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Article

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ARCHITECTURE TO TRANSFORM CLASSIC ACADEMIC COURSES INTO ADAPTIVE LEARNING FLOWS WITH ARTIFICIAL INTELLIGENCE

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Abstract
The literature on adaptive learning suggests that it can provide significant improvements to the educational process and numerous studies have found a necessity for personalised learning, which is one of the strong suits of adaptive learning. Adaptive learning platforms require that content be effective, and lack thereof has hindered large-scale adoption by adding the cost of content creation to the upfront implementation cost and creating a 'critical mass' type problem where a platform without content is ineffective and unattractive, leading to lack of interest from users and lack of funding for developing new content. Artificial intelligence (AI) technology has the potential to aid in content creation by taking on a significant part of the workload. This paper aims to explore this possibility and propose an architecture based on current artificial intelligence technologies that will help teachers and experts transform classic course materials into adaptive learning flows. The system is not autonomous and will not replace a human expert but rather will take on some of the more straightforward, but time-consuming, work. The proposed approach results in a distinct system, independent of the adaptive learning platform itself, that can help rephrase, restructure and enrich the content, resulting in an automated digital narrative, or fragment thereof, that can be exported in a format based on open standards and used within an adaptive learning platform of choice.

Keywords: AI content generation, artificial intelligence, adaptive learning, learning flows, personalised learning, educational content.

JEL Classification: A20, I20, I21

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Introduction

The report Markets and Markets (2020) shows that the adaptive learning market was valued at USD 1.9 billion in 2020 and is expected to reach USD 5.3 billion by 2025. This growth is driven by the demand for eLearning solutions, especially personalised learning, initiatives government, and the perception of online education (Tartavulea et al., 2020). Adaptive learning is thus of significant interest from an economic, technological and educational point of view.

Adaptive learning itself aims to improve learning for every student; however, adaptive learning platforms require a considerable amount of content to be effective and impactful. As such, they have not been widely adopted due to the cost associated with creating appropriate educational content.

Recent developments in educational technologies, adaptive learning and artificial intelligence have given way to new possibilities in education and have the potential to generate significant improvements across the board. The developments observed in the field of artificial intelligence, especially with the recent GPT-3 Large Language Model, show promise to help solve the classic "critical mass" problem described by Evans and Schmalensee (2010), namely the lack of content for adaptive learning platforms.

The purpose of this article is to create an architectural proposal to transform existing educational material into adaptive learning flows using artificial intelligence. This endeavour involves testing current generative artificial intelligence technologies to determine whether they can assist in the process of converting educational materials or the creation of new educational materials based on a prompt (a textual input detailing desired outcomes, interaction method specific to artificial intelligence). The end result of such a transformation process is an automated digital narrative, or part of it, that can be used within an adaptive learning platform.

The paper proposes an architecture based on current artificial intelligence technologies that will help teachers and experts transform classic course materials into adaptive learning flows. The proposed architecture does not depend on the use of a certain adaptive learning platform, being independent of it.

1. Literature review

Adaptive learning is a method of teaching that tries to address the individual needs of learners using artificial intelligence and other computer algorithms to customise the learning experience of each unique user (Kaplan, 2021). The need for adaptive learning stems from the difficulty of teaching in a uniform way in a class of students with varying levels of understanding of the subject and of the prerequisite concepts or knowledge necessary. The need for personalised learning is well recognised (Duncan, 2013) and three kinds of adaptive learning approaches (or levels of personalization) have been proposed: Individualisation, Differentiation and Personalization. (U.S. Department of Education, 2010).

Individualisation refers to pace, it is about the speed with which different students reach the same learning goals. In differentiation, the approach is customised based on the learning preferences of the student. Finally, in Personalization, the method, as well as the learning objectives and content, are tailored to the individual learner, in addition to being paced

according to the needs of the student. Personalization encompasses both Individualisation and Differentiation (U.S. Department of Education, Office of Educational Technology, 2010; Kerr, 2016).

In a classic instructional learning paradigm, the teacher is tasked to transfer knowledge to all of his students, bringing them to a targeted minimum level of understanding (equivalent with a passing grade in most scenarios). As such, the teacher needs to discover their current level of understanding and account for variations between students and the mismatches between them in other factors such as learning style and motivational structure that affect their performance in class and the effectiveness of any one teaching strategy (Simelane and Mji, 2014).

Starting from Wright's basis for learning curve theory (Wright, 1936) we can attribute a similar graph to student learning and consider that they are in varying positions on the said graph, with the graph being slightly different for each student due to their individual differences in learning style, performance, motivation, mental state, cognitive ability and any multitude of other factors that can make the learning curve appear steeper, requiring more effort upfront or smoother, suggesting an accelerated learning process. Therefore, it is reasonable to consider that a graph showing the distribution of the student's learning performance (as expressed in time needed to progress, or the rate of learning) would follow a Gaussian distribution. This graph can also be interpreted as a distribution of the needs of the students in terms of the attention needed and the appropriate challenge needed to encourage learning, but not overwhelm the student.

The outer edges of the Gaussian distribution described earlier represent students with special needs, one end representing students with learning deficiencies (challenged students) while the opposite end represents gifted students, which classify as special needs due to the increased attention and level of challenge necessary (Osborn, 1996; Kelemen, 2014) as opposed to the usual meaning of special needs students (students with learning deficiencies) which require a smaller challenge and a slower approach to learning.

An adaptive learning system aims to provide an appropriate challenge to each student and adjust the pace to their needs (Essalmi et al., 2010), dynamically customising their personal learning trajectory, building interactive digital narratives and identifying concepts that have not been fully understood yet or competencies that can be further developed. This is an inherently difficult task due to differences between learners and their learning styles, difficulty which an adaptive learning system aims to alleviate (Anane, Alshammari and Hendley, 2014). While a normal teacher, in an instructional paradigm, can only teach at one specific difficulty level and speed at one time, aiming to synchronise to the median student in the class from our normal distribution. This situation can become unmanageable in online learning environments or situations where the number of students per teacher can exceed their capacity. This situation is also known as "The teacher bandwidth problem" (Kotzee and Palermos, 2021). An adaptive learning system can provide unique learning experiences for each student, reducing the overall workload of a teacher and allowing more attention and time to be dedicated where necessary.

This is achieved through connecting the student with the necessary resources and tools to better understand and retain the material being studied and at the same time adapting the material to their needs and abilities to keep them engaged.

Additionally, in the above context of an instructional paradigm, there is an overhead of time spent on tasks that are not part of the educational process themselves but must be performed and fall upon the teacher. This is the case with tech support in classes that utilise hardware such as any kind of lab equipment or even basic devices such as screen projectors, computer science classes where students may encounter unknown errors, and particularly in the case of distance learning where setup-specific problems may arise that are outside of a teacher's control and often beyond a student's expertise. These tasks are mandatory, but at the same time, they reduce the overall efficiency of the teacher (Windelspecht, 2001). Such tasks block the teaching itself until the issues are resolved; however, in the case of a class that utilises an adaptive learning platform, the teacher is free to deal with them while the platform delivers the educational content to all the other students. A sufficiently advanced adaptive learning platform can diagnose and provide solutions to student issues automatically based on a series of knowledge bases that can be queried and that can be expanded so that every new error or problem encountered is automatically added and addressed in the future.

Adaptive learning systems also have the benefit of covering multiple learning styles. While some students may prefer or perform best with a direct knowledge transfer approach, research suggests that students obtain better results when they are actively engaged in discovery, such as the self-explaining method, which has students generate an explanation using their reason, rather than taking a fact that is presented to them for granted (Hausmann and VanLehn, 2007). This process involves accessing prior knowledge and reasoning based on it, so that the new knowledge is connected or linked to prior knowledge that improves learning. Knowing the level of prior knowledge of a student is a difficult task that teachers can perform with limited precision through various means, such as testing and direct observation; however, an adaptive learning system can evaluate this with more precision. Knowing a student's current level of understanding, prior knowledge, and underlying presuppositions can greatly affect knowledge acquisition (Shing and Brod, 2016), both explicit and implicit (Ziori and Dienes, 2008), this is also deeply tied to the student's interests due to the linear correlation between interests and prior knowledge (Tobias, 1994), and as such an adaptive learning system can greatly improve the learning process by helping the teacher better understand a student's needs and providing the appropriate content.

An adaptive learning system requires content to be efficient and provide the most value it can. Intuitively, if there is no content, then the adoption rate will be low, and if the adoption rate is low, then the interest and resources needed to make new content will also be minimal, creating a classic 'critical mass' type of problem and a race to the bottom, rather than the top. As such, ways to produce significant amounts of decent quality content with limited resources are an interesting proposition and potential solution to this problem.

Using AI to generate educational content, part of educational content, or just to enhance and transform existing content is not a new idea. (Diwan et al., 2023) used artificial intelligence to generate relevant definitions, section overviews and reflection quizzes based on existing educational resources. The process of generating summaries involves the use of the Artificial Intelligence component to process multiple sections of text and obtain a coherent description of the topic addressed within them.

The generation of verification questions has the role of producing content that helps the student retain the information presented, and the teacher (or an automatic system) to identify gaps in knowledge early, thus improving both the educational content itself and the effectiveness of the educational act.

The authors suggest automating the generation of educational content for training in divergent question asking using a large language model (LLM). Through comparisons with hand-generated information and human expert annotations, they assess the effectiveness of this strategy. The outcomes illustrate the potential of artificial intelligence methods in assisting children's learning and point to the relevancy and use of the LLM-generated content.

Although large language models, such as GPT-3, have shown significant promise in content generation, their effectiveness depends on training on an enormous amount of high-quality training data. LLMs attempt to develop answers based on patterns they have identified in their training data (Brown et al., 2020). In the context of education, this suggests that they may provide in-depth explanations on a wide range of subjects or even replicate problem-solving techniques used in scientific or mathematical procedures. However, there is a risk of overgeneralization or an excess of very broad answers that might not be accurate or nuanced enough to address specific academic issues.

With the surging popularity and availability of transformer-based large language models, such as GPT-3, generation of full content can be attempted. The models may still be trained further or contextualised using existing educational resources and research to improve accuracy with the purpose of generating valid, relevant and useful educational content that can be verified by a human being and subsequently be improved based on feedback.

2. Methodology

In an adaptive learning context we consider a learning flow to be the equivalent of a lesson, lecture, or laboratory session from a classic classroom, taking a constructivist approach with emphasis on learning by doing and practical experiments that develop knowhow and a practical understanding of the subject, rather than a purely theoretical one. A learning flow consists of a series of steps; these steps are a simple form of instructions or information and may contain other educational resources (videos, images, 3D animations, documents, code sections, equations, etc.). These steps are often related to concepts which are presented within the step, and are described as atomic because they represent the simplest and indivisible form of the information or instructions presented within them. The purpose of a learning flow is to provide these simple atomic steps that help the student move towards an end goal and understand the process, whether that end goal is building and programming a robot, training a neural network, making a simple electric circuit, producing a chemical reaction, or any other lesson subject imaginable.

The steps of a learning flow reveal new concepts and ideas or reinforce previously learnt ones to achieve progressive disclosure, with the aim of reducing friction in the learning process and minimising the chances that the students become overwhelmed by the new information (Spillers, n.d.). Each step provides not just instructions but also open educational resources such as short videos, documents, diagrams, graphs, etc. to create an additional learning opportunity for students who learn best by discovery and want or need more resources. The steps may also contain an evaluation component, asking relevant questions, both to reinforce the learnt concepts and to evaluate the degree of understanding, providing an early detection mechanism for students who are falling behind or are disengaged.

Based on a series of engagement metrics (correct response rate, completion rate, time spent per step, etc) the system adjusts each student’s experience by providing the appropriate

content in terms of difficulty, additional information, or additional challenges. Flows can have a branching tree-like structure to account for prerequisite concepts that were not well understood previously or concepts that require further explanation.

The basic premise is that such a system will allow and encourage the student to ask questions, request assistance and have access to a vast library of open educational resources. The branches would eventually merge back into the main flow, leading to the same goal and allowing each student to reach it at his own pace. Due to the interactive nature of an adaptive learning system, the pace is performed automatically through the student's interaction and is based on the analytical data collected. With the appropriate pacing and challenges that are adjusted to be rewarding without seeming insurmountable, the system will have a higher chance to keep the students engaged for longer periods of time, thereby transferring knowledge and creating skills.

In order to evaluate the degree of understanding of the students and identify gaps in their knowledge, a series of question types and practical assessment exercises can be used within the flows, the most common answer types being multiple choice, survey/scale, true/false, numeric answer, audio/video, file or short text. A significant part of these can actually be represented by multiple-choice or open ended questions (short text answer). Audio/video or file responses are less common in automated systems due to the technical difficulty of automatically grading them.

While multiple-choice questions are a common occurrence and go-to method of evaluation, we consider that natural language-based, open-ended questions are more flexible, more appropriate, and in line with the philosophy behind such a system. In an online only system (which is a requirement to access the generous amount of open educational resources from the public domain and access the functionality of the system), it is reasonable to assume that students have access to the Internet as a whole, as such it cannot be treated as an isolated system, and any testing should be assumed to be an open book, regardless of the type of question or the answer format. In this scenario, in the case of multiple choice questions students that do not know the correct answer may feel inclined to pick the closest answer, or that which they think is most likely to be correct, while a natural language question may encourage them to search for the right answer before answering. Additionally, ideas expressed in natural language can be evaluated automatically with Natural Language Processing, providing a more in-depth conclusion than a simple right/wrong answer. Current NLP technologies can extract a range of information from a textual response, their most common uses being for extracting entities from text, recognising terms, recognising relationships between extracted entities, sentiment analysis and automatic summarization. Using a small subset of the common functions of NLP technologies is sufficient to classify a student's answers, based on a predefined training set, specific to each question, and this classification to be validated by a human operator (a teacher for example) to compensate for possible mistakes of the automatic process, thus retraining the classifier and improving its performance with each intervention.

The purpose of a flow within an adaptive learning system is to present concepts and ideas in such a way that it creates know-how and practical skills in the long term, with an emphasis on learning by doing and on experimentation as a method of discovery.

3. Converting classic learning materials into adaptive learning flows

In its most basic form, a flow is a linear sequence of steps, as described earlier. A flow must have a series of additional elements such as suggestions, help, or additional Open Educational Resources that are relevant to the step they are associated with. With these elements in mind, the flow will have a branching structure, allowing the student more freedom in the way they interact with the content. The flow could potentially contain jump points into other flows, in the case that it is identified that a necessary concept is not yet well understood, or to certain materials that aim to further emphasise the current knowledge and help students understand before moving forward. Such a structure is visible in Figure no. 1.

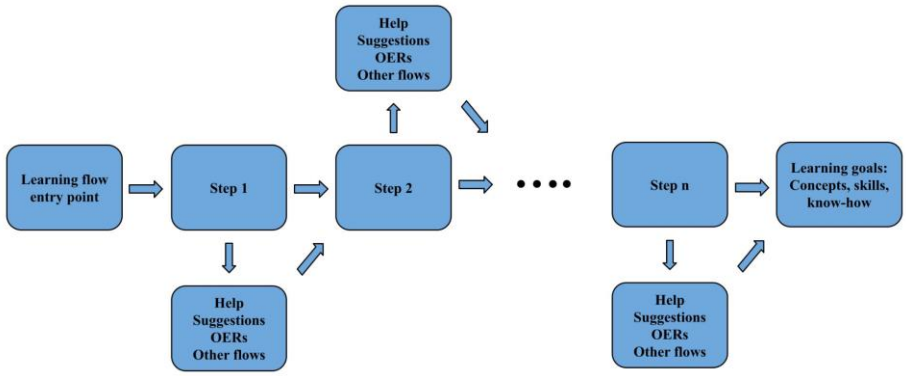

Figure no. 1 - Structure of a learning flow

From all of the above we understand that existing learning materials in various formats (PDFs, E-books, presentations, etc.) from which text can be extracted automatically can be put through a conversion process, as in Figure no. 2, which will use a Generative AI model and Open Educational Resources to transform the content into an interactive learning flow that can be imported directly into an adaptive learning solution.

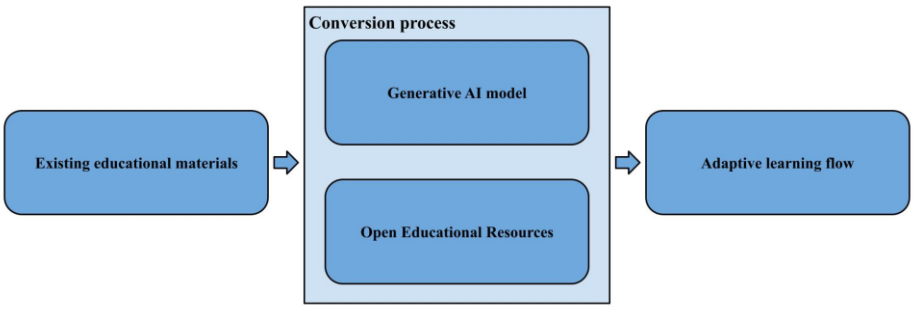

Figure no. 2 - Conversion process diagram

The conversion process must be partially automated to reduce the overall workload of a content creator and, as such, has a net benefit over creating content from scratch. Human intervention is still required as the content must be validated and the AI can be directed towards the intended level of difficulty and complexity for the content being generated.

The content can be greatly enhanced by adding Open Educational Resources such as tutorials, 3d animations, code snippets or repositories, diagrams and other resources. Some of these resources can be provided directly by the system by querying a database of resources such as Wikimedia Commons or automatically by the AI model, provided that they were part of the training data of the model.

We have identified several approaches, based on generative Artificial Intelligence models, which we propose and which can be used independently or combined to achieve the best results:

- Direct material transformation
- Topic extraction

-Topic based generation

-Augmented topic based generation

The performance of the AI models is largely dependent on the training data and on the prompt that was used for generation. From our experiments we have concluded that current generation generative AI models such as GPT-3 and GPT-4 can achieve satisfactory performance. Techniques that fall under the category of prompt engineering can be useful in improving results by adjusting the input rather than retraining the AI model, where possible.

The most straightforward approach is direct material transformation, and it involves using paragraphs of existing educational materials as part of the prompt and generating a series of steps that summarise the content and the concepts within the educational material. This will have drawbacks if the text itself is already a plain series of factual statements, as there may not be much to summarise or paraphrase. In the case of such material, the second approach may be useful: Topic extraction of the text or paragraph and content generation from scratch (described and exemplified as 'Topic-based generation' in figure no. 3) or using both the topic and the original text as part of a prompt engineered to generate a lesson or the structure of one, which can subsequently be further improved (described and exemplified as 'Augmented topic-based generation' in Figure no. 3).

Due to the nature of AI, the limitations of the model, the training dataset and the prompt itself, all results will have to go through a validation process to ensure the accuracy of the factual information within. Once the content has been generated, validated and corrected if necessary, it can be enhanced by inserting Open Educational Resources, either manually or automatically, and by generating relevant verification questions. Following a final validation step, the assets generated according to the steps above can be easily exported to any available format, such as JSON, and subsequently imported into an adaptive learning platform of choice.

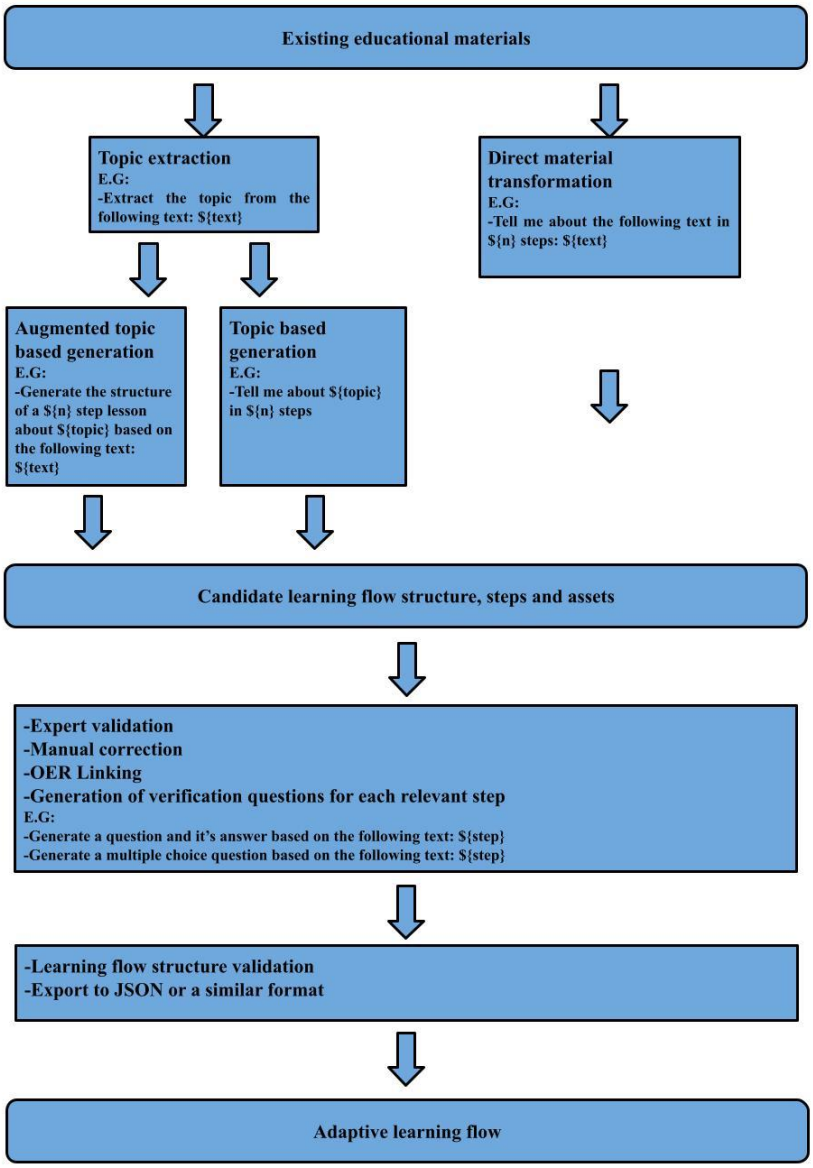

Figure no. 3 - Detailed conversion process diagram

To validate the viability of these approaches and the technology behind them, several texts with educational value were put through this process. One of these experiments is described below, the original input text has been replaced by the [text] token, and the results have been obtained using generative artificial intelligence tools based on an LLM (OpenAI, n.d.). In this example, a text discussing sorting algorithms and their implementation in JavaScript engines was processed. The method used was **Topic based Augmented Generation** (table no. 1). The prompt used to extract the topic was of the form: "Extract the topic from the following

text: [text]", and the response was: "The topic of the text is 'Sorting algorithms and their implementation in JavaScript engines".

Table no. 1. Sorting Algorithms and their Implementation in JavaScript Engines – Augmented Topic Based Generation

Task	Process a text discussing sorting algorithms and their implementation in JavaScript engines.
Method	Augmented topic based generation
Prompt	Generate the structure of a 5-step lesson on "Sorting Algorithms and Their Implementation in JavaScript Engines" based on the following text: [text]
Result	**Step 1**: Introduction to sorting concepts Objective: Introducing the fundamental concept of sorting. Key points: Sorting involves arranging data in a specific order, such as numerically, alphabetically, or based on specific criteria (for example, sorting people by height or age). In programming, sorting often deals with arrays of numbers or strings. Didactic approach: Discuss real-world examples of sorting (e.g., sorting numbers, names, or people by attributes) to contextualise the concept. Use code snippets or visual aids to illustrate the sorting process. **Step 2**: Importance of Sorting in JavaScript Objective: To understand the importance of sorting algorithms in JavaScript programming. Key points: Sorting is a fundamental operation in programming that optimises the arrangement of data for efficient manipulation. In interviews or coding tasks, sorting algorithms are typically tested to sort arrays of numbers or strings. Didactic approach: Engage students in scenarios where sorting algorithms are essential in real-world programming tasks. Provide sample interview questions or coding challenges related to sorting algorithms. **Step 3**: Overview of JavaScript Engines and Array.sort() Objective: Introduce JavaScript engines and the built-in Array.sort() method. Key points: JavaScript engines execute JavaScript code in browsers (e.g., Chrome V8, Firefox SpiderMonkey). Array.sort() is a built-in method in JavaScript to sort arrays. Didactic approach: Explain how different browsers use different JavaScript engines. Demonstrate the basic use of the Array.sort() method with simple code examples.

	Step 4: Comparison of Sorting Algorithms in JavaScript Engines Objective: Explore the differences in the sorting algorithms used by different JavaScript engines. Key points: Different JavaScript engines use different sorting algorithms for Array.sort(). For example, the Chrome V8 engine uses Timsort, while Mozilla Firefox uses sort sort. Didactic approach: Give an overview of common sorting algorithms and their efficiency. Illustrate how these algorithms are implemented in various JavaScript engines. **Step 5**: Practical applications and optimization strategies Objective: Discuss practical applications and optimisation techniques for sorting in JavaScript. Key points: Optimise the classification algorithms based on factors such as data size, engine differences, and time complexity. Discuss strategies to select appropriate sorting algorithms for different scenarios. Didactic approach: Engage students in exercises or coding challenges to implement and optimise sorting algorithms in JavaScript. Highlight the importance of selecting the right algorithm for improved performance in web development. This structured lesson plan covers fundamental concepts, the specifics of the JavaScript engine, and practical considerations related to JavaScript sorting algorithms.

Source: OpenAI, n.d.

The other methods described in (Figure no. 3) obtained similar results, with small structural differences. Other notable mentions include using the **Topic Based Generation** method without starting from an existing text, or using the processing result as input to another processing step. The lesson plan generated by **Augmented topic-based generation** within the example in (table no. 1) can be used as input data in an **Augmented topic-based generation** step. The description of the individual steps in the lesson can be used to generate lesson content based on the generated plan,

The content of the prompt is the main determining factor of the format of the response generated by the generative model. Increasing the degree of specificity, including a context, and describing in as much detail as possible the form of the desired end result (structure of a lesson, segment of text, etc.) increases the chances that the output generated will have a predictable format. Due to the nature of AI, the limitations of the model, the training dataset, and the prompt itself, all results will need to go through a validation process to ensure the accuracy of the information within. Once the content has been generated, validated and corrected if necessary, it can be enhanced by inserting Open Educational Resources, either manually or automatically, and by generating relevant verification questions (Table no. 2):

Table no. 2. Generation of verification questions

Prompt	Response
Generate an open-ended question and a short answer based on the following text: JavaScript engines implement efficiency-optimised sorting algorithms, taking into account factors such as time complexity and data characteristics. These engines optimise sorting methods to efficiently handle different data sizes and minimise resource consumption.	**Question** How do JavaScript engines improve the efficiency of sorting algorithms and what factors do they consider? **Answer** JavaScript engines improve the efficiency of sorting algorithms by customising them to be more efficient in handling data. They consider factors such as time complexity and data characteristics. Time complexity refers to the efficiency of the algorithm in terms of the time required for execution relative to the size of the input. Data characteristics include the type, structure, and arrangement of the sorted data. By optimising sorting methods based on these factors, JavaScript engines aim to efficiently handle different data sizes while reducing resource usage.

Source: OpenAI, n.d.

After a final validation step, the elements generated according to the steps above can be easily exported to any available format, such as JSON, and subsequently imported into an adaptive learning platform of choice. The validation step and potential manual correction can take up to two hours per hour of content produced. This step involves reviewing the content, the duration of the review being influenced by the validator's expert quality, but also by the increased attention required to observe possible errors. From our experiments, exemplified above, this two-hour time covers most cases.

This time is significantly less than the time required to manually develop this educational content or other types of content. Manual development time for educational content for adaptive learning platforms is estimated at more than 50 hours per hour of content and 25 hours per hour of content using specialised software tools (Khosravi, 2019).

For classic instructional content of the "Instructor-led training" type and eLearning content of various levels of complexity, the time spent on average is significantly higher (Figure no. 4), using the definitions for the level of complexity of the e-Learning content presented by Chapman (2010).

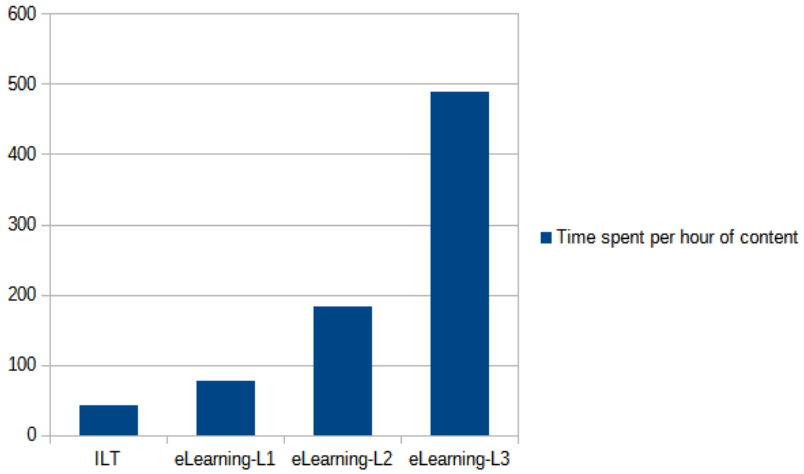

Figure no. 4. Time spent per hour of content
Source: Chapman, 2010

The types of content presented do not involve the same types of development activities, and thus, in order to be able to have a comparison term, only those activities were extracted that are comparable in purpose to the transformation of existing materials using Artificial Intelligence (Table no. 5).

Table no. 5 - Time spent per hour of content (comparable activities)

	Time spent per hour of content (hours)			
Activity	**ILT**	**eLearning-L1**	**eLearning-L2**	**eLearning-L3**
Instructional design	6.84	10.88	24.69	61.97
Development of the lesson plan	5.06	0	0	0
Creation of handouts	3.38	0	0	0
Student Guide/Workbook development	4.83	0	0	0
Test and exam creation	3.42	0	0	0
Storyboarding	0	9.03	20.88	53.22
Total	**23.53**	**19.91**	**45.57**	**115.19**

Source: Chapman, 2010

Comparing these data (Figure no. 5) we notice that by introducing an automated process based on Artificial Intelligence we can significantly reduce the time needed to develop educational material and thus the related cost.

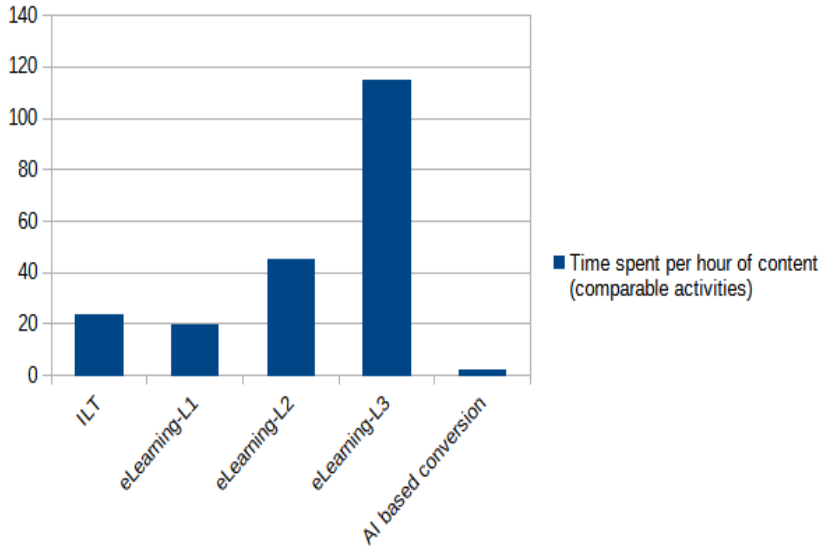

Figure no. 5 - Time spent per hour of content (comparable activities)

Other technologies based on Artificial Intelligence can be introduced to bring additional efficiency improvements to the other activities specific to the development of educational content, such as the generation of video content (Text-to-video) or images (Text-to-image). Additionally, open educational resources, in the public domain, produced by other entities (such as OER Commons or UNESCO) can be introduced for reuse in educational content.

4. Comparative analysis of the proposed approach and other works

Previous works have proposed using AI mainly as a conversation partner, in the form of a chatbot, that helps the student learn, or to provide lightweight content creation tasks such as section summarization or generation of multiple-choice verification questions.

Using AI as a chatbot has been proposed, tested, and even implemented with promising results (Bii, 2023). The implementation of a voice chatbot called 'Ellie' in Korean EFL classes has had a high success rate and improved classroom participation (Yang et al., 2022). The feedback based on talking with a chatbot during class is presented in Figure no. 6.

This approach presents a couple of challenges and limitations: If the underlying AI model is not a generative AI model, then it must be trained explicitly for all the tasks it is expected to perform, for all the questions it is supposed to answer and all the explanations it is supposed to provide. This involves a significant amount of effort and time, possibly that of a data scientist. If the model is generative, such as the current generation GPT-3 and GPT-4, then it is susceptible to 'hallucinations', a phenomenon in which the AI model generates an answer that seems plausible, but on closer inspection it is invalid, as it is factually incorrect or not related to the given prompt (Daniel, 2023; Marr, 2023). This phenomenon may be avoided by using a highly specialised model or with significant efforts on the part of prompt engineering by providing more contextual information, but it remains a concern when used for education.

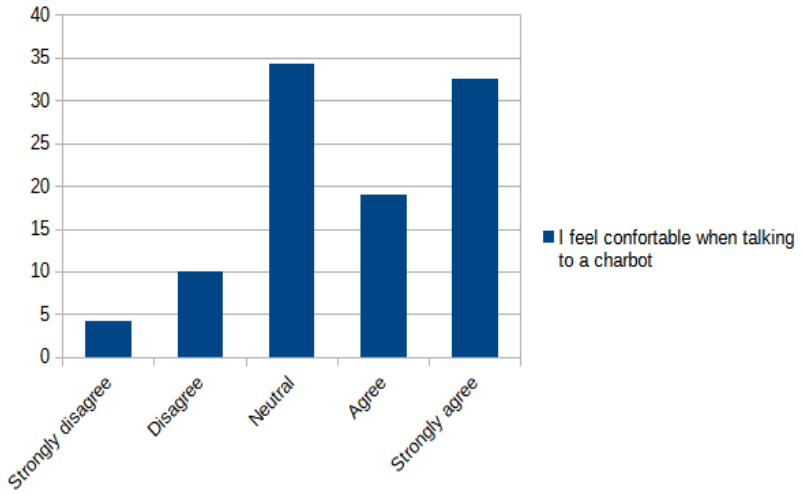

Figure no. 6 - Improved classroom engagement
Source: Yang et al., 2022

The second approach we have mentioned, proposed by (Diwan et al., 2023), is closer to our proposal. It involves using generative AI models (in particular, GPT-2) to enhance existing content, with the goal of increasing learner engagement. This is achieved by providing relevant section summaries, generated upon the learning materials that the learner is about to encounter, and by generating relevant verification questions based upon those same materials.

Our proposal is the use of generative AI models such as current-generation GPT-3 and GPT-4 to transform existing learning materials into adaptive learning flows, thereby lowering the implicit adoption cost of creating educational materials for a new learning platform. This involves a conversion process in which much of the structure of the existing learning materials is significantly altered, but the underlying information and concepts are retained. The AI component is used in this process to do the conversion itself, fill the gaps where necessary, generate new content where existing materials are insufficient, and enrich the learning flow with elements such as Open Educational Resources and relevant verification questions. This architecture does not aim to replace, but rather to aid creators of educational content, to ease their workload and improve productivity.

Conclusions

Current generative AI models are able to facilitate the transformation of classic academic course materials into learning flows, lowering adoption costs for adaptive learning systems, thus confirming our research hypothesis. The comparative analysis shows that this ability exists largely due to the significant advances in the field of generative Artificial Intelligence models and further developments are possible as the models themselves are improved, specialised, or fine-tuned for specific tasks including educational content generation.

Future research may involve collecting and analysing data on the adoption, user experience, efficiency, and cost benefits of integrating generative Artificial Intelligence models into a content generation workflow and of using the resulting content in a broader academic context.

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