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Revolutionizing Education in Industry 4.0: Eye-Tracking and AI for Personalized Learning

Cella-Flavia Buciuman[a*], Sabina Potra[a]

[a]Politehnica University Timisoara, Timisoara, 300191, Romania
[a]Politehnica University Timisoara, Timisoara, 300191, Romania

Abstract

Artificial intelligence is already regularly used in education in various ways, but integrating AI into daily teacher work is not easy. The learning process involves a complex link between the learner's learning style and the content to which the learner is exposed. This research aimed to identify learning styles using eye tracking technology for students from Politehnica University of Timisoara, Romania. The results of the eye tracking experiment were corelated with the learning patterns identified using the Index of Learning Styles Questionnaire (ILS) developed by Felder and Silverman (FSLSM). Results indicated that the eye tracking technology can assist in identifying learning styles, especially in real time, with some limitations. At the same time, the article also shows multiple perspectives through which artificial intelligence can be used to build a personalized learning pathway by exploring the possibilities that exist in this field up to this point.

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Keywords: eye tracking, learning styles, Education 4.0, FSLSM;

1. Introduction

Exploring learning methods has been a long-standing research concern for decades. The learning process is very complex and requires a complete link between the learner, the tutor, and the learning content. Research on adaptive learning systems has been conducted over the years to help teachers understand as accurately as possible the learning needs of their students and help them develop learning content more adapted to these needs [8,16,19].

*Corresponding author:
Email address: cella.buciuman@upt.ro

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Understanding and accommodating different student learning styles can improve educational outcomes but, nonetheless, as [19] mentions, student academic achievement can also be related to several internal and external factors, such as personality, gender, family environment, or socioeconomic level. Despite this assumption, research in [3] states that student academic success is significantly influenced by their individual learning styles and strategies, regardless of socioeconomic background, nationality, or geographic location. This underscores the importance of providing students with effective learning methods to improve their academic performance. According to [7], learning styles refer to the different preferences and affinities that students reveal when it comes to processing and interacting with information within various educational settings. By adapting to their learning styles and creating a learning environment tailored to their needs, students can minimize the probability of poor academic performance and achieve better results [4]. Students are more likely to succeed when teaching methods align with their preferred learning methods. Every student-centered technology enhances the pedagogical landscape of the future: project-based learning, self-regulated learning, flipped classrooms, and conventional lectures evolve into participatory sessions that no longer resemble an instructor speaking in unison. Unevenly, these new Education 4.0 pedagogies are being adopted worldwide [20].

Earlier research on adaptive learning systems has been challenging for education researchers due to the need for custom software to control variables. Furthermore, while the goal is to enhance real-life learning with complex and unpredictable materials, most studies used controlled experimental settings with custom materials, which differs significantly from authentic learning environments [16]. Education 4.0 is now emerging, utilizing new technologies in education that are based on a variety of instruments in a variety of settings. It is in answer to every demand that the Industry 4.0 economy will make of future workers [20].

With the advance taken by AI-based learning tools, adaptive learning systems can now offer an even more customized and engaging experience for learners and can be considered a very powerful solution for personalized education. Adaptive learning systems are strengthened by artificial intelligence (AI), which combines natural language processing, predictive analytics, and machine learning algorithms to handle massive volumes of data. This makes it possible for AI-driven adaptive learning platforms to dynamically modify techniques, content, and feedback to meet the needs of all learners. The use of artificial intelligence in adaptive learning has improved academic performance and learning engagement, with encouraging results. However, it is essential to handle moral dilemmas and guarantee successful execution [12]. AI can process large datasets to identify patterns that humans would find difficult to recognise, and it can adapt and personalise educational content in real time, providing customised learning experiences. As claimed in [12], AI-powered adaptive learning systems comprise a network of interconnected components that collaborate to provide a customised learning experience. AI algorithms use learner profiles and real-time feedback to dynamically modify the complexity, format, sequence, and delivery of learning materials. The learners modelling implies identifying the learner's learning style and providing learning resources according to her preferences. Despite the growing interest in AI-enabled learning systems, there is a scarcity of research on their implementation in real educational settings. As a result, the integration of these systems into educational settings appears to be in its early stages of development [13].

This article proposes an approach in which it compares the learning styles of the students identified with the iMotions screen-based eye tracking technology and the results obtained using the FSLSM learning style model developed by [5]. This study also offers various perspectives on how artificial intelligence can be harnessed to build a customised learning pathway by exploring current possibilities in this field. Personalized learning shifts the paradigm from viewing students as passive learners to recognizing them as active contributors in shaping their own learning journey.

The present paper aims to address the following research questions:

RQ1: How closely do the learning styles identified with eye tracking technology match the student reports of their learning styles in the FSLSM questionnaire?

RQ2: Using eye tracking and learning questionnaires, what are some ways that artificial intelligence could be applied to create individualized learning strategies that accommodate students' varied learning preferences?

RQ3: What are the challenges in implementing AI-powered personalized learning methods?

2. Felder-Silverman learning style model

The current research is based on the FSLSM model proposed by Felder and Silverman in the late 1980s and reiterated in the literature in many studies that have explored the issue of learning styles among students. A learning styles model identifies a limited number of key dimensions that serve as a foundation for crafting effective instructional strategies. Like all models in various scientific disciplines, they are incomplete, but can still be valuable representations of reality. The effectiveness of these models should be evaluated based on their ability to accurately describe and interpret observations, as well as their utility in guiding professional practice. Although these findings have been repeatedly published, they have little impact on the widespread adoption and continued development of learning style models and assessment tools within the academic community [6]. The Felder and Silverman Learning Styles Model is a comprehensive framework designed to categorize the different ways in which students learn. This model identifies specific dimensions along which individual learning preferences can be described. Understanding these preferences enables educators to customize their teaching approaches to better accommodate the varied needs of their students. The model outlines four primary dimensions of learning styles.

The first dimension is Sensing vs. Intuitive (Perception). Sensing learners prefer concrete, practical, and methodical information. They like to learn facts, solve problems using well-established methods, and are generally detail-orientated. Intuitive learners prefer conceptual, innovative, and abstract information. They enjoy discovering new relationships and feel more comfortable with theories and principles.

The second dimension is Visual vs. Verbal (Input). Visual learners learn best through images, diagrams, charts, and other visual means. They often find it easier to remember information presented in a visually engaging format. Verbal learners prefer written and spoken explanations. They benefit from detailed written descriptions and enjoy discussions and lectures.

The third dimension is Active vs. Reflective (Processing). Active learners learn by doing and collaborating. They prefer to participate in physical activities and discussions and often learn best when they can try things out and discuss with others. Reflective learners prefer to think things through and work alone. They learn best when they have time to reflect on the information.

The fourth dimension is Sequential vs. Global (Understanding). Sequential learners understand in linear steps. They learn best with information presented in a logical, step-by-step progression Global learners grasp information in large jumps, often suddenly seeing the big picture. They tend to learn in a more holistic manner and may struggle with details initially but can make broad connections and integrate information in creative ways.

To identify an individual's learning style according to the Felder-Silverman model, a self-assessment questionnaire known as the Index of Learning Styles (ILS) is used. This questionnaire typically consists of a series of forced-choice questions in which individuals must choose between two options that correspond to opposite ends of each dimension. In this study, the ILS questionnaire was used to help determine students' preferences on each of the four dimensions. Each dimension contains 11 questions [8]. Based on their responses, students receive scores that indicate their preferences on a scale for each dimension. According to [7], learning styles should not be viewed as fixed categories, but rather as preferences that can vary in intensity from mild to strong. Assigning labels such as "sensing learners" fails to account for other cognitive strengths, such as intuitive capabilities or sensory aptitudes. Therefore, individuals of any learning style have the potential to succeed in various professions. Making career or educational decisions solely based on learning styles is misguided and could be considered unethical, as it oversimplifies the multifaceted nature of individual talents and abilities.

3. Eye tracking to explore learning styles

Eye tracking technology is a technique that tracks and examines the direction and manner in which a subject looks at visual stimuli. This involves tracking the eyes' motions in relation to the head, as well as the point of fixation, or the place where they focus. This device carefully tracks eye movements using complex sensors and algorithms, providing insightful information about visual attention, cognitive functions, and behavioural intentions. There are two main categories of eye-tracking technology. The first one is screen-based eye tracking, where a device monitors eye movements and gaze patterns as individuals view a screen. The device captures information about the location, timing, and duration of an individual's gaze on various elements of the screen, in addition to pupil dilation and the frequency of blinking. Applications for screen-based eye trackers can be found in a variety of areas, including consumer behaviour and academic research. The second eye-tracking technolgy are the eye-tracking glasses. These wearable devices observe eye movements and gaze behaviour in real-world environments. They provide information on attention, cognition, emotions, and behaviours as individuals interact naturally with their surroundings. According to [11], eye tracking glasses are frequently used for training and assessment, consumer behaviour analysis, and academic research.

4. Related Work

To better understand the complexity of individual learning preferences and their impact on academic performance, academics have recently investigated student learning styles from a variety of perspectives. The ILS questionnaire has been showed to be an excellent tool for identifying student learning styles, which can be used to customize teaching strategies for individual students [8]. [9] investigated learning styles in a variety of fields using the ILS questionnaire, showing its applicability in a variety of educational settings and providing insightful information, but it is nevertheless not without limits. More specifically, the study did not consider the possible impact of additional environmental or personal context that may influence learning styles. These aspects may be investigated in more detailed studies. In addition, recent studies have explored the use of data-driven approaches and literature-based approaches to automatically detect learning styles. These methods can track changes in learning styles and provide more accurate results than traditional manual methods [18]. [16] examined the efficacy of using eye tracking technology in conjunction with standard educational resources to identify learning styles and evaluated the precision of this determination. Additionally, it included the behavioural patterns linked to the discovery of the eight learning styles described in the Felder-Silverman learning style model (FSLSM) as a framework. With accuracy rates ranging from 63.50% to 84.67%, the results demonstrated that eye tracking technology can successfully distinguish between various types of learners, as described by the FSLSM theory. However, several variables that impacted the various levels of identification accuracy were discovered, highlighting the need for more study in subsequent explorations.

5. Research Methodology

In the current study, 40 undergraduate students from the Faculty of Management in Production and Transportation, Politehnica University Timisoara participated in the study. Fig. 1 shows the main stages of the research through which it is intended to respond to the three research questions.

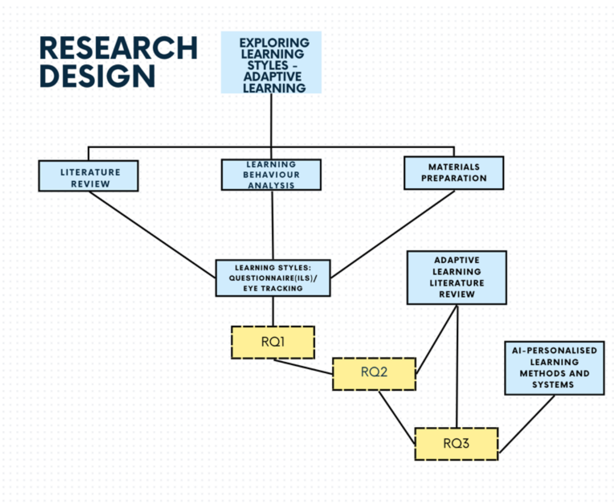

Fig. 1. Research design stages.

During the first stage of the study, students were asked to complete an ILS electronic questionnaire containing 44 questions, each question having two available options. Once all answers for each question have been selected, students could view the percentage breakdown of their individual learning styles, as shown in Fig. 2.

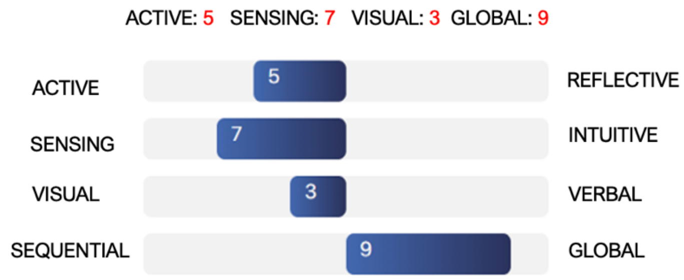

Fig. 2. Example of a result for exploring learning styles using the ILS questionnaire.

According to [8] the scores of 9-11 indicate a strong learning style, where students exhibit a dominant tendency towards one learning style and a relatively weaker inclination towards the other. Scores between 5 and 7 belong to the intermediate category, suggesting a moderate preference for one learning style and a less strong inclination toward the other. Scores of 1 to 3 rank in the balanced range, indicating that students exhibit a balanced learning style with a slight preference for one style over the other.

Based on the results of the experiment, Fig. 3 shows the results obtained using the questionnaire:

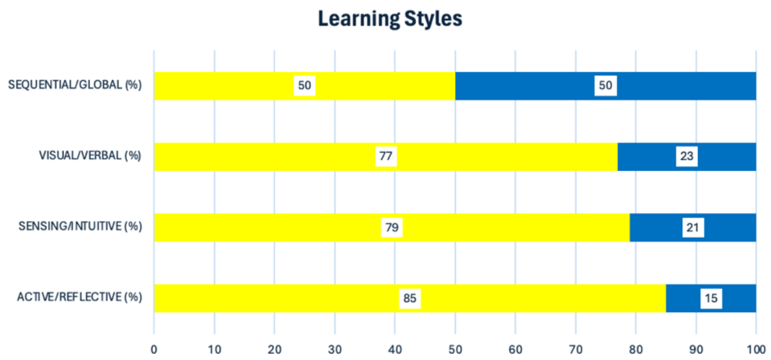

Fig. 3. Learning styles for students attending the study.

Most students are rather active than reflective learners, with a majority of 85%. Furthermore, 79% of students fall into the category of sensing learners and prefer concrete, practical, or methodical information, compared to the remaining 21% who prefer abstract information. Regarding information input, most students (77%) are visual learners, with a strong preference for images, videos, or other types of visual content. The remaining 23% of the students prefer written or spoken explanations. In terms of how they understand information, sequential and global learners are in equal proportions, indicating that analytical thinking and a holistic approach to learning are equally present among students.

The second stage of the study involved exploring the learning style using screen-based iMotions eye tracking technology. Students were asked to complete four tasks as presented in Fig. 4:

1. Read the description of the concept of Muda from Lean methodology presented in text format.
2. Observe the elements of Muda presented in a visual form with the help of pictures.
3. Watch a video about Muda.
4. Choose a response from several available about the Muda concept.

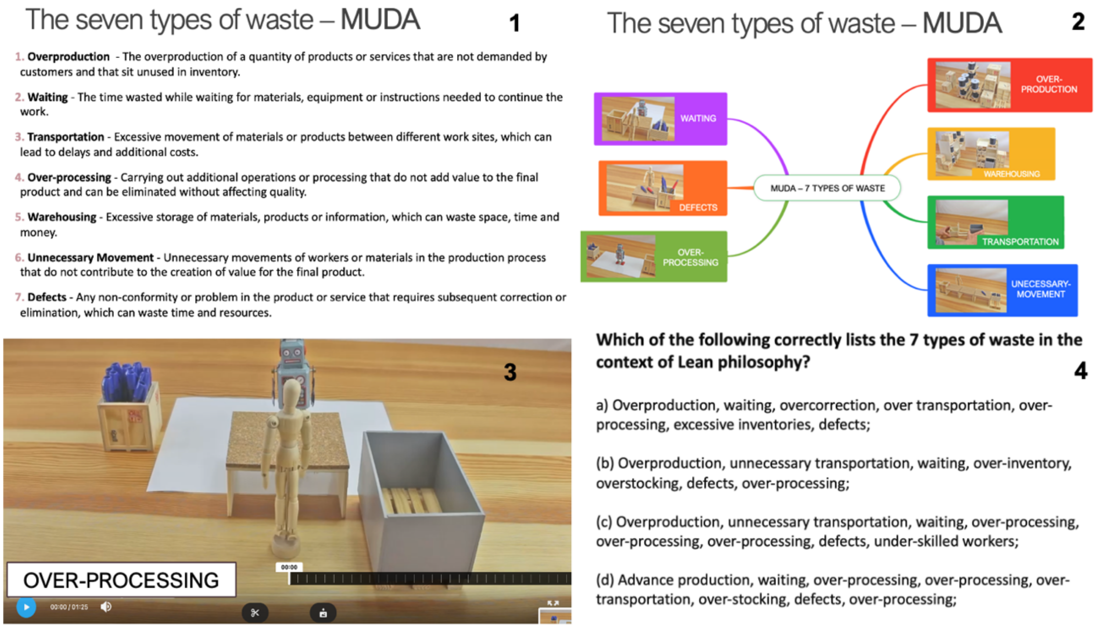

Fig. 4. Materials used in the learning-style exploration phase using eye tracking technology.

The materials shown in Fig. 4 have been chosen to allow students to go through the same information presented in several ways: static written text, video, and diagram. In Fig. 4 the materials are presented in English but in the study, materials were in Romanian, as this is the mother tongue of the students participating in the study.

The data collected with the eye tracker were gaze duration, fixations, and heat maps. Going through all the material, each student generated a gaze path for that material. The gaze path is made up of several gaze points. The basic unit of measurement is the gaze point, which corresponds to a single raw sample captured by the eye tracker. Since the eye tracker measures 60 times per second, each gaze point symbolizes a 16.67 millisecond interval. When a series of gaze points are closely spaced in both time and distance, they form a gaze cluster, indicating a fixation where the eyes are focused on a specific object. Typically, fixation durations range from 100 to 300 milliseconds [11]. Heat maps are graphical representations of the collected data. To be able to make a comparison of how the learners have gone through the materials based on their learning styles previously identified with the ILS questionnaire, we present below some of the gaze points maps for the four dimensions of learning styles. Fig. 5 shows the differences in the way active learners and passive learners process information. The exploration of eye tracking revealed different gaze paths for active and reflective learners. The active learner often shifted and actively engaged with different parts of the text, while the reflective gaze path is more linear, showing a methodical progression. Fig. 6 shows how the information is parsed by a sequential learner compared to a global learner. The sequential learners' gaze path followed a linear, left-to-right, and top-to-bottom pattern and moved systematically from one sentence to the next without skipping much information. For the global learner, the gaze path jumps from one sentence to another, focusing on headings and key points. In Fig. 7 the visual learner spent more time on the images, while the verbal learner spent more time on the text blocks with fewer interactions with the visual elements. Fig. 8 offers the perspective of a sensitive learner paying much more attention to the details of the content, while intuitive focusses on the overall structure of the content having fewer fixations. To answer RQ1, both methods of exploring student learning styles offer valuable insights, with eye tracking providing more objective behavioural data, and FSLSM capturing subjective self-assessments of learning preferences. It is important to mention that eye tracking alone may not directly measure sensing/intuitive preference as it focusses more on visual attention rather than cognitive processing style, and, for sequential/global learners, eye tracking might show different scanning patterns, but interpreting these as sequential or global preferences requires additional cognitive data.

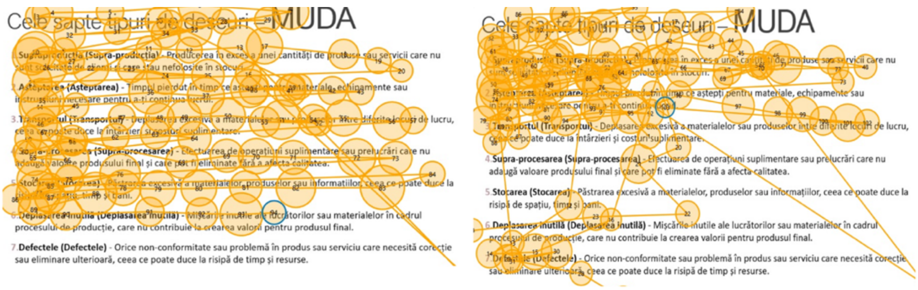

Fig. 5. Reflective (left) vs. Active (right) learners.

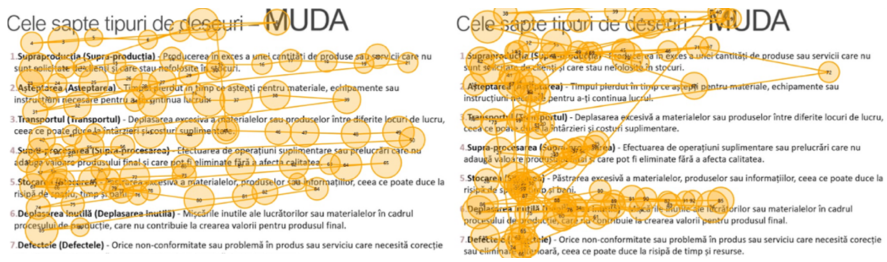

Fig. 6. Sequential (left) vs. Global (right) learner.

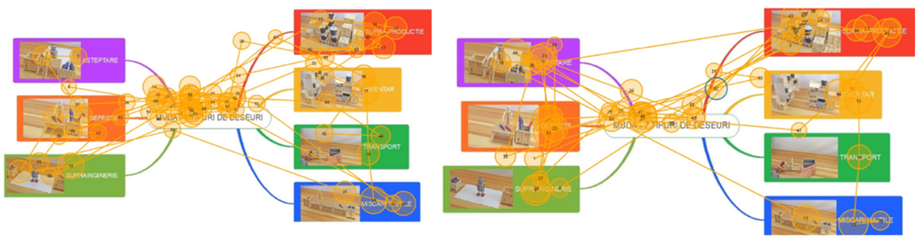

Fig. 7. Visual (left) vs. verbal (right) learner.

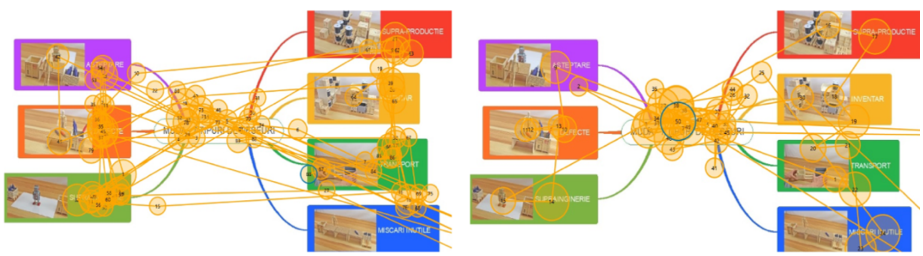

Fig. 8. Sensitive (left) vs. Intuitive (right) learner.

6. Adaptive learning based on student learning styles

6.1. Artificial intelligence approaches to learning

The goal of adaptive learning is to provide each student with individualized learning experiences that are tailored to their specific needs. This goal can be accomplished in a number of ways, such as adaptive pathways, which allow students to move through the content at their own speed; adaptive feedback, which is customized based on the actions and needs; adaptive content, which adapts to the unique needs of each student's unique needs; or personalized exercise recommendations, which can take the form of problems, quizzes or other assessment activities based on the current level of knowledge of each student and learning objectives [21].

The use of eye tracking and the FSLSM model allowed for the identification of differences in the way the four dimensions of learners navigate the learning content. We can say that the challenge now is to deliver content in line with these learning trends so that it is as customised as possible to the learning needs of the learners. Incorporating artificial intelligence (AI) into adaptive learning systems could transform the way schools identify and respond to these learning styles. As [12] claims that machine learning algorithms can analyse large amounts of data, including learner profiles, performance metrics, and instructional materials. AI algorithms can predict learner preferences, needs, and future academic performance by identifying patterns, trends, and correlations in these datasets. This enables adaptive learning systems to dynamically adjust content, pace, and teaching strategies to meet the needs of the individual learner, providing a personalized and efficient learning experience. Recent advances in deep learning and neural networks have opened new avenues for learning-style analysis. These technologies can handle complex nonlinear relationships, providing more accurate predictions of student learning styles. For example, a study by [21] used neural networks to track real-time behaviour and generate adaptive recommendations for the learning style identification process in MOOCs (Massive Open Online Courses). This approach showed the promise of deep learning in personalized education by showing a considerable improvement in the accuracy of learning style identification. In response to RQ2, Fig. 9 presents AI-integrated tailored learning recommendations that provide more inclusive and productive learning environments for each learning style mentioned in the preceding section.

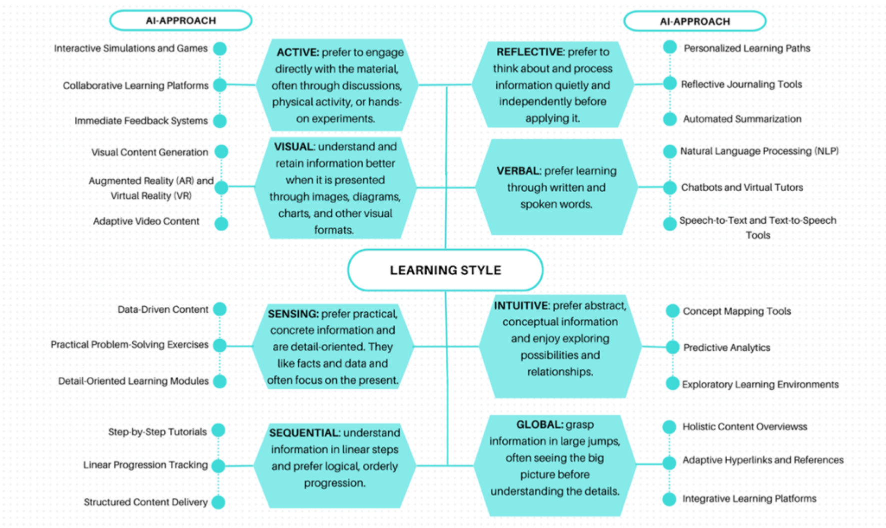

Fig. 9. AI approaches for different learning styles

[21] presents a complex synthesis of several examples of the use of adaptive learning systems in practice, adapted to different learning styles. [17] discussed the development of a sophisticated model for personalized learning management at San Agustin University in Arequipa, Peru. Research focusses on adjusting virtual environments' learning experiences to each learner's unique style. To customize learning paths, the approach incorporates the Honey-

Alonso Learning Styles approach and case-based reasoning (CBR). With the use of this technology, teachers can provide students with individualized information that fits their learning preferences to improve their overall academic performance. A study by [15] involved 98 German university students and used a customized framework built on real-time analytics. Through real-time analysis of student interactions in the learning environment, including page views, mouse clicks, and keystrokes, the study offered customized support. The detection and immediate support of self-regulated microlevel learning activities during learning activities was made possible by the AI-based rule-based system, which improved the overall learning process. [2] created the open source EduChat model, which combines educational and psychological theories. Provides several features, such as heuristic instruction, composition correction, emotional support, and open questions. Through addressing the issue of delayed knowledge updates and enhancing the current generative model's capacity to produce material with minimal information, EduChat presents a fresh method to personalized learning, which holds the promise of a more comprehensive and effective educational experience.

In this section, we have presented how AI can address the different needs of learners and provide an answer to RQ2. The potential of AI to personalize learning based on individual styles is transformative. By utilizing AI approaches tailored to each learning style, educators can create adaptive learning environments that not only enhance engagement and comprehension but also empower students to leverage their strengths and address their weaknesses. This synergy between AI and personalized education sets the stage for enhanced and inclusive learning experiences.

6.2. Challenges of using artificial intelligence to shape the learning process

Although artificial intelligence provides remarkable developments in education, this inevitable process of evolution is not without challenges. These include data privacy concerns, the need for large datasets to train AI models, the potential for algorithmic biases, the integration of technology in education, and the readiness of the education sector to assimilate the rapid introduction of AI into so many branches of the educational process, and of course also ethical considerations.

It is essential to recognize that artificial intelligence (AI) is a tool that enhances, not replaces, human skill. To make full use of the assets of both, it is imperative to promote efficient human-AI collaboration [12]. While governments acknowledge AI's significance for development in the future, there are notably few comprehensive policies or recommendations regarding the use of AI in education. Moreover, comprehensive student behaviour data are needed for personalized learning systems, which can cause privacy issues if proper security measures are not taken. Therefore, careful attention to data quality, standardization, and privacy protection is crucial to the development of personalized learning systems, as highlighted by the complex data collection and privacy issues process [10, 21]. The privacy of learners is a very important aspect and, to process such large amounts of information about learners, it is important that they give their consent and are informed of how this information is used.

Unintentional disadvantages to student demographics, such as ethnicity, gender, or socioeconomic class, could be caused by bias in AI-driven educational technologies. According to Open AI, these cultural prejudices can be present in AI-generated material and potentially reinforce past discriminatory trends. Students whose learning patterns match those that predominate in the training data may inadvertently benefit from adaptive learning systems, which are intended to tailor learning experiences to each individual student's learning style. This can intensify the inequality and increase the attainment gap [14]. According to [1], the community must continue to be educated, involved, and engaged to foster a culture of ethical adoption of AI in education. Teachers must be equipped with the information and tools necessary to critically assess AI technology, identify ethical issues, and promote ethical behaviour. Students also need to be given the tools they need to comprehend AI-driven systems and engage with them in ways that advance their responsibility, autonomy, and well-being. The aspects addressed in this section can also offer a comprehensive response to RQ3. Addressing these issues requires ongoing research and collaboration between educators, technologists, and policy makers to ensure ethical implementation of AI in education.

7. Discussion and Conclusions

The present study explored the effectiveness of combining the Index of Learning Styles (ILS) questionnaire with eye tracking technology to identify learning styles in 40 students from the Faculty of Management in Production and

Transportation, Politehnica University Timisoara. In addition, this article summarizes the ways in which personalized learning experiences can be provided using artificial intelligence according to the learning styles explored.

The integration of the ILS questionnaire with eye tracking technology offered a more accurate and comprehensive method to identify student learning styles. Eye tracking data provide objective, real-time insights into students' visual attention and engagement, which complements the subjective data from self-reported questionnaires. Combining the ILS questionnaires and the eye tracking results offered a holistic view of student learning behaviours, but in this situation, we did not calculate the accuracy with which eye tracking can identify learning styles determined according to the ILS questionnaires.

AI technology can use detailed data from ILS questionnaires and eye tracking to provide highly personalized learning experiences. This includes dynamically adjusting instructional formats (visual versus verbal), pace (sequential versus global), and interaction styles (active versus reflective) based on real-time needs of learners.

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