used [1]. This is mainly due to the promising potentials of the systems such to provide customized learning to students (adaptive learning), to offer fast feedback and dynamic assessments, and to facilitate meaningful group collaborations and engagements in learning settings [15].

The design of AI-ALS has been influenced by research on AI, learning analytics, educational data mining techniques, learning taxonomies and cognitive theories [10]. The essential and underlying design characteristics of these systems consist of user interface (that handles the interaction between the learning system and students); monitoring of the students' internal state (e.g., cognitive, behavioural, and emotional); observation of the external state of the learning environment; and adaptation [7, 16]. However, while numerous AI-ALS are modelled as above, the inherent and basic design principles that guide the design, development and even implementation of these systems are not clearly known. Most of these AI-ALS are still "restricted to research projects and a few commercial applications" despite their known potential [12]. Not only that, but design issues of these systems are also still mentioned in literature [7]. There are still several problems that have yet to be addressed by AI-ALS. These issues include difficulty in attaining learners' skills, issues related to students' backgrounds and profiles and personalization issues [3, 7]. Thus, this research aims to address the above-mentioned gaps by deriving fundamental and common user-centred DPs for AI-ALS.

3 Research Method

The authors accomplished the empirical examination of the DPs via expert inter-views and content analysis. Expert interviews, in a semi-structured format, were used to obtain, explore, and understand the perspectives of AI technological subjects in-volved on developing, designing, and implementing AI-ALS. Experts are defined as people who have the technical, process and interpretive knowledge in their areas of expertise [17, 18].We defined and categorized our experts in three major interview sub-jects: Developer & Designer and Researchers. Developer & Designer is an inter-view subject that discussed on the design and developing aspects of AI-ALS. The researchers group consisted of AI technological experts that are interested and re-search extensively on AI in education. The authors identified 143 experts, based on literature search and their Google Scholar profiles, and who appeared to be active in the AIEd community, based on their publications on AI-ALS. They were randomly selected using convenience sampling technique. The experts were then contacted via email. Data were collected until theoretical saturation was achieved on various aspects of participant experiences and perspectives regarding the development, design, and implementation of AI-ALS, which was the focus of this study. A total of 22 experts were interviewed. Table 1 shows the profile of our experts.

The interviews were conducted face-to-face, using videoconferencing tool. The interviews were conducted in English. The interviews were transcribed verbatim, focusing mainly on the spoken word. Qualitative content analysis was used to evaluate expert interviews. This method is the most comprehensive and exact way to analyse data collected

Table 1. Respondents profile

Expert ID	Category	Profession	Country
1	Designer & Developer	Professor	Australia
2	Designer & Developer	PhD Student	Switzerland
3	Researcher	Project Manager	France
4	Researcher	Lecturer	Tunisia
5	Researcher	Professor	Switzerland
6	Designer & Developer	Software Engineer	United Kingdom
7	Researcher	Professor	Germany
8	Researcher	Senior Lecturer	United Kingdom
9	Researcher	Assistant Professor	United States of America
10	Designer & Developer	PhD Student	United States of America
11	Designer & Developer	Head of Research Lab	Russia
12	Researcher	Professor	China
13	Researcher	Professor	United Kingdom
14	Designer & Developer	Professor	United States of America
15	Researcher	Professor	Brazil
16	Designer & Developer	Lecturer	Singapore
17	Designer & Developer	Professor	Morocco
18	Designer & Developer	PhD Student	South Korea
19	Researcher	Lecturer	Ukraine
20	Researcher	PhD Student	United States of America
21	Researcher	Professor	United Kingdom
22	Researcher	Professor	United States of America

qualitatively [19]. The data analysis involved transcribing the recorded conversation with interviewees. The interviews were recorded, both in video and audio formats, total approximately 22 h of conversation. This is a large amount of qualitative data, where each recording took 6 to 8 h of transcription work. Qualitative content analysis orders the obtained information according to certain theoretically and empirically reasonable points. In this study, the information obtained from experts, was analysed using codes. All transcriptions were entered into NVivo 12 software for qualitative analysis. An initial list of generated codes was created, based on identified and placed phrases, sentences, and paragraphs. Using an iterative approach, the patterns were revised, updated, and recategorized. In the next section provides the resultant first order categories, in form of requirements are provided.

4 Presentation of Results

This section presents the findings of our data collection. The findings reported in this paper are based on the analysed data collected from 22 interviewees. Of the 22 experts who were interviewed, 6 were female, and 16 were male. Majority came from USA (5) followed by UK (4) and Switzerland (2). Moreover, majority of these experts came from universities and research groups. Three types of results are provided be-fore discussing the findings of the study, as seen below.

4.1 Meaningful Features and Functionalities of AI-ALS

Based on the experts' answers, both functional and non-functional requirements for AI-ALS were gathered. The author derived and formed several categories. The first category, based on experts' answers on Part 2 questions, included identified meaningful features and functionalities of AI-ALS (features that worked well).

Experts identified Game-based learning component (F1) important and that worked well. Specifically, expert No.18 stated, "*Many of my students like to "play games"; gamifications seem nice to "catch" the student's attention*". Moreover, experts identified Individualized/Personalized Feedback and Remediation as an important feature, and thus was coded as (F2). In particular, expert No.7 justified this by explaining that "*There are some students that really like that they get personalized feedback"*." Other themes that were coded as features and functionalities that worked well, are depicted in Table 2.

Table 2. Meaningful features and functionalities of AI-ALS

ID	Features and Functionalities of AI-ALS that worked well
F1.	Game based Learning Component
F2.	Individualized/Personalized Feedback and Remediation
F3.	Adaptation mechanisms - Adaptivity Methods
F4.	Effective Learning Analytics
F5.	Measurement Of Skills, And Thus Attainment of Mastery of Skills
F6.	Interactive visualized educational dashboard (e.g., LA dashboards)
F7.	AI & ML Techniques/Algorithms
F8.	Facial Affective Computing to Develop an Affective Interface
F9.	Application Of Learning Theories/Taxonomies
F10.	Affective Model (based on emotions)-Multimodal Analytics
F11.	Student Model -Knowledge Model
F12.	Learner Profiles
F13.	Teacher Writing their own Content for Assessment
F14.	Learning Early-Warning Model (based on Knowledge Points)
F15.	Well-scaffold activities and Interventions

4.2 Features and Functionalities of AI-ALS that Had Issues

The other category, based on experts' answers on Part 2 questions, included identified features and functionalities of AI-ALS that did not work well. Algorithm Not Recognizing the Level of Skill You need To Master was identified in this category, and thus was coded as (C1). Expert No.2 gave an example that highlights on this issue: *""If, if there's like a, you get like an augmentation, highlighting aggregation…and you think OK, you write a new argument, but the algorithm doesn't recognize it, and that's probably like the biggest flaw, right?".*

Another feature that did not work well was coded as No Assessment of Open-Ended Questions as expected (C2). Expert No.1 gave an example of a scenario where such an issue occurred *"Another thing that we did not like is not to have any functionality that would assess an open-ended question*". Lack of "Human in the Loop" Model was another functionality of AI-ALS that users complained on as an issue. More themes that were coded as features and functionalities of AI-ALS that did not work well, are identified in the Table 3.

Table 3. Meaningful features and functionalities of AI-ALS

ID	Features and Functionalities of AI-ALS that had issues
C1.	Algorithm Not Recognizing the Level of Skill You need To Master
C2.	No Assessment of Open-Ended Questions
C3.	Facial Affective Computing to Develop an Affective Interface is Missing
C4.	Not Enough Graduations of Difficulty for A student
C5.	Lack of "Human in the Loop" Model

4.3 Meaningful Features and Functionalities of AI-ALS

Purposes for developing and using AI-ALS was the type of results identified, based on the experts' answers on Part 2 questions. Our experts identified the reasons of developing and using AI-ALS in a learning environment. The main coded purpose stated by our experts was mainly to enhance Students' Cognitive & Learning Skills that need to be Mastered (i.e., Mastery Learning) (P1). Expert No. 20 highlighted the significance of enhancing students' skills: "*It's important to know when the students reach mastery…so that you can get them out of the current problem set ….and move them onto a new one….and keep them you know working efficiently….and not practicing problems that they don't need to practice.*"

Another major identified and coded purpose was (P2) to provide (Adaptive, Individualized and Peer) feedback. Expert No.5 explained that such systems that provide peer feedback, or individualized feedback "*…try to inform your learning progress because it's important to reflect upon… like have I really understood this, am I really capable of applying this or something where you need?…….Something like feedback on right*?".

To have AI techniques, ML, Adaptation mechanisms to provide recommendations and enhance adaptiveness was also coded as a theme (P3). Expert No.3 indicated that *"But in reality, an adaptive system is based really in some basic characteristic to adapt some aspects of the content…"*. Expert No.17 stated that *"The objective is to offer learners adaptive learning processes based on their style and knowledge. This will allow a personalized and efficient learning since the learner could use resources that he prefers and could advance on his own pace"*. Other coded themes that were mentioned by our experts as Purposes, and its frequency, are highlighted in the table below (Table 4).

Table 4. Purposes for developing and using AI-ALS

ID	Purposes for developing and using AI-ALS
P1.	Enhance Students' Cognitive & Learning Skills that need to be Mastered (i.e., Mastery Learning)
P2.	Provide (Adaptive, Individualized and Peer) Feedback
P3.	Have AI techniques, ML, Adaptation mechanisms to provide recommendations and enhance adaptiveness
P4.	To help students with boredom, frustrations, and emotion issues
P5.	Know Students' Personal Preferences and Skill Level
P6.	To detect Student's Progression
P7.	Provide Adaptive Assessment
P8.	To predict how the student is learning to determine what to do next
P9.	To be able to detect student inquiry
P10.	Enhance the Cognitive State and Abilities of Students
P11.	Provide Adaptive Support To students based on Learning Analytics Data

5 Discussion

As illustrated above in the Results Sections, 13 Features and Functionalities that worked well (F), 5 Features and Functionalities that had issues (C) and 11 Purposes of building AI-ALS (P) were identified. These Features, Functionalities and Purposes were identified as requirements for designing and developing AI-ALS. An interesting insight that is revealed from this study is the importance to enhance Students' Cognitive & Learning Skills that need to be Mastered (i.e., Mastery Learning). Moreover, provide (Adaptive, Individualized and Peer) Feedback is also identified as an important theme. These themes have been identified in accordance with the recommendations of [3, 7] for the design of AI-ALS to address issues such as difficulty obtaining learners' skills, background and profile issues, and personalization issues. Other relevant themes that were identified in this study included Learning Analytics and Automated Assessment. The functional requirements, that include the 13 Fs and 5 Cs emphasize on the features and functions AI-ALS should have and perform. The 11 Ps that comprises the non-functional requirements, emphasize more on the performance characteristics (i.e., what the system intends to do and help) of AI-ALS. Both these functional and non-functional requirements are used to build up the expected preliminary empirically DPs of an AI-ALS.

The importance of these features and functionalities were also identified during the expert interviews' session. Specifically, expert No. 22 stated that *"….to create mastery learning requires a complex interplay between the analytics,* ***the model design, the system activity design*** *and then how you deploy it in interventions*". Furthermore, expert No. 19 also highlighted the essence of such models by stating *"if you don't use* ***the model of this student (student model) and the model of the of his knowledge****, you cannot automatically……Uh, consider the progress of the student"*. Thus, these functional and non-functional requirements are used to build up the expected preliminary empirically DPs of an AI-ALS. The requirements were analysed based on their similarities, differences, and dependencies, and then grouped to avoid differences.

It must be noted that the DPs are not organized in any prioritized order. Moreover, the author understands that these categorized and identified parts of the system are not separated but are so interconnected to form the complex connected AI-ALS environment. Expert No. 22 elaborated on these by stating "*In general, the design of these systems is a highly complex integrated process, and if you don't get all aspects of what you talked about …for a certain kind of technology, the technology won't work*.". Thus, 13 preliminary DPs for an AI-ALS based on these results were formulated, and the number of experts that stated them are depicted below (Table 5).

Table 5. Preliminary DPs for an AI-ALS

Design principle	Requirements	Expert ID
Principle of Automated Assessment: AI-ALS should include more specialized AI-techniques and ML algorithms to detect and assess well the open-ended questions	F7. AI & ML Techniques/Algorithms	1, 7, 9, 11, 12, 13, 16, 17, 19, 20
	C1. Algorithm Not Recognizing the Level of Skill You need To Master	
	C2. No Assessment of Open-Ended Questions	
	P3. Have AI techniques, ML, Adaptation mechanisms to provide recommendations and enhance adaptiveness	

(*continued*)

Table 5. (*continued*)

Design principle	Requirements	Expert ID
	P8. To predict how the student is learning in order to determine what to do next	
	P9. To be able to detect student inquiry	
Principle of Human-in-the Loop (HITL): AI-ALS should incorporate Human in the Loop Model	C5. Lack of "Human in the Loop" Model	1, 16
Principle of Students' Skills Mastery: AI-ALS should have distinct Modules for Building and Measuring students' Cognitive & Learning Skills that need to be Mastered (i.e., Mastery Learning)	F5. Measurement Of Skills, And Thus Attainment of Mastery of Skills	2, 5, 7, 9, 10, 11, 13, 14, 15, 17, 18, 20, 21, 22
	P1. Enhance Students' Cognitive & Learning Skills that need to be Mastered (i.e., Mastery Learning)	
	P5. Know Students' Personal Preferences and Skill Level	
	P6. To detect Student's Progression	
	F11. Student Model-Knowledge Model	
	P10. Enhance the Cognitive State and Abilities of Students	
Principle of Early-Warning Model: AI-ALS should include an Early-Warning Model for Learning, based on Knowledge Points	F14. Learning Early-Warning Model (based on Knowledge Points	10, 11, 12, 19, 20, 22
Principle of Games-based learning: AI-ALS should include games resources and components for learning	F1. Game based Learning Component	10, 13, 14, 15
Principle of Learning Analytics (LA): AI-ALS should include an effective LA module	F4. Effective Learning Analytics	1, 2, 11, 12, 13, 14, 16, 19

(*continued*)

Table 5. (*continued*)

Design principle	Requirements	Expert ID
	P6. To detect Student's Progression	
	F6. Interactive visualized educational dashboard (e.g., LA dashboards)	
	P11. Provide Adaptive Support To students based on Learning Analytics Data	
Principle of Affecting Learning Model: AI-ALS should include an Affective Model (based on emotions), where Multimodal Analytics will be done. It should also include an Affective Interface	F10. Affective Model (based on emotions)-Multimodal Analytics	2, 6, 10, 13, 14, 16, 20, 21
	P4. To help students with boredom, frustrations, and emotion issues	
	F8. Facial Affective Computing to Develop an Affective Interface	
	C3. Facial Affective Computing to Develop an Affective Interface is Missing	
	P4. To help students with boredom, frustrations, and emotion issues	
Principle of Personalized and Adaptive Feedback: AI-ALS should provide Individualized/Personalized, Adaptive and Peer Feedback; and Remediation	F2. Individualized/Personalized Feedback and Remediation	2, 5, 7, 11, 12, 13, 16, 20, 22
	P2. Provide (Adaptive, Individualized and Peer) Feedback	
Principle of Sustainable Design: AI-ALS should be context-sensitive i.e., integrate environmental affordances and learning theories/taxonomies into the design	F9. Application Of Learning Theories/Taxonomies	1, 2, 5, 7, 11, 12

(*continued*)

Table 5. (*continued*)

Design principle	Requirements	Expert ID
Principle of Recommender and Adaptations Mechanisms: AI-ALS should include adaptation mechanisms, to provide recommendations, enhance adaptiveness and ensure graduations of difficulty	F3. Adaptation mechanisms - Adaptivity Methods C4. Not Enough Graduations of Difficulty for A student P7. Provide Adaptive Assessment P3. Have AI techniques, ML, Adaptation mechanisms to provide recommendations and enhance adaptiveness	3, 4, 9, 10, 11, 12, 13, 15, 18, 22
Principle of Actionable information: AI-ALS should have "advanced/updated" learner profiles - classification of students based on their learning strategies	F12. Learner Profiles i.e., providing actionable information about learners and their learning, and give the right type of assessment tasks (whether to learn by text or videos) F13. Well-scaffold activities and Interventions	11, 13, 17, 22
Principle of Teacher–AI Complementarity: Teachers should be included in the design and development of AI-ALS e.g. write and create their own content	F13. Teacher Writing their own Content for Assessment	2, 4, 10, 11, 14, 16, 20, 21, 22
Principle of Responsible AI: AI-ALS should be fair, transparent, explainable, and human-centric. Privacy and Security aspects should be considered	F14. Learning Early-Warning Model (based on Knowledge Points C5. Lack of "Human in the Loop" Model	12, 14, 20, 21

6 Implications and Future Recommendations

The study contributes to the ongoing research on the digitalisation of education. We have identified a set of empirically grounded design principles (DPs) of AI-ALS that show how IS research can lead the way in designing the learning systems of the future. The findings presented above have both theoretical and practical implications. This study contributes to the field of AIEd, by identifying a set of empirically grounded design principles that can be used to develop, implement, and improve AI-ALS. This paper contributes to AIEd research by following the recent call for future work to build evidence-based guidelines and design principles for AI-ALS applications [7, 11]. Most of these design statements, support main findings in existing research such as of [4, 9, 10] and emphasize them. The findings of this study showed the essence analytics of learners' data, behaviour, and emotions, to support learning and teaching activities in education [10, 20]. This study also serves as a guide for developers and AIEd technological experts on how to better design AI-ALS, that will solve identified learning challenges and improve learning experiences of students. The study not only guide AI-ALS designers, developers, and technological experts, but also educators and researchers, who spearhead AI based learning interventions through research and practice.

The formulated DPs are not theoretically grounded only, but also empirically as they have been utilized to develop existing AI-ALS such as Smart Sparrow and ASSISTMENTS. However, the extent of applicability of these DPs is not well known. Thus, our findings can help researchers and practitioners to better design the learning systems of the future and conduct studies on validating and examining the effectiveness of these DPs. In the long term, we aim to not only provide preliminary DPs, but also empirical evaluations of our DPs for AI-ALS. The preliminary empirically DPs serves as a snapshot of the current AIEd practice, which may stimulate more empirical studies in this field.

The study, especially with the methodology used, is not without limitations. The sample population chosen might hinder the transferability and generalizability of the study given that the author worked with a small sample within the context of AIEd field. Thus, given the small sample size of the study, further research should focus on incorporating more perspectives and opinions from other experts in AIEd community. Moreover, the provides perspectives from experts in a developed context (U.S and Europe) and little from the developing countries. This might lead a potential bias in our findings. Further research should include and compare from other countries, especially in the developing context.

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