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Generative AI and Personalised Learning Planning

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1. Executive Summary

While the use of AI to deliver personalised learning has been common for many years, leveraging Generative AI for personalised learning planning is still in its infancy. This is reflected in the literature where examples of research into the use of Generative AI for personalised learning plans is relatively sparse.

AI for personalised learning planning uses a number of different approaches that studies have shown to be effective in improving both the learning experience and the learning outcomes. AI-powered Adaptive Learning solutions are built using three key components: the curriculum model that details the overall learner journey and desired outcomes; the content model that details the learning resources required to build an effective, personalised learning path; and the learner model that builds a detailed profile of the learner to be used to tailor the learning path to their needs.

While there are clear benefits to using AI to adapt a learner's journey, it is not without its challenges. Among these challenges are the need to avoid the risk of undermining the learner's 'agency' (or control over their own learning) by dictating the learning path they should take. The need for the AI to be 'explainable' is also an important challenge to confront - what is the pedagogic logic used to propose one path over another?

Investigating a sample of Adaptive Learning solutions in the market demonstrates how solution providers employ a number of AI techniques and strategies to deliver personalised learning paths.

In exploring the potential for using Generative AI for Adaptive Learning, the report highlights the fact that by nature of the fact that Generative AI models are 'pre-trained' with prior knowledge, they can deliver effective personalised learning paths with smaller amounts of data than traditional AI-powered solutions. However, overall, the findings of this report are that the affordances of Generative AI in the area of personalised learning planning are yet to be explored in detail and further research is required before judging any potential benefits.

2. Introduction

This report looks at the possibilities afforded by Generative AI for the creation of a personalised learning plan.

Generative AI refers to deep-learning models that can generate high-quality text, images, and other content based on the data they were trained on[1]. As such, it is distinct from the range of existing techniques including Rule-based AI, AI-Planning and Recommender Systems, which has been used to deliver personalised learning for many decades.

A Personalised Learning Plan (or Personalised Learning Pathway) can be defined as 'customised, flexible routes that learners can take to gain knowledge, skills and competencies [based] on their individual needs and preferences'[2]. Many different technological approaches have been taken to creating personalised learning plans ranging from expert systems, recommenders, AI Planning to name a few.

In its broadest form, personalisation of the learning experience can be delivered in a number of ways[3]:

- Personalisation of **why** something is to be learned (the learning aims).
- Personalisation of **how** it is to be learned (the learning approach).
- Personalisation of **what** is to be learned (the learning content and learning pathway).
- Personalisation of **when** it is to be learned (the learning pace).
- Personalisation of **who** is involved in the learning (the learner or learning group).
- Personalisation of **where** the learning takes place (the learning context).

Adaptive or Personalised Learning has been the focus of research for many years and is now incorporated into many Learning Management Systems (LMSs). The recent evolution of Generative AI has raised interesting questions about how it can be used to support personalised learning. We have previously explored the potential impact of Generative AI on

[1] https://research.ibm.com/blog/what-is-generative-AI
[2] https://cpduk.co.uk/news/personalised-learning-pathways-how-to-meet-the-diverse-needs-of-learners
[3] https://oro.open.ac.uk/56692/1/TEPL_en.pdf

the authoring of learning content and the opportunities for deeper levels of personalisation at the content level in a related Learnovate report on authoring learning content using Generative AI while this report focuses specifically on how the content is presented to the learner.

This report focuses on learning paths, current approaches to personalising them to the needs of individual learners and the potential for Generative AI to complement or enhance these approaches. It looks first at personalised learning pathways and Adaptive Learning before then exploring the use of AI (including Generative Ai) in Adaptive Learning. The report also examines a sample of solutions in the market using AI to deliver Adaptive Learning.

3. Learning Pathways and Adaptive Learning

3.1 Overview

The use of Generative AI to deliver personalised learning plans is a relatively new phenomenon. However, AI has been used for many decades to provide adapted learning.

The purpose of this report is to explore how Generative AI fits into the existing landscape of AI-powered Adaptive Learning. What additional benefits does the use of Generative AI bring to the task of delivering personalised learning paths that have a meaningful impact in terms of learning outcomes?

Generative Pre-Trained Transformer models (such as GPT-4), the AI technology that currently underpins tools such as ChatGPT, process large amounts of data (Natural Language Processing (NLP)) and transform this into writing that can be output as text (ChatGPT4) (Aydin & Karaarslan, 2023). The outputs resemble human speech very closely and can engage users in conversation. This capability makes it attractive for education and student learning.

The use of AI in learning opened up the possibility of designing and developing better technology-enhanced learning systems that use Adaptive Learning systems to deliver personalised learning experiences. Early iterations of these AI-powered learning platforms include Intelligent Tutoring Systems - computer-based educational systems that provide immediate and personalised instruction or feedback to learners, usually without intervention from a human teacher.

3.2 Learning Pathways

A Learning Pathway can be simply defined as the implementation of a curriculum design consisting of a set of learning activities that help users achieve specific learning goals (Nabizadeh et al., 2020).

In its simplest manifestation, this can take the form of pathways or connections between learning concepts in a domain built up by taking into account prerequisite knowledge.

However, this doesn't take into account principles from either pedagogy or instructional design and more sophisticated systems use a blend of a pedagogical model (the learning science) and a domain model (the subject matter expertise) when it comes to sequencing concepts in a learning pathway.

3.3 Adaptive Learning

Adaptive learning is “an educational approach that utilises technology to provide personalised learning experiences tailored to individual students’ needs, preferences, and progress” (Gligorea, 2023).

It makes use of data-driven algorithms and AI to dynamically adjust the content, the delivery, and the pace of instruction based on learners’ performance and engagement. By adapting to the specific requirements of each student, adaptive learning promotes effective and efficient learning, maximises engagement, and enhances educational outcomes.

Adaptive learning can be used not just to address different levels of understanding, but also to account for diverse backgrounds, learning preferences, and cognitive abilities. It has a significant advantage over the 'one-size-fits-all' which can lead to poorer learning experiences and outcomes.

The learning pathway can be adapted either at the 'macro level' where the learning pathway is adapted to learning cohorts, or at the 'micro-level' where the learning pathway is adapted for each individual learner (Santally et Senteni, 2013).

Adaptive Learning is also increasingly incorporating collaborative and social learning components. Here, AI can analyse learner interactions and group dynamics to provide personalised learning resources and activities for group work. However, the difficulties associated with implementing Adaptive Learning in group learning environments should not be underestimated.

It has been argued that when adapting the learning pathway, psychological factors such as cognitive styles, learning preferences and strategies should be taken into account (Brusilovsky and Peylo, 2003).

When talking about cognitive styles here it refers to how the learner approaches their learning activities. It refers to 'a person's characteristic mode of perceiving, thinking, remembering, and problem solving[4]'. Do they perform better when given tough challenges? Do they perform better learning in a group or individually? It should in no way be equated with the concept of 'learning styles' that has been largely discredited by the research.

3.4 The Pedagogy of Adaptive Learning

Pedagogy is the method and practice of teaching and Adaptive Learning allows the focus of the instruction to shift from an instructor-centred pedagogic model to a learner-centred pedagogic model (Taylor et al., 2021).

In order to deliver a meaningful learner-centred experience, any learning path presented by an Adaptive Learning platform needs to incorporate elements of Pedagogy. It has been argued that one of the most important pedagogical principles to apply in Adaptive Learning

[4] https://dictionary.apa.org/cognitive-style

environments is to ensure that the content is broken down into small, bit-size units of learning (Cavanagh et al., 2020). By breaking down the learning content into small components, this reduces the Cognitive Load on the learner, while also allowing the Adaptive Learning platform to construct learning paths in a more ‘granular’ fashion.

4. AI and Adaptive Learning

4.1 Overview

AI is playing an increasing role in adaptive learning systems with its advanced technology and capabilities. Machine learning algorithms are used to analyse large amounts of data such as learner profiles, performance data, and learning resources. By identifying patterns, trends, and relationships in data, AI algorithms can make intelligent predictions about learner needs, preferences, and future performance. This enables adaptive learning systems to dynamically adapt content, pacing, and teaching strategies to individual learner needs, facilitating a personalised and streamlined learning experience.

AI-powered adaptive learning systems consist of multiple interconnected components that work together to deliver a personalised learning experience. Learner modelling involves creating and maintaining individual learner profiles, as well as collecting data such as assessment scores, learning preferences, progress tracking, and even socio-emotional factors. Content customisation uses AI algorithms to dynamically adjust the complexity, format, order, and delivery of learning materials based on learner profiles and real-time feedback. Feedback mechanisms in adaptive learning systems provide timely and customised feedback to learners, allowing them to monitor learner progress, identify opportunities for improvement, and make necessary adjustments to increase learning strategies.

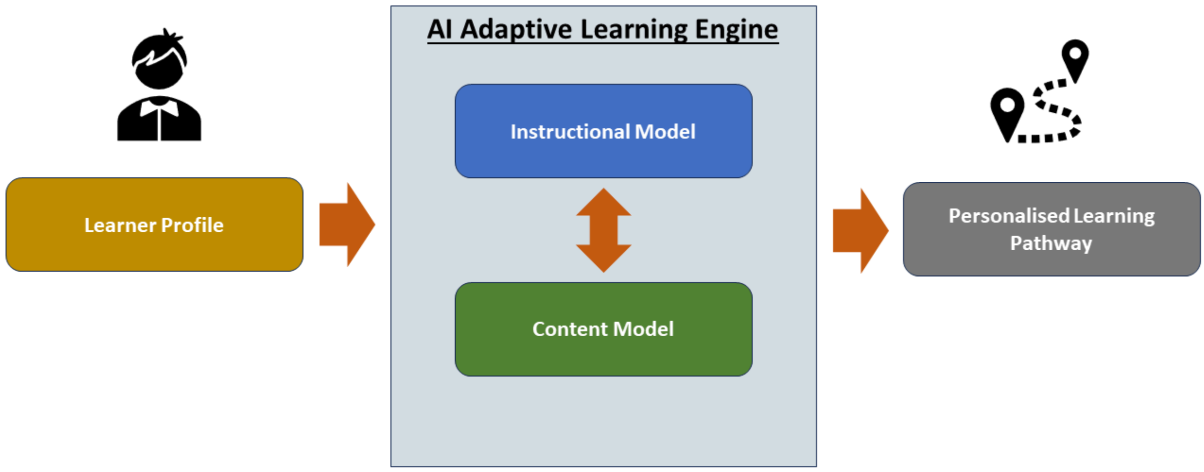

Fig 1: Overview of AI-powered Adaptive Learning

Implementing adaptive learning with AI is not without challenges and considerations. Privacy issues and data security must be carefully considered to protect learner information and ensure compliance with data protection regulations. Algorithmic bias must be mitigated to ensure fairness, impartiality, and inclusiveness in the learning experience. Ethical considerations such as informed consent, responsible use of data, and transparency should guide the development and implementation of AI-powered adaptive learning systems. Furthermore, recognizing that AI is a tool that enhances and supports, rather than replaces, human expertise, effective collaboration between humans and AI is essential to harness the strengths of both. Continuous monitoring and updating of algorithms are necessary to maintain their accuracy, relevance, and alignment with evolving educational goals. The expertise of educators and curriculum her planners remain critical to using AI effectively and ensuring educational integrity in adaptive learning systems.

4.2 The Benefits of Adaptive Learning

The use of AI for Adaptive Learning has a number of benefits (Gligorea, 2023):

Personalised Learning: AI algorithms allow learning platforms to tailor the learning experience to the individual learner's interests, needs, and skills.

Improved Learning Outcomes: By tracking and analysing learner performance, AI can identify knowledge gaps and offer remedial content or activities to address these.

Real-time Feedback: AI can be used to provide instant feedback to learners helping them understand their mistakes and make corrections.

Enhanced Engagement: By providing a tailored learning experience, AI can increase learner motivation and engagement.

Furthermore, research has shown that using Adaptive Learning can improve learning outcomes and reduce the time taken by learners to reach those desired outcomes (Kurilovas, Zilinskiene and Dagiene, 2015).

A study conducted with pharmacy students to examine the effect of adaptive learning interventions on students' learning demonstrated a statistically significant difference between students that completed at least one learning path for the chemistry module compared to those for whom the learning pathway was not adapted (Liu et al., 2017).

4.3 The Challenges of using AI for Adaptive Learning

There are, however, a number of challenges with using AI for Adaptive Learning. One particular issue is the use of complex models that make it difficult to deliver the optimum tailored experience to the learner (Kabudi, Papas and Olsen, 2021). Many of the AI models used to deliver Adaptive Learning make it quite complicated to deliver an optimum tailored learning experience since they often use generalised data from a large cohort of learners.

Other challenges include what are described as 'cold-start problems' where the AI system has little data on learners (Gligorea et al., 2023). Without a detailed understanding of the learner (what they know, what they need to learn and how they learn most effectively) it can be very difficult to tailor the learning path to the learner's preferences and abilities.

However, this problem can be tackled by the use of expert systems that rely on a profile built around data collected from the learner before they start their learner journey. For example, this can include assessing the learner's General Mental Ability which refers to their ability to learn, understand instructions, and solve problems. The relevance of assessing General Mental Ability (GMA) has been well researched and documented (Schmidt & Hunter, 1998).

Furthermore, an over-reliance on technology can relegate the human aspects of learning as well as raising questions about data privacy and security.

Also, it cannot be assumed that learners will automatically accept the recommendations of an AI-driven learning tool. Research has shown that learners often ignore such systems and ensuring their acceptance is critical when developing any personalised learning platform (Kerres and Buntins, 2020). Here, the recommendations of the system collide with the learner's desire for 'agency' or 'the feeling of ownership and sense of control that students have over their learning'[5].

Recently, there has been a growing emphasis placed on the concept of explainable AI which aims to provide learners and educators with understandable explanations of how the algorithms make decisions. In this way, explainable AI endeavours to foster trust through accountability and the ethical use of AI technologies.

4.4 AI Recommender Systems for Learning Pathways

There are a large range of approaches that can be employed by AI in Adaptive Learning to decide how to personalise learning paths and one of the most commonly used computational strategies are Recommender Systems.

The goal of a Recommender System is to generate meaningful recommendations to a collection of users for items or products that might interest them[6]. How they are designed depends on the domain and the particular characteristics of the data available. Examples of

[5] https://teachingenglishwithoxford.oup.com/2021/12/10/introduction-learner-agency/
[6] https://www.vikas.sindhwani.org/recommender.pdf

the use of AI Recommender Systems to propose content are Netflix and Amazon which use data from similar users' preferences (as well as ratings) to propose options to users with tastes and interests deemed to be similar. Likewise, LinkedIn Learning uses an AI Recommender System to propose courses in a personalised learning pathway.

Broadly speaking, Recommender Systems can use two techniques for deciding what content to propose and, thus, in a learning context, what pathway to present to each learner.

Collaborative Filtering

The Collaborative Filtering technique works by collating user feedback and exploiting similarities in rating behaviour amongst several users in determining how to recommend an item or learning resource.

Content-based Filtering

The Content-based Filtering technique works by analysing the content the user or learner has already 'consumed', and proposing content based on its similarity to what has previously been presented.

A third, hybrid technique involves combining both Collaborative and Content-based Filtering to produce a ranked list of recommendations which, in a learning context, can be used to propose the next resources in the learning path. This is the technique used, for example, by the Adaptemy platform discussed later in this report.

One of the drawbacks of Recommender Systems is that, while each step or learning activity in the path may be logical, it does not necessarily guarantee that the overall learning pathway represents a cohesive learning journey that will get the learner to the desired outcomes.

4.5 Gen AI for Adaptive Learning

During the research for this report, the literature on the use of Generative AI is currently scant, perhaps reflecting the fact that Generative AI is still an emerging technology.

As we have seen, learning material recommendation through personalised learning pathways is a key component of Adaptive Learning systems.

However, an important challenge that Adaptive Learning systems face is the fact that, to provide a meaningful learning pathway, the system requires either a large amount of data or a detailed level of indicators to effectively align any proposed content to the learner's specific needs. But one of the most powerful and interesting characteristics of Generative AI is that it has the ability to accurately learn from a relatively small set of annotated data. Added to the fact that Generative AI models can be endowed with strong prior knowledge through pre-training, means that it offers exciting possibilities for streamlining AI-powered Adaptive Learning systems. Thus, it has been argued that the use of Generative AI in Adaptive Learning systems will give these even stronger adaptation capabilities while ensuring the recommendation process will be more transparent and convincing to users. Moreover, the recent advancements in LLMs (the models used by Generative AI) when it comes to understanding context, gives them added ability when it comes to enhancing the learning experience.

Unlike traditional approaches that rely on standardised content, generative AI can leverage advanced algorithms to analyse vast datasets and understand the individual nuances of learning journeys. This level of personalisation enhances learner engagement and accelerates the mastery of relevant skills. Furthermore, generative AI fosters adaptability by identifying and addressing gaps in knowledge or skills in real time . This means that learners receive precisely what they need at the right time, whether it's through targeted microlearning modules or interactive simulations[7].

[7] https://elearningindustry.com/2024-trends-ai-powered-learning-analytics

Future directions in adaptive learning will involve integrating contextual information to further personalise the learning experience (Gligorea et al., 2023). This includes incorporating data from wearable devices, environmental sensors, or other sources to adapt content based on factors such as location, time, or learner's emotional state. Context-aware adaptation will enable adaptive e-learning systems to provide even more tailored relevant content.

4.6 Ensuring the Quality of AI Generated Learning Paths

Key to ensuring the quality of any learning paths generated by AI are the explainability, transparency, and scrutability of the AI techniques that were employed (Balog Radlinski and Araklyan, 2019).

Explainability

This refers to AI techniques that not only provide the learner with recommendations, but also make them aware of why certain learning activities have been proposed.

Transparency

Closely related to Explainability, Transparency crucially involves providing an honest account of how the recommended learning activities are proposed and how the overall AI technique operates.

Scrutability

This refers to offering the learner the ability to correct the AI system's reasoning or modify their preferences to improve the accuracy of the recommended learning activities.

Importantly, the above concepts need to apply to the learner model used by the AI system as well as the content model. Thus, how the learner profile and preferences are arrived at must be explainable, transparent and scrutable to the same degree as the recommended learning content.

Furthermore, the quality and (accuracy) of any learning pathway proposed by Generative AI would need to be scrutinised to ensure it is following a structure that is coherent from a learning perspective. If not, how could the Generative AI model be improved? This is an important question that needs further research.

5. Market Solutions Using AI in Adaptive Learning Systems

5.1 Overview

There are a number of Adaptive Learning platforms that integrate AI to deliver personalised learning paths. In this section, we look at three examples: Adaptemy, Knewton Alta, and Century. How each platform uses AI to deliver Adaptive Learning is examined with the aim of demonstrating the real-world application of the technology.

5.2 Adaptemy

Adaptemy is an Irish tech firm that specialises in providing AI-powered adaptive learning solutions.

Their solution integrates with an existing Learning Management System (LMS) such as Blackboard, Moodle or Canvas and offers a range of off-the-shelf adaptive learning strategies to enable clients to personalise the learning experience for their learners.

Using the Adaptemy platform involves four key steps:

1. On their LMS, the client creates a curriculum 'map' which details the learning pathway and adds content metadata to provide the AI engine with the information it needs for adaptation
2. Detailed learning data is extracted from the LMS to 'train' Adaptemy's AI engine
3. This learning data (including learner profiles) is then used to recommend personalised learning pathways on the LMS

4. Using learning analytics, the Adaptemy platform can be refined for optimum performance

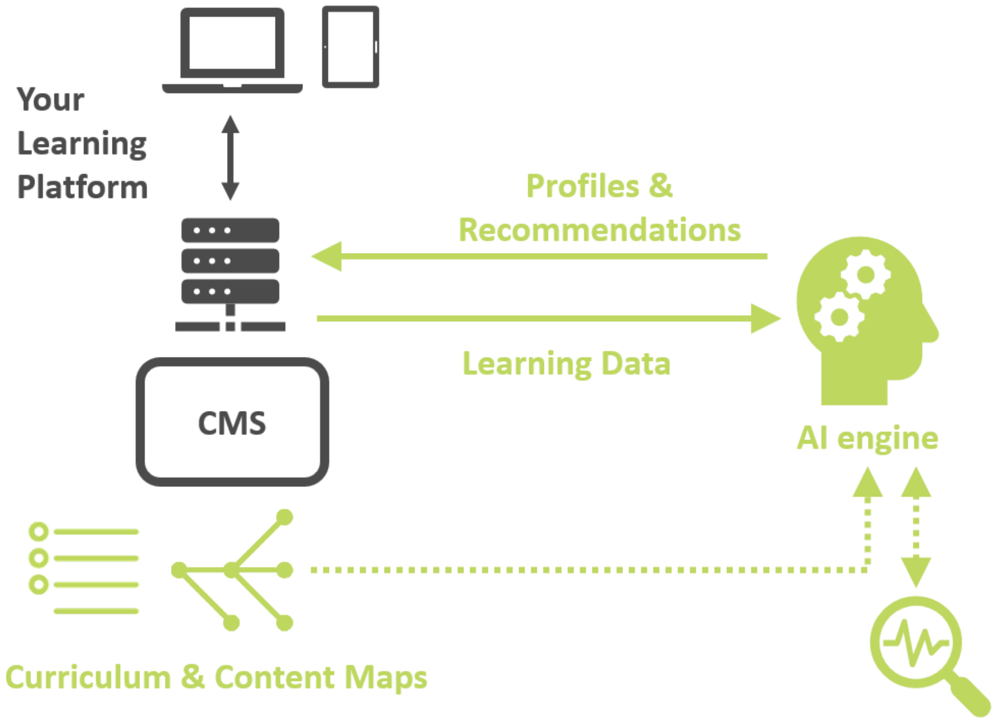

Fig 2: Overview of Adaptemy platform

For Adaptemy, the Curriculum Model is central to their platform as it represents the 'knowledge domain' detailing what the learner needs to learn - or, put simply, the learning outcomes. To optimise the effectiveness of their Curriculum Model, Adaptemy's AI engine uses two strategies: Bayesian Networks and Knowledge Space Theory. In AI, a Bayesian Network uses probability to determine the occurrence of an event while Knowledge Space Theory uses mathematical formulas to represent knowledge in a particular domain.

At the same time, the Adaptemy platform builds a Content Model that contains all the metadata about the content such as: difficulty level, discriminance, probability of guessing, probability of having a slip, and expected time to solve a question. The Adaptemy AI engine uses Collaborative Filtering (the grouping of data from similar learners) and Item Response Theory (which calculate the probability of a correct answer based on the learner's ability).

The third cornerstone of the Adaptemy platform consists in building a detailed profile of each learner by evaluating their ability across the whole course, while also detecting their emotional state. It can also capture misconceptions and predict knowledge retention.

The Adaptemy platform then uses data analytics to dynamically update and refine the three models (curriculum, content, and learner).

5.3 Knewton Alta

Owned by the American publishing company Wiley, Knewton Alta is an AI-powered personalised learning platform that according to its website offers a 'learning experience [that] goes beyond homework – it pairs practice with personalised learning that offers detailed answer explanations, integrated just-in-time instruction, and remediation of prerequisite skill gaps, all based on student performance'[1]. As well as adapting the content to the student's proficiency, Alta delivers feedback to students for what it calls 'dynamic remediation' to address weaknesses in the student's understanding.

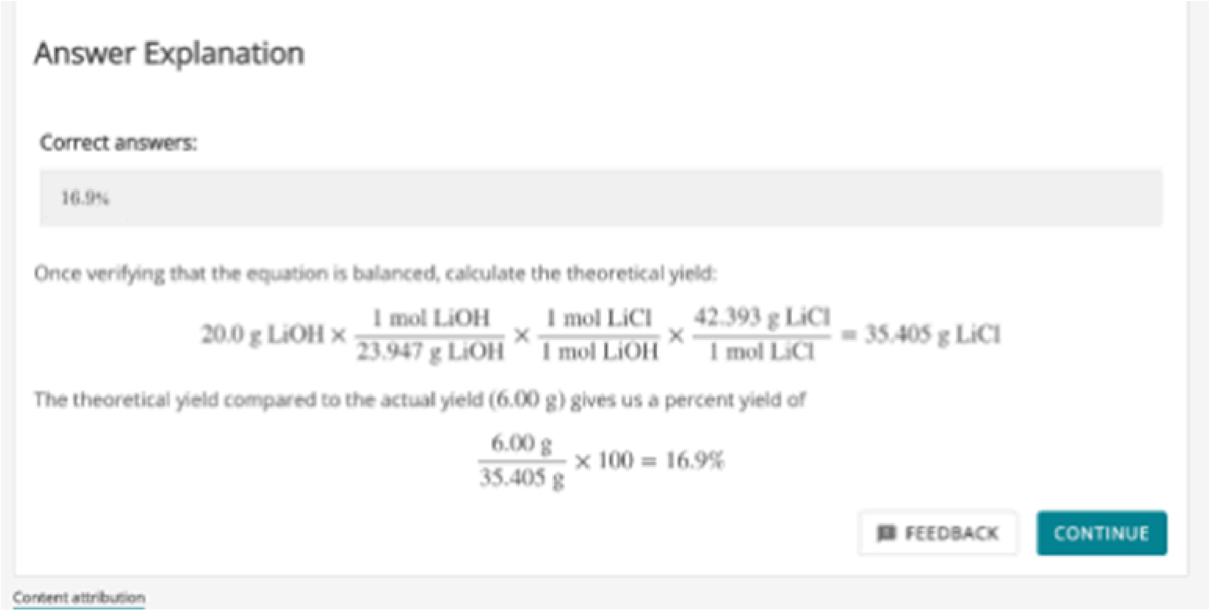

Fig 3: Knewton Alta Answer Explanation with Feedback option

It is a complete courseware solution that combines adaptive learning with openly available content with the aim of identifying student's knowledge and providing the appropriate learning resources (Owoc, Sawicka and Weichbroth, 2021). The Alta platform currently covers the following subjects: Mathematics, Economics, Statistics, Chemistry, Physics, Biology and Psychology.

Knewton Alta provides teachers with a 'Test Readiness' analysis aimed at giving them insights into how well students are prepared before an exam.

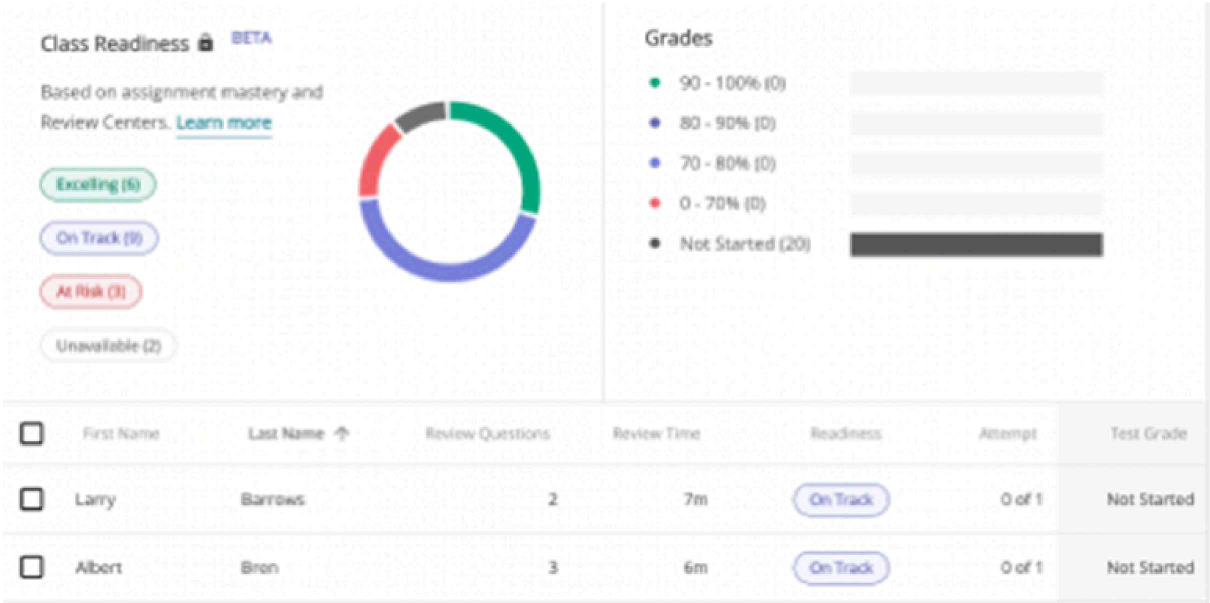

Fig 4: Knewton Alta Educator Dashboard

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[1] https://www.wiley.com/en-ie/education/alta

5.4 Century

The British company Century markets an AI -powered learning planner aimed primarily at school students in the age range 11 to 16. According to their website, Century 'uses AI to recommend learning to students and provides teachers with easy to access data to support assessment, interventions and planning' [8].

[8] https://www.century.tech/explore-century/secondary-schools/

For the subjects of Mathematics, English and Science, the Century platform provides a range of learning resources mapped to the English national curriculum. Students are presented with a learning plan composed of 'micro-lessons' based on their strengths but also areas for improvement. The content in these 'micro-lessons' has been developed exclusively for the Century platform by a team of former teachers.

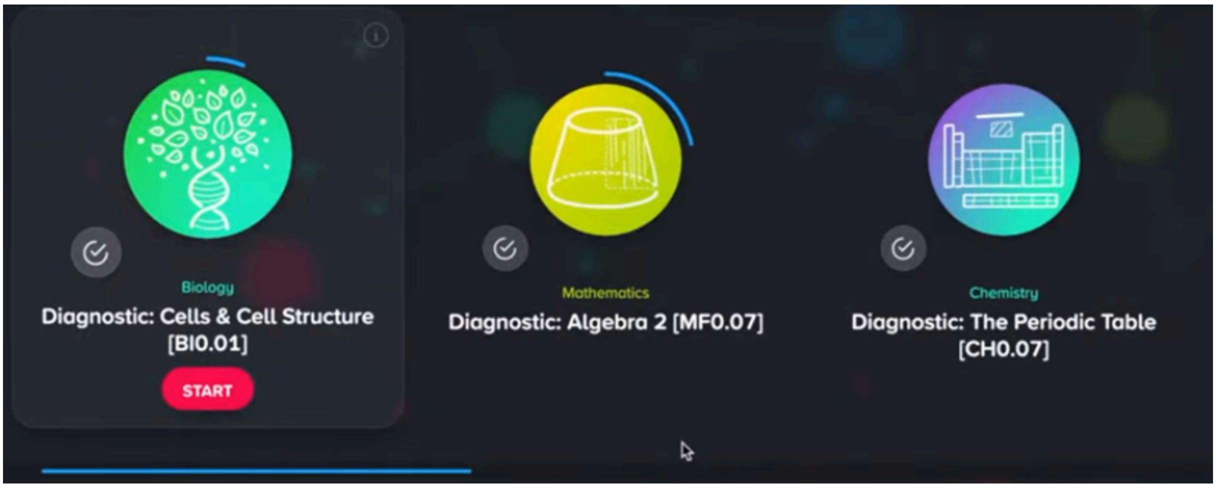

Fig 5: Century Micro-learning Modules

To evaluate a student's knowledge and provide data to the AI recommender system, each student completes a baseline diagnostic activity to determine their current level of understanding. Every time a student completes a diagnostic activity, the Century platform updates their learning plan based on what the AI engine thinks they should study next.

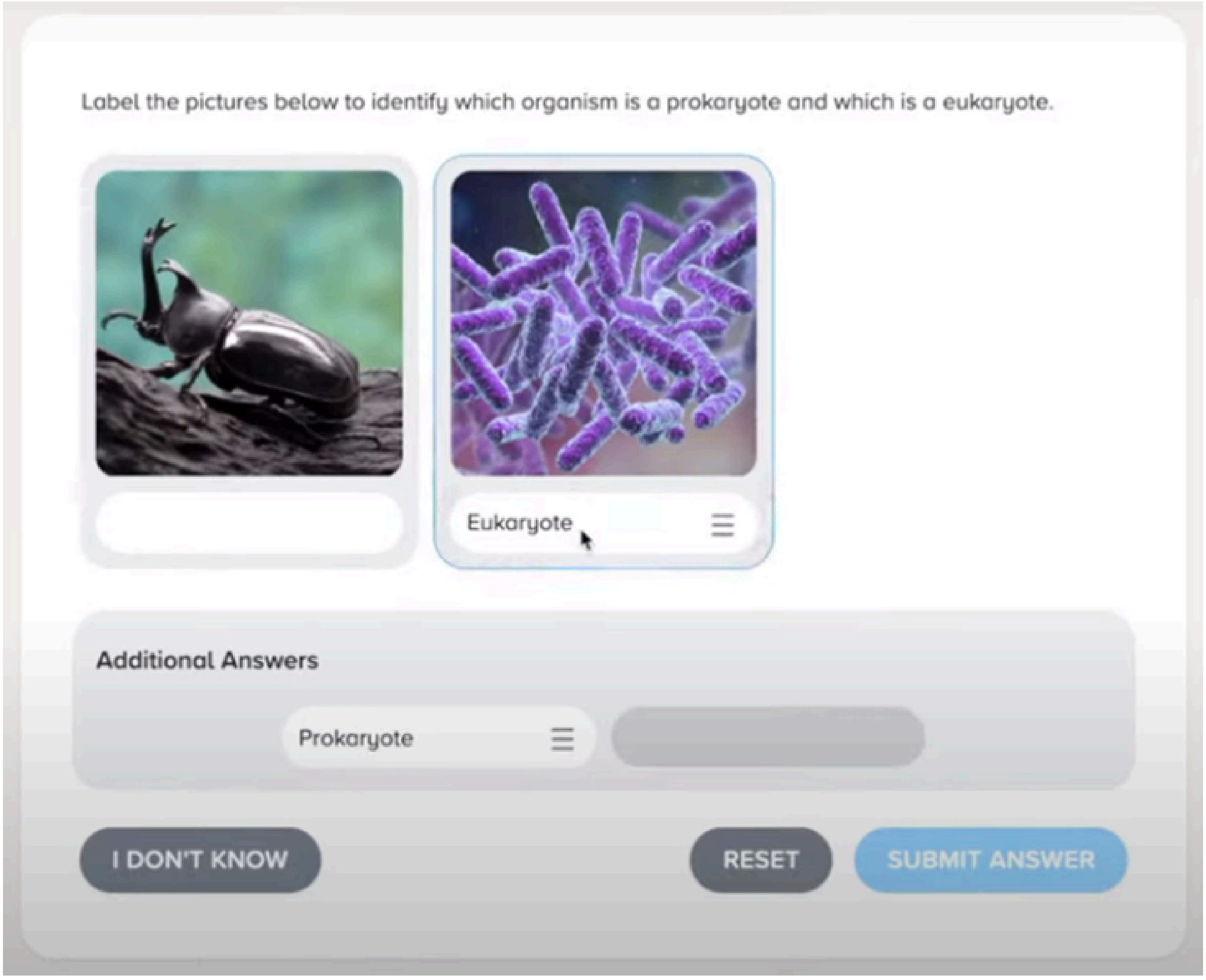

Fig 6: Century Assessment Component

The Century platform has a comprehensive range of functionality to support teachers including a dashboard where they can track the progress of each student. Among the analytics presented on the teacher dashboard, is a chart plotting the performance of each student on which teachers can clearly identify those students needing additional support. Teachers can then use this data to modify the learning plan for each student by adding or re-ordering 'micro-lessons'.

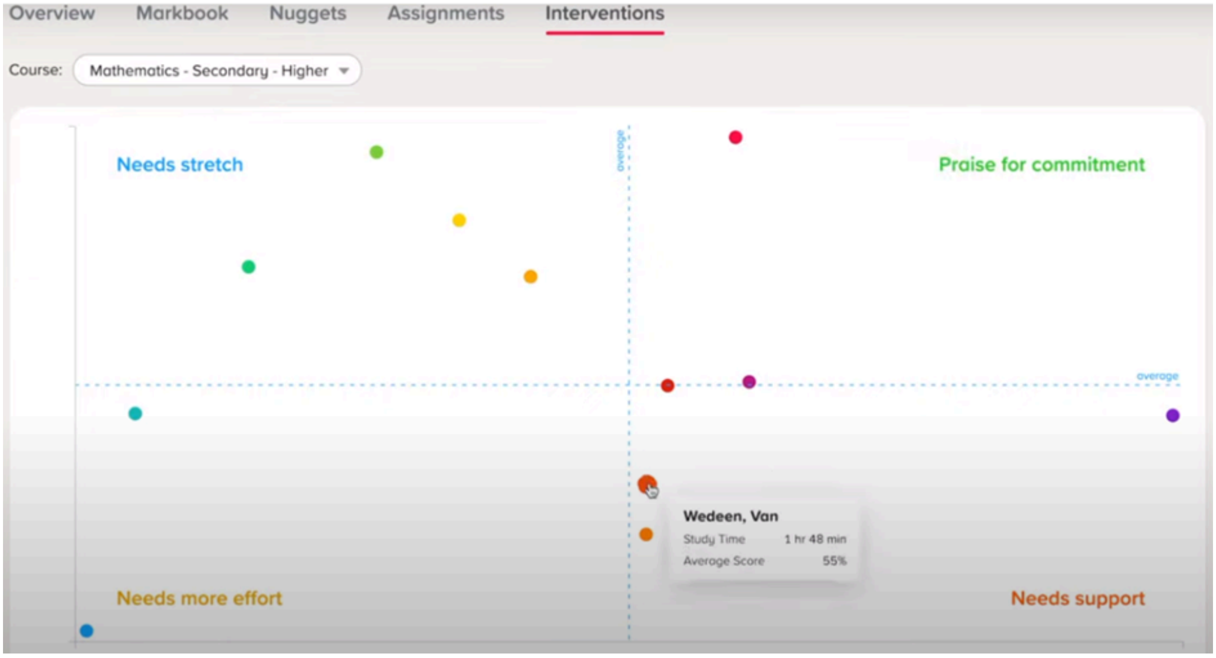

Fig 7: Century Teacher Dashboard

5.5 Summary of Solutions

The three platforms presented above are representative of the Adaptive Learning solutions currently available in the market.

The Adaptemy solution employs sophisticated AI strategies (Bayesian Networks and Knowledge-based Theory) to build personalised learning paths based on curriculum, content and learner models.

In addition to personalising the learning path, Knewton Alta uses data gathered by the AI engine to deliver tailored feedback.

The Century platform focuses primarily on AI-driven Adaptive Learning with the aim of supporting teachers by simplifying and automating the task of personalising learning paths and, thus, reducing the administrative overhead involved in this task.

Interestingly, none of the above solutions currently leverage Generative AI - an indication of the fact that its use for personalised learning paths is still in its infancy.

6. Discussion and Conclusions

Adaptive Learning now has a well-established history and its efficacy in helping learners achieve enhanced educational outcomes has been consistently demonstrated by the research. The integration of Generative AI into Adaptive Learning solutions can build on this success by both simplifying the process of personalising the learning experience, but also shortening the time taken to build appropriate learning paths by leveraging two of the key strengths of Generative AI: the fact that the AI model can be 'pre-trained' with prior knowledge and the ability of Generative AI models to work on smaller data sets when deciding what learning content to propose.

There are, however, some challenges involved with the use of Generative AI for Adaptive Learning. Not least the notion of fairness: can a Generative AI powered Adaptive Learning system build a profile of the learner that is both fair and accurate? Also, the issue of reliability cannot be ignored: does the proposed learning pathway stand up to examination from an instructional design perspective?

This report clearly highlights the need for further research to ensure that the potential benefits of Generative AI-powered Adaptive Learning clearly out-weigh any possible downsides.

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Appendix A - AI Algorithm Strategies

The following are some of the key AI algorithm strategies currently used to deliver Personalised Learning Pathways:

Machine Learning: Involves algorithms that learn patterns from data without being explicitly programmed for specific tasks. Key ML strategies include:

- *Supervised Learning*: The algorithm learns from labelled data to predict outcomes.
- *Unsupervised Learning:* The algorithm identifies patterns or groupings in data without labelled outcomes.
- *Reinforcement Learning*: The algorithm learns to make decisions by receiving rewards for certain actions.

Deep Learning: A subset of machine learning using artificial neural networks with multiple layers (hence "deep") that can learn from large amounts of unstructured data, such as images and texts. Common models include Convolutional Neural Networks and Recurrent Neural Networks.

Evolutionary Computation: Inspired by biological evolution, algorithms like genetic algorithms use processes such as selection, crossover, and mutation to evolve solutions to optimization and search problems.

Fuzzy Logic: Mirroring human reasoning by allowing for approximate values rather than exact, this approach is beneficial in dealing with uncertainty and imprecise information.

Agent-based Systems: These systems simulate the actions and interactions of autonomous agents to assess their effects on the system as a whole. Agents can learn and adapt to their environment to optimise their behaviour.

Metaheuristics: High-level, procedural frameworks like simulated annealing and ant colony optimization algorithms designed for finding good enough solutions to optimization and search problems by exploring the space of possible solutions. These methods aim at obtaining a sufficiently good solution where an exhaustive search is not practically feasible.

Hybrid AI Systems: Combining two or more techniques to leverage the strengths of each. An example is neuro-fuzzy systems, which integrate neural networks and fuzzy logic.

Different strategies are chosen depending on the complexity and the nature of the task at hand. For example, deep learning is often used for image and speech recognition due to its ability to process large amounts of data, while agent-based systems might be employed in logistics and supply chain optimization. AI in finance, such as for algorithmic trading, leverages a mix of techniques to analyse market trends and execute trades.

Each strategy has its advantages and limitations, and the choice of which to use is dependent on the needs of the application and the nature of the data available. Some common supervised learning algorithms used in AI include:

Support Vector Machines: SVMs are used for classification and regression tasks. They find the hyperplane that best separates the data into classes.

Decision Trees: Decision Trees are used for classification and regression by learning simple decision rules inferred from the data features.

Random Forest: An ensemble learning method that creates multiple decision trees and combines them to get a more accurate and stable prediction.

Logistic Regression: Although the name suggests regression, logistic regression is used for binary classification tasks. It predicts the probability that a given instance belongs to a particular class.

Linear Regression: Used for predicting a continuous value. It assumes a linear relationship between the input variables and the single output variable.

Naïve Bayes: A classification technique based on Bayes' Theorem with an assumption of independence among predictors.

K-Nearest Neighbours: KNN algorithm is used for classification and regression. It predicts the label of a data point by looking at the 'k' closest labelled data points and picking the most common label (classification) or averaging the labels (regression).

Neural Networks: Particularly useful for complex problems, neural networks use interconnected nodes or neurons in a layered structure that can learn to perform tasks from labelled data.

These methods have different advantages and are chosen based on the particular characteristics of the problem, such as the complexity of the model, the size and type of data, and the desired accuracy and interpretability of the results.