



HAL
open science

Systematic literature review (SLR) of research on adaptive/personalized learning and artificial intelligence in learning

Vikhram Kofi Duffour

► To cite this version:

Vikhram Kofi Duffour. Systematic literature review (SLR) of research on adaptive/personalized learning and artificial intelligence in learning. Business administration. 2020. dumas-03151973

HAL Id: dumas-03151973

<https://dumas.ccsd.cnrs.fr/dumas-03151973>

Submitted on 25 Feb 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0 International License



**SYSTEMATIC LITERATURE REVIEW (SLR) OF RESEARCH ON
ADAPTIVE/PERSONALIZED LEARNING AND ARTIFICIAL INTELLIGENCE IN
LEARNING.**

Submitted by:

Vikhram Kofi DUFFOUR - 11922102

Supervised by:

Carine DOMINGUEZ-PÉRY, Ph.D., Full Professor
Samuel FOSSO WAMBA, Ph.D., HDR

June 2020

**M2 - ADVANCED RESEARCH IN MANAGEMENT OF INFORMATION
SYSTEMS (ARAMIS)**
2019 - 2020



ACKNOWLEDGEMENTS

First and foremost, praises and thanks to the God, the Almighty, for His showers of blessings throughout my research work to complete the research successfully.

I would like to express my deep and sincere gratitude to my research supervisors, Dr. Carine DOMINGUEZ-PÉRY, Ph.D., Full Professor and Head, Advanced Research in Management of Information Systems (ARAMIS), Grenoble IAE and Dr. Samuel FOSSO WAMBA, Ph.D., Full Professor, Information Systems and Head of Artificial and Business Analytics Cluster, Information, Operations and Management Sciences, Toulouse Business School, for inspiring me to do this research and providing invaluable guidance throughout this research. Your dynamism, vision, sincerity and motivation have deeply inspired me. It was a great privilege and honor to work and study under your guidance and I am grateful.

I am extremely grateful to my parents for their love, prayers, caring and sacrifices for educating and preparing me for my future. I express my thanks to my sister and brothers for their support and valuable prayers. My Special thanks goes to my friend and brother Samuel Oteng-Seifah for the keen interest shown to complete this thesis successfully.

TABLE OF CONTENTS

1.0 INTRODUCTION	1
2.0 LITERATURE REVIEW	3
2.1 Adaptive/Personalized Learning	3
2.2 Role of Technology in adaptive/personalized learning	6
2.3.0 Artificial Intelligence as enabler of adaptive/personalized learning?	11
2.3.1 Artificial Intelligence (AI): An introduction	11
2.3.2 Role of Artificial Intelligence in the context of education	12
2.4 AI in adaptive/personalized learning	14
2.4.1 Intelligent Tutoring System	15
2.4.2 Swarm Intelligence	15
2.4.3 Game-Based Learning	16
3.0 METHODOLOGY	20
3.1 Search Process	23
3.2 Research Question	27
3.3 Research Methods	27
3.3.1 Inclusion and exclusion criteria	27
3.3.2 Coding Scheme	32
4.0 RESULTS	33
4.1 Similarities between adaptive learning and personalized learning.	33
4.2 Distribution of Artificial Intelligence (AI) techniques	33
4.3 Distribution of learning outcomes.	35
4.4 Distribution of technologies contribution to assessing personalized learning to help students' achievement.	35
5.0 DISCUSSION	36
5.1 Research issues related to similarities and AI techniques	36
5.2 Research issues related to learning outcomes	36
5.3 Research issues related to the role of AI in learning	37
6.0 CONCLUSION	38
REFERENCES	39
GLOSSARY	49
APPENDIX A	51

List of Tables

Table 1. Summary of the role of technology in adaptive/personalized learning.....	10
Table 2. Continued.....	10
Table 3. Summary of the use of AI in Personalized Learning.....	18
Table 4. Emphasizes of Quantitative, Qualitative and Mixed Methods.....	21
Table 5. Selected journals and conference proceedings.....	24
Table 6. Top 1 & 2 CNRS Journal for publications.....	25
Table 7. Comparison between adaptive learning and personalized learning.....	33
Table 8. Adaptive/personalized learning system.....	37

List of Figures

Figure 1. A typical classroom of Personalized Learning Environment. <i>Source: Transforming the culture of teaching and learning: four race to the top – district grantees' implementation of personalized learning.</i>	5
Figure 2. Fuentes' (2008) sequential exploratory mixed methods design. Source (Hesse-Biber, 2010: 459).	22
Figure 3. The distribution of articles published on personalized learning, adaptive learning and artificial intelligence in learning from 2002-2020.	26
Figure 4. The procedures for data collection and processing. (Primarily adapted from Zawacki-Richter et al., 2019: 7).....	28
Figure 5. Density of Keywords co-occurrence network of adaptive/personalized learning.	29
Figure 6. Co-citation analysis network of references cited by adaptive/personalized learning and artificial intelligence in learning publications period 2000-2020.	30
Figure 7. Bibliographic coupling based on documents published between 2000 and 2020.	31
Figure 8. Distribution of AI techniques	34
Figure 9. Distribution of sub-categories of learning outcomes.....	34
Figure 10. The distribution of technologies contribution to assessing personalized learning to help students' achievement.	34

ABSTRACT

This study aims to explore adaptive/personalized learning and artificial intelligence in learning geared towards students' achievement or outcome of related articles. It begins with some definitions of the concepts. A systematic literature review was conducted and identified 68 articles from two decade, i.e., 2000-2020. It also presents the research methodologies/approaches used during the study and investigates similarities between adaptive learning and personalized learning, learning outcomes, artificial intelligence techniques and contribution of artificial intelligence and other technologies in assessing adaptive/personalized learning. In addition, adaptive/personalized learning have the same element i.e. individual differences, individual performance and artificial intelligence techniques such as artificial neural network, fuzzy logic, decision trees, etc. are enablers to deliver adaptive instructions, guidance and evaluate learners and role of AI in learning. The conclusions reflect on discussions, limitations etc., and the study recommended the development AI in learning on higher order thinking and wearable devices evaluation in personalized learning.

1.0 INTRODUCTION

With the recent rapid advances in computer technologies, educational researchers have developed computer-assisted learning methods, tools, and environments (Hwang, 2002). Computer-assisted learning systems aid with learning tools to provide a more adaptive/personalized learning environment. Adaptive/personalized learning has become possible through the implementation of intelligent learning systems, the integration of preferences of the learners, the analysis of individual learning data, etc. These systems use artificial intelligent (AI) techniques or technologies in fostering learning processes. AI has emerged within the education sector, in which users interact and learn with hard and soft technologies, apparently, many AI-based applications have become part of our routines. As Housman (2018: 50) emphasized, "AI is capable of two things: (1) automating repetitive tasks by predicting outcomes on human-labelled data, and (2) enhancing human decision-making by feeding problems to algorithms developed by humans."

AI and adaptive/personalized learning technologies are seen as important within educational technology. According to experts, AI in education is anticipated to grow by 48% in the 2018 to 2022 period, although the Horizon Report 2019 Higher Education Edition (EDUCASE, 2019) predicts that teaching and learning related to AI applications are expected to grow even more significantly. Adaptive learning technologies dynamically adjust to the level or type of course content based on the abilities or skill achievement of an individual, in ways that accelerate the performance of a learner with both automated and instructor interventions (EDUCAUSE 2016).

Personalized learning refers to a learning paradigm aimed at promoting the individual development of students, emphasizing that the learning process should adopt appropriate teaching methods, techniques, content, starting points, processes and assessment methods to meet the students' individual characteristics and development potential, so that all aspects of students can be fully developed (Li 2015). Klačnja-Milićević, Vesin, Ivanović, and Budimac (2011: 885) claimed that "personalized learning occurs when e-learning systems intentionally seek to develop educational environments that fit in with each other" while (Chen et al, 2005: 239) suggested a personalized system that offers "learning paths that can be tailored to the various levels of complexity of course materials and learners' skills".

The aim of this study is to provide an overview of the influence of artificial intelligence (AI) in the learning process and how adaptive/personalised learning affects student achievements in light of the dynamic development in recent years and the growing interest in this field, a systematic review is needed to identify the development, patterns and future directions of study and focus on learning. Specifically, this research addresses the following research questions by means of a systematic review:

- What is the purpose of artificial intelligence (AI) and adaptive/personalized learning?
- How does personalized learning affect student achievements?

After the introduction of the research (Section 1), Section 2 provides definitions for adaptive learning, personalized learning and artificial intelligence respectively with a table to summary the role of technology, highlight artificial intelligence as enabler of adaptive/personalized learning. Section 3 introduces the research methodology, followed by section 4, which presents the results and Section 5 discusses the results, while Section 6 serves as the conclusion.

2.0 LITERATURE REVIEW

2.1 Adaptive/Personalized Learning

The concept of adaptive/personalized learning differs in the contexts in which it is being applied today. Adaptive learning is one methodology that provides personalized learning, with the goal of providing secure, effective and tailored learning paths for engaging every learner. They adapt dynamically to the student experiences and performance levels, presenting the content types in an acceptable sequence that individual learner need to make progress at different points in time. Adaptive learning system uses data-driven, curriculum and remediation methods, which employ algorithms, evaluations, student feedback, instructor adjustments/interventions, and multiple media to deliver new learning material to students who have achieved mastery and remediation to those who have not.

Snow and Farr (1987) suggested that sound learning theories are incomplete or unrealistic if they do not provide a whole person's point of view, including both cognitive and affective aspects, implying that no educational program can be successful without due attention to the personal learning needs of individual students. On the other hand, Russell (1997) suggested that educators should identify and acknowledge learning differences and make maximum use of the available technology to support them accordingly. The use of adaptive hypermedia to support individual learning was proposed by Brusilovsky (1998). The concept of adaptive hypermedia is to adapt the course content for a particular student based on the profile or records of the learner. Paolucci (1998) discussed the value of hypermedia individualisation to adapt and personalize every strategy. Adaptive hypermedia systems should be capable of diagnosing and recognizing the biases of each student in order to ensure personalisation.

Lo, Wang, and Yeh (2004) developed a Hypermedia-based English Learning system for Prepositions (HELP) based on the definition, which provides non-native English language diagnosis speakers with remedial instruction according to their assessment results. Brusilovsky and Peylo (2003) argued that adaptive learning systems were built upon the development of adaptive media in the web, and defined adaptive learning as generally referring to how to use computer systems or tools to provide tailored learning materials or activities to cater to personalized learning needs.

On the other hand, constructivist views of learning emphasize a radically different set of principles and could require a different kind of intelligent system to support learning (Leidner & Jarvenpaa, 1995, O'Loughlin, 1992). The constructivist approach sees knowledge as being built independently from what the learners do in their experiential environments, and cannot be described objectively. Because what is learned at a given time is unique to the individual learner and is based on previously acquired information, during the instructional process the structured instruction may need to be tailored to the particular characteristics of the learners.

Shute (1995) suggested a computer-based education system with a personalizing component might be superior to a “non- intelligent” version. Martinez (2001) claimed that learners achieved greater

success in learning environments that adapted to and supported their individual learning orientation, and that the fundamental “one-on-one” approach solution using reliable “meta-level” learner difference or performance difference criteria would replace the “one-fits-all” solution.

According to the United States National Education Technology Plan 2017, personalized learning is “instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) may all vary based on learner needs. In addition, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated.” (U.S. Department of Education, 2017: 9).

In this general context, personalized learning is a potential approach to meeting future educational needs and may provide new alternatives that foster learning capacity among individual learners (Bentley and Miller, 2004). Personalized learning emphasizes student-driven instructional objectives, content, pace, and sequencing. Ideally, learning activities are frequently student-initiated, meaningful, and relevant to the learner (U.S. Department of Education, 2017).

Personalized learning also requires the use of technology to facilitate student learning and to provide tools for individual pacing and more efficient assessments to inform and tailor instruction. A crucial component of this modern learning paradigm is its focus on promoting learning among students in areas of key importance to academic and career performance. A personalized learning has many of the characteristics listed in **Figure 1** within the scope of the classroom settings in term of:

- Student can choose where, what, when and in what way they will study.
- Provide real world engagement to enhance student skill for job career purpose.
- Assessment with simultaneous comment.
- Technology utilization.
- Centralized facilities for student and teacher.
- Stimulate student for collaboration and engagement.
- Learning for mastery not grade level.
- Numerous trails for learning.



Figure 1. A typical classroom of Personalized Learning Environment. *Source: Transforming the culture of teaching and learning: four race to the top – district grantees ' implementation of personalized learning.*

A survey by the Alliance for Excellent Education concluded that 79% of parents and 73% of teachers do not agree with the one-size-fits-all approach to education schools still have nowadays. Due to clear evidence of math and reading test scores improvement in schools that have shifted their approach to personalized learning, 71% of parents and 77% of teachers would be comfortable with the change. There are some examples of schools following the personalized approach in the US, but they had to tailor it to fit their circumstances. Here are some approaches:

- Competency-based approach in which students’ progress at their own pace mastering key concepts as opposed to strictly learning in class.
- Interdisciplinary student-directed approach through projects with the purpose of developing critical thinking and collaboration.
- A mix of the two approaches mentioned above based on rigorous academic content and work-based learning.
- A student-centered approach using personalized data to identify gaps in knowledge for a more autonomous learning.

The common ground for all approaches to adaptive/personalized learning is the teacher-student relationship based on trust, which helps students progress at their own pace by reflecting on their strengths and weaknesses and the flexibility and real life applicability of the learning process.

2.2 Role of Technology in adaptive/personalized learning

Many countries in Europe have made efforts to use information and communication technology (ICT) in education. For example, the Finnish strategy says: “In developing the use of information and communication technologies in education, the objective is to shift the focus from hardware to pedagogic renewal and help increasing numbers of pupils to learn increasingly demanding information structures and problem-solving skills. In education, the emphasis lies on high-quality contact education, communality, interaction, open and flexible expression, and the use of distributed expertise through networks.” (Information Strategy for Education and Research 2000-2004, Ministry of Education in Finland).

ICTs are often used to expand access to and enhance the importance and quality of education. ICTs have shown opportunities for all students to improve their options, access, participation and achievement. Because of ICT, unparalleled pace and general availability of accessible and appropriate information expands educational opportunities among the other disadvantaged to the excluded and vulnerable groups. Research has shown that the proper use of ICTs will catalyse the paradigmatic change in both content and pedagogy at the heart of 21st century educational reform.

ICT-supported education will promote information and skills development that will enable students for lifelong learning. ICTs, in particular computers and Internet technology, allow new forms of teaching and learning, rather than merely allowing teachers and students to do more than they have done before. Such modern ways of teaching and learning are founded on constructivist learning theories, which represent a change from teacher-centered pedagogy to learner-centered.

The use of technology in education opened up new possibilities for providing adaptive/personalized learning to learners and significantly enhanced the potential of adaptive/personalized learning. Technology is a key component of this model; often each learner is provided with a device (Johnson & Sherlock, 2014). Most recent work on adaptive/personalized learning is closely linked to technology-enhanced learning, allowing learning systems to provide personalized learning that otherwise is not feasible given the traditional classroom constraints.

These systems mimic the actions of human teachers (Mitrovic, Martin, Suraweera, 2007), in order to provide a comparable experience without human intervention to personal tutoring. Usually, they have an atmosphere in which all students can exercise their skills and solve problems. Through the development and usage of learning systems, large numbers of learners in a class have been able to use and benefit from personalized learning as evident in literature (Graf, 2007). Throughout several of these researches, an intelligent learning system is able to recognize individual learners' characteristics such as prior experience, personality styles, cognitive abilities, personality preferences, learning objectives, and motivation (Graf, Yang, Liu, and Kinshuk, 2009) from individual feedback received.

Aforementioned, the role of technology in personalized learning involves adjusting the objective, pathway, and pace of instruction based on learner expectations, ongoing performance and empower students. Some roles for technology are highlighted:

- **Automated adaptation of learning opportunities.** Theories of learning suggest that students better when they're tested optimally, when content is challenging enough to involve them in deep cognitive work but not so challenging that they can't understand or get frustrated. Adaptive learning systems track student progress and change the curriculum accordingly to help and enhance learning. These systems can promote an instructional model focused on competencies by allowing students the opportunity to learn content at their own speed or through a preferred pathway. They are also used to incorporate blended models of learning in which students cycle between online and offline stations.
- **Resource curation and management.** There are several online learning programs, applications, instructional videos, educational games, interactive websites, and the like, and teachers and students need help in identifying the ones that suit the needs of the individual students. A class of technology systems offers assistance in identifying and choosing tools that match the learning needs, controlling the access and usage of tools for students, and evaluating how well students have performed with the resources. Using these systems can promote student preference, and learning based on agency and competency. They may be used in the implementation of blended learning models, along with adaptive technologies.
- **Use of student data.** A crucial challenge for educators is to make sense of data from a number of sources assessments and other data from online systems, state assessments, district benchmark examinations, student school reports, analyses of the needs and desires of students, and measures of behavioural issues and to use the data productively to personalize learning. Many technical supports include data integration mechanisms and data displays that allow personalization, either on their own or as part of particular systems. Data displays can also be an important part of adaptive learning frameworks and networks to curate tools. Providing intelligible and actionable data can be a vital help for student organization, skill-based learning and blended learning model management.

Perhaps the most common and widely accepted types of technology that support personalized learning are adaptive educational systems. Whatever the characteristics of the individual learner or the dimensions of the learning environment depicted in the program, the main distinguishing feature of adaptive education technologies is that one or more elements of the program are changed in response to learner knowledge. It is this adaptivity that creates the personalized learning experience intended to maximize the learning of each student (Natriello, 2013: 1). This adaptation can be continuous, and according to researchers Shute and Zapata-Rivera (2012: 7), “Adaptive educational systems monitor important learner characteristics and make appropriate adjustments to the instructional milieu to support and enhance learning”.

Adaptive educational systems take students through tailoring processes in such a way that the program offers a learning environment in which a student participates, data is collected on what the student knows or how he or she is learning, data is interpreted on learning path knowledge, and the program then adapts the learning experience based on the actual needs of the student.

Essentially, the technologies change teaching or pedagogical behavior intended to affect learning, using perceptions of what and how students are learning (Koedinger, Booth, & Klahr, 2013). An adaptive technology can be modified in a number of ways based on a learning assessment: it can provide specific instructional assignments, tips, prompts, related tools to study; extra homework; and/or content that is more difficult where appropriate. Engineering may vary the ratio of examples to problems, the concreteness of examples, the timing of feedback, the grouping or sequence of topics, and whether the student or the program describes how to solve problems.

Two specific kinds of adaptive systems that are popular in many schools are cognitive tutors and competency-based systems. Cognitive tutors are systems that clearly assess what the students understand, what they do not, and why to offer the kinds of tips, prompts, and scaffolds a human tutor might have. Unlike human tutors, cognitive tutors are adapted to the kinds of information or skills that are being taught, the kind of student doing the learning (e.g., based on previous achievement), and the learning background. One example of a method like this is the MATHia of Carnegie Learning. MATHia offers interactive math tutors to assess the problem-solving activities of the students and offer advice for supporting them in the different areas they need support. These tutors often provide worked examples or examples of the work of other students as additional scaffolds, if needed. Another example is DreamBox Learning, which offers additional elementary grade maths games that tracks what learners are doing, trying to spot common errors and misconceptions. Then, depending on the types of mistakes detected, the program adjusts the difficulty, scaffolding, sequencing, number of hints, and/or pacing.

Adaptive competency-based systems, most common for math and reading, tailor the pace at which learners or students advance through learning experiences by monitoring what each student has learned and tailoring a suitable sequence of corresponding learning objectives. Such objectives that include the basic skills for next learning and the level of maturity at which those skills are developed. In mathematics, some examples are Khan Academy and Reasoning Mind, each of which takes students through a set of learning objectives for a specific subject area or grade level. Khan Academy does not recommend how teachers use their commodity, as there are so many different implementation models (Murphy, Gallagher, Krumm, Mislavy, & Hafter, 2014).

It usually serves as a supplementary curriculum for any degree, and teachers choose to assign those topics to specific students, assign the same topic to all students, or advance students through the sequence set out by Khan Academy. To prove mastery of a skill and move on, students must answer a certain number of questions correctly, and they can use videos or tips for help. Reasoning Mind is used as a central curriculum for mathematics. It delivers direct guidance as a teacher might while students' record notes in a paper notebook before being assessed on their understanding of material and the quality of those notes. It then offers basic practical problems, and if students demonstrate expertise in solving them, it adapts to give problems that need deeper understanding and approaches that are more complex. Teachers play a significant role in the system, providing regular input on the success of the students that they can use to offer additional behavioural training

strategies. **Table 1** and **2** provides summary of the role of technology in adaptive/personalized learning.

Table 1. Summary of the role of technology in adaptive/personalized learning.

Authors	Finding/Focus
(Johnson & Sherlock, 2014)	Identifies technology as a key component of adaptive/personalized learning; often each learner is provided with a device as technology-support.
(Mitrovic, Martin, Suraweera, 2007)	Identify constraint-based tutors that have been thoroughly to evaluate and proven to achieve significant learning gains by mimicking human.
(Graf, Yang, Liu, and Kinshuk, 2009)	Intelligent learning system is able to recognize individual learners' characteristics such as prior experience, personality styles, cognitive abilities, personality preferences, learning objectives, and motivation
(Natriello, 2013)	Based on learner characteristics or the dimensions of the learning experience represented in the system, the key defining feature of adaptive educational technologies is that one or more elements of the system are modified in response to information about the learner.
(Shute and Zapata-Rivera, 2012)	Identifies educational systems that monitor learner characteristics and appropriate instructional milieu to support and enhance learning.
(Koedinger, Booth, & Klahr, 2013)	Based on the assessment of learning, an adaptive technology offer instructional tasks, hints, prompts and/or provides a learning experience in which student engages and data are collected.
(Murphy, Gallagher, Krumm, Mislevy, & Hafter, 2014)	Cognitive tutors assess what the students understand, what they do not, and why to offer the kinds of tips, prompts, and scaffolds a human tutor might have and Adaptive competency-based systems tailor the pace at which learners or students advance through learning experiences by monitoring what each student has learned.

Table 2. Continued

Role of technology	Finding/Focus
Automated adaptation of learning opportunities	Students' or learners' have the opportunity to learn content at their own speed or through a preferred pathway.
Resource curation and management.	Assists students in finding and selecting the right tools that match their learning needs as well as evaluate students' performance with the resource.
Use of student data.	Many technical systems include data integration mechanisms; data acquired from these systems can be used to productively personalize students learning.

2.3.0 Artificial Intelligence as enabler of adaptive/personalized learning?

2.3.1 Artificial Intelligence (AI): An introduction

Artificial Intelligence (AI) is a field of computer science that studies how machines can imitate the intelligence of their human counterparts. In computer science, artificial intelligence (AI), sometimes-called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and animals. Leading AI textbooks describe the discipline as the study of "intelligent agents": any system perceiving its environment and taking action that maximizes its chance to achieve its goals successfully (Poole, Mackworth & Goebel 1998: 1).

As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect (McCorduck, 2004: 204). A quip in Tesler's Theorem says, "AI is whatever hasn't been done yet." (Maloof Mark, 2017: 37). Nabyev (2010) roughly defines AI as the ability of a computer-controlled device or system to perform tasks in a human-like way. As indicated by the author, human-like qualities include mental processes like reasoning; sense making, generalization and learning from previous experiences have human-like qualities.

Developments in AI evolution have been mind-blowing, and the incredible role it has played in human lives. There have been a few clear examples recently of AI being able to know how to think like a human being. Such studies have also shown that AI-based systems can perform as well as humans, in some situations. For example, in 2016 Google DeepMind's AlphaGo defeated Lee Sedol, a South Korean champion, one of the most experienced "Go" players in the world (Sang-Hun, 2016). As the strongest proof of the human-like reasoning and abilities of AI, the outcome of this match shows that a very artificially intelligent machine is one that can learn by itself (Adams, 2017).

Today's AI is not yet about machines that can comprehend human concepts such as love, creativity and strategy. The implementations are probably much narrower right now, in that they seem to be excellent in solving one particular problem and that is about it. AI is usually divided into three groups, each of which is an evolution of the next.

1. **Artificial Narrow Intelligence (ANI):** Commonly known as machine learning or also known as Narrow AI or Weak AI, is a form of Artificial Intelligence based on one narrow area and one problem at a time. This is the form of AI that we see in the market today and complete tasks like recommending a product or predicting the weather forecast. Narrow AI is something about which most of us communicate on a regular basis. Talk of an assistant to Google, Google Translate, Siri, Cortana or Alexa. Both of them are artificial intelligence, using Natural Language Processing (NLP). NLP is used in chatbots and related applications. They are programmed to communicate with humans in a customized, natural way by understanding speech and text in the natural language.

2. **Artificial General Intelligence (AGI):** AGI is the next level up from ANI and refers to AI that has a “human level of cognitive function.” However, AGI is still an emerging field. To be successful, an AGI system would need to connect potentially thousands of ANI systems together to imitate human behaviour. To put it into context, the market leading IBM Watson system took 40 minutes to simulate just one second of neuro-activity. Big companies are striving to achieve AGI and we will get there.
3. **Artificial Super Intelligence (ASI):** Is way into the future. An ASI system is one that can completely surpass any sort of human intelligence. This type of AI will be able to perform extraordinary well at things such as arts, decision making, and emotional relationships. It is thought that the progression from AGI to ASI would not necessarily be that huge. If machines can start coming up with their own concepts with AGI, a super intelligent system would be the next logical step.

Artificial Intelligence technology brings many benefits to various fields, including education. Many researchers claim that Artificial Intelligence can improve the level of education.

2.3.2 Role of Artificial Intelligence in the context of education

Chaudhri, Lane, Gunning, and Roschelle (2013) discussed application of AI in education (AIEd) to improve teacher effectiveness and learners’ engagement. AI and its learning applications have been instrumental in delivering intelligence in e-learning tools and techniques. The idea behind using AI in learning is to encourage quality education and training in a computer-based program that is essential for teachers who work positively on these factors can improve the student's performance. AI that can contribute to the development of learning programs that will greatly benefit from a more personalized and better decision support system for the facilities.

By providing such approach, the education system will play much better toward positive improvement of their results for student centric. Surely, the critical presences of teachers and tutors are irreplaceable. According to (<https://www.teachthought.com/the-future-of-learning/10-roles-for-artificial-intelligence-in-education/>), below are some role of AI in the educational system:

1. AI can automate basic activities in education, like grading.

In college, grading homework and tests for large lecture courses can be tedious work, even when TAs split it between them. Particularly in lower grades, teachers often find grading takes up a large amount of time, time that could be used to connect with students, to plan for class, or to focus on professional development. While AI may never be able to completely replace human grading, it is getting close. Teachers can now automate grading for almost any form of multiple choice, and fill-in-the-blank testing and automatic grading of student writing will not be far behind. Today, the essay grading program is still in its infancy and not fully up to scratch, but it can (and will) evolve in the coming years, enabling teachers to concentrate more on in-class activities and student engagement than grading.

2. AI-driven programs can give students and educators helpful feedback.

AI can not only help teachers and students design courses that are specific to their needs, but it can also provide input to each of them on the overall progress of the course. Many schools, especially those with online offerings, use AI systems to track student progress and to alert teachers when there might be a problem with student performance. These types of AI programs make it possible for students to get the help they need and for teachers to find places where they can improve instruction for students who may struggle with the subject. AI services are not only providing guidance on individual courses at these colleges, however. Others are creating programs that can help students select majors based on areas where they are productive and fail.

3. Data powered by AI can change how schools find, teach, and support students.

Intelligent data collection, driven by smart computer systems, is already changing how colleges communicate with prospective and current students. Intelligent computer systems help to make any aspect of the college experience more closely tailored to student needs and interests, from recruiting to helping students select the best courses. In today's cutting-edge world, data mining systems already play an integral role but artificial intelligence could further alter higher education. At several colleges, programs are already underway to provide AI-guided training to students that can ease the transition from college to high school.

4. AI can make trial-and-error learning less intimidating.

Trial and error is a vital part of learning but the fear of failing, or just not knowing the answer, is paralyzing for many students. Some just do not like being put on the spot before their peers, or figures of authority like a teacher. An intelligent computer program built to help students learn how to manage trial and error is a far less challenging solution. In a relatively judgment-free environment, artificial intelligence may offer students a way of experimenting and learning, particularly when AI tutors can offer solutions for improvement. In reality, AI is the perfect format to help this kind of learning, as AI systems often learn by a trial-and-error method themselves.

5. AI can point out places where courses need to improve.

Teachers may not always be aware of differences in their lectures and instructional materials, which may leave students uncertain about certain concepts. Artificial intelligence provides a solution to the issue. Coursera, a huge, free online course provider, is already putting it into action. If a large number of students find themselves sending the wrong answer to a homework assignment, the program warns the instructor and sends a personalized message to potential students that provides tips for the correct response. This form of program helps to fill in the holes of description that can arise of classes, and helps make sure all students create the same logical base. Instead of waiting for the professor for feedbacks, learners get instant feedback to help them understand a concept and know how to do it better next time around.

AIED can contribute to collaborative learning by supporting adaptive group formation based on learner models, by facilitating online group interaction or by summarizing discussions that can be used by a human tutor to guide students towards the aims and objectives of a course. With the advancement of AIED and the availability of (big) student data and learning analytics, Luckin et al. (2016: 35) claim a “renaissance in assessment”. AI can provide just-in-time feedback and assessment rather than stop-and-test. The educational environment of today is clearly affected in artificial intelligence solution, which is fitted with artificial intelligence by digital learning and adaptive/personalized learning.

2.4 AI in adaptive/personalized learning

Artificial Intelligence plays a key role in adaptive learning by providing personalized experience of learning. AI's adaptive/personalized learning strategies can help interpret the work of the learner, learning style, resource sharing, and even his own academic achievement and hobbies information. For example, these specifics can help gather automatically learners who have different skills to work together in an effective group structure on a particular assignment at schools. That is, instead of following a "one size fits all" approach, using AI in education allows tailor-made learning by putting learners at the core of learning environments.

Personalization of a student's learning experience has been achieved in such systems through the detection of emotional and cognitive states (Garcia et al., 2007; Garcia-Valdez et al., 2010); affective states including facial and body language (D'Mello and Graesser, 2012a, 2012b); personality (Leontidis and Halatsis, 2009); learning progressions (Rus et al., 2013) and learning styles (Latham et al., 2014). A recent analysis of 50 ITS-related journal papers published between 2008 and 2013 by Sani and Aris (2014) shows a strong trend in the use of artificial intelligence technologies to enhance the intelligent tutoring system performance and quality.

Intelligent tutoring systems (ITS) are such learning systems that provide adaptive/personalized learning supports or feedback to help individual students improve their learning performance based on their personal information, such as the records in their profiles or learning portfolios (Walonoski and Heffernan 2006). Adaptive learning systems can be viewed as a special kind of intelligent tutoring system that adapts the presentation of educational materials to students' needs.

Researchers have studied various issues concerning learning styles to better understand the model of learning and the learning dispositions/preferences of learners. Educators have suggested that teachers and course designers will pay attention to the learning styles of the students and appropriately plan teaching and learning activities (Coffield et al. 2004). Brusilovsky (2001) has indicated that two adaptation approaches can be used in developing such systems, that is, “adaptive presentation” that presents personalized content for individual learners, and “adaptive navigation support” that guides individual students to find the learning content with a personalized path.

2.4.1 Intelligent Tutoring System

Intelligent Tutoring Systems enable diagnostic assessment in order to identify student's awareness, misunderstandings and unique tutoring needs. The goal of the Intelligent Tutoring Systems is to create content that effectively adapts to the knowledge and learning abilities of the learner to optimize learning (Samuelis, L., 2007). Based on the evaluation the intelligent tutoring systems are able to choose correct individualized tasks from a question bank (VanLehn K., 2011).

In contrast to computer-based systems such as CAL (Computer Aided Learning) or CBT (Computer Based Training) intelligent tutoring systems adapt to the individual pupil's cognitive profile and thus develop a model of their skills and expertise (Phobun, P., & Vicheanpanya, J., 2010). In addition, intelligent tutoring systems are responsible for providing feedback based on the mistakes, suggestions and tips of the student for each subject, resolving systematic solutions for each question, as well as sample exercises that have been solved. An Intelligent Tutoring System usually consists of four parts: the domain expertise, namely the knowledge of the subject to be learned by the program, the pedagogical expertise, which is the control mechanism that directs the teaching, the learner model, which is responsible for documenting all relevant student information and for developing an specific learning profile for each student, and the interface.

Intelligent tutoring systems (ITS) extend the 'one-size-fits-all' approach of traditional computerized learning systems by capturing and modeling tutoring systems (ITS) expanding the 'one-size-fits-all' approach of traditional computerized learning systems by capturing and modeling individual traits used to personalize instruction (Brusilovsky and Peylo, 2003). This includes delivering learning material in a style and order to fit the learner (e.g., by delivering learning material tailored to preferred learning styles), as well as proactively assisting learners, e.g. by offering informed input on in-complete or incorrect approaches and advice to assist learners in problem-solving approaches. Within the area of study full or erroneous approaches and advice to assist learners in problem solving.

2.4.2 Swarm Intelligence

A personalized approach to learning will involve students and provide timely input and effective support to the students. The concept of Swarm Intelligence (SI), with its proven ability to solve e-learning problems (Semet, Lutton, & Collet, 2003) through distributed and evolving behaviour and the concepts were influenced by the study of various natural and social phenomena developed to mimic bird flocking or insect swarming. Swarm Intelligence System (SIS) do not interact directly; rather, they share information by leaving marks by studying their peers' surrounding positions. Through the reactions of the individual agents to these indirectly transmitted knowledge, the entire swarm will slowly become self-organized, and collective behaviours will emerge which can demonstrate high intelligence. Swarm intelligence's main function is "to balance exploitation (of the best known solution) and exploration (of the unknown solutions)" (Dagli & Kilicay, 2006). This function in such SIS facilitates adaptability in complex or unpredictable conditions, for example in the next moment the best solution can become invalid (Di Marzo, Gleizes, & Karageorgos, 2006; Holland, 1992).

From the perspective of artificial intelligence (AI), the use of ant colony optimization (ACO), algorithms are a subset, and one of SI's most successful strands (Bonabeau, Dorigo, & Theraulaz, 2000). Bonabeau and Meyer (2001) suggested that social insects are an evolutionarily productive class of insects due to versatility, robustness and self-organization capacity that allows ACO accept a natural process towards seeking the optimal solution for unknown open systems. The basic philosophy of the ACO algorithm is as follows: a colony of ants' moves through different nodes and their movement decision is influenced by trails and attractiveness, i.e. each ant gradually constructs a solution to the problem by depositing the pheromone information. This pheromone information will direct the search for following ants.

Swarm intelligence methods like ACO and Particle Swarm optimization are the most promising social sequencing methods, while genetic algorithms and Memetic algorithms are the most often used individual sequencing methods. The social sequencing approach does not take into account the individual characteristics of both the learner and learning objects. The choice of the optimal curriculum sequence is based on the collective path and performance of the entire learners' society. Several researchers are found which deal with selection of personalized learning paths dependent on learning styles and use of the social sequencing approach to attain the selection.

2.4.3 Game-Based Learning

Game-based learning is the teaching learning practices that aim to improve problem-solving skills of learners through the use of games in educational settings (Kirriemuir & McFarlane, 2004). Computer games technology typically takes advantage of this to create a fun, inspiration, and interactive experience (Tang & Hanneghan, 2011). Creation of game-based learning systems has recently been seen as a groundbreaking trend in education. A study of the relevant literature indicates that games for students of all ages can be a motivating motivator (Amory, 2011). Prensky (2001) also noted that computer and video games are a combination of fun, play, rules, goals, and challenges that offer learners pleasure, enthusiastic engagement, and motivation; moreover, games' interactive features encourage learning.

Therefore, game techniques are included frequently as a positive component of personalized learning. For example, Jung and Graf (2008) proposed an approach to Web-based learning of vocabulary via personalized word association games to make learning vocabulary more attractive to learners. Kalloo, Kinshuk, and Mohan (2010) employed personalized game-based mobile learning to help secondary school students improve their mathematical skills. Moreover, it has been found that game scenarios can provide learners with immediate rewards (Burguillo, 2010).

Some researchers have advocated that the school of future should be developed based on the integration of innovation, interactive creativity, and new technology (e.g., Craft, 2005; Natriello, 2007; Sawyer, 2006). Games include problem-solving and adaptive learning (Prensky, 2005); by proving difficult tasks and feedback, learners build their skills, create creative problem-solving solutions, and ignite their flow and imagination further (Kiili, 2005; Prensky, 2001). Accordingly, game-based learning should be an ideal tool for personalized learning.

To date, however, only a few game based learning systems have been developed for creativity. For instance, Yeh (2012) created a game-based learning framework to provide an interface for evaluating the creativity of the learners. Chang, Wu, Weng, & Sung (2011) found that game-based learning improved cognitive efficiency and motivation important to creativity. In the same vein, Kangas (2010) used a creative playground filled with technical resources to build a curriculum-based learning in which games were combined with co-creation, play, and computer games. The findings showed that the incorporation of a playful learning atmosphere into teaching and learning is a successful way of promoting creativity. **Table 3** highlight the summary of the use of AI in personalized learning by some authors in general.

Table 3. Summary of the use of AI in Personalized Learning.

Authors	Finding/Focus
(Chaudhri, Lane, Gunning, and Roschelle, 2013)	The authors recognize the need to increase the effectiveness of teachers, to increase student participation, and to build a twenty-first century education system that maximizes every student's potential using AI's intelligent tutoring systems (ITSs) that could adapt and customize the instruction to the student's individual needs.
(teachthought.com)	Highlighted on some roles of AI in education such as systems to track student progress and to alert teachers when there might be a problem with student performance, intelligent computer systems help to make any aspect of the college experience more closely tailored to student needs and interests, help students learn how to manage trial and error is a far less challenging solution etc.
(Rudd, 2008)	Outlines the key principles of personalized learning and proposes that personalization "increase learner choice and voice" with delegated powers and greater locus of control.
(Garcia et al., 2007)	Evaluate Bayesian networks in detecting a student's learning styles in a web-based education system based on how the student learns: reflecting or acting; slowly or in fit and start; intuitively or sensitively.
(Garcia-Valdez et al., 2010)	Examines the use of fuzzy inference for the recommendation of learning objects, this allows the teacher to assume the role of facilitator, making recommendation where necessary, but encouraging students to cooperate where possible.
(D'Mello and Graesser, 2012a, 2012b)	Proposed AutoTutor and Affective AutoTutor as an intelligent tutoring system that assists students by communicating with them in natural language with adaptive conversation movements close to those of human tutors with descriptions of complex concepts and critical thinking.
(Leontidis and Halatsis, 2009)	Integrate the learning style and personality traits into an improved Affective Style that is stored in the learner's model.
(Latham et al., 2014)	Computerised learning has shifted from content delivery towards personalised online learning with Intelligent Tutoring Systems, adaptation algorithm and its application to the Felder–Silverman learning styles model.

- (Walonoski and Heffernan 2006) Proposed a personalized game-based learning approach focused on the gaming style sequential suggested by Felder and Silverman through which a role-playing game was implemented.
- (Phobun, P., & Vicheanpanya, J., 2010) The authors define a conceptual for the integration of ITS and adaptive hypermedia into Adaptive Intelligent Tutoring System (AITS) for e-learning systems that enables information to be stored in a manner that is not only independent of the knowledge domain, but also supports the storing of knowledge transfer relationships and pre-requisite knowledge relations.
- (Semet, Lutton, & Collet, 2003) Identifies ability to solve e-learning problems using swarm intelligence through distributed and evolving behaviour developed to mimic bird flocking or insect swarming.
- (Bonabeau, Dorigo, & Theraulaz, 2000) Adopting AI, this research examines intelligent multi-agent system using ant colony optimization algorithms by taking inspiration from the collective behaviour of social insects.
-

3.0 METHODOLOGY

Johnson and Christensen (2012: 31) stated that a paradigm is an approach about research or doing research. The authors identified qualitative, quantitative, and mixed research as the three main paradigms of research in education.

Quantitative research relies on the quantitative data collection (i.e., numerical data) and follows the other characteristics of the quantitative research model shown in **Table 4**. The quantitative research methodology follows mainly the confirmatory scientific method, as its emphasis is on testing theories and testing theory. Quantitative researchers find it primarily necessary to state one's hypotheses and then use empirical evidence to check those hypotheses and see whether they are supported (Johnson & Christensen, 2014: 82).

Qualitative research relies on the collection of qualitative data (i.e., non-numerical data such as words and pictures) and follows the other characteristics of the qualitative research paradigm shown in **Table 4**. Qualitative research primarily follows the scientific method of discovery and is used to explain what is found locally, and often to create or produce new hypotheses and theories. Qualitative research is used when a subject or phenomenon is little understood and one wants to explore or understand more about it. It is commonly used to understand the experiences of people, and to express their views (Johnson & Christensen, 2014: 82).

Mixed methods include the combining of processes, techniques, or other model properties in quantitative and qualitative study. The exact mixture deemed acceptable will depend on the research questions and the situational and realistic issues a researcher is facing (Johnson & Christensen, 2014: 82). Researchers promoting mixed research claim that the use of both the exploratory and confirmatory methods in one's work is necessary (R. B. Johnson & Onwuegbuzie 2004).

Table 4. Emphasizes of Quantitative, Qualitative and Mixed Methods.

	Quantitative	Qualitative	Mixed Methods
Scientific Method	Confirmatory or “top-down”- the researcher test hypothesis and theory with data.	Exploratory or “bottom-down”- the researcher generates or construct knowledge, hypotheses.	Confirmatory and Exploratory.
Ontology (i.e., nature of reality or truth)	Objective, material, structural, agreed-upon	Subjective, mental, personal, and constructed.	Pluralism, appreciation of objective, subjective and intersubjective realities and their interrelations.
Epistemology (i.e., theory of knowledge)	Scientific realism; search for truth; justification by empirical confirmation of hypothesis	Relativism; individual and group justification; varying standards.	Dialectical pragmatism; pragmatic justification (what works for whom in specific contexts).
Most common research objective	Numerical description, casual explanation and prediction	Subjective description, empathetic understanding, and exploration	Multiple objectives; provide complex and fuller explanation and understanding; understanding multiple perspectives.
Form of data collected	Data based on precise measurement using structured and validated data-collection instrument	Data such as in-depth interviews, open-ended questions and field-notes. The researcher is the primary data-collection instrument.	Collect multiple kinds of data.
Nature of data	Variables	Words, images and categories	Mixture of variables, words, categories and images.
Data analysis	Identify statistical relationships among variables	Use descriptive data; search for patterns, and holistic features; and appropriate difference/variation	Quantitative and qualitative analysis used separately and in combination.

Note: This was primarily adapted from Johnson & Christensen, 2014: 84.

The three main educational research trends are qualitative research, quantitative analysis, and mixed analysis. These three practices are all-important and have meaning. Qualitative research tends to use the scientific exploratory method to generate hypotheses and develop understandings about specific people, places, and groups (e.g., in case studies, ethnography, phenomenology, and historical research). On the other hand, quantitative work is usually carried out under more closely regulated conditions and aims to use the confirmatory scientific method, concentrating on the testing of theories and theory. Quantitative researchers are aiming to identify specific patterns of thought and action and to generalize broadly. Mixed methods involves mixing qualitative and quantitative research into single studies and combining them. This is based on the pragmatism principle (i.e. what works are important to remember when addressing research questions) and critical principle (i.e. what works are compatible with the methodological characteristics of the research questions). Mixed methods sequential exploratory design was used to aid this study through the qualitative (first) phase to the quantitative (second) phase (**Figure 2**), the first phase was open and closed-ended interviews and analysing data and the second phase was surveys and analysing data but due the time constraints, the study cannot maximize the phase to its potential.

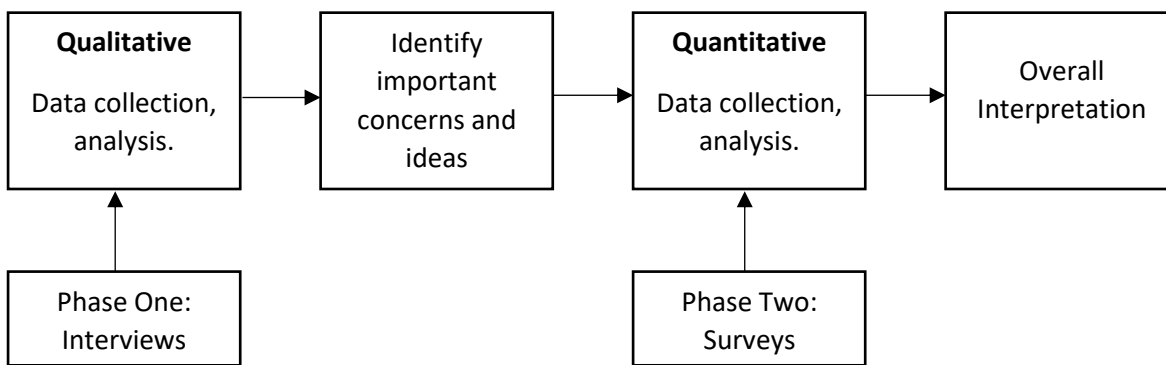


Figure 2. Fuentes' (2008) sequential exploratory mixed methods design. Source (Hesse-Biber, 2010: 459).

The aim of this research is to gain an understanding of existing studies and discussions relating to the study area. As with all research, the value of an academic review depends on what was done, what was found, and the clarity of reporting (Moher et al., 2009). Regardless of the discipline when reading article, the author begins by describing previous research to map and assess the research area to motivate the aim of the study and justify the research question and hypotheses. A literature review may be the best methodological tool for providing answers for a number of research questions. For example, reviews are useful when the researcher needs to test theory or evidence in a given area or investigate the validity or consistency of a specific theory or competing theories (Tranfield et al., 2003).

According to Akobeng, 2005, in management sciences, where random controlled trials are often not available, the next 'best' form of proof is a systematic literature review of other published studies and involves the assembly, critical evaluation, and synthesis of all applicable studies

answering a particular question. The aim of a systematic review is to find all empirical evidence that matches the pre-specified inclusion criteria to answer a particular question or hypothesis of the study. Bias can be reduced by using clear and systematic methods when evaluating papers and all available facts, thus presenting accurate results from which conclusions can be drawn and decisions made (Moher et al., 2009). Therefore, this study review journal articles that fall within the scope of both “personalized learning”, “adaptive learning” and “artificial intelligence” in learning.

3.1 Search Process

The search process was a manual search of specific conference proceedings and journal papers since 2000 to ensure that there are adequate data to observe and how these articles can be mapped using the various techniques and also the term systematic literature review was not in common usage in the time period during which literature reviews was published in 2000. The selected journals, conferences and the number of articles published are shown in **Table 5**. The journals were selected because they were known to include either empirical studies or literature surveys, and to have been used as sources for other systematic literature reviews related to either both “personalized learning”, “adaptive learning” ,“artificial intelligence in learning”, “machine learning” and “deep learning”. **Table 6** shows a list of selected Top 1 and 2 CNRS journals for this research publication.

Table 5. Selected journals and conference proceedings.

Sources	Articles
Computers & Education	55
IEEE Transactions On Learning Technologies	21
Educational Technology & Society	6
Artificial Intelligence In Education AIED 2019 Pt Ii	3
Edulearn15: 7th International Conference On Education And New Learning Technologies	3
BMC Medical Education	2
Journal Of Engineering Education	2
10th International Conference Of Education Research And Innovation (Iceri2017)	1
2011 4th International Conference Of Education Research And Innovation (ICERI)	1
2016 IEEE 8th International Conference On Technology For Education (T4e 2016)	1
2017 IEEE 17th International Conference On Advanced Learning Technologies (ICALT)	1
26th International Conference On Computers In Education (ICCE 2018)	1
8th IEEE International Conference On Advanced Learning Technologies Proceedings	1
9th International Conference The Future Of Education	1
Best Practices For The Knowledge Society: Knowledge Learning Development And Technology For All	1
Edulearn14: 6th International Conference On Education And New Learning Technologies	1
Eurasian Journal Of Educational Research	1
Hybrid Learning And Education Proceedings	1
IEEE International Conference On Advanced Learning Technologies Proceedings	1
Inted2012: International Technology Education And Development Conference	1
Inted2016: 10th International Technology Education And Development Conference	1
Intelligent Tutoring System Proceedings	1
Interactive Learning Environments	1
International Journal Of Stem Education	1
International Journal Of Technology And Design Education	1
Journal Of Computing In Higher Education	1
Learning And Collaboration Technologies: Novel Learning Ecosystems LCT 2017 Pt I	1
New Technologies And Redesigning Learning Spaces Vol I	1

Proceedings Of The 11th European Conference On E-Learning	1
Proceedings Of The 14th European Conference On R-Learning (ECEL 2015)	1
Proceedings Of The 2018 International Seminar On Education Research And Social Science (ISERSS 2018)	1
Proceedings Of The 8th European Conference On E-Learning	1
Proceedings Of The 8th International Conference On Computer Supported Education Vol 1 (CSEDU)	1
Proceedings Of The 9th European Conference On Games Based Learning (ECGBL2015)	1
Proceedings Of The 9th International Conference On Computer Supported Education (CSEDU) Vol 1	1
Proceedings Of The 9th International Conference On Computer Supported Education (CSEDU) Vol 2	1
Proceedings Of The International Conference On The Development Of Education In Russia And The Cis Member States (IICEDER 2018)	1
Proceedings Of The Third (2016) ACM Conference On Learning @ Scale (L@S 2016)	1
Science & Education	1

Table 6. Top 1 & 2 CNRS Journal for publications.

Sources	ISSN	Domaine	Category (Cat)
European Journal of Information Systems	0960-085X	SI	1
Information Systems Research	1047-7047	SI	1
Journal of MIS	0742-1222	SI	1
Information and Management	0378-7206	SI	2
Information and Organization	1471-7727	SI	2
Information Systems Journal	1350-1917	SI	2
Journal of the Association for Information Systems	1536-9323	SI	2
Journal of Information Technology	0268-3962	SI	2
Information Technology and People	0959-3845	SI	3

As shown in **Figure 3** there were 124 articles from the aforementioned journals and conference proceedings (**Table 6**) in the area of Educational Education Research with an Annual Percentage Growth Rate of 8.01%. On average, 7.22 related articles are published in these journals each year with 2009 and 2019 recording the highest years of publications that is 15 and 16 respectively. There was a decrease in the number of publications in 2010, but it then rose to by the end of 2019, thus highlighting an increased interest in artificial intelligence technologies. In 2020, up to the beginning of this SLR (April 2020), only four (4) studies were identified.

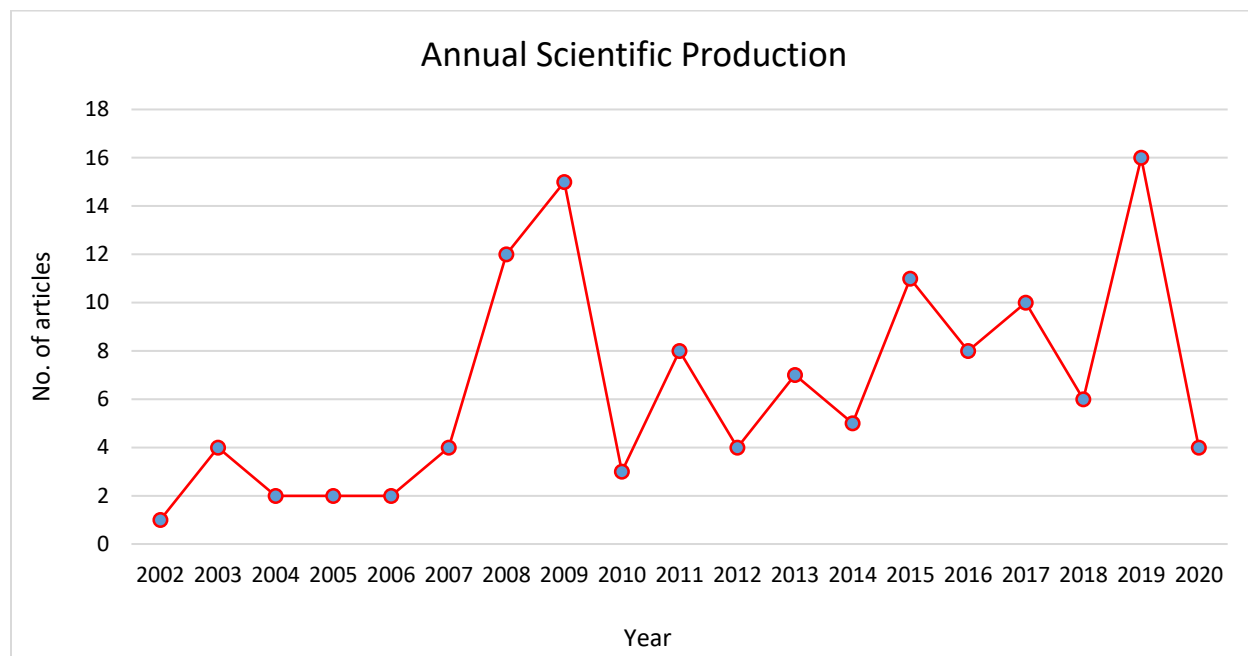


Figure 3. The distribution of articles published on personalized learning, adaptive learning and artificial intelligence in learning from 2002-2020.

In addition, some studies have been widely accepted and frequently cited. For example, Chen and Chung (2008) proposed a personalized mobile English vocabulary learning system based on item response theory and the learning memory cycle, which recommended appropriate acquisition of English vocabulary receiving 448 citations in Google Scholar.

Amandi, Garcia, Schiaffino, & Campo (2008) proposed eTeacher: Providing personalized assistance to e-learning students, the proposed agent, eTeacher, detects a student’s learning style automatically using Bayesian model to infer the learning style given the observation of certain student behaviours. This study has also received 290 citations.

Hussain, Zhu, Zhang, Abidi, and Ali (2019) have recently developed a framework using machine learning algorithms such as Vector Machine Support, Logistic Regression, Naïve Bayes Classifier, and Artificial Neural Networks. The objective of this study is to predict the difficulties that students will encounter in a subsequent digital design course session thereby providing guidance to teachers using the Technologically Enabled Learning (TEL) method. This research is motivated by the influence of artificial intelligence (AI) in the learning process, a systematic review of

adaptive/personalised learning is needed to identify the development, patterns and future directions of study, and focuses on learning technologies such as language learning (Golonka, Bowles, Frank, Richardson, & Freynik, 2014), mobile learning (Fu & Hwang, 2014)

Towards promoting a learner-centric learning experience, personalization techniques and intelligent methods are employed in digital learning environments that is worth investigating. More importantly, such a review of adaptive/personalized learning can facilitate the understanding of “how ICTs are exploited for implementing and supporting adaptive/personalized learning” (Dawson et al., 2010) and “what are the appropriate contexts for providing adaptive/personalized learning” (Butoianu, Vidal, Verbert, Duval, & Broisin, 2010).

3.2 Research Question

In view of the above, the following research questions are investigated in the study and the sub-questions were derived to answer them:

- i. **RQ1:** What is the purpose of artificial intelligence (AI) and adaptive/personalized learning?
 - a. Definitions of adaptive/personalized learning.
 - i. Certain similarities between the two terms i.e. adaptive learning and personalized learning.
 - b. Definitions of artificial intelligence.
 - i. Intelligent Tutoring Systems (ITSs) in personalized learning.
 - ii. Game-based learning (GBL) in personalized learning.
 - iii. Swarm Intelligence (SI) in personalized learning.
- ii. **RQ2:** How does personalized learning affect student achievements?
 - i. Can personalized learning improve students/learners’ achievement.
 - ii. Highlight the role of AI in students’ evaluation.

3.3 Research Methods

This research has been undertaken as a systematic literature review as proposed by Kitchenham et al., 2004. A systematic review includes a thorough search of designated databases or repositories (e.g., Web of Science and Scopus). Reviews of related literature used Boolean parameters such as “adaptive learning” or “personalized learning”, “artificial intelligence in learning”, (“adaptive learning” OR “personalized learning”) AND (“artificial intelligence” OR “machine learning” OR “deep learning”) concerning the research questions and limitation and filters within **Web of Science** and **VosViewer** was used for analyzing bibliometric network.

3.3.1 Inclusion and exclusion criteria

The publication period was set as two decades (2000 to 2020) to ensure sufficient data is available on relevant data, and the form of publication set as “article” and “conference proceedings”. Since "adaptive learning" is also a concept in computer science in the field of machine learning, we set the category as “education educational research.” There were totally 124 articles in the query

results and evaluated using the following inclusion criteria to ensure that these articles were genuinely relevant to adaptive/personalized learning and artificial intelligence in learning.

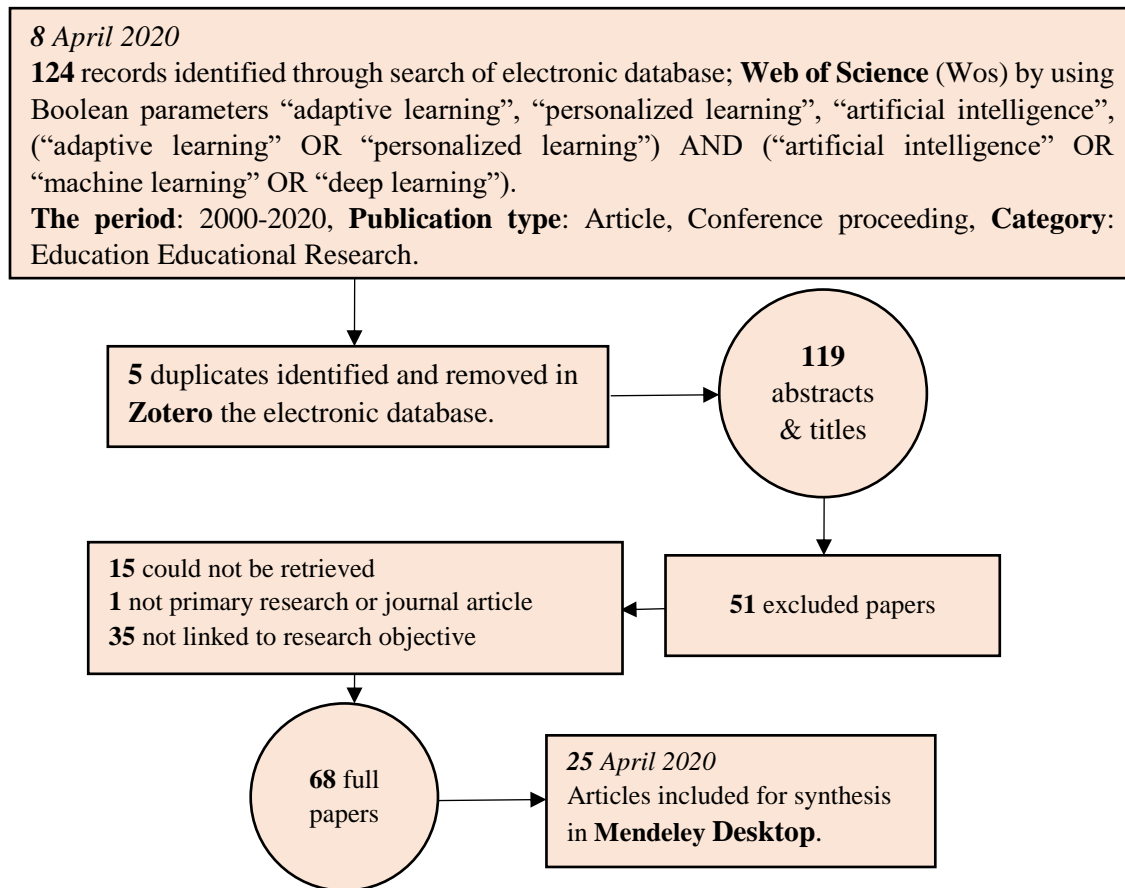


Figure 4. The procedures for data collection and processing. (Primarily adapted from Zawacki-Richter et al., 2019: 7)

Each article must be relevant to the use of e-learning systems and AI techniques to support adaptive/personalized functions, e.g. learning paths to incorporate specific adaptive/personalized teaching and learning activities and learners’ achievement or performance as shown in **Figure 4**. By double-checking the articles, five (5) articles were eliminated for been duplicate and based on the inclusion criteria, 51 irrelevant articles were filtered out, 68 articles included for synthesis for this research. For example, Christos, Akrivi and Cleo (2019) designed and implemented Quiz Time that is an intelligent mobile game-based learning application for assessing and advancing learners’ knowledge in the programming language C# and Wakelam, Jefferies, Davey and Sun (2015) discussed existing intelligent learning/training systems and explored the contemporary AI techniques to improve e-learning systems.

In VosViewer, co-occurrence analysis was used to generate this research's network of co-occurrence keywords, as shown in **Figure 5**. A density heat map that visually displays the occurrence of high frequency and related words in “adaptive learning”, “personalized learning” and “artificial intelligence in learning” and its publications. The data in **Figure 5** is displayed as labels and the corresponding heat map area. The colour of the area centered the corresponding label (all keywords) which depends on the number of articles published. The larger the number is the warmer (redder) the colour is while the smaller the number is, (bluer) the colour is. As shown in **Figure 5**, the keywords with larger nodes are at the central positions of blocks in this density view.

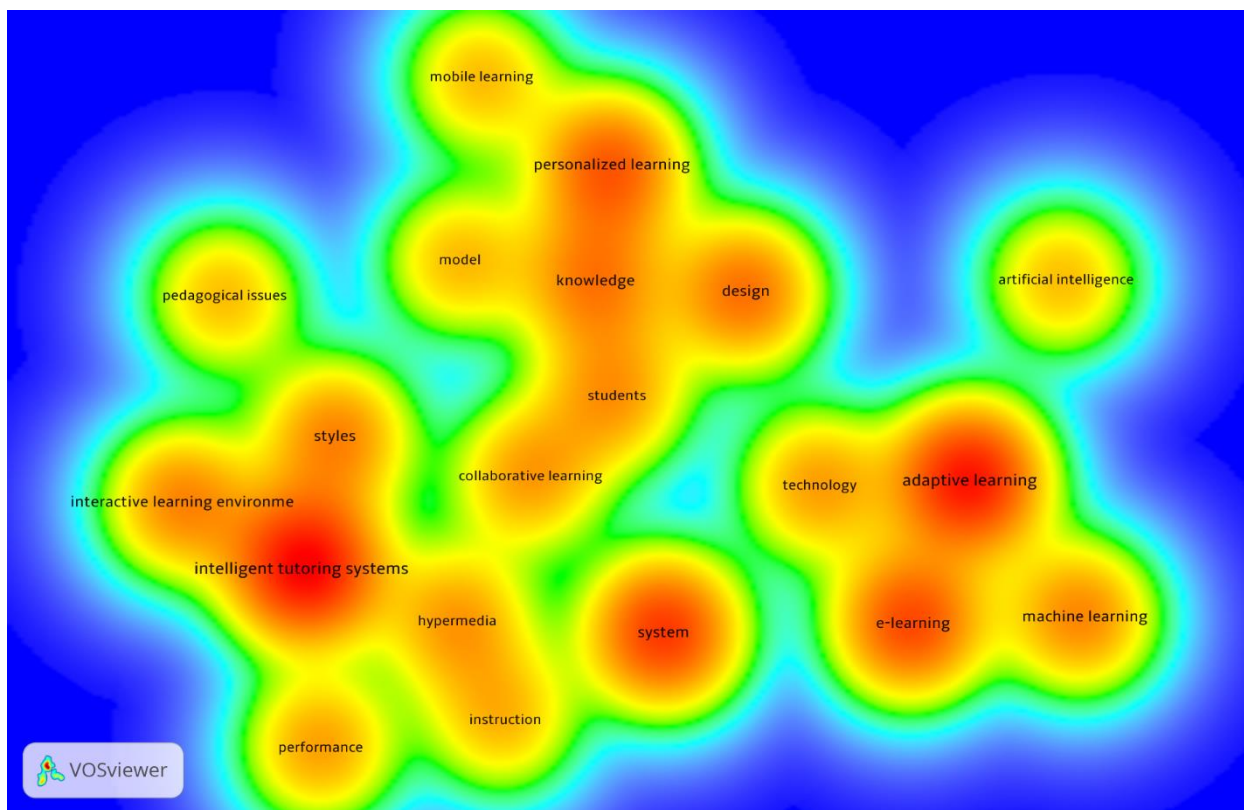


Figure 5. Density of Keywords co-occurrence network of adaptive/personalized learning.

Observe that personalized learning, intelligent tutoring system and adaptive learning are in the central positions (reddish) of the map. Keywords co-occurrence analysis is used by analysing their co-occurrence relationship in a large number of documents to examine the correlation strength between co-occurrence keywords. *Cluster 1*, label item: intelligent tutoring system has the highest occurrence of 14 with links of 13 and a total link strength of 24. *Cluster 2*, label item: adaptive learning has the second occurrence of 13 with links of 10 and a total link strength of 17 and *Cluster 3*, label item: personalized learning has the least occurrence of nine (9) with links of nine (9) and a total link strength of 19.

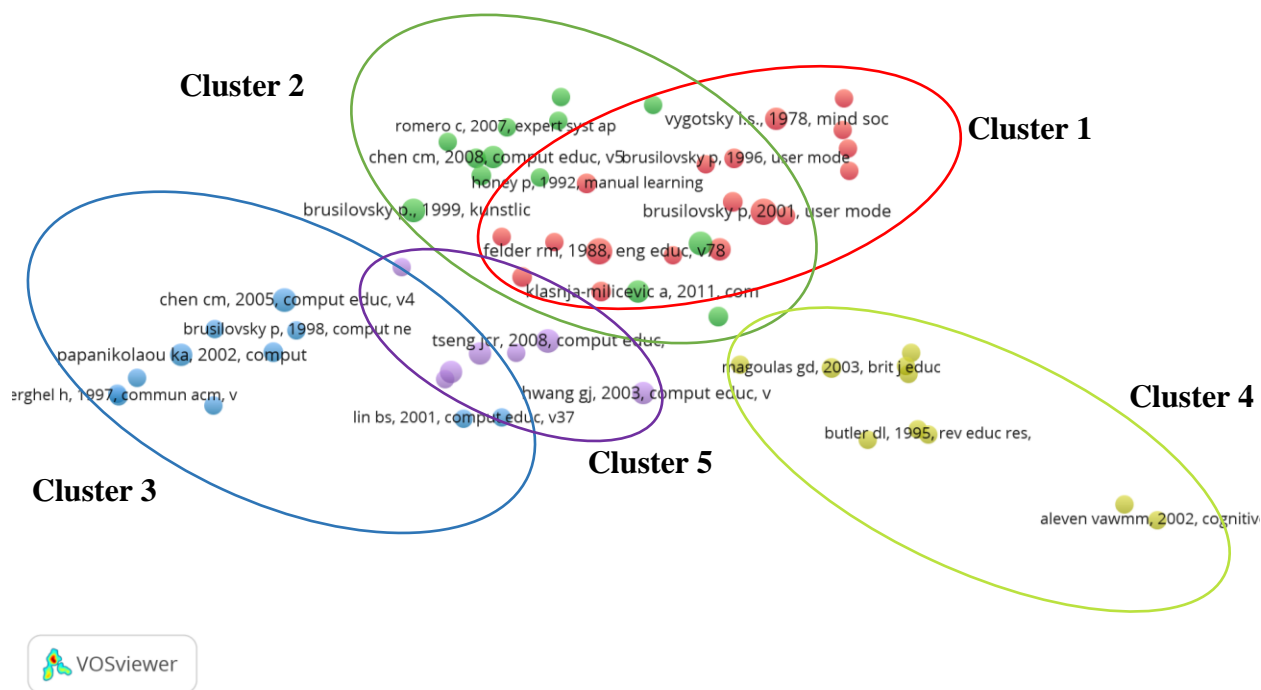


Figure 6. Co-citation analysis network of references cited by adaptive/personalized learning and artificial intelligence in learning publications period 2000-2020.

In **Figure 6**, the co-citation analysis network was conducted to see the trends within the cited references $n=4190$, when the minimum number of citations of a cited reference was adjusted and restricted to $n=3$, the results showed that only 61 met the threshold. However, since the minimum number of citations was adjusted in the co-citation included a large proportion of the data and old publication and recent publications were included. The result in **Figure 6** was presented based on the total linking strength of the co-citation with other cited references; the size of the corresponding circle indicates the importance of publications within the network map, the distance between articles and the number of citations received by those articles. The distance between two articles explains the overlap between them that is the closer they are; the more overlap between cited works by these publications.

The Clusters identified were Cluster 1 (*Red Colour*), Cluster 2 (*Green Colour*), Cluster 3 (*Blue Colour*), Cluster 4 (*Purple Colour*) and Cluster 5 (*Light Green Colour*). According to Cluster 1 ($n=18$), Brusilovsky (2001) has reviewed existing work on Adaptive Hypermedia, which constructs an individual user model and applies adaptation to that user knowledge, goals or suggests the most relevant links to follow. In Cluster 2 ($n=13$), (Aroyo et al., 2004) proposes a modular semantic-driven and service-based interoperability framework for accessing, exchanging and reusing educational systems' material and information components, Cluster 3 ($n=11$), Chen et al., 2005 proposes PEL-IRT that considers learning materials' difficulty and learners' ability to provide individual learning paths. Moreover, Cluster 4 ($n=10$), a content analysis on educational hypermedia to address learning styles which one third of the study presented a model with the student without empirical evaluation, however, several studies reported that the suggested models affected student satisfaction and performance (Akbulut, 2012). In addition, Cluster 5 ($n=7$), Chen

and Li (2010) proposed that ‘context’ is an important consideration in the language learning process and can enhance learner learning interest and efficiency through a personalized context-aware ubiquitous learning system.

In **Figure 7**, illustrates bibliographic coupling of documents. According to Van Eck and Waltman (2014: 3), bibliographic coupling is useful for displaying the overlap of references in the research results by showing the strengths of an output based on the number of citations that two outputs might have in common. The bibliographic network with five clusters of references cited by the 119 publications between 2000 and 2020 with a minimum number of citations of a documents ($n=30$), of the publications 33 meet the threshold.

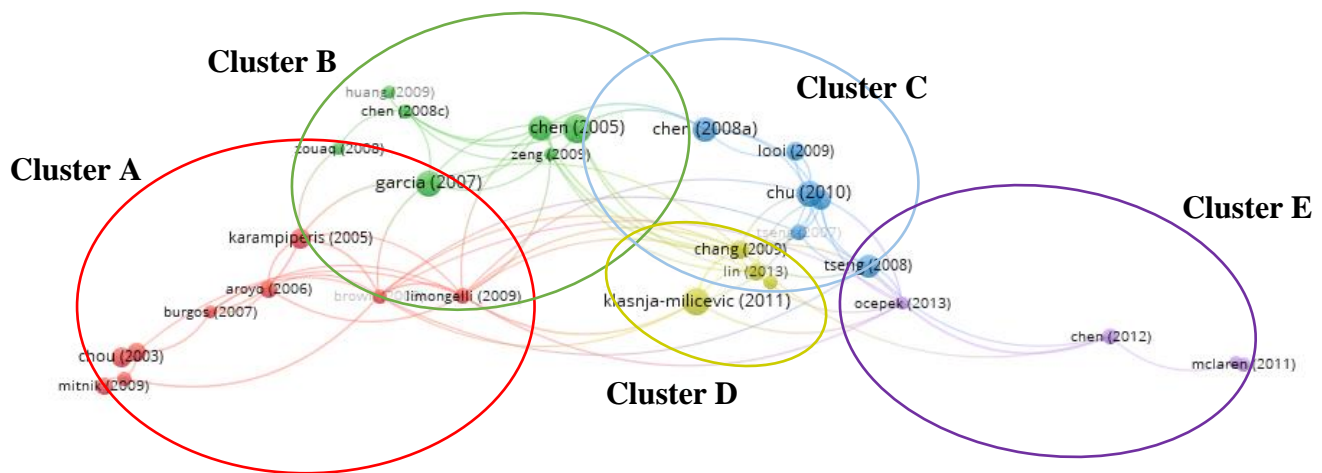


Figure 7. Bibliographic coupling based on documents published between 2000 and 2020.

Cluster A ($n=9$), Learning style framework for tailoring and adapting to eLearning. It manages the generation of personalized courses from suitable learning node repositories and ensures the maintenance of such courses, for continuous adaptation of the learning material proposed to the learner (Limongelli, Sciarrone, Temperini & Vaste, 2009), and this cluster was located at the center with a total link strength of 21 to other clusters.

Cluster B ($n=7$), Bayesian network models proposed in a Web-based education system since all the students can learn despite their different learning styles was evaluated in the context of AI Web-based course to detect how students can learn: reflecting or acting; intuitively or sensitively (García et al., 2007) and has a citation reference of 194.

Cluster C ($n=6$), (Tseng et al., 2008) focuses on innovative adaptive learning based on two sources of personalization information, that is; learning behavior and personal learning style but previous research of adaptive learning was centered on enhancing student learning performance based solely on a single source such as learning style or learning experience.

Cluster D ($n=4$), Lin, Yeh, Hung and Chang (2013) developed a personalized creativity learning system based on data mining technique of decision trees to provide personalized learning paths for optimizing the performance of creativity.

Cluster E ($n=4$), emotions assessment instrument emWave is applied to assess variations in emotional states for verbal and visuals during learning processes to investigate how different multimedia materials affect individual performance and emotion (Chen & Sun, 2012).

3.3.2 Coding Scheme

To investigate and analyse the impact of artificial intelligence in adaptive/personalized learning, the coding scheme of this study was developed. These are as follows; code for similarities between adaptive learning and personalized learning, code for artificial intelligence techniques or technologies, code for learning outcomes or achievements and code for contribution of AI and other technologies in assessing personalized learning as a technology to help students' achievement.

4.0 RESULTS

As aforementioned in **Figure 2**, phase one (interviews) in this research aimed at explanatory interview with a researcher in the domain of educational technology in the classroom then followed by phase two (surveys).

4.1 Similarities between adaptive learning and personalized learning.

To understand adaptive learning as a methodology that provides personalized learning through effective and tailored learning for every learner, there is the need to compare some similarities between the two concepts in **Table 8**.

Table 7. Comparison between adaptive learning and personalized learning.

Adaptive Learning	Personalized Learning
Adaptive learning uses a data-driven approach to change the learning direction and speed, which enables personalized learning to be implemented on a scale.	Personalized learning is learner-centered which emphasizes on student-driven instructional objectives, content and pace.
Adaptive learning refers to the technologies monitoring student progress using data to modify instruction at any time.	Personalized learning refers to instruction in which the learning pace and the teaching approach are optimized for each learner's needs.
Adaptive learning uses hypermedia to adapt dynamically to the student experiences and performance levels of a course content based on the profile of the learner.	Personalized learning also requires the use of technology to facilitate student learning and to provide tools for individual pacing and more efficient assessments to inform and tailor instruction.

4.2 Distribution of Artificial Intelligence (AI) techniques

Of the relevant articles ($n=32$), focused on artificial intelligence techniques that can be used to improve technology-enhanced learning. Various AI techniques have been used in adaptive educational systems. Neural networks, fuzzy logic, ant colony optimization, decision tree and Bayesian networks with 40%, 20%, 13% and 7% frequency respectively, were the most frequent artificial intelligent techniques applied as shown in **Figure 8**.

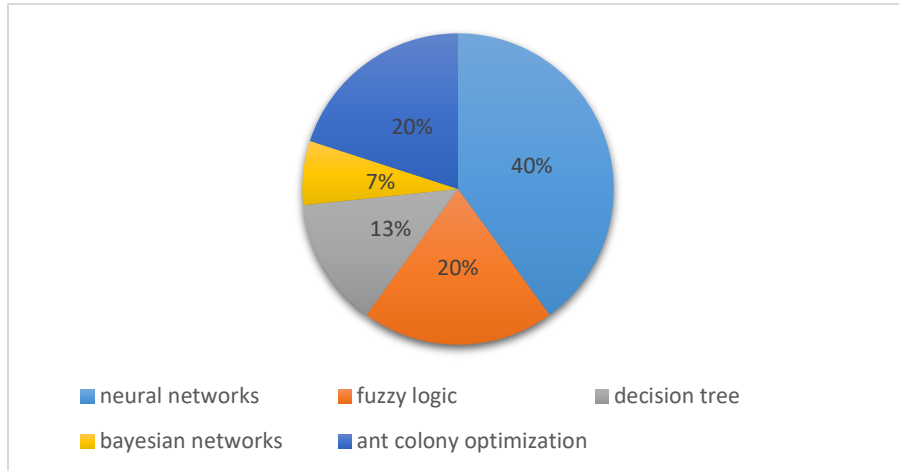


Figure 8. Distribution of AI techniques

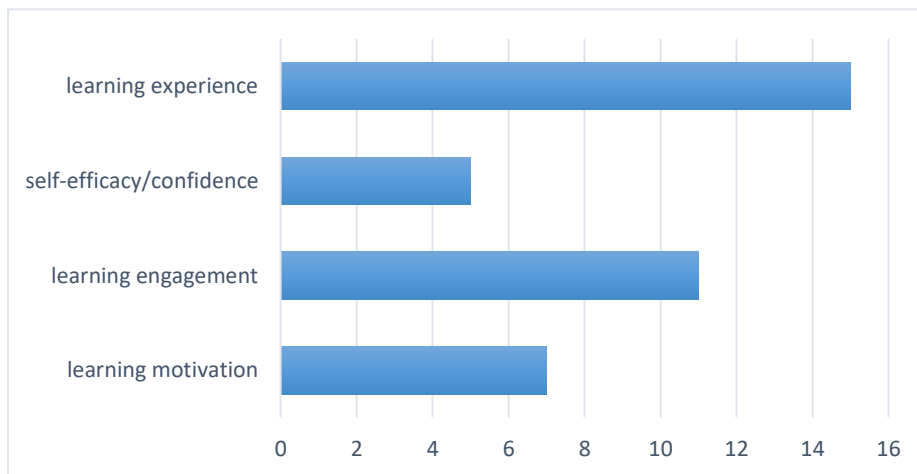


Figure 9. Distribution of sub-categories of learning outcomes

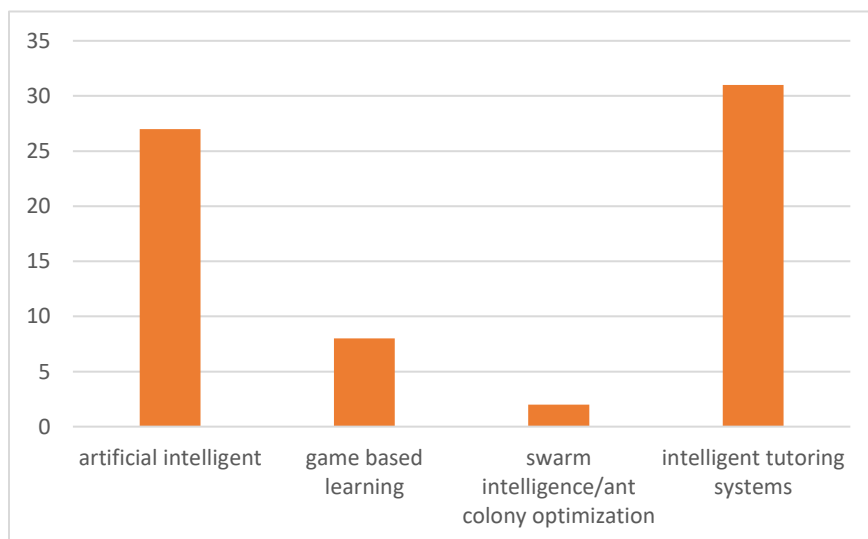


Figure 10. The distribution of technologies contribution to assessing personalized learning to help students' achievement.

4.3 Distribution of learning outcomes.

Among the inclusion articles ($n = 23$), focuses on reporting learning outcomes as reviewed by the authors. The learning outcomes was categorized into the following sub-categories: expectation of learning engagement, learning motivation, self-efficacy/confidence and learning experiences of students. **Figure 9** illustrates the distribution; learning experience is the most frequently measured in these studies. For example, (Looi et al., 2009) used mobile, handheld technologies to create a broad variety of personalized learning experiences through group meetings to exploit the variability in lesson enactment to students or learners. Wang and Kang (2005) create a cybergogy model to create cognitive, socially and emotionally engaging learning experiences for distance learners with diverse backgrounds. In which learners set their own goals, explore suitable resources, work with others in groups and build knowledge in meaningful ways.

Individualized learning paths will contribute to increased motivation as students engage with subjects they are interested in and feel responsible for developing their own learning paths with regard to material, preferences, needs, and skills to allow a more comprehensive and transdisciplinary information evolution. (Tseng et al., 2008) uses post-hoc comparisons between two groups that showed that adaptive learning facilities are helpful to students in improving their learning achievements or learning efficacy. The system (TSAL) record the online behaviours of each student, including unit learning time, idle time, response time, unit test score, unit learning efficiency, absorbed, and difficulty level then perform a test to evaluate the learning achievements of students, such that the feasible version of the next subject unit can be determined.

4.4 Distribution of technologies contribution to assessing personalized learning to help students' achievement.

There are four (4) main categories, namely intelligent tutoring systems, artificial intelligent, mobile game based learning/gamification/mobile learning and swarm intelligence/ant colony optimization for distribution of technologies contribution to assessing personalized learning to help students' achievement as shown in **Figure 10**. Among the articles ($n=68$), 45.6% ($n=31$) involved intelligent tutoring systems (ITS) contribution to adaptive/personalized learning, 39.7% ($n=27$) involved artificial intelligence, 11.7% ($n=8$) involved game based learning/mobile game-based learning/gamification, while 2.9% ($n=2$) involved swarm intelligence/ant colony optimization.

5.0 DISCUSSION

5.1 Research issues related to similarities and AI techniques

As noted in **Section 4.1**, there are similarities between adaptive learning and personalized learning. Adaptive learning is about making learning personal that enables educators to help their students or learners achieve learning outcomes through personalization. Personalized learning is about what you want, while adaptive learning is about what you need, however, both help in personalized learning experience. From the explanatory interview, it was found that adaptive learning aims at providing efficient, effective and learning paths for engaging every student while, personalized learning focus on learning path of each student. Furthermore, adaptive/personalized learning being seen as a technology or teaching methods, both have the same elements that is; individual differences, individual performance, and adaptive adjustment that make learning more individually meaningful.

In addition, **Section 4.2** indicates that artificial neural networks is the most frequently used AI technique of the relevant articles ($n=68$). Hussain et al., 2019 developed a system that uses machine-learning algorithms predict students' difficulty while undergoing courses taken online, thus giving instruction to teachers using the Technology Enabled Learning (TEL) system, while, an in-depth survey of the different artificial intelligence techniques employed for adaptive educational systems within e-learning platforms like fuzzy logic, Bayesian networks, and genetic algorithms (Almohammadi et al., 2017). These techniques enable AI to deliver adaptive instruction, guidance and evaluate learners or students.

- Neural networks consisting of a large number of highly connected processing nodes which work in unison to solve specific problems.
- Decision trees that allow us to create a tree-like picture of decisions and alternative next steps and to identify a strategy for achieving a defined objective.
- A dynamic advice generator that uses fuzzy logic to provide learners with adaptive help based on learner assumptions and their profile. The advice generator offers cognitive advice for learners, namely descriptive feedback to improve the learning strategy. (Troussas et al., 2020)
- Ant Colony optimization is an algorithm used to evaluate the optimal paths in data and processes in a manner close to the way the ants behave.
- Bayesian networks detect the learning style of a student or learner in a web-based education system which is used to detect how students learn: reflecting or acting; steadily or in fits and starts; intuitively or sensitively (García et al., 2005)

5.2 Research issues related to learning outcomes

As mentioned in **Section 4.3**, learning experience and learning engagement were with high frequency per the articles. During the interview; it was found that adaptive/personalized learning is very good at improving rote learning based on performance however there is a lot of work around higher order thinking since its attract less attention due to the complexity processes and are not

easy to measure. For example, (Xie et al., 2019) critical success factors to evaluate the higher order thinking in adaptive learning environment using qualitative comparative analysis (QCA) and the method cannot be used on a large scale. In terms of learning engagement, it was found from the interview that the use of electroencephalogram (EEG) has shown to improve learner’s engagement in terms of their attention through the indirect process and that has actually improved their overall performance on a basic knowledge test.

5.3 Research issues related to the role of AI in learning

According to **Section 4.4**, the four (4) main categories are all using AI techniques or technologies in adaptive/personalized learning. **Table 9** shows adaptive/personalized learning system in facilitating learning per the inclusion study, these systems adjust the learning experience based upon the student’s progress, increasing the level of difficulty when they are progressing well, and slowing down if they need further instruction and below are systems that are dominated by those focussed upon the education sector.

Table 8. Adaptive/personalized learning system.

System/Method	Developed By	Type
AutoTutor	University of Memphis	Intelligent tutoring system
ALEKS (Assessment and Learning in Knowledge Spaces)	New York University and the University of California, Irvine	Intelligent tutoring system
PEL-IRT (Personalized e-learning system based on Item Response Theory)	Sponsored by National Science Council of the Republic of China	Intelligent tutoring system
AXIS (Adaptive eXplanation Improvement System)	Presented by (Williams et al., 2016)	Adaptive Learning
Protus	Presented by (Klašnja-Milićević et al., 2010)	Personalized learning
PeRSIVA	Department of Informatics, University of Piraeus	Adaptive and/or personalized tutoring system
TenseITS		Intelligent tutoring system
DreamBox	DreamBox	Adaptive Learning
eTeacher	Presented by (García et al., 2005)	Personalized learning
MATHia		Adaptive Learning (Cognitive Tutor)
SmartTutor	University of Hong Kong	Adaptive Learning

In addition, results from the conducted interview indicate that because AI technologies are already developed for mobile phones. For example, Chen and Chung (2008) adopted the Item Response Theory (IRT) to recommend the appropriate English vocabulary based on individual learning capabilities and memory curves to facilitate personalized vocabulary learning.

6.0 CONCLUSION

This study presents a systematic review of academic literature that explores AI's role in learning and answered some important research questions regarding similarities between adaptive/personalized learning, learning outcomes and some AI techniques in the relevant literature published between 2000 and 2020.

Also, the similarities between adaptive/personalized learning were made clear based on the three (3) element found that is individual differences, individual performance, and adaptive adjustment that make learning more individually meaningful. However, the terms "adaptive learning" and "personalized learning" are different; in different studies they are often used interchangeably (Lin et al., 2013). As the number of smartphones or mobile devices is increasing rapidly on learning process and facilitating adaptive/personalized learning, the results has recommended AI in learning and adaptive/personalized systems on wearable devices. According to (Borthwick et al., 2015), wearable devices can serve as a valuable asset in the classroom, enhancing instruction differentiation and student engagement. In terms of learning outcomes and the process of adaptive/personalized learning, higher order thinking attracted little attention due to complexity processes, difficulty of measurement, and limited types of learning support.

To sum up, this study suffers from a number of limitations; in particular, the study was restricted to a manual search of articles on Web of Science, time constraint since the study was to conduct more explanatory interviews from researchers in the subject domains. Moreover, this study discusses the AI techniques such as fuzzy logic, Bayesian network, artificial neural networks, etc. that are contributing to adaptive/personalized learning, learning outcomes, technologies contribution to assessing personalized learning to help students' achievement and swarm intelligence, game-based learning, intelligent tutoring systems which helps to facilitate learning process in adaptive/personalized learning.

REFERENCES

- Adams Becker S., M. Cummins, A. Davis, A. Freeman, C. Hall Giesinger, V. Ananthanarayanan, NMC Horizon Report: 2017 Higher Education Edition (The New Media Consortium, Austin, 2017).
- Adams, R. L. (2017). 10 Powerful examples of artificial intelligence in use today. Forbes. Retrieved from <https://www.forbes.com/sites/robertadams/2017/01/10/10-powerful-examples-of-artificial-intelligence-in-use-today/#329329a0420d>
- Akobeng, A. K. (2005). Understanding systematic reviews and meta-analysis. *Archives of Disease in Childhood*; 90:845-848
- Akbulut, Y., & Cardak, C. S. (2012). Adaptive educational hypermedia accommodating learning styles: a content analysis of publications from 2000 to 2011. *Computers & Education*, 58(2), 835–842.
- Amandi, Garcia, Schiaffino, & Campo (2008). eTeacher: Providing personalized assistance to e-learning students. *Computers & Education Journal*.
- Amory, A. (2011). Play games to learn: pre-service teacher development. In *The proceedings of world conference on educational multimedia, hypermedia and telecommunications* (pp. 2118–2119).
- Arlene C. Borthwick, Cindy L. Anderson, Elizabeth S. Finsness & Teresa S. Foulger (2015) Special Article Personal Wearable Technologies in Education: Value or Villain?, *Journal of Digital Learning in Teacher Education*, 31:3, 85-92, DOI: [10.1080/21532974.2015.1021982](https://doi.org/10.1080/21532974.2015.1021982)
- Aroyo, L., King, M. L., Drive, J., & Salem, W. (2004). International Forum of Educational Technology & Society The New Challenges for E-learning : The Educational Semantic Web Author (s): Lora Aroyo and Darina Dicheva Published by : International Forum of Educational Technology & Society Stable URL : [http://www.ijer.technology.com/issue/7\(4\)/Aroyo%20et%20al%20-%20The%20Educational%20Semantic%20Web](http://www.ijer.technology.com/issue/7(4)/Aroyo%20et%20al%20-%20The%20Educational%20Semantic%20Web). *Journal of Educational Technology & Society*, 7(4), 59–69.
- BECTA. (2007). Personalizing Learning: The Opportunities Offered by Technology. <http://archive.teachfind.com/becta/feandskills.becta.org.uk/display806e.html?resID=31571>. Accessed 05 May 2020
- Bentley, T. and R. Miller (2004), “Personalization; Creating the Ingredients for Systematic and Society-wide Change”, a paper presented in Personalized Learning Conference, London, 17-18 May (see Chapter 8).
- Bonabeau, E., & Meyer, C. (2001). Swarm intelligence: A whole new way to think about business. *Harvard Business Review*, 79, 106–114.
- Bonabeau, E., Dorigo, M., & Theraulaz, G. (2000). Inspiration for optimization from social insect behavior. *Nature*, 406, 39–42

- Brusilovsky, P. (1998). Methods and techniques of adaptive hypermedia. In A. Kobsa & J. Vassileva (Eds.), *Adaptive hypermedia and hypermedia* (pp. 1–43). London: Kluwer Academic Publishers.
- Brusilovsky, P. (Mar. 2001). Adaptive hypermedia. *User Modeling and User-Adapted Interaction*, 11(1-2), 87–110.
- Brusilovsky, P., & Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education*, 13(2–4, Special Issue on Adaptive and Intelligent Web-based Educational Systems), 159–172.
- Burguillo, J. C. (2010). Using game theory and competition-based learning to stimulate student motivation and performance. *Computers & Education*, 55(2), 566–575
- Butoianu, V., Vidal, P., Verbert, K., Duval, E., & Broisin, J. (2010). User context and personalized learning: A federation of contextualized attention metadata. *Journal of Universal Computer Science*, 16(16), 2252–2271.
- Chang, K. E., Wu, L. J., Weng, S. E & Sung, Y. T. (2011). Embedding game-based problem-solving phase into problem-posing system for mathematics learning. *Computers & Education*, 58(2), 775–786.
- Chaudhri, Lane, Gunning, and Roschelle (2013). *Intelligent Learning Technologies: Applications of Artificial Intelligence to Contemporary and Emerging Educational Challenges*. Association for the Advancement of Artificial Intelligence
- Chen, C. M., & Chung, C. J. (2008). Personalized mobile English vocabulary learning system based on item response theory and learning memory cycle. *Computers & Education*, 51(2), 624–645.
- C. Limongelli, F. Sciarrone, M. Temperini and G. Vaste, "Adaptive Learning with the LS-Plan System: A Field Evaluation," in *IEEE Transactions on Learning Technologies*, vol. 2, no. 3, pp. 203-215, July-Sept. 2009, doi: 10.1109/TLT.2009.25.
- C. M. Chen and Y. L. Li (2010) "Personalized Context-Aware ubiquitous learning system for supporting effective english vocabulary learning," *Interactive Learn. Environ.*, vol. 18, no. 4, pp. 341–364.
- Chen, Lee, and Chen (2005). Personalized e-learning system using Item Response Theory. *Computers & Education*, p.239.
- Christos, Akrivi and Cleo (2019). Collaboration and fuzzy-modeled personalization for mobile game- based learning in higher education. *Computers & Education*. Vol. 144.
- Coffield, F. Moseley, D. Hall, E., & Ecclestone, K. (2004). Learning styles and pedagogy in post-16 learning: A systematic and critical review. London, Learning and Skills Research Centre. <http://www.ncl.ac.uk/cflat/projects/item/1927>

- Colchester, K., Hagraas, H., Alghazzawi, D., & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e- learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, 7(1), 47–64. <https://doi.org/10.1515/jaiscr-2017-0004>.
- Craft, A. (2005). *Creativity in schools: Tensions and dilemmas*. Routledge, NY: Abingdon
- D’Mello, C., Graessner, A., 2012b. Dynamics of affective states during complex learning. *Learn. Instr.* 22 (2), 145–157.
- D’Mello, S.K., Graesser, A.C., 2012a. AutoTutor and affective AutoTutor: Learning by talking with cognitively and emotionally intelligent computers that talk back. *ACM Trans. Interact. Intell. Syst.* 2 (4), 23.
- Dawson, S., Heathcote, L., & Poole, G. (2010). Harnessing ICT potential: The adoption and analysis of ICT systems for enhancing the student learning experience. *International Journal of Educational Management*, 24(2), 116–128.
- Di Marzo, Gleizes, & Karageorgos, 2006; Holland, 1992. *Self-Organisation and Emergence in MAS: An Overview*.
- EDUCAUSE. (2016). *Adaptive Learning Systems: Surviving the Storm*. <http://er.educause.edu/articles/2016/10/adaptive-learning-systems-surviving-the-storm>. Accessed 05 May 2020
- EDUCAUSE. (2019). *Horizon report: 2019 higher education edition*. Retrieved from EDUCAUSE Learning Initiative and The New Media Consortium website: <https://library.educause.edu/-/media/files/library/2019/4/2019horizonreport.pdf>
- Felder, R. M., & Soloman, B. A. (2000). *Learning styles and strategies*.
- Felder, R. M., & Solomon, B. A. (1998). *Index of learning styles*. Retrieved April 24 2020 from [http:// www.engr.ncsu.edu/learningstyles/ilsweb.html](http://www.engr.ncsu.edu/learningstyles/ilsweb.html).
- Fu, Q. K., & Hwang, G. J. (2018). Trends in mobile technology-supported collaborative learning: A systematic review of journal publications from 2007 to 2016. *Computers & Education*, 119, 129–143.
- García, P., Amandi, A., Schiaffino, S., & Campo, M. (2005). Evaluating Bayesian networks’ precision for detecting students’ learning styles. *Computers & Education*, 49(3), 794–808. <https://doi.org/10.1016/j.compedu.2005.11.017>
- García, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks’ precision for detecting students’ learning styles. *Computers & Education*, 49, 794–808.
- Garcia-Valdez, M., Alanis, A., Parra, B., 2010. Fuzzy inference for learning object recommendation. *IEEE Int. Conf. Fuzzy Syst.*, 1–6. <http://dx.doi.org/10.1109/FUZZY.2010.5584322>

- Golonka, E. M., Bowles, A. R., Frank, V. M., Richardson, D. L., & Freynik, S. (2014). Technologies for foreign language learning: A review of technology types and their effectiveness. *Computer Assisted Language Learning*, 27(1), 70–105
- Graf, S., & Kinshuk. (2007). Providing adaptive courses in learning management systems with respect to learning styles. In T. Bastiaens, & S. Carliner (Eds.), *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and higher Education* (pp. 2576–2583). Chesapeake, VA: AACE
- Graf, S., Liu, T.-C., Chen, N.-S., & Yang, S. J. H. (2009). Learning styles and cognitive traits – their relationship and its benefits in web-based educational systems. *Computers in Human Behavior*, 25(6), 1280–1289.
- Griffin A. Stephen Hawking: Artificial Intelligence could wipe out humanity when IT gets too clever as humans will be like ants [Electronic resource] // Independent. 2015. URL: <https://www.independent.co.uk/life-style/gadgets-and-tech/news/stephen-hawking-artificial-intelligence-could-wipe-out-humanity-when-it-gets-too-clever-as-humans-a6686496.html>. Accessed on 26 May 2020.
- Hesse-Biber, S. (2010). Qualitative approaches to mixed methods practice. *Qualitative Inquiry*, 16(6), 455–468. <https://doi.org/10.1177/1077800410364611>
- Honey, P. and Mumford, A., (1992). *The Manual of Learning Styles (3rd Ed.)*, Maidenhead: Peter Honey.
- Housman, M. (2018). Why ‘augmented intelligence’ is a better way to describe AI. *AINews*. Retrieved from <https://artificialintelligence-news.com/2018/05/24/why-augmented-intelligence-is-a-better-way-to-describe-ai/>
- Huang, C. S., Yang, S. J., Chiang, T. H., & Su, A. Y. (2016). Effects of situated mobile learning approach on learning motivation and performance of EFL students. *Educational Technology & Society*, 19(1), 263–276.
- Huovinen, L. (2001). Developing Virtual Learning Environments: Finnish Information Strategy for Education and Research 2000-2004. In C. Montgomerie & J. Viteli (Eds.), *Proceedings of ED-MEDIA 2001--World Conference on Educational Multimedia, Hypermedia & Telecommunications* (pp. 798-802). Norfolk, VA USA: Association for the Advancement of Computing in Education (AACE). Retrieved May 28, 2020 from <https://www.learntechlib.org/primary/p/8743/>.
- Hussain, M., Zhu, W., Zhang, W., Abidi, S. M. R., & Ali, S. (2019). Using machine learning to predict student difficulties from learning session data. *Artificial Intelligence Review*, 52(1), 381–407. <https://doi.org/10.1007/s10462-018-9620-8>
- Hwang, G. J. (2002). On the development of a cooperative tutoring environment on computer networks. *IEEE Transactions on System, Man and Cybernetic Part C*, 32(3), 272–278.

- Hwang, G. J., Kuo, F. R., Yin, P. Y., & Chuang, K. H. (2010). A heuristic algorithm for planning personalized learning paths for context-aware ubiquitous learning. *Computers & Education*, 54(2), 404–415.
- J. K. Waters (2014). The Great Adaptive Learning Experiment. <https://campustechnology.com/articles/2014/04/16/the-great-adaptive-learning-experiment.aspx>. Accessed 05 May 2020.
- Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, 31(8), 651–666.
- James, W. B., & Gardner, D. L. (1995). Learning styles: Implications for distance learning. *New Directions for Adult and Continuing Education*, (67), 19–31 1995.
- Johnson R. B., & Onwuegbuzie, A.J. 2004. *Mixed Methods Research: A Research Paradigm whose Time Has Come*. Sage Publications, Inc.
- Johnson, R. R. B., & Christensen, L. B. (2007). *Educational research: Quantitative, qualitative, and mixed approaches*. Sage Publications, Inc.
- Jung, J. Y., & Graf, S. (2008). An approach for personalized web-based vocabulary learning through word association games. In *International symposium on applications and the Internet* (pp. 325–328)
- Kaloo, V., Kinshuk, K., & Mohan, P. (2010). Personalized game based mobile learning to assist high school students with mathematics. *International Conference on Advanced Learning Technologies*, 2010, 485–487
- Kangas, M. (2010). Creative and playful learning: learning through game co-creation and games in a playful learning environment. *Thinking Skills and Creativity*, 5(1), 1–15.
- Kiili, K. (2005). Digital game-based learning: towards an experiential gaming model. *Internet and Higher Education*, 8, 18.
- Kinshuk, Y. Sakurai, S. Graf, A. Zarypolla, K. Takada, and S. Tsuruta, “Enriching Web Based Computer Supported Collaborative Learning Systems by Considering Misunderstandings among Learners during Interactions,” *Proc. Ninth IEEE Int’l Conf. Advanced Learning Technologies (ICALT ’09)*, pp. 306-310, 2009.
- Kirriemuir, J., & McFarlane, A. (2004). *Literature review in games and learning*, Vol. 8 Bristol, UK: Futurelab.
- Kitchenham, B., 2004. *Procedures for Performing Systematic Reviews*. vol. 33. Keele University, Keele, UK p. 2004.
- Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education*, 56(3), 885–899.

- Koedinger, K. R., Booth, J. L., & Klahr, D. (2013). Instructional complexity and the science to constrain it. *Science*, 342, 935–937.
- Kolb, D. A. (1971). *Individual learning styles and the learning process*. Cambridge, MA: Sloan School of Management, Massachusetts Institute of Technology.
- Latham, A., Crockett, K., Mclean, D., 2014. An adaptation algorithm for an intelligent natural language tutoring system. *Comput. Educ.* 71, 97–110.
- Leontidis, M., Halatsis, C., 2009. Integrating learning styles and personality traits into an affective model to support learner's learning. In: Spaniol, M., et al. (Eds.), *Advances in Web Based Learning – ICWL 2009* 5686. Springer LNCS, pp. 225-234.
- Li, K. D. (2015). Personalized Learning in E-Learning Environment. <http://www.docin.com/p-1199857000.html> Accessed 05 May 2020.
- Lo, J. J., Wang, H. M., & Yeh, S. W. (2004). Effects of confidence scores and remedial instruction on prepositions learning in adaptive hypermedia. *Computers & Education*, 42(1), 45–63
- Luckin, Rose; Holmes, Wayne; Griffiths, Mark and Forcier, Laurie B. (2016). *Intelligence Unleashed: An argument for AI in Education*. Pearson Education, London.
- Magnisalis, I., Demetriadis, S., & Karakostas, A. (n.d.). Adaptive and Intelligent Systems for Collaborative Learning Support: A Review of the Field. *IEEE Transactions on Learning Technologies*, 4(1), 5–20. <https://doi.org/10.1109/tlt.2011.2>
- Mark William Johnson & David Sherlock (2014). Beyond the Personal Learning Environment: attachment and control in the classroom of the future, *Interactive Learning Environments*, 22:2, 146-164, DOI: 10.1080/10494820.2012.745434
- Martinez, M., & Bunderson, C. V. (2000). Building interactive world wide web learning environments to match and support individual learning differences. *Journal of Interactive Learning Research*, 11(2), 131–162.
- McCorduck, Pamela (2004). *Machines who think: a personal inquiry into the history and prospects of artificial intelligence*, Natick, MA: AK Peters, (p.204).
- McKenzie, W. A., Perini, E., Rohlf, V., Toukhsati, S., Conduit, R., & Sanson, G. (2013). A blended learning lecture delivery model for large and diverse undergraduate cohorts. *COMPUTERS & EDUCATION*, 64, 116–126. <https://doi.org/10.1016/j.compedu.2013.01.009>
- Mitrovic, A., Martin, B., & Suraweera, P. (2007). Intelligent tutors for all: constrained-based modeling methodology, systems and authoring. *IEEE Intelligent Systems, Special Issue on Intelligent Educational Systems*, 22(4), 38–45.

- Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of Internal Medicine*, 151(4), 264–269
- Murphy, R., Gallagher, L., Krumm, A., Mislevy, J., & Hafter, A. (2014). Research on the use of Khan Academy in schools. Menlo Park, CA: SRI International. Retrieved from <http://www.sri.com/sites/default/files/publications/khan-academy-implementation-report-2014-04-15.pdf>
- N. H. Kilicay et al., "Multi-Agent Architectures for Analysis of Complex Adaptive Systems," *Proceedings of the 7th International Conference, Adaptive Computing in Design and Manufacture (2006, Bristol, UK)*, Institute for People-centred Computation (IP-CC), Apr 2006.
- Nabiyev, V. V. (2010). *Yapay zeka: İnsan bilgisayar etkileşimi*. Seçkin Yayıncılık.
- Natriello, G. (2007). Imagining, seeking, inventing: the future of learning and the emerging discovery networks. *Learning Inquiry*, 1, 7–18.
- Natriello, G. (Ed.). (2013). *Adaptive educational technologies: Tools for learning, and for learning about learning*. Washington, DC: National Academy of Education.
- Nye, B. D., Pavlik Jr., P. I., Windsor, A., Olney, A., Hajeer, M., & Hu, X. (2018). SKOPE-IT (Shareable Knowledge Objects as Portable Intelligent Tutors): overlaying natural language tutoring on an adaptive learning system for mathematics. *INTERNATIONAL JOURNAL OF STEM EDUCATION*, 5. <https://doi.org/10.1186/s40594-018-0109-4>
- Paolucci, R. (1998, June 20–25). Hypermedia and learning: The relationship of cognitive style and knowledge structure. In *Proceedings of ED-MEDIA/ED-TELECOM 1998*, Freiburg, Germany.
- Patrick Wang; Pierre Tchounikine; Matthieu Quignard. Chao: a framework for the development of orchestration technologies for technology-enhanced learning activities using tablets in classrooms // *Int. J. Technol. Enhanc. Learn.* 2018. Vol. 10, № 1/2.
- Phobun, P., & Vicheanpanya, J. (2010). Adaptive intelligent tutoring systems for e-learning systems. *Procedia-Social and Behavioral Sciences*, 2(2), 4064-4069. <http://dx.doi.org/10.1016/j.sbspro.2010.03.641>
- Poole, D., Mackworth, A. & Goebel, R. (1998) *Computational Intelligence: A Logical Approach*, Oxford University Press.
- Prensky, M. (2001). *Digital game-based learning*. New York: McGraw-Hill.
- Prensky, M. (2005). Complexity matters. *Educational Technology*, 45(4), 5–20.
- RAND Corporation (2015). *Continued Progress: Promising Evidence on Personalized Learning*. http://www.rand.org/pubs/research_reports/RR1365.html (Accessed April 23, 2020)

- Rudd, T. (2008). Learning spaces and personalization workshop outcomes. Bristol, UK: NESTA Futurelab. Retrieved 5 January, 2009, from http://www.futurelab.org.uk/resources/documents/event_presentations/Learning_Spaces_and_Personalisation_workshop.pdf
- Rus, V., Baggett, W., Gire, E., Franceschetti, D., Conley, M., Graesser, A.C., 2013. Towards learner models based on learning progressions in DeepTutor. In: Sottolare, R. (Ed.), *Learner Models*. Army Research Lab.
- Russell, T. (1997). Technology wars: Winners and losers. *Educom Review*, 32(2), 44–46.
- Samuelis, L., (2007). Notes on the Components for Intelligent Tutoring Systems.
- Sang-Hun, C. (2016). Google's Computer Program Beats Lee Se-dol in Go Tournament. *The New York Times*. Retrieved from <https://www.nytimes.com/2016/03/16/world/asia/korea-alphago-vs-lee-sedol-go.html>
- Sani, S., Aris, T., 2014. Computational intelligence approaches for student/tutor modeling: a review. In: *Proceedings of the 2014th International Conference on Intelligent Systems, and Simulation*, IEEE Computer Society, doi: <http://www.dx.doi.org/10.1109/ISMS.2014.21>.
- Sawyer, R. K. (2006). Educating for innovation. *Thinking Skills and Creativity*, 1, 41–48.
- Semet, Y., Lutton, E., & Collet, P. (2003). Ant colony optimization for E-learning: Observing the emergence of pedagogic suggestions. In *IEEE SIS'03: IEEE swarm intelligence symposium* (pp. 46–52).
- Shute, V. J., & Zapata-Rivera, D. (2012). Adaptive educational systems. In P. Durlach (Ed.), *Adaptive technologies for training and education* (pp. 7–27). New York, NY: Cambridge University Press.
- Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist*, 38(2), 105–114.
- Snow, R., & Farr, M. (1987). Cognitive-conative-affective processes in aptitude, learning, and instruction: An introduction. *Conative and affective process analysis*, 3, 1–10.
- Tang, S., & Hanneghan, M. (2011). State-of-the-art model driven game development: a survey of technological solutions for game-based learning. *Journal of Interactive Learning Research*, 22(4), 551–605
- Tranfield, D, Denyer, D. and Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of semantic review. *British Journal of Management*. Vol. 14 No.3, pp.207-222.
- Troussas, C., Krouska, A., & Sgouropoulou, C. (2020). Collaboration and fuzzy-modeled personalization for mobile game based learning in higher education. *COMPUTERS & EDUCATION*, 144. <https://doi.org/10.1016/j.compedu.2019.103698>

- Troussas, C., Krouska, A., & Sgouropoulou, C. (2020). Collaboration and fuzzy-modeled personalization for mobile game based learning in higher education. *COMPUTERS & EDUCATION*, 144. <https://doi.org/10.1016/j.compedu.2019.103698>
- U.S. Department of Education. 2017 National Education Technology Plan. Future Ready Learning: Reimagining the Role of Technology in Education. <http://tech.ed.gov/files/2015/12/NETP16.pdf> (Accessed April 23, 2020)
- Van Eck, N. J., & Waltman, L. (2014). Visualizing bibliometric networks. In *Measuring scholarly impact* (pp. 285-320). Springer, Cham. Available Online: https://link.springer.com/chapter/10.1007%2F978-3-319-10377-8_13
- Almohammadi, K., Hagra, H., Alghazzawi, D., & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, 7(1), 47–64. <https://doi.org/10.1515/jaiscr-2017-0004>
- Chen, C.-M., & Sun, Y.-C. (2012). Assessing the effects of different multimedia materials on emotions and learning performance for visual and verbal style learners. *COMPUTERS & EDUCATION*, 59(4), 1273–1285. <https://doi.org/10.1016/j.compedu.2012.05.006>
- García, P., Amandi, A., Schiaffino, S., & Campo, M. (n.d.). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education*, 49(3), 794–808. <https://doi.org/10.1016/j.compedu.2005.11.017>
- Hesse-Biber, S. (2010). Qualitative approaches to mixed methods practice. *Qualitative Inquiry*, 16(6), 455–468. <https://doi.org/10.1177/1077800410364611>
- Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (n.d.). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education*, 56(3), 885–899. <https://doi.org/10.1016/j.compedu.2010.11.001>
- Lin, C. F., Yeh, Y., Hung, Y. H., & Chang, R. I. (2013). Data mining for providing a personalized learning path in creativity: An application of decision trees. *COMPUTERS & EDUCATION*, 68, 199–210. <https://doi.org/10.1016/j.compedu.2013.05.009>
- Looi, C.-K., Wong, L.-H., So, H.-J., Seow, P., Toh, Y., Chen, W., Zhang, B., Norris, C., & Soloway, E. (2009). Anatomy of a mobilized lesson: Learning my way. *COMPUTERS & EDUCATION*, 53(4, SI), 1120–1132. <https://doi.org/10.1016/j.compedu.2009.05.021>
- Troussas, C., Krouska, A., & Sgouropoulou, C. (2020). Collaboration and fuzzy-modeled personalization for mobile game based learning in higher education. *COMPUTERS & EDUCATION*, 144. <https://doi.org/10.1016/j.compedu.2019.103698>
- Tseng, J. C. R., Chu, H.-C., Hwang, G.-J., & Tsai, C.-C. (2008). Development of an adaptive learning system with two sources of personalization information. *COMPUTERS & EDUCATION*, 51(2), 776–786. <https://doi.org/10.1016/j.compedu.2007.08.002>
- Williams, J. J., Kim, J., Rafferty, A., Maldonado, S., Gajos, K. Z., Lasecki, W. S., Heffernan, N., & Acm. (2016). AXIS: Generating Explanations at Scale with Learnersourcing and Machine Learning. In *Proceedings of the Third. Assoc Computing Machinery*. <https://doi.org/10.1145/2876034.2876042>

- Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, 140(June), 103599. <https://doi.org/10.1016/j.compedu.2019.103599>
- VanLehn, K (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education*, 16(3), 227–265.
- VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197-221. <http://dx.doi.org/10.1080/00461520.2011.611369>
- Villaverde, E., Godoy, D., Amandi, A., 2006. Learning styles' recognition in e-learning environments with feed-forward neural networks. *J. Comput. assisted Learn.* 22, 197–206.
- Wakelam, Jefferies, Davey and Sun (2015). The Potential for Using Artificial Intelligence Techniques to Improve e-Learning System. *Proceedings of the European Conference on e-Learning, ECEL*. p. 762-770
- Walonoski, J. A., & Heffernan, N. T. (2006). Detection and analysis of off-task gaming behavior in intelligent tutoring systems. *Lecture Notes in Computer Science*, 4053, 382–391.
- Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers and Education*, 140(May), 103599. <https://doi.org/10.1016/j.compedu.2019.103599>
- Y. Huang and C. Liu, “Applying Adaptive Swarm Intelligence Technology with Structuration in Web-Based Collaborative Learning,” *Computers and Education*, vol. 52, no. 4, pp. 789-799, 2009.
- Yeh, Y. C. (2012). Deconstructing and reconstructing the cognitive process of creativity via digital games (NSC 100-2511-S-004-002-MY3). Taipei: The National Science Council of the Republic of China in Taiwan.
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1). <https://doi.org/10.1186/s41239-019-0171-0>
- <http://www.dreambox.com>
- <http://www.reasoningmind.org>
- <https://carnegielearning.com/>
- <https://www.khanacademy.org>

GLOSSARY

Adaptive Intelligent Tutoring Systems (AITS) for e-learning systems that allows knowledge to be stored in such a way that is not only independent of the knowledge domain, but also supports the storage of transfer knowledge relationships and prerequisite knowledge relationships.

Ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs.

Artificial General intelligence or “Strong” AI refers to machines that exhibit human intelligence. In other words, AGI can successfully perform any intellectual task that a human being can.

Artificial Intelligence (AI) sometimes called machine intelligence is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and animals.

Artificial Intelligence in Education (AIEd) is applying artificial intelligence technology to the field of education and using it in students’ learning at schools.

Artificial Narrow Intelligence (ANI) also known as “Weak” AI is the AI that exists in our world today.

Artificial Super Intelligence (ASI) will surpass human intelligence in all aspects from creativity, to general wisdom, to problem solving.

Computer Aided/Assisted Learning (CAL) is a self-descriptive term that literally means learning with computers.

Computer-based training (CBT) is any course of instruction whose primary means of delivery is a computer.

EDUCASE is a nonprofit association whose mission is "to advance higher education through the use of information technology." Membership is open to institutions of higher education, corporations serving the higher education information technology market, and other related associations and organizations.

Game-based learning (GBL) can be defined as “learning that is facilitated by the use of a game.”

Hypermedia-based English Learning system for Prepositions (HELP) provides non-native English language diagnosis speakers with remedial instruction according to their assessment results.

Information and communications technology (ICT) is an extensional term for information technology (IT) that stresses the role of unified communications and the integration of telecommunications (telephone lines and wireless signals) and computers, as well as necessary

enterprise software, middleware, storage, and audio visual systems, that enable users to access, store, transmit, and manipulate information.

Intelligent Tutoring Systems (ITS) is an eLearning system that can adapt to an individual learner.

Item Response Theory (IRT) (also known as latent trait theory, strong true score theory, or modern mental test theory) is a paradigm for the design, analysis, and scoring of tests, questionnaires, and similar instruments measuring abilities, attitudes, or other variables.

Natural Language Processing (NLP) is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages, in particular how to program computers to process and analyze large amounts of natural language data.

Qualitative comparative analysis (QCA) is a data analysis technique for determining which logical conclusions a data set supports.

Swarm Intelligence (SI) is the collective behavior of decentralized, self-organized systems, natural or artificial. The concept is employed in work on artificial intelligence.

Systematic Literature Review (SLR) is a type of literature review that uses systematic methods to collect secondary data, critically appraise research studies, and synthesize findings qualitatively or quantitatively.

Teaching Assistant (TA) is a person who helps a teacher in a school classroom but who is not a qualified teacher.

Technology Enabled Learning (TEL) aims to focus on increasing access to quality teaching and learning by supporting policy formulation and innovation in the application of ICT in education, and the development of ICT skills.

The electroencephalogram (EEG) is a method of brain exploration which measures the electrical activity of the brain through electrodes placed on the scalp often represented as a route called electroencephalogram.

The French National Centre for Scientific Research (French: Centre national de la recherche scientifique, CNRS) is the French state research organization and is the largest fundamental science agency in Europe.

APPENDIX A

Research Interview Guide

Objective: The objective of this research is to conduct a SLR on exploring the impact of Artificial Intelligence in learning and adaptive/personalized learning geared towards learners' achievement.

In-depth Questions

1. In your opinion, what is adaptive learning (examples here) and personalized learning (examples here)?
2. Are there any similarities between adaptive learning and personalized learning? What are the similarities?
3. What are the differences between personalized learning and traditional learning approach?
4. Does adaptive/personalized learning technologies support traditional learning?
5. What are some of artificial intelligence technologies or techniques that are used to facilitating learning? How?
6. Can adaptive/personalized learning help in improving learners' achievement or outcomes? How?
7. What are the roles of artificial intelligence in learning and does it support adaptive/personalized learning and its purpose?
8. Is artificial intelligence an enabler to adaptive/personalized learning? How? / Why?
9. How do you see the future of AI in learning?

Conclusions

1. Is there anything else that you would like to add?
2. Is there somebody who you can recommend me to converse related to my study?
- 3.