Leveraging Generative AI, Knowledge Graphs and Personalised Learning Paths to Improve the Learning Experience of Neurodivergent Students in E-learning Courses

Giacomo Nalli[1], Yoshi Malaise[2], Stelios Kapetanakis[3], and Beat Signer[2]

[1] Computer Science, Science and Technology, Middlesex University, London, UK
g.nalli@mdx.ac.uk
[2] WISE Lab, Vrije Universiteit Brussel, Brussels, Belgium
ymalaise@vub.be, bsigner@vub.be
[3] Distributed Labs, Distributed Analytics Solutions, 30 Churchill Pl, London, UK
stelios@dstr.co.uk

Abstract. Around 20% of the world's population is affected by neurodiversity, often leading to increased difficulties when operating in an educational setting designed for neurotypicals. There is a strong need for effective, tailored education to help reduce the friction between the different lived experiences of members of affected groups. Although e-learning systems, especially those with personalised learning paths, provide significant support in overcoming the limitations of teaching strategies, they typically do not offer sufficient customisation options to meet the needs of neurodivergent students. While e-learning systems offer assistive tools, they lack empathy and adaptive information structuring, both of which are essential for providing adequate support to neurodivergent individuals and enhancing their learning experience. We propose a framework for personalised learning paths based on knowledge graphs, incorporating an LLM solution that can customise content for neurodivergent learners, helping them improve their knowledge and skills. By leveraging matchmaking software that evaluates content quality using *empathy*, *creativity* and *tone sensitivity* metrics, the framework can effectively assess responses and alignment to address the needs of neurodivergent individuals.

Keywords: Neurodiversity, Knowledge Graphs, Personalised Learning Paths, Adaptive Learning, Generative AI, Distance Learning

1 Introduction

E-learning systems seem rather popular nowadays, as most institutions have a system for delivering online courses [13]. The recent Covid-19 pandemic increased the use of e-learning platforms, a trend that persisted even after the pandemic due to their flexibility, ease of use, and reliability, making e-learning an effective option in both traditional and crisis-driven contexts [15]. In particular, institutions in the post-pandemic period had to adapt to the demands of new students in order to provide online materials not only for "emergency" reasons, but also to harness the benefits of an e-learning environment, such as self-assessment activities, pre-recorded lectures and online simulations, to maximise engagement and the overall learning experience [10, 1]. During the accelerated transition from face-to-face to online learning, some challenges arose. Many institutions and individuals suddenly had to experiment with new delivery methods and online assessments. Although these actions were a positive response to the demands of the new reality, they unfortunately had a disproportionate impact on students with neurodiverse profiles—particularly those who required additional support to meet their learning needs [2]. E-learning platforms have sought to provide solutions for neurodivergent people, supporting them in their studies by including plug-ins with assistive tools such as voice recognition, text-to-speech, talking calculators and spell-checking programs [18]. Nevertheless, so far they have been unable to fully meet the needs of neurodivergent students, since neurodiversity is an umbrella term relating to several different areas of difficulties, some of which require a tutor's intervention [23]. The online, self-paced nature of the courses makes it difficult to find an effective tutor who can support students. Several intelligent tutoring systems have been developed for e-learning platforms with very promising results in terms of engagement and performance, such as online tutors to help students with Java programming [20] or a gamification e-learning platform to improve the quality of feedback [19].

However, online tutors often struggle to address students' diverse learning needs in real time, which disadvantages neurodivergent students in their study planning [12]. Providing solutions for each type of neurodiversity can also be challenging, as not all neurodivergent students experience the same difficulties. Some may encounter only a few specific challenges, while others struggle across multiple areas of difficulty [11]. For example, some areas of difficulty can be related to dyslexia, such as *spelling* and *reading*. *Number confusion* could potentially refer to dyslexia, dyscalculia and dyspraxia [11].

In recent years, extensive preliminary research has been conducted on enhancing online learning platforms to better accommodate neurodivergent learners. For instance, some promising papers have proposed studies such as the use of LLMs to increase emotional support and productivity [5] or the development of adaptive learning strategies for complex neurodivergent profiles [25].

Nevertheless, we feel that a more generalised approach combining these new generative AI-driven techniques with the traditional insights from decades of digital learning systems is missing. This study is a first step towards a conceptual framework and solution that combines e-learning, knowledge graphs and LLM tools to create an adaptive tool that tailors learning content to meet students' learning needs. Rather than focusing on neurodiversity, our solution should identify specific areas where students struggle and dynamically adapt content to bridge skill gaps, enabling them to maximise their learning potential.

We start in Sect. 2 by describing the main research and related work on content adaptation and recommendation. Section 3 describes our conceptual solution, including the architectural design of the knowledge representation framework and the learning design service, which provides the best learning experience for students. It also covers the course delivery service, including a recommendation system that tailors content to users' learning needs, and the final evaluation. Finally, in Sect. 4, we summarise the main results, strengths and weaknesses, and discuss some future work.

2 Background and Related Work

Over the past years, research on reducing dropouts and early school leavers has been conducted in the context of the TICKLE European research project [8]. Findings from this project highlight that interest-driven learning that emphasises a *student-centred* approach can reignite learners' motivation to explore and engage with educational content. This becomes especially important when we consider modern-day inclusive classrooms, where we also strive to provide a welcoming environment for neurodiverse individuals and people from diverse backgrounds.

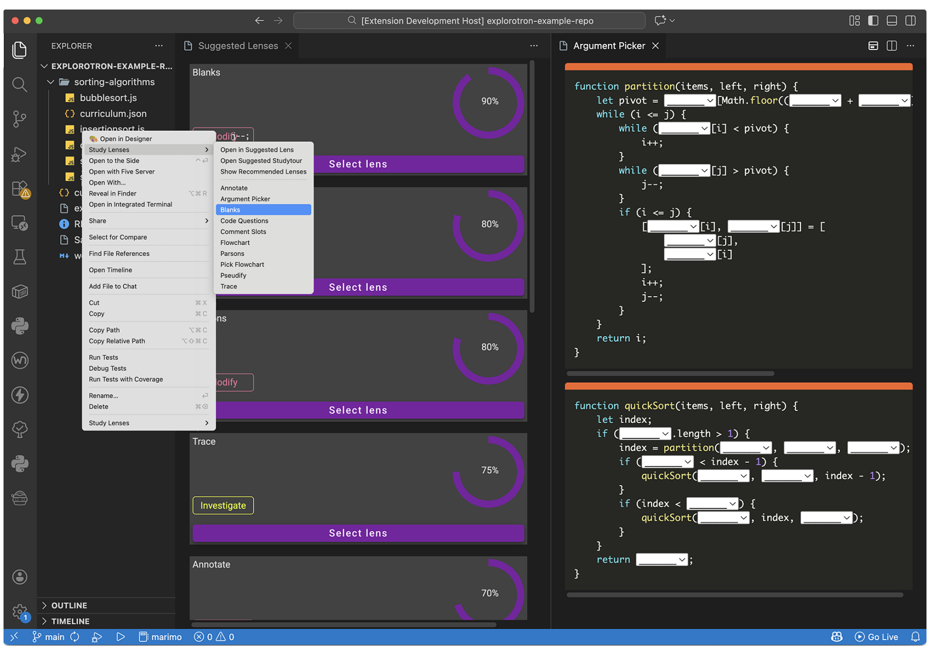

Fig. 1. Explorotron Visual Studio Code extension showing recommended study lenses on the left-hand side and the *Argument Picker* study lens where students have to decide which argument goes where in the code on the right-hand side [17]

2.1 Content Adaptation

A first way to tailor learning content to users is to present it in a way that is compatible with the user's current situation. The environment of a traditional classroom might often not be the best fit for many learners who do not conform to the expected image of a neurotypical student with proper access to a quiet and safe environment. We should strive to take advantage of the e-learning capabilities of mobile devices such as smartphones or laptops that allow learners to acquire knowledge at their own pace. Preliminary research as early as 2016 has shown positive outcomes from the use of adaptive web-based educational applications for autistic students [9].

An interesting example of content adaptation can be found in the design of Explorotron [17], an interactive Visual Studio Code plug-in that aims to help students learn to code by providing multiple different views, referred to as lenses, to explore a piece of JavaScript code. Each of these views focuses on distinct aspects of the code and can help the student focus on the elements they are struggling with. In Fig. 1, we can see a lens in action that allows students to practise their understanding of a piece of code by allowing them to reconstruct a function by selecting which argument goes where in the function body. Note the clear separation between the content that needs to be learned and the way it is presented to the learner.

2.2 Content Recommendation

Another way to adapt the learning materials to the user is to select the topics the participant is ready to learn, with proper guidance—the collection of all this material is called the *zone of proximal development* by Vygotsky [29]. Picking content from outside of the zone of proximal development is said to be actively harmful towards the learner, as it could hurt a learner's confidence and self-image as well as demotivate them from trying to continue learning since they feel hopeless [26]. In order to know which content to suggest, it is therefore essential to know the dependencies and prerequisites between pieces of knowledge. One way of representing this concept is by providing a semantic representation of all topics and their relations within a given domain [24] in the form of a so-called *knowledge graph*. Having this formal representation is a powerful tool as it allows us to automatically reason about suggested study topics for learners. This can be used by the learner to self-navigate the knowledge domain and decide for themselves which direction to take, without risking "hitting a brick wall" due to missing background knowledge.

We strongly believe that the added self-efficacy of an integrated solution for assessing learners' knowledge gaps and providing personalised learning suggestions can be particularly effective in the learning environments of the learners we are targeting. In terms of the added diagnostic insights that help students catch up and also to help guide and provide structure to students who might prefer to study in episodes of deep dives (also referred to as hyperfocus), as is common with people on the autism and ADHD spectrum.

3 Conceptual Solution

In this section, we propose a conceptual design for a digital learning platform based on the architecture shown in Fig. 2. The system is an online learning environment, accessible by a web browser or a mobile device. The central part is the *knowledge representation framework*, which models a learner's current knowledge level. In the *learning diagnosis service*, our system will continuously update each learner's individual model based on their performance in assessments. The *enhanced curriculum* contains all domain-specific information, including knowledge graphs, learning paths, assessments, as well as tagged/adaptive learning content related to one domain. It is the only part of the system that needs to be adapted to support another domain, while the other components remain unaffected. The *course delivery service* will leverage the *recommendation* and *adaptation engines* to provide a user-friendly interface for learners that presents content in the most appropriate way for each user.

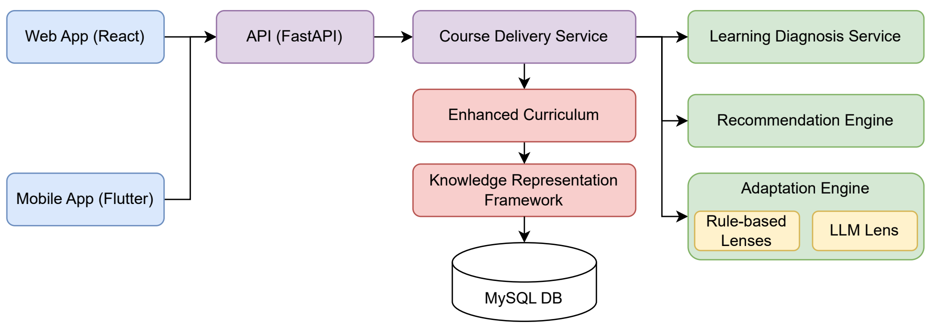

Fig. 2. General architecture of the proposed extensible learning platform

The system is designed to be open and extendable, enabling users to create a custom, enhanced curriculum and add their own custom content plug-ins to the adaptation and recommendation engines. A more detailed description of the different components is provided below.

3.1 Knowledge Representation Framework

Our architectural design is built upon a knowledge representation framework that models individual learners. We build this framework based on the model presented in [16] and an updated version of the model is illustrated in Fig. 3.

To save space, we refer readers to the original paper [16] for full details of the original model's meaning, but we will briefly discuss key aspects and changes made compared to the sports-specific model. In the conceptual model, the knowledge graph is encoded by the `Topic` entity, which may require knowledge or skills about another topic at a specific `ProficiencyLevel`. A topic can

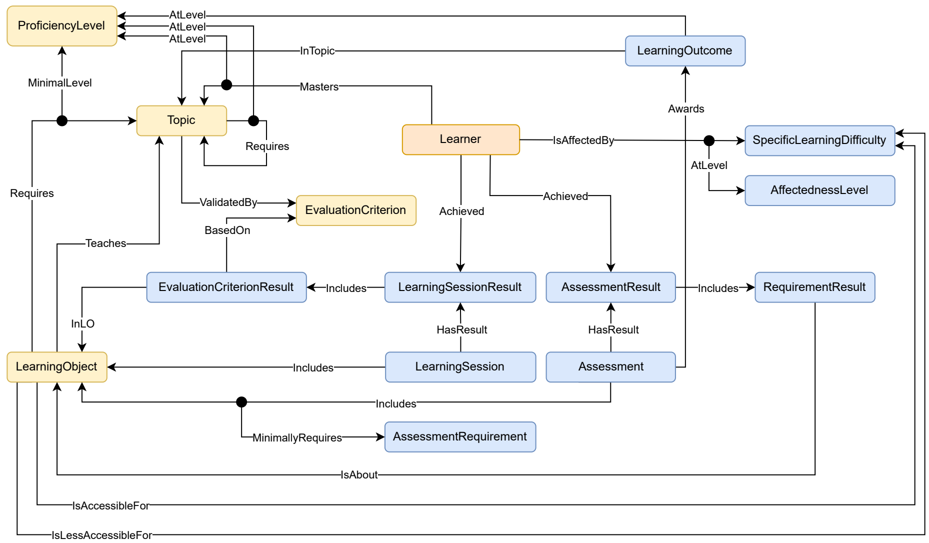

Fig. 3. Conceptual model for personalised learning environments based on knowledge graphs and learning paths

be learned via a `LearningObject` (e.g. exercises or resources). However, this learning object may require proficiency in other topics, even if there is no direct relationship between the two. This requirement modelling is necessary in order to hide `LearningObjects` that are out of reach for the scholar at this time. The specific knowledge or skills of a `Learner` can be represented by the mastery of certain topics at specific levels. To assess the learner and assign them proficiency levels, a learner must participate in diagnostic `Assessments`. Passing all the requirements specified in an assessment will lead to a `LearningOutcome` describing which proficiency levels will be added to the learner. Further, the model supports a continuous feedback loop by checking how well a learner has performed against a given `EvaluationCriterion` for each topic covered during a `LearningSession`. A learning session in this context can be quite flexible, ranging from a single hour of classroom teaching to a student following a short interactive tutorial, some experiments in an interactive lab environment or performing data exploration in a digital notebook.

In our conceptual model, proficiency levels are based on the levels defined by the taxonomy of Bloom [4] and SOLO [3]. Individual `LearningObjects` are abstract concepts for which specific implementations can be provided for each specific application, enabling dynamic content that adapts based on the user's model. The `SpecificLearningDifficulty` will be used to represent specific learning difficulties encountered by the neurodiverse population as described in the work of Hudson [11]. Individual learners can be affected by any number of these difficulties at varying levels. If specific `LearningObjects` have been designed with specific challenges in mind, this can be represented so that this content is preferred over other `LearningObjects` on the same topic. Similarly, if problems are encountered while interacting with certain learning objects, this can be reported so we can avoid recommending this `LearningObject` to people affected by the relevant learning difficulty.

3.2 Learning Diagnosis Service

To provide users with the best possible learning experience, it is essential to understand their current knowledge and skills regarding the topics they are learning. In order to achieve this goal, a diagnostic service will be developed based on an extended version of the knowledge representation framework. This module will focus on both generating and analysing the results of diagnostic assessments designed to detect knowledge gaps. This will allow us to perform a root-cause analysis of why students are struggling to complete certain exercises. Aside from knowledge gap detection, the module can also track metadata, such as engagement rate and usage patterns, to further update the preference profile.

3.3 Enhanced Curriculum

A unique, subject-specific curriculum will be provided for each subject that needs to be taught. In this enhanced curriculum, we envision specific knowledge graphs that map the content in the domain, learning paths suggested by educators and pre-made assessments. Finally, to support the adaptive learning environment, we will need some educational content. We separate this into two categories: the first category consists of pre-existing content that will be tagged and linked to specific nodes in the knowledge graph, allowing us to clearly identify it and combine it with the recommendation engine without requiring all content to be created from scratch. The second category will consist of new content built from the ground up, separating content and presentation to optimally support the environment's adaptive features. Over time, the goal should be for the second category to overtake the first, but we cannot expect educators to put in all the effort up front.

3.4 Course Delivery Service

At the core of our online platform is the *course delivery service*, which supports the actual transformation of learning content for individual learners. We provide recommendations for the content based on both the topics themselves as well as the additional constraints (e.g. learning styles, environment or learning challenges) the students might face. Afterwards, the recommended content is passed through the *adaptation engine*, which applies transformations to the base content to tailor it to specific learners. For this, we suggest a filter ranking pipeline, similar to the one described in [17], as illustrated in Fig. 4. Whenever the student indicates that they would like to study a specific piece of content, the system will analyse which visualisations and supporting tools can be applied to the content, taking into account the learner's unique circumstances.

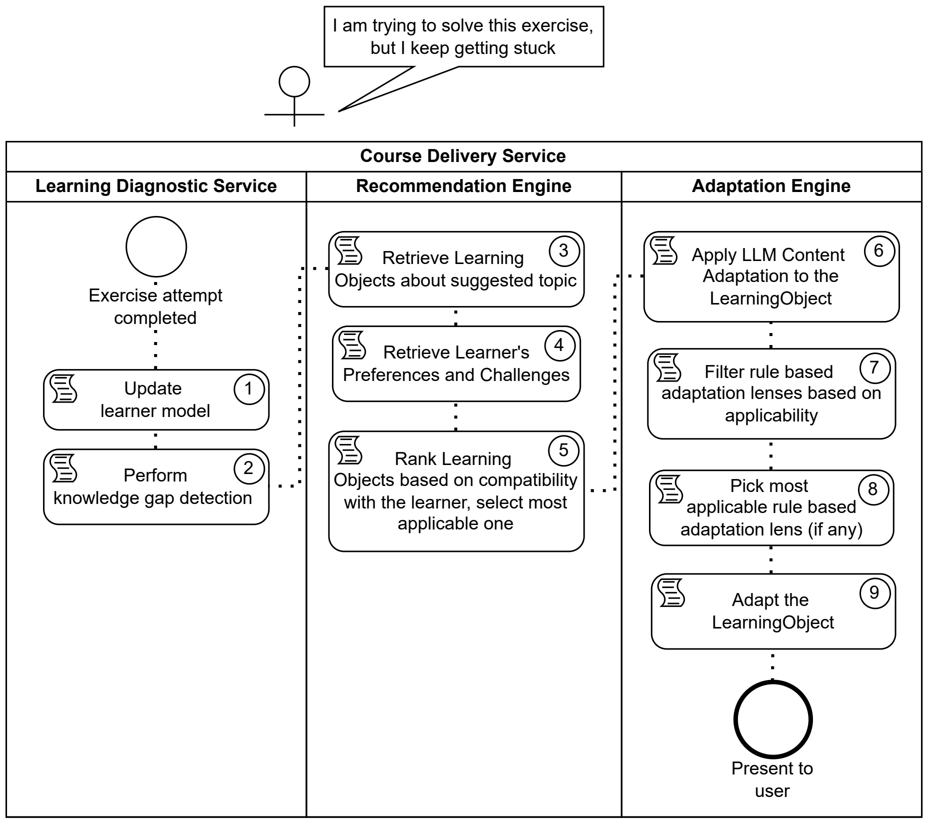

Fig. 4. Overview of the steps taken by the Course Delivery System when a student fails an exercise

The engine works progressively, taking into account each individual learner's needs. For example, learners with ADHD prefer vivid and creative environments [6] while learning, whereas introverts prefer noise-free, reflective and controlled settings [28]. To that end, the framework takes into account 1) individual learning characteristics, 2) constructs a personal learning profile based on the type of neurodiversity, and 3) interacts with the individual to determine learning context and motivation.

One major new plug-in of the adaptation engine that we propose in this research is the 'LLM lens'. In contrast to our earlier rule-based lenses, this new lens tailors the recommended content by using generative AI, taking into consideration the student's learning difficulties.

A preliminary study was conducted to determine whether such a plug-in would yield adequate results. This study focused on the areas of difficulties better aligned with the online learning environment, such as spelling, reading, reading comprehension, number confusion, letter confusion, symbol confusion, short-term memory, distraction, poor organisation, getting lost, time keeping, like order and details, social skills, literal translation, routines and special interests. They are part of the most popular types of neurodiversity considered in this study, such as dyslexia, dyscalculia, dysgraphia, dyspraxia, ASD, ADHD, OCD and Tourette syndrome [11].

These difficulties are identified when students first access the e-learning platform to profile their preferences. They are asked to select from a list of common learning differences to indicate their own difficulties [11]. This information is stored in the e-learning database for easy access from the LLM adaptive tool. The database is constantly updated by an *assessment analyser*, which updates learners' profiles after assessments and identifies knowledge gaps. The *recommended content tool* suggests relevant content to support students in their studies and help them develop their skills. Specifically, the *recommended content tool* tailors learning materials to the learning challenges of different students, driven by fine-tuned prompts implemented specifically for this purpose at the backend.

The quality of the LLM engine adaptive tool is evaluated using matchmaking software to identify key metrics (empathy, creativity and tone Sensitivity) that characterise effective content for neurodivergent students. The text generated by the LLM is evaluated using a matchmaking software, previously used to assess the quality of an intelligent tutoring system for neurodivergent students [21], to identify key metrics such as creativity, empathy and tone sensitivity, which can affect the quality of the feedback [14, 7, 22]. Specifically, the matchmaking tool used in this paper consists of cross-matching tailored learning materials for each neurodiversity generated by the LLM ChatGPT 3.5 Turbo, with open online dictionaries to evaluate the effectiveness of the content. The software has already been developed and adopted in another study to evaluate the quality of feedback tailored for neurodivergent students, generated by an LLM-based intelligent tutoring system [21].

Table 1. Evaluation of the adaptive tool based on the neurodiversity

Neurodiversity	Empathy	Creativity	Tone Sensitivity	Inclusivity	Pacing
ADHD	0%	21.7%	0%	21.7%	0%
ASD	0%	15.6%	0%	15.6%	30%
Dyscalculia	12%	8%	4%	24%	0%
Dysgraphia	0%	0%	0%	14%	0%
Dyslexia	0%	0%	0%	31%	0%
Dyspraxia	6.4%	0%	0%	32%	10%
OCD	11.9%	6%	6%	17.9%	0%
Tourette	10.1%	10%	15.1%	15.1%	70%

The adaptive tool processed the same content for each neurodiversity using dedicated fine-tuning prompts that describe the neurodiversity's areas of learning difficulties to be addressed, thereby maximising a student's learning. The LLM engine tailors only the written content, thereby preserving the personalised learning paths and ensuring that all students can access the same learning materials. Table 1 shows the results of the evaluation of the LLM-based adapted text for each[4]. Despite the evaluation being conducted on only one content, the table returned promising results. First, it shows in all neurodiversities a good percentage of inclusivity from 15% to 32%, leading to a more confident language, increasing their sense of belonging [27]. Nevertheless, as there will be no generation of images or sounds, neurodiversities that usually require more graphical and audio assistive solutions, such as mind maps and text-to-speech, for reading comprehension, e.g. dysgraphia, dyslexia and dyspraxia, were slightly penalised by returned null values, particularly for the creativity and tone sensitivity values. In contrast, neurodiversities that often lead to distraction, such as ADHD, ASD, OCD and Tourette syndrome, obtained good results in terms of creativity. This was often accompanied by empathetic language and tone sensitivity and pacing, particularly in the case of OCD and Tourette syndrome, as shown in the table. This reflects the care that the tutor provided to students affected by these neurodiversities during class activities. On the other hand, the neurodiversities which required a strict structure of the content or sorted instructions, such as ADHD, ASD, dyspraxia and dyslexia, returned lower scores in those areas. Overall, the table results show the potential of the LLM engine and its effectiveness at addressing the main difficulties faced by each neurodivergent student.

4 Conclusion

The paper proposes an adaptive learning framework designed to effectively address the needs of neurodiverse learners. We have outlined the key challenges and limitations of current e-learning environments when accommodating neurodiversity and provided a strong rationale supported by a robust knowledge representation framework tailored to the field of neurodiversity. The proposed conceptual framework enables personalised learning by first profiling students through an initial survey to assess learning difficulties, followed by knowledge gap detection to identify specific weaknesses. Based on these insights, the recommendation engine suggests targeted topics to help learners overcome limitations, while the adaptive LLM component dynamically tailors written content to address individual skill gaps. Individual parts of the framework have been evaluated and the results are promising enough to allow for further research in this area. The matchmaking software achieved strong results, generating tailored text by identifying key metrics for different types of neurodiversity. For instance, the percentage of 'inclusivity' ranged from 15% to 32% and the percentage of 'creativity' in text tailored for individuals affected by ADHD, ASD, OCD, and Tourette syndrome ranged from 6% to 21%. In future work, we plan to deploy the solution in real-world learning scenarios with control groups to rigorously assess its effectiveness. Additionally, a large-scale comparative study across UK and EU educational contexts might provide deeper insights and strengthen the applicability of the presented adaptive learning framework.

[4] https://github.com/giacomonalli2/its

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