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# Comparative Review of Selected Adaptive e-Learning Platforms

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***Abstract***

*This work was centered on reviewing the ten most adaptive e-learning platforms; identifying features, functionalities and the overall appearance of the application. The main objective was to enable educationist, institution heads, technologist, and other learning stakeholders to make knowledgeable decisions in regards to adaptive learning platforms. The reviewing took 2 dimensions; reviewing of related literature, and the hands-on review. In the course of the review, some were identified to be more suitable for corporate trainings with very minimal educational or learning pedagogy consideration. A comparison table was created, summarizing each for easy selection and choice.*

## Introduction

There is a tremendous effort to annex technology into education due to its unquantifiable benefits, such as better content development and presentation, availability and accessibility, cost effectiveness, collaboration, learner orientation and more. (Koukopoulos and Koukopoulos, 2017). Examples include Content management software (Moodle), LAMP/Pulu, Collage, a CME and other online or E-Learning applications.

Cingi (2013) in his research reiterated the important role of Computer Aided Education (CAE) systems. According to him, it is a key to improve the effectiveness and quality of education system. However, its autonomy and model creation is a complex process in which both human and technical resources should be utilised in a carefully balanced way. The evolving of technology is so rapid that technologically influenced sectors can hardly keep up with the changes. The challenge therefore is to develop and use modern technology in education, while the curriculum is continuously evaluated and modified to include new ideas, thinking, and learning methods. In other to achieve this complexity, artificial intelligence is the element to integrate.

In annexing technology with education, Budiharto et al. (2017) posits that artificial intelligence plays a vital role. It creates the opportunity for a humanly based task to be completed in a computing system or other machines. This means transferring human responsibility to a computer that has the ability to intelligently and logically deduce or perform an activity. Adaptive Learning Application, Intelligent Tutoring System, Virtual Education, Smart Education, EduRobot are some examples of artificial intelligence implementations in computer aided interactions, that simulate the process of human thought within a specific area.

Popenici and Kerr (2017) stated in their research that the ability of artificial intelligence is further enhanced with its sub field, ‘machine learning’ that includes software that is able to recognise patterns that make predictions and apply the newly discovered pattern to situations that were not included or covered by the initial design. There is no doubt that artificial intelligence in learning has enhanced human thinking and augmented the educational process to a set of procedures that is not just for content delivery, control, and assessment, but a tool to leverage in order to achieve set goals.

This is by no means ignoring the effects of artificial intelligence when it goes wrong or its limitations such as inability of recognise certain statements and act differently.

This gives a good premise for further research, as there is the possibility for creating multiple learning areas in a single application. This is what the research is all about.

**Literature review**

The capability of an E-Learning system depends on the objectives of the stakeholders. For instance, there are E-Learning systems that provide feedback on learners’ activities, performances, and user experiences.

Veeramanickam and Mohanapriya (2016) presented a paper on E-Learning Application Design in which it proposed using Cloud Computing because most computing services are Cloud-oriented. Then, it implemented the application in the cloud using Software as a Service, Hardware as a Service, and Storage. These provided the enabling tools for the designing of the E-Learning application. Since the emphasis is on the Cloud, the application is unable to service non-Cloud users, and those who do not have access to internet services. Other issues associated with making E-Learning systems completely Cloud-based, are affordability, availability and reliability of the system

The work of Elumalai et al. (2020) stated the perspectives of student towards E-Learning. Using variables such as course design, course content, instructors’ characteristics, learners’ characteristics and others, the work shows that there is a positive relationship among the variables and how students perceive E-Learning. The findings also showed that there are significant differences when gender, course level and quality of E-Learning variables are used.

Due to its multi-disciplinary nature, the designing and development of E-Learning systems require a group of professionals such as educators, sociologists, psychologists, software engineers, analysts, and end-users to come together in order to serve a community of learners (Stoyanov and Valkanova, 2011). In their work, they identified the essence and relevance of developing an E-Learning system that meets the aspirations of the users. It is, therefore important to integrate the views of all the categories of users, into the system for effective learning to occur. However, it is difficult to ignore the cost implications of adopting E-Learning facilities in places of learning, even if there are Open Source E-Learning applications. Be that as it may, the free applications offer institutions the opportunity to leverage a large community of Open Source E-Learning software, rather than developing it from scratch.

Reasons for the implementation of E-Learning systems in places of learning vary widely. In the work of Alkhalf et al (2010), E-Learning in higher institutions in Saudi Arabia was aimed at facilitating distance learning and cultural acceptance of gender collaboration. Distance learning was used to remedy the high demand for higher education. Thus, the E-Learning system is used as a tool to support the traditional teaching-learning process where there are inadequate facilities such as classroom, man-power etc. This means that there is a heavy dependency on the E-Learning system and if the educational sector must survive, the creators, developers and planners of the E-Learning system will have to continuously look for means of improving the system in adherence to the changes that occur in the curriculum, technology and the need of the learners.

Conlan, et al. (2012) identified learner adaptivity as one of the reasons for implementing E-Learning. Learners learn in different ways, and the idea of one-size-fits-all is no longer effective in the teaching-learning process. According to their work, E-Learning is a means of implementing personalised learning in which the individual characteristics of the learner is considered, and learning content and presentation is tailored to meet those characteristics. This is not to claim that all E-Learning systems are adaptive or personalised; however, E-Learning systems create the enabling environment to do so.

Re-use of learning resources is important considering the time and effort put in to produce the materials—content and presentation. This is the premise of Colan et al. (2017), work which postulated that E-Learning is a platform in which the re-use of learning resources (materials) is possible and available for several learners at the same time. Content in E-Learning is shareable, downloadable, and learners can keep visiting over and over again without altering the original content. Updated versions can also be uploaded, which means that content is reviewed regularly.

The use of E-Learning facilities has made learning seamless and in some cases real-time. It has taken learning to the comfort of homes, offices and made it doable on-the-go. One of the most outstanding benefits of E-Learning is the fact that it enables access to learning resources without any boundaries (Yakubu and Dasuki, 2018). It creates an avenue for collaboration, group interaction, proper monitoring, feedback, mentorship, and easy adjustment of content. Needless to say that the coverage is wide, as more and more people are now inclined to E-Learning, but all these came with challenges.

In considering the impact of using E-Learning, Saleem and Rasheed (2014) stated that there are independent variables that influence and affect the use of E-Learning on students. The variables were identified as time, workload and technology, which in research determines how useful an E-Learning system is to a user. The findings were however based on a relative small sample size, and it did not use artificial intelligence in determining the variables.

The findings of Kim et al. (2019) showed that although students have higher positive perceptions of E-Learning applications due to previous experiences with digital application, they will still need to develop strong digital skills to participate in academic work and be committed to it effortlessly. It therefore advocates for practical adoption of E-Learning in educational institutions. This recommendation however, does not make the students automatically become better academically. There is no scientific proof that students become academically keen with the use of E-Learning. No doubt, it improves their performance and motivation, but these are relative.

The view of Kim et al. (2019) was also supported in the work of Tegegne (2014) who performed a quasi-experiment on Mathematics students at a university based on their performance levels at different grade points. The findings showed that there was no significant performance difference between the traditional or conventional learning and ICT-supported learning, as each had its own pros and cons associated with it during the time of experiment. This finding is challenged by several other researches that claim significant performance difference even though it was not on the same subject matter.

Lauran et al. (2014) showed that there was a significant acceptance of E-Learning by the student study group that was used in its research. Though, they were already exposed to E-Learning, the participants' perspectives strongly favoured E-Learning as they found it flexible enough to be adapted into their schedules and selections such as self-study or tutor-based learning. The finding also stated that it lacked face to face interaction with others, plus the fact that the data size is relatively small and its composition is not adequately representative.

Despite the enumerated benefits of the E-Learning system, there are several challenges in developing and implementing it.

Brooks et al, (2014) work highlighted that E-Learning problems are encapsulated within itself. This is as a result of it been classified into broad qualitative spectrum and the different names are associated with it. This creates a lot of complexities as critics have attacked its authenticity. While some authors claim that the Intelligent Tutoring System (ITS) is different from E-Learning based on tools, technology and concept, the fact remains that the ITS is still an E-Learning application. It is believed that the variation in name is as a result of the features implemented in every E-Learning application, which shows that it lacked standardisation. If the generic meaning of E-Learning is referenced, it then implies that any electronic format learning is E-Learning.

Brooks et al. (2014) in their work on Intelligent Tutoring System, enumerated other issues such as the commercialisation of prospective standards of E-Learning systems, integration with learning styles, and lack of adaptivity as major setbacks. The findings are worth researching on, but the fact remains that E-Learning systems varied widely due to expectation and purposes. Every E-Learning application is aimed at a specific learning community and if such a system serves or meets the aspirations of the community, it would be said to be successful.

Another challenge is usability as identified by Weber (2018) in the paper, Lesson for Pedagogic Usability of E-Learning Systems, it was stated that after an evaluation of E-Learning systems, learners found it difficult to adapt to the system. They could not use it correctly and thus did not improve their learning skills. They suggested interactive design mechanisms to improve learner usability of E-Learning systems. This necessitates the importance of collaboration with relevant professionals before and during the design of E-Learning Systems.

Paranythis and Loidi-Reisinger (2004) advocated for interoperability of adaptive E-Learning systems. This is a welcome development, but it may have problems except generally accepted standards are set up just like hardware manufacturing companies follow standards set up by the IEEE. The reasons as stated in their research include collaboration, reusability, support, content delivery, and enhancement of research.

Leany et al. (2019) stated that despite the 'hip' in technological disruption of all sectors including education, reviews revealled weaknesses and ineffectiveness of technology on learning and only minor reforms to date within the educational system. This is an arguable fact considering the rise in the number of students willing to use adaptive learning systems and the ongoing researches. Despite the seemingly low impact of technology on education, the paper focused on the possible education future, and identified three key elements: the open learning spaces, augmented reality, and artificial intelligence.

Koukopoulos and Koukopoulos (2019) worked on integrating the three main characteristics of educational theories: learning objectives, collaboration and mobile technology in an adaptive system. It was used to test the three highlighted areas.

Mehta et al. (2019) identified the need to include values as an attributes in determining learning styles in an adaptive E-Learning system. The acceptance or rejection of E-Learning or digital education could be based on conservation of the status quo and self enhancement. The study showed that rather than the general perception that social influence, price value and performance expectancy are the rationales behind setbacks, it is the influence of self enhancement values that undermines the adoption of digital education. This could be verified when we consider why software deployment is always considered a failure in traditional or government-owned establishments.

Machado et al. (2016) introduced the methodology behind an adaptive E-Learning system; i.e. how individual learning styles are formulated within the system. The research unveiled the use of Fuzzy Logic—an algorithm that calculates and manipulates given variables, to display results based on set parameters. In their work, they introduced a computer system for learning called Intelligent Tutoring System (ITS) that could help the teaching and learning process by stimulating internal cognitive changes, using artificial intelligence techniques as a teaching support tool and Fuzzy Logic. They were able to demonstrate through electronic ways that teaching will be more efficient and adapted to students' necessities, in groups or individually. The research showed the equivalent of an agent for the resolution of problems in a multi-agent ITS that evaluates users. However, it is a single course or modular based system. The sample questions are not structured in the conventional way, and interfaces are not user-friendly.

Ciloglugil (2016) used the Felder and Silverman learning style to develop an adaptive E-Learning system. The research is based on the two main areas: the automatic classification of learners by their learning style and application of learning styles models to provide an adaptive E-Learning system. The work scaled learners based on the index of learning styles (ILS) which contains 11 questions for each dimension as stated in the model that was been used. Despite the outstanding results, they are still subject to evaluation because of the data sources and attributes used in learning style prediction models and tools.

Ben-Naim et al. (2016) created a new technique for adaptive learning called the Solution Trace Graph, a visualisation tool that visualises students' interactions and gains insights into the refinement of the system.

Ben-Naim et al. (2014), presented an adaptive E-Learning platform called AeLP for creating a rich, interactive, and highly visual adaptive E-Learning system designed with activities that use Virtual Apparatus Framework (VAT). The system requirements include: promotion of usability, rapid prototyping, delivery of feedback, and adaptive sequencing of activities based on student learning model. The framework embedded tools that will enable teachers to create interactive content and adaptive tutorials. The emphasis is on presentation, and the look and feel of the system, not necessarily the internal workings of the adaptivity.

The fact that adaptive learning is been used across all grade levels, learning ages and for different subjects, shows its usefulness. Prusty et al. (2011) worked with engineering students to study mechanics and strengthen the multipurpose uses of adaptive learning. The important thing was preparation of the content by the educators. With the recent development of the adaptive system, content developed is included as a feature in the system. It may not be as comprehensive as required, but it serves as starting point for the teachers.

Balasu et al. (2016) took a different approach in their work by laying emphasis on creating a reinforcement model for an adaptive learning environment based on the cognitive skills of the learner. The research has a three-fold approach: first, to detect the learning style based on the cognitive skills of a learner dynamically; second, to map cognitive skills with the learning object; and third, to create a reinforcement model to track and provide feedback on the knowledge-competency level improvement. This is an improved version, as it includes a feedback mechanism within the system itself, which evaluates over a period of time. This means that as learners use the system, there is a data collection which will be analyzed eventually and used for prediction.
Basing the work only on the cognitive parameter, may not give an accurate learning style of the learner. This is because it is not only the cognitive aspect that influences or pre-determines a learner's learning style.
A learning environment is considered adaptive if the system is capable of:

i. Dynamically and intelligently determining the learning style of users
ii. Monitoring the activities of the users and interpreting the activity history as input to determine user preferences in the future
iii. Appropriately representing associated models (Paramythis and Loidl-Reisinger, 2003)

iv. Specifying models and inferring user requirements and preferences out of interpreted activities
v. Recommending learning paths (Liu et al., 2019)

The main objective of adaptive E-Learning is the recommendation and provision of a personalised sequential learning path, in form of learning items that will lead to the occurrence of learning in the individual. It is a customized learning path for a specific learner.

Several researches have been done to demonstrate how an adaptive learning system can be used in different areas of education and other fields of study.

The work of Dina et al. (2016) used adaptive learning to demonstrate how it can improve silent reading among primary school pupils. The research was carried out with 144 pupils, comprising high level and low level readers. The result of the experiment showed that there was a significant measurable improvement when they were given technological support (TERENCE program) to aid their reading. The smart games related to the stories and silent reading stimulated them to learn and understand information better using the technological interactive tool.

Adaptive learning can also be used to integrate and bridge the technological gap between learning style models and technology in the learning process. The work of Arovo et al. (2006) showcased how heterogeneous information can be efficiently managed through sematic interoperability. The technological differences can be bridged by means of standard via approaches based on semantic web. This, according to the research, creating basic requirements that can be generalized and become part of the developing system is essential.

Adaptive learning paved way for the integration of learning models in technology-oriented learning software or applications. The use of advanced computing such as Artificial intelligence and machine learning in determining learning preferences and the automation of learning content, creates the avenue for seamless integration. The work of Trunong (2016) reviewed 51 studies that gave insight into the impact of learning models in the development of adaptive learning. Series of researches have been done, and the result is an advocacy for incorporating learning models in the educational technology applications. BaitiAfini et al. (2019) also pointed out how to use adaptive learning to identify personal traits that will guide and improve the learning processes that involve technology. The research subdivided the adaptive learning model or components as: learner model, domain model, instructional model, and adaptive engine. Each model according to him is responsible for an activity within the system. The adaptive engine is where the automation and linkages occur. The learning model contains the learning traits or preferences of the learner either from the history log or predefined preferences that could be worked on to present the adaptiveness of the system.

Despite the enthusiasm about adaptive learning and its benefits in higher education and other learning institutions, there is a lack of evidence-based research that showed the correlation between personalized learning, behavioral patterns and how it is affected by adaptive learning as stated in Liu et al. (2017). This assumption may not necessarily be true as other reviewed works stated otherwise. However, it is the opinion of the researcher that further investigation is necessary, in order to understand the learning processes that can also be used for design purposes. The focus of their work is the analysis performed on participants' behavioral patterns through the usage of data; to understand how they used the adaptive system based upon their needs and interests.

Sundararai (2019) applied adaptive learning in an Electrocardiogram (ECG) signal to accurately analyze noisy electrocardiographic signals. It automated the analysis, and the noises present in the electrocardiogram signal were detected and processed for proper diagnosis. It used a system known as Wavelet-based threshold mechanism to de-noise the electrocardiogram signals. The wavelet is based on a self-adaptive learning principle in which the particles are optimized in a dual tree complex wavelet packet scheme. This is a complex application that shows that adaptive learning is not limited to education only, but a machine or device can be trained to be adaptive even though it may not use real time data (unsupervised data).

The primary reason for adaptive system is reusability. The high investment required in the development of an adaptive system makes it necessary to reuse materials, i.e. recycle data which also makes the system more efficient. Learners' preferences change according to age, gender, family background, cultural inclination and subject matter, and the fact that it is an adaptive system would make learners want the changes to be almost real time. Students have failed examinations, tests, quizzes and other assessments, not necessarily because they are not intelligent but due to their state of mind, when the assessment was being done. The learner's history and produced learning materials should be reusable. However, if it is proprietary-bound, it becomes difficult for teachers to reuse such materials or even improve on them, especially if they are not the original creators of such materials.

Adaptive learning is all about the learner. It entails moving away from the traditional treatment of the learner as a solitary or passive receptor of information. No learning is passive; there will always be a corresponding action. A learner has not learnt if he or she is unable to use that which has been assumed to be taught. Adaptive learning is a means of reorganizing the learning process in which the learner is the focal point. The content is developed to suit the learner and not the learner adjusting to fit into the learning content.

Adaptive learning can also be used to teach large groups of learners. In the work of Ben-Naim et al. (2009). They experimented adaptive learning on an Anatomy and Pathology class of 198 students. The findings show that adaptive learning enhanced learning and interaction among the students.

The categorization of adaptive learning is done based on two classifications:

i. Design model
ii. Functionalities

In the design model, Weir, (2021) chronologically categorized adaptive learning based on the level of intelligence. According to the research, adaptive learning 1.0 is a basic branching application that makes adaptations a pre-diagnosed decision tree structure. That is to say, it is based on pre-assessment results which then creates a pseudo-personalized learning plan for the individual that is still generalized. It is similar to the traditional learning method except that an attempt is being made to consider the learners' preferences based on pre-determined values. This is static and often misrepresents the individual.

The second classification in this category is the adaptive learning 2.0 with limited algorithms. This automates some of the functions, however, it is still limited and does not become more intelligent over time. It uses simplified algorithms and it is not AI or machine learning driven. It mimics the learning experience of a human teacher, it is not scalable and do not deliver adaptivity in learning.

The adaptive learning 3.0 is characterized by the application of AI and Machine Learning to accurately replicate the one to one instructor experience in learning. It is powered by AI and machine learning technology which makes it improvable, scalable, and expandable. It leverages network knowledge maps, the use of log files and user history to constantly determine user preferences, as it changes. It is able to create deeper relationships between the content, presentation and user behavior. The system enables complex and real-time adaptations of users' performances, it is data-driven with personalized feedback and provision of knowledge reinforcement, detailed application-level mastery of skills, knowledge and tools, and reduction in learning times. What the adaptive learning 3.0 solves, is the problem of a 'never-ending' learning loop associated with the adaptive learning 1.0 and 2.0. In the older editions, a user keeps going through same assessment over and over again especially when the answers to the questions are wrong. This unending adaptive loop results in the learner getting frustrated or not learning at all. With the help of AI in adaptive learning 3.0, feedback helps to guide the learner towards moving forward with adjustable questions. For instance, questions will be presented based on difficulty levels, so a learner learns from the basic to more advanced levels.

The functionality categorization is based on;

i. Adaptive Content and Instruction
ii. Adaptive Sequence
iii. Adaptive Assessment

Adaptive content and instruction presumes tailoring learning content to individual similarities and differences, in order to enable learners gain mastery of the subject matter. When a student answers a question and responds to feedback, his or her specific response will be used to create content. It builds on a variety of theoretical perspectives in Aleven et al. (2013) that included documenting aptitude interaction, individual differences in learning, as well as assistance.

Adaptive sequence is a continuous collection and analysis of student data to automatically change what the students sees next from the order of skills. It is a walkthrough of series of skills based on the type of content received. It is an upward movement of skills from one level to another in a sequential order.

Adaptive Assessment is based on changing the question a student sees based on his or responses to the previous questions. The difficulty of questions increases as the learner makes progress.

Despite these categorizations, no adaptive learning system is designed based on one categorization. It is usually a hybrid of two or more. As earlier stated, the objectives and the stakeholders' interest is paramount. More often, the available resources dictate the design. For instance, an institution with limited resources will prefer to use openSource learning system which may have some form of adaptive design. Looking at Moodle for instance, it will be challenging to have Adaptive 3.0, AI and machine learning embedded in it. In the assessment of Moodle, it failed to have such capabilities regardless of the several plug-ins and add-ons provided. Consequently, using openSource means a trade-off of heavy AI and machine learning components as well as adjusting or configuring the learning application to accommodate the basic level. In that regard, the content can be personalized to the extent of possible class size and manageable varied learners' preferences.

It worthy of note that in as much as adaptive learning aims at automating every process in almost real-time, taking cognizance of users' constant changing preferences, no system has perfectly done that.

Adaptive learning despite its numerous advantages, is still faced with series of challenges; one of which is acceptance. Acceptability of the adaptive system by the stake holders especially teachers, is still low. It has been identified that the exclusion or partial inclusion of teachers in the process of design, development, deployment and reflection could be the cause. Ben-Naim et al. (2009) stated that if teachers' reflections are taken into consideration and brought to the mainstream; including support for the system, the adaptive system will be accepted more amongst teachers.

The core element of adaptive learning is the use of computing technology. This includes multimedia, social media tools, analytic tools, machine learning algorithm, data mining, and many others. The front end (users) presentation includes icons, menu buttons, links, and other navigation tools that make the application beautiful and easy to use for the user. However, more often than not, this is not the case as users grope around the system without success. Forsyth et al. (2016) explored an automated grading system and found out that students and teachers who had previously trained on the technology used in the automated system performed better than those who were not trained. Technology makes the adaptive learning experience possible, thus it cannot be removed from adaptive learning. However, every prospective user of the system should be introduced to system tools and their workings from inception. A support and user manual / guide also serves to reduce technology fright, but hands-on training on the system prior to usage is extremely important to reduce the challenge that may be encountered.

Another issue associated with technology is stabilizing, accelerating convergence and improving generalization for adaptive optimization algorithms which affects or reduces the adaptive learning rate (Liu et al., 2020). The differences in algorithm response rate and its data mining capability slows down the adaptive system processes.

The porous level of standardization is another challenge and the result of this is evident in the research of Liu et al. (2017), where an adaptive learning intervention system was administered to students in four different subjects, in order to access the impact level. It was discovered that the results were not uniform. The impact was great in some subjects, while there was no significant impact in others. The research also discovered that Mathematics anxiety was the only student characteristic that showed a significant relationship with students' participation. While there was an overall positive experience, these findings postulate the inadequacies of the adaptive system as not having basic standards for design and deployment, which resulted in the flaws that contributed to the lack of student success.

The fact that the designed framework of adaptive learning has flaws, affects the learning rates and convergence of the system. In three different works Shazeer and Stern, (2018), Xu et al. (2019), and Zhou et al. (2019), raised the issue of learning rate. Shazeer and Stern (2018) proposed the use of sublinear memory to maintain the metrics of the system in order to scale and optimize results instead of the RMSProp. The work argues that using the sublinear method presents a relatively accurate rate level. Despite the demonstration carried out, it was not implemented in a learning system with unsupervised data.

Xu et al. (2019) proposed the Adam or Adadelta methods as a reinforcement learning based framework that can automatically learn an adaptive learning rate schedule by leveraging the information from past training histories. The work states that the learning rate will dynamically change based on the current training dynamics. The level of accuracy of this claim cannot be ascertained because, the user history will contain errors as well as relevant and irrelevant activities. It also failed to implement the methods on an existing system or created a system using the proposed methods.

Zhou et al. (2019) in their research stated that there is an inappropriate correlation between the variables which results in a large gradient. The work proposed AdaShift as an adaptive learning rate method that de-correlates the variances and temporarily shifts the gradient. The work is technical and may not be necessary for an adaptive learning system for primary and secondary school students. In addition, the use of heavy technology does not necessarily improve the performance of the adaptive rate ratio.

Huang et al. (2017) said that performance degradation is caused by a variety of interfering factors and proposed a low computational cost, to mitigate the effect of these factors in unsupervised learning scenarios like the adaptive learning system. The work presents a particle adaptive classifier that compares the incremental support vector classifier (ISVC) and the non-adaptive SVC (NSVC) for a long-term pattern recognition task. Despite the proposed classification technique, it was not demonstrated in a system with unsupervised data.

Adaptive learning according to Tyre and Hippel (1997) is a situated process in an organizational setting that influences the different components of the system. This setting contains different methods of resource generation, how underlying issues are identified, and the different assumptions made in the development of the system. Consequently, integration and seamless usage of the system becomes difficult as learners are required to go through some difficulties when getting familiar with the system. If the process of synchronization is not effectively and efficiently managed, there is the likelihood of abandoning the system for a simpler one or reverting to the traditional learning system.

Hedberg (1981) argues that "attempts to act exposes the conditions for acting; casual relations, gradually untangled." What it means is that the fraction that comes with using new technology and trying to adapt to it, is all part of the learning process. The movement of people from one scenario to another creates opportunities for them to learn. Thus, the process of learning should not be challenged, rather it should be encouraged. Learning is also enhanced, when there is interaction amongst learners and the different tools, but it has to be properly managed and the tools should be familiar, else not much learning will take place.

Since decision outcomes are often uncertain and change frequently, they create a challenge for the adaptive learning system. Generally, humans are not static, they process and make decisions intermittently, and these decisions and choices are influenced by various factors especially the disposition of the mind. Thus, not every outcome should substantially influence or be taken as learners' preference that determines or affects learning (Soltani and Izquierdo, 2019). Although a lot of research is ongoing in adaptive learning, the ability to distinguish or separate the relevant and irrelevant experiences of a learner has not been done. Successful learning and decision-making should expressly reflect experiences that will directly impact the learning outcomes, if considered a learning preference for the individual.

The research of Farashahi et al. (2017) attributed value-based decision making as integration of reward outcomes overtime. Despite the several models for integrating reward under uncertainty, there are still unknown determinants. The work therefore proposes the use of a neural mechanism―Reward-dependent Metaplasticity (RDMP) to robustly perform the probabilistic reversal learning using dynamic adjustment of learning. It is able to predict time dependency and choose specific learning rates that strongly depend on reward history.

Based on the work of Chen et al. (2018), the issue of uncertainty and irrelevant experiences can be resolved through a recommendation system for adaptive learning. The recommendation of learning materials in form of video lectures, demonstrations, practices and others to the learner will be based on psychometric assessment results and individual characteristics. The work is in order to recommend a mathematical framework that characterizes the recommendation process of Markov's decision problem for an optimal recommendation.

In designing an adaptive learning system, incorporating the interest of the different prospective learners is a major issue. There are varied interest variables, and it is almost impossible to identify all possible or likely interests of the learners. The fact that interest is usually influenced by several other factors, makes it more difficult. In other to remedy this, designers will have to use the system to arouse learners' interest by considering the age-grade of the learners and identifying what interests them. This is important when we consider the research of Walkington (2013) where he demonstrated how students were able to quickly solve algebraic problems associated with personalized out-of-school interest. The association of personalized out-of-school interests like sports, music, movie etc., to solving Mathematics questions is remarkable. This shows that in as much as adaptive learning in structured (curriculum-based), there is a recommendation to include aspects of unstructured content that helps.

The categorization of adaptive learning systems also poses a challenge. Basically, there are three categories, and adaptive learning will take the perception of the major stakeholder. A software engineer will think strongly in line with heavy technological implementation. That means the system is most likely to have extreme and complex computing technology. Same can be said of the other categories: Content and Instruction Adaptive Learning. Each aspect is relevant in the overall functioning of the system; however, there has to be a trade-off at some point, because it cannot be 100 percent implemented for obvious reasons. The question is how can a designer balance these three?

First, the stated objectives will guide the design of the system. The objectives reflect the essence or reason for the adaptive system, the community of learners, and the cost implication.

Second, is the system going to be developed in-house, outsourced or an off-the-shelf purchase (proprietary)? Proprietary adaptive learning system do not allow significant modification. The look and feel in terms of color and position could be altered at the point of installation and configuration, but no dramatic changes are permitted.

In summarizing the challenges of an adaptive learning system in learning centers and institutions, Mirata et al. (2020) performed a study of two universities to categorize the challenges faced by higher education institutions in adopting adaptive learning in their teaching process. The areas identified are: organization, technology, pedagogy, and social economy. According to their findings, the pedagogical challenges relate to the need to re-design the curriculum and scheme of work. Most curriculums and lesson plans state what the teacher is expected to do and subsequently, a classwork or an assignment for the students. Universities present a lecture method of teaching in a large hall especially for general courses. Translating or transferring this into a technology-based learning system will require an adjustment of the curriculum content. It is also additional workload on the part of the teachers, as they are required to break down work to minute details with no assumptions. The question then is who pays for this extra work? This is one area the socio-economic state of the university comes into play. Universities in developing countries especially, may not necessarily have access to grants and huge subventions. Also, due to the high demand for education and its necessity, education is taken as a required service. Thus, the government directly funds the universities, in order to control the fees charged. Consequently, the universities are incapable of implementing an adaptive learning system; they are still strongly affiliated to manual documents.

The work of Mirata, et al. (2020) also shows that faculties show resistance towards using technology for case studies and other activities, as they feel it diminishing their role. Also, the fragmentation of implementation of the learning system due to the level of technology usage makes it difficult to fit into an already existing system.

With all these challenges, the issue then is, which one takes precedence? The organizational structure is important because if there is no support, it is bound to fail even before it starts. The base to support the system should exist before implementation, then it will receive acceptance from all parties. It suggested the following as a practice for higher education institutions that intend to adopt adaptive learning:

i. There should be commitment to adaptive learning, and it should be part of the university's strategy. If the leadership of the university is willing to factor in adaptive learning as part of its strategic plan, there will be alignment by the faculty members. It has to be clearly communicated at the various board meetings, and the procedure diligently followed.

ii. Build the necessary infrastructure such as the hardware, software, internet access and security. If the fundamental infrastructure is not in place, it will be difficult to deploy adaptive learning no matter the drive from the head of the organization. Accessibility to adaptive learning should be made seamless.

iii. Establishing and building the needed support, resources and capabilities is necessary. System deployment fails not because the people do not want to use it, but because problems are unresolved or there is no technical support as at when it is required. Initial training should therefore be done, and strong technical support should be established. Allocating the necessary resources for the developers and technical team will enable the system to work. Since the implementation process takes time, the calculation of the workload and delivery time should be realistic. Adaptive learning is data driven, consequently, there has to be feedback from time to time from the prospective end users—the teachers and the students. Nothing should be done completely in isolation as it will affect the overall output of the system.

The challenges discussed in this section are relatively broad, however, they explain in general terms relevant aspects to consider when deciding to implement adaptive learning. The benefits of adaptive learning in theory and practice are enormous; the balancing act the organization is required to do is to checkmate the likely possibility of a failing system.

The recent drive for flexibility to individualized learning through custom adaptation in schools and institutions is gaining momentum (Billington and Billington, 2010). As adaptive learning technology proliferates learning places, so does the advocacy on infusing learning style in the system. Learners learn in patterns or styles, and it is difficult to determine how a learner will learn if there is no link between the learner’s characteristics, the existing learning styles and the technology that is being used. The integration of these three (3) elements or factors will determine how successful an adaptive learning system is or not.

Different adaptive learning systems have incorporated different learning style theories. Systems such as Moodle, iLearn and Blackboard, Forsyth et al. (2016) has accommodated learning styles, but it is usually based on a specific learning style model.

Despite the strong recommendation of adopting learning styles in adaptive learning, researches done by Mainemelis et al. (2002) and Murray (2015) has shown that the impact of including learning styles in adaptive learning does not improve students’ performances significantly. This according to Stutsky and Laschinger (1995) is as a result of the inconsistencies that exist between learning style classification and adaptive flexibility.

Also, the cited adaptive learning systems used a singular learning style which is not adequate to predetermine the learning preferences of users, and the use of a single subject for evaluation is not adequate enough to make a generalized conclusion.

Adaptive learning is all encompassing and sometimes, it becomes difficult to ascertain a content or system as adaptive. The question that often runs in readers' mind is "What makes a system adaptive? The content or the technology"? Judging from Cavanagh et al. (2020), a system can be described as adaptive and content can also be described as adaptive. However, the two usually co-exists. Considering the general notion of adaptive learning as a user-centric learning process, it means that the system can automatically detect or determine how a learner wants to learn using certain parameters or attributes of the learner. These attributes are gotten using different sources such as previous usage (history, log files), pre-assessment form (based on learning styles or models), pre-subject assessment, generalized or assumed learner attributes for a specific learning community (age grade) etc.

If a learning system can automatically recommend or suggest a learning format to a learner, does it make the system an adaptive one? The answer to this question will be yes, if you are asking a technologically savvy person, and no if the person is an educationist. This was identified by Cavanagh et al. (2020) in their research postulating that the variety of adaptive learning platforms adopted by their institutions did not all function in the same way even though the systems were all labelled 'adaptive'. The underlying adaptive schemes differed in the features, and the emphasis between coursework, assessment and instructional content were not consistent. In considering their work in adaptive learning framework design, the features combined technology and lesson plan. While the teachers and instructors are to design and develop learning content aimed at achieving adaptive learning, technology (via automated actions) is used to transcode the content, thereby making it adaptive. This is to say that the working of technology on already prepared content results, is adaptive learning. Neither technology nor content alone can create adaptive learning in its totality, as shown in the research. The findings were not demonstrated in any adaptive system

However, due to constraints of time and resources, this research looks at adaptive learning from the technological perspective, while using learning model attributes as the input variables. Content is derived from already established curriculum from examining bodies and educational authorities (Ministry of Education, Secondary and Primary Department) to validate content used in preparing lesson content. Also, qualified teachers with years of teaching experience and professionals (trained teachers) were used.

Being a research work in the department of Computer science, the emphasis is on the application of computer science knowledge and integration of technology to achieve the stated objectives.

Hands-On Review of Selected Adaptive Learning Platform

The criteria for a platform selection was simply its popularity (what bloggers and internet surfers said) regardless whether it is proprietary or an OpenSource platform. Ten adaptive learning platforms were selected. These are;

i. SC Training (formerly EdApp)
ii. Adaptemy
iii. Knewton
iv. CogBooks

v. Realizeit
vi. Smart Sparrow
vii. Pearson Interactive Labs
viii. Adaptive Learning
ix. Designing Digitally
x. Impelsys Scholar ALS

**SC Training (formerly EdApp)**

This is a cloud based platform that requires registration and verification for email. On successful logging in, the home page is displayed. See figure 1. The dashboard of the user contains; home, search, notification, templates, inspections, schedule, and actions. On click, it will display sub-selection options. The platform can be used to create and customize templates, and also upload content. It has provision for creating content for the user automatically, when a topic or key words are given in the course of creating a training, as you see in figure 2. There is provision to utilize templates and modify to suite what you want, scheduling and creating of report can be done using the app.

The SC Training as the name implies for corporate organization. It is designed for easy training content development, and monitoring of activities of employees and work done by the various teams. Prior to purchase or procurement of the solution, a user has the opportunity to play around it. There is provision for trial version.

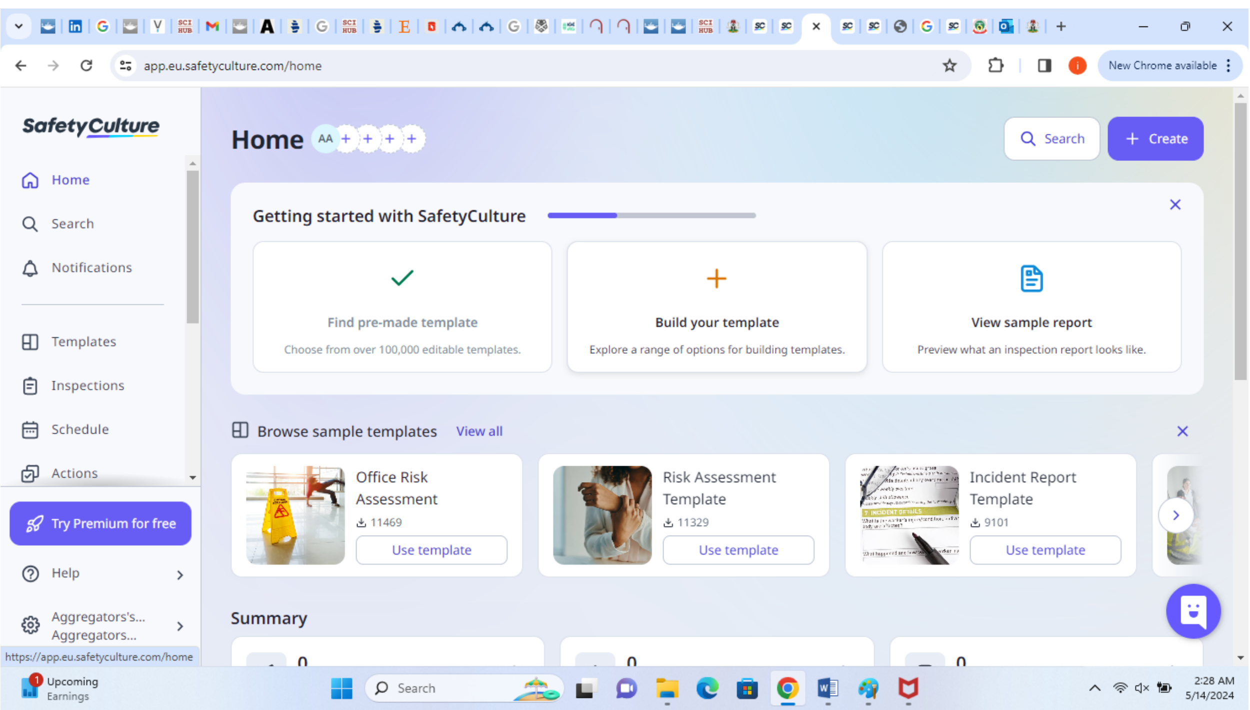


Figure 1: home page

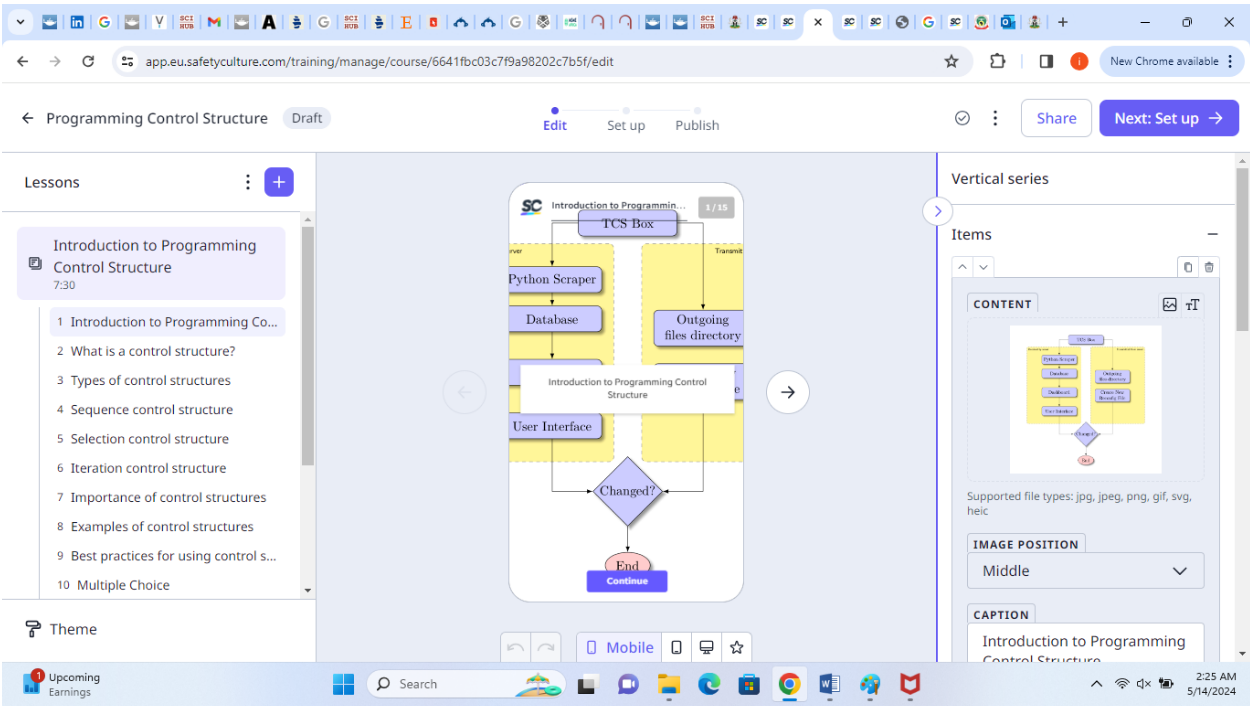


Figure 2: auto generated content

## Adaptemy

This is an integrated solution base. That means, it requires you to integrate it into an existing platform the organization is already using. It is said to be AI adaptive that assist in creating the roadmap for a company or organization adaptive learning process. There is no provision for trial, so decision for procurement is based on information given by the company directly or obtained from the website. Even though, it is stated that it can be integrated into Learning Management System (LMS), only three LMS were listed, leaving out a great number.

## Knewton

Knewton is an enterprise solution that provides variety of solutions for different purposes. It aims to provide as much information to higher education educators and learners as much as possible. Knewton Atta is accessible and affordable adaptive courseware that provides students with the support they need at the moment they need it. Its AI embellishment makes it suitable for auto generation of content.

Knewton requires 2 basic users; the instructor and the learner. Each user will have to register with a recognized school email in other to have access. The dashboard for each user is dependent on the privileges granted to such a user. It is purely a cloud based solution that does not require installation nor integration into existing platform.

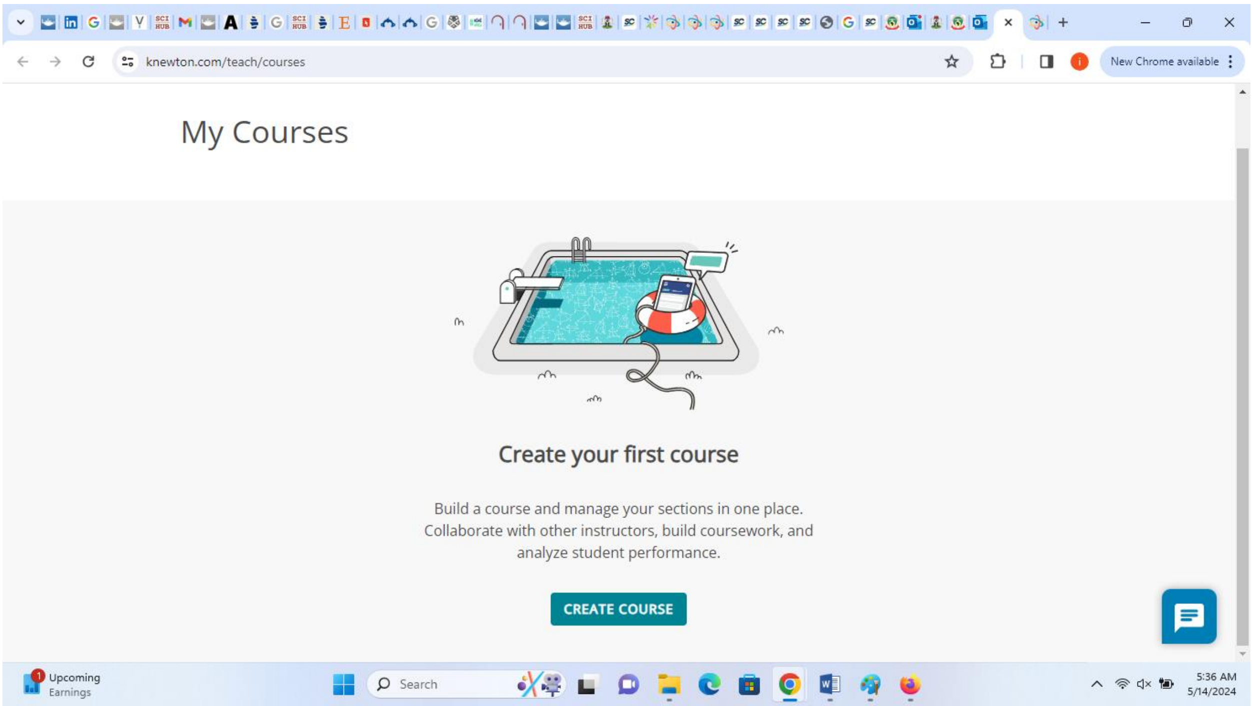


Figure 3: Screen for creating a course

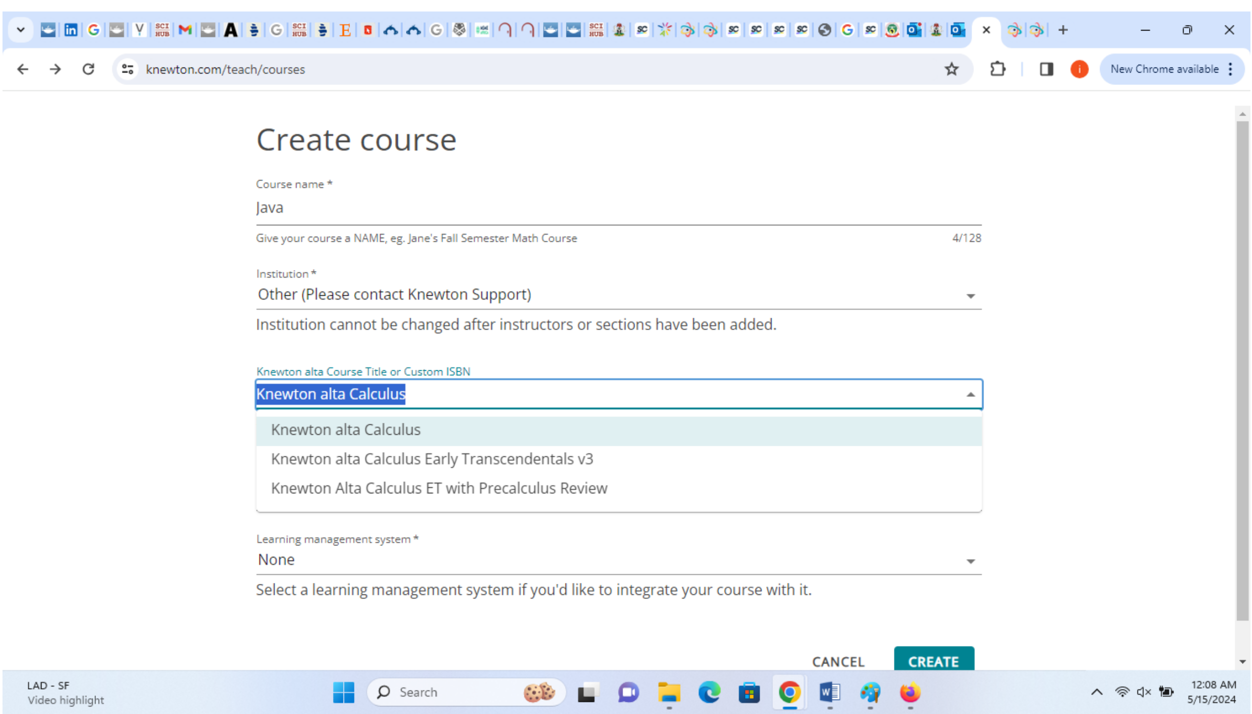

Figure 4: course creation process

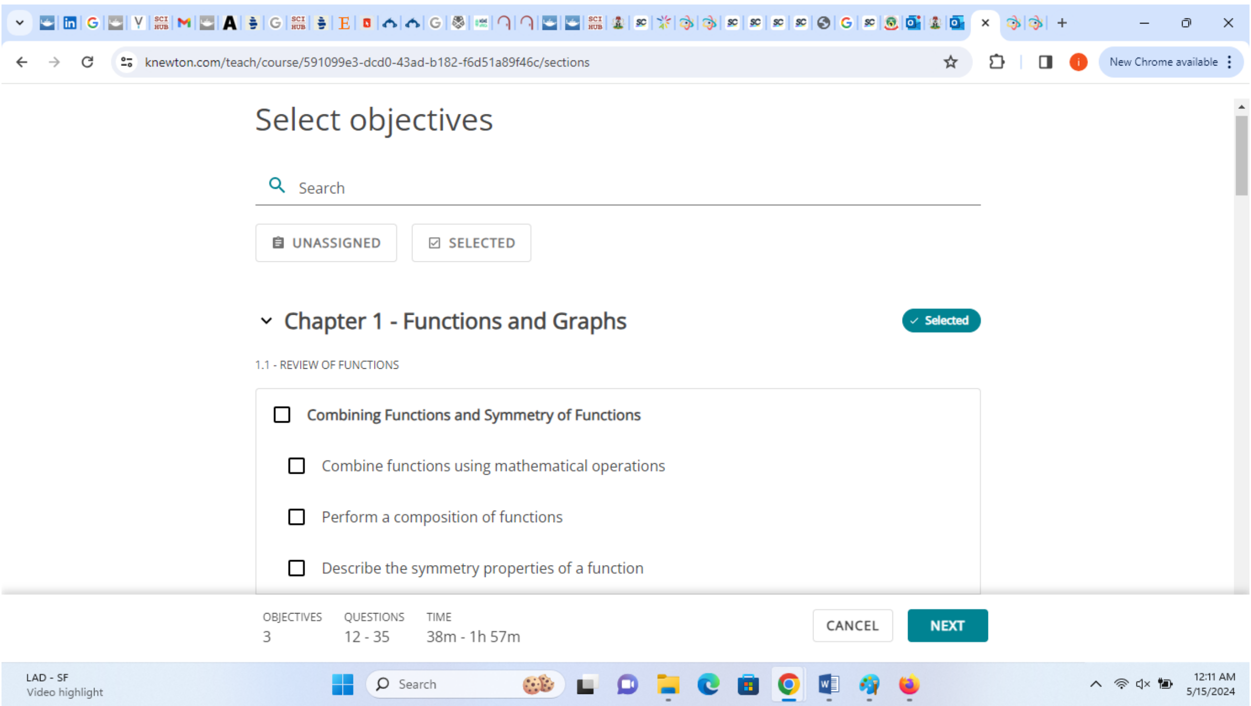


Figure 5: inclusion of adaptive assessment to course

Sessions can be created and student invited to participate or take the lesson. The instructor can change the settings, with the possibility of charging a few on the students.

The platform is centers within the ambience of learning as both instructors and learners could have access to it. There is the provision of integration with existing LMS if the institution has one in place.

The major set of the platform is that, to successfully create a course, it has to be linked to a Knewton course or include an ISBN (international standard book number). That by implication, every course content has to be based on a recognized published book.

**CogBooks**

The CogBook is an adaptive technology that measures and reports to each activity as a student moves through the content supplied by their instructors. It is a low cost product that drastically enhances course outcome whether the student is taking the course in the classroom or online. The same experience is expected in both cases. Going through the demo video, the courseware is provided by the Cambridge University, and other educational partners. Real-time hands-on on the platform could not be achieved.

**Realizeit**
Realizeit is a customizable learning platform that caters for academic requirements and workforce. It is adaptive that enable instructors to create a one-on-one personalized learning paths. It is a self-learning that adjust to the changing abilities for each learner. Its high level of accuracy and performance rate in determining a learner's path.

**Smart Sparrow**
Features of Smart Sparrow includes; adaptive learning, active learning, accessibilities, LMS integration, grade book sync, lesson templates, mobile and tablet ready, and analytical report. Smart Sparrow caters for 3 groups; higher education, training, and publishers. Its credibility is linked with the collaboration it has established with universities and colleges. Consequences, detailed content for learning according to established and approved curriculum are developed and uploaded for students and trainers to use.

**Pearson Interactive Labs**
This is one solution of the Pearson company which is purely a business oriented. It is said to be adaptive, scientific, and hybrid labs. Not much information could be obtained, as such it is difficult to categorically state that it is an adaptive learning platform.

**Adaptive Learning**
Adaptive Learning otherwise referred to as Artificial Intelligence in Corporate Education has the Dutch and English versions. The features are; plug and play, time saving, and adaptivity. It can be made to function on educational platform using the adaptive learning service engine which can be used as a plug-in to your learning environment or self-learning. It adapts to complexity, and the embedded AI uses the data to figure out and anticipate how quickly, and at what level learner learns. This enables the appropriate learning material to be presented.

**Designing Digitally**
This is a workspace that aims at matching it to organizational goals and challenges. It is basically for training of employee. It helps for collaboration, and personalized training. The solution is fully integrated with tracking, allowing the trainer to quantify the value and estimate the entire impact of the training solution.

**Impelsys Scholar ALS**
Impelsys allows you to design individual learning experiences for students using the power of AI. It adapts to learners, similar to other adaptive learning platforms. It is also involve in other areas such as health

Other adaptive learning platform worth mentioning is whatfix and the opensource OpenEdX. These have similar fixtures just like the previously mentioned ones.

**Discussion of Results**

*Summary Table 1*

| Platform | Features | Target Audience | Ownership | Comments |
|---|---|---|---|---|
| SC Training | Cloud based, auto generation of content, easy work through, suitable for trainers and trainees | Teams, organizations | Proprietary | Suitable for organizational training, adaptive but not necessarily for student learners. Provision for trial before purchase |
| Adaptemy | AI embedded, create road map for learning path, allows for LMS integration but not for all | This cannot be determined except with request | Proprietary | It is restrictive in nature |
| Knewton | Easy content creation, requires registration for both the instructor and the learner | Student and instructors in educational system | Proprietary | Allows for trial, cloud enabled, requires the use of approved and know text books when creating content. Otherwise, you rely on the content developed within |
| CogBooks | Collaboration with University of Cambridge Press, high course content quality, great content presentation and user friendly content | Instructors and student learner | Proprietary | Despite the rich content, an instructor could develop their own content |

| | | | | |
|---|---|---|---|---|
| Realizeit | One-on-one personalization, high level of accuracy and performance. Adaptive in nature | Could not be determined | Proprietary | As at the time of this work, direct contact could not be made with the providers, and the website could not be access |
| Smart Sparrow | Grading system, adaptive, AI embedded, LMS integration, active learning, high performance | Organizations, student learners and instructors | Proprietary | No provision for trial. It is complex |
| Pearson Interactive Labs | Hybrid lab, scientific | Open ended. Combination of various elements that suits organization and student learners | Proprietary | It is generic. No provision for trial |
| Adaptive Learning | Highly adaptive for student learners | Student learners and instructors | Proprietary | No provision for trial. Available in English and Dutch |
| Designing Digitally | Developed for organizations | Organization | Proprietary | Good platform for collaboration and encouraging team work within an organiszation |
| Impelsys Scholars ALS | Powered by AI, and it is adaptive | Student learners and instructors | Proprietary | No provision of trial |

**Conclusion and Recommendations**

In reviewing the various adaptive learning platforms, it was obvious that while each has certain elements of adaptivity, others are clearly more adaptive than others in relation to core learning principles. An adaptive learning platform is an infusion of technology and learning pedagogy. Depending on the stakeholders of the platform, either can super influence the other in the final product. Also, even though trainees could be describe as learners, when researching on educational styles, the definition of a learner is taking as a students. Consequently, while some of the highlighted platforms are proficient in organizational training, it is not suitable for student learners.

Prior to procuring or adopting any platform, a team of technologist and educationist should tactfully look available platforms, and make recommendation. The outcome of this research is a starting point. Also, other researchers in education, can research on the details (course content relevance in relation to adopting institution curriculum) to ascertain its relevance.

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