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Supporting learning style identification with eye-tracking technology in an adaptive e-learning system

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Abstract: *In my study, I propose an approach for automatic detection of visual and verbal learning styles in an adaptive e-learning system (https://aes.negyesipeter.hu) I have developed, based on eye-tracking technology. In the online study, I used GazeRecorder eye-tracking software to record the time participants spent looking at text- or graph-based learning objects. The entire study lasted an average of 25 minutes, depending on the participants' reading speed, reading comprehension and calibration process. 255 participants took part in the current study, 60% of whom were high school students (N_1 = 153) and 40% of whom were first-year university students (N_2 = 102). However, due to a calibration problem, 204 valid data were obtained. Of these, 179 had normal vision and the rest (25) wore glasses. A cross-sectional analysis of the heat maps for each user showed that there was a significant difference between visual and verbal learners; verbal learners spent most of their time looking at the textual part of the screen, while visual learners spent more time looking at the graphical part of the screen. Moreover, the results show a high correlation between Felder-Silverman learning style and eye movements recorded during learning. The results have important implications for the development of more effective adaptive e-learning systems. The ability to automatically identify learning styles can greatly improve the personalised learning experience.*

Keywords: *adaptive learning; adaptive e-learning system; eye-tracking; learning style identification; GazeRecorder*

1. Introduction

Traditional education systems, which allow the learner to learn independently without meeting the teacher in a classroom, are not able to adapt dynamically to the learner's needs. Consequently, they are not able to improve learner performance. In this respect, the concept of adaptation has recently become an important research issue in the field of learning; ensuring adaptivity in learning systems helps learners to achieve desired learning outcomes in a personalised way.

Learning style theories have been widely used in adaptive e-learning systems to improve learning outcomes (Bertea & Hutanu, 2019). However, the majority of adaptive learning systems that take learning styles into account use questionnaires based on the Felder-Silverman Learning Styles Index (TSI) to identify learning styles (Khenissi et al., 2016), while this method has several drawbacks. For example, it is not suitable for certain types of respondents, it is time-consuming to complete, the respondent may misunderstand, etc. In addition, a new adaptation problem has emerged, namely the automatic recognition of the learner's learning styles.

Nowadays, learners' learning styles can be detected using biometric technologies such as eye movement tracking; it is widely used in a number of areas such as diagnostics (Alamudun et al., 2017), interaction and accessibility (Rajanna et al., 2018), and analytics (Kaul et al., 2016).

Taking the above into account, the main goal of my empirical research was to investigate the feasibility of supporting visual and verbal learning style identification in my new adaptive e-learning system (https://aes.negyesipeter.hu) using eye-tracking technology, which allows automatic understanding of the learner's individual learning preferences by capturing the point of gaze (TP). A further aim was to increase the effectiveness of my adaptive e-learning system through the test results, bearing in mind the importance of applying didactic design.

2. Theoretical background

Thanks to technological determinism and the rapid pace of technological development, ICT tools are also becoming increasingly common in education. This requires teachers to change their methods and didactic processes of teaching and learning, in order to keep pace with the changing needs and learning habits of learners (Racsko, 2017).

The appropriate use of digital tools encourages learners to overcome their fear of making mistakes, helps them to gain a deeper understanding of how the ICT systems they use work through experimentation, develops their digital competences and teaches them to be more autonomous (Szűts, 2020).

The teacher continues to play a key role in the choice of teaching tools and digital technology. It is his/her motivation, competences, personality and attitude that determine the extent, form and purpose with which digital technology is integrated into the classroom and into the personal learning environment of the learners. The use of digital technology in the pedagogical process is not an end in itself, but a tool to facilitate more effective acquisition of knowledge (Szűts, Lengyelné & Racsko, 2022).

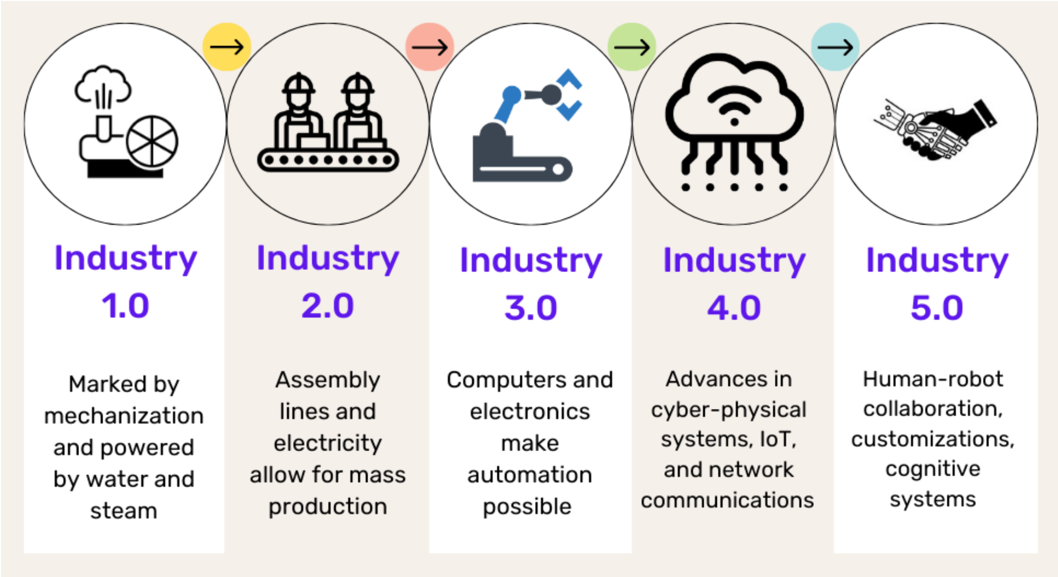

Fig. 1. Industrial revolutions (Source[1])

Although machines took the lead in the 4th industrial revolution, the human factor may again be the key in the current 5th industrial revolution (Fig. 1). Industry 5.0 builds on the achievements of Industry 4.0, but it does not seek to replace humans, but to exploit the potential of human intelligence in human-machine interaction more than ever before (Kővári, 2024).

One of the potential applications of Industry 5.0 in education is the integration of artificial intelligence and machine learning to personalise the learning experience for each individual student. This can be achieved through the use of adaptive learning software that adjusts the curriculum and level of difficulty based on the learner's performance and needs. This allows students to learn at their own pace and ensures that they receive the best possible education.

Educational technologies play a vital role in education by making it easier for teachers to personalise the learning experience and by giving learners access to advanced learning tools. These technologies can revolutionise student learning and lead to a more effective, personalised and efficient education system.

Learners have different ways of learning; each with their own level of understanding and unique ways of building and retaining knowledge. As a result, no single style will be appropriate for all learners. It is therefore essential to first understand the learning style of the learners in order to choose the right strategies and adapt the system accordingly.

[1] https://alwaysai.co/blog/industry5.0

All existing eye-trackers work without contact with the user and use infrared or near-infrared light: they track the eyes by measuring how light is reflected back through the retina and cornea across the pupil (Jarodzka et al., 2021; Duchowsky, 2007).

Gaze data can provide much needed vision and directions for the development of online learning systems (Alemdag & Cagiltay, 2018). The accuracy of eye-tracking technology in identifying visual and verbal learners ranges from 38% to 77% (Luo et al., 2020).

3. Experimental tool

The Gaze Recorder software can effectively record and analyse eye movements using a simple webcam, although accuracy and reliability may be somewhat lower than systems using specialised infrared cameras. The advantage of webcam-based eye tracking is its wide availability and low cost, which allows the technology to be used more widely in both research and practice.

For webcam-based eye movement tracking (Fig. 2), the user uses an ordinary, high-quality webcam, which is usually built into the laptop or can be connected separately to the desktop computer. Once the Gaze Recorder online eye movement tracking software is configured, it uses the webcam images to record eye movements.

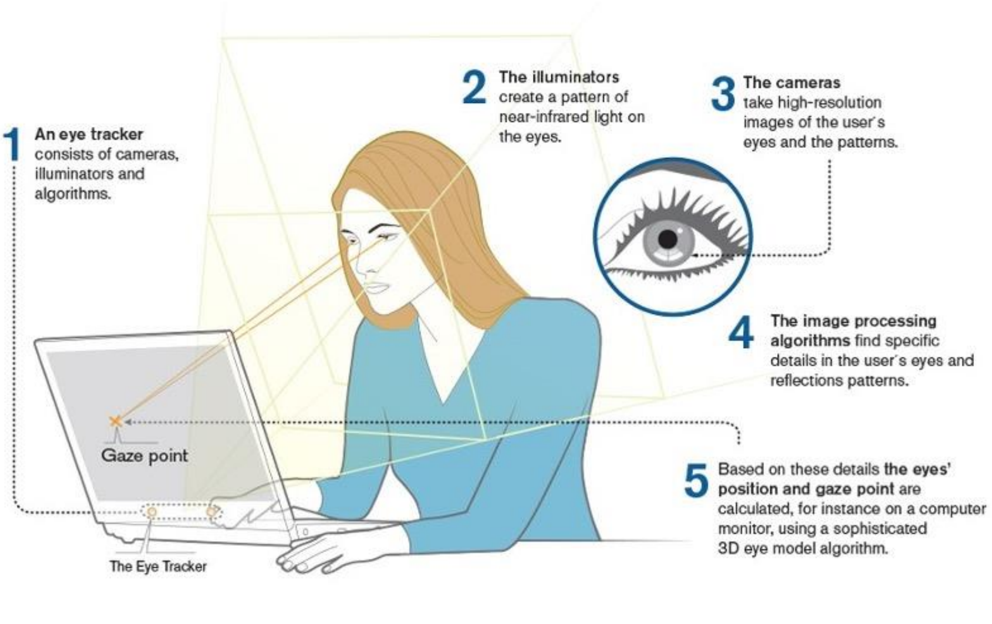

Fig. 2. The principle of eye movement tracking (Source[2])

[2] https://connect.tobii.com/s/article/How-do-Tobii-eye-trackers-work?language=en_US

The software's algorithms process data from webcam images. Machine learning and image processing techniques are used to identify the contrast between the pupil and the white of the eye, which helps determine the position of the eye. The data is then analysed and visualised in various ways, in our case into heat maps.

The software uses face detection algorithms that identify the user's face in the webcam image. The eye detection algorithms then locate the exact position of the eyes.

The software employs pupil tracking techniques that use the contrast between the pupil and the white of the eye to determine the direction of the eye. Image processing algorithms monitor the movement of the pupil and calculate the direction of the gaze.

Since webcam-based eye tracking can be sensitive to head movements, the software's algorithms can compensate for minor head movements to ensure that eye movement tracking remains accurate. This is achieved through face detection and head position tracking.

4. Methodology

In the online study, I used the GazeRecorder eye-tracking device to record the time participants spent looking at text- or graphics-based learning objects. The entire study lasted an average of 25 minutes, depending on the participants' reading speed, reading comprehension and calibration process. 255 participants took part in the current study, 60% of them were high school students (N_1= 153) and 40% were first-year university students (N_2 = 102). All participants signed ethical forms, following the established rules and regulations, before taking part in the experiment. However, due to problems with calibration, 204 valid data were obtained. Of these, 179 had normal vision and the rest (25) wore glasses.

4.1. Experimental process

Figure 3 shows the steps of using the Gaze Recorder online eye movement tracking software. Each step and decision point can be interpreted as follows:

- START: Start the process.
- Accept the ethical rules: The user must first accept the ethical rules. This is an important step, especially in a research environment, to ensure that privacy and user rights are respected.
- Turn on the webcam: The next step is to turn on the webcam, which allows you to record eye movements.

- Calibration: A calibration process (Fig. 4) is required to ensure the accuracy of the webcam usage.
- Success: This is a decision point to determine if the calibration was successful. If the calibration fails, the test ends here. If calibration is successful, the process continues with the next step.
- On-screen learning (AES): the user performs learning tasks on the screen. This step allows the software to collect data on eye movements in real time.
- Eye movement tracking in real time: the software tracks the user's eye movements in real time while he or she is performing learning tasks.
- Generate results: the software generates results based on the collected data.
- Display results: The results are displayed as heat maps.
- EXIT: End the process.

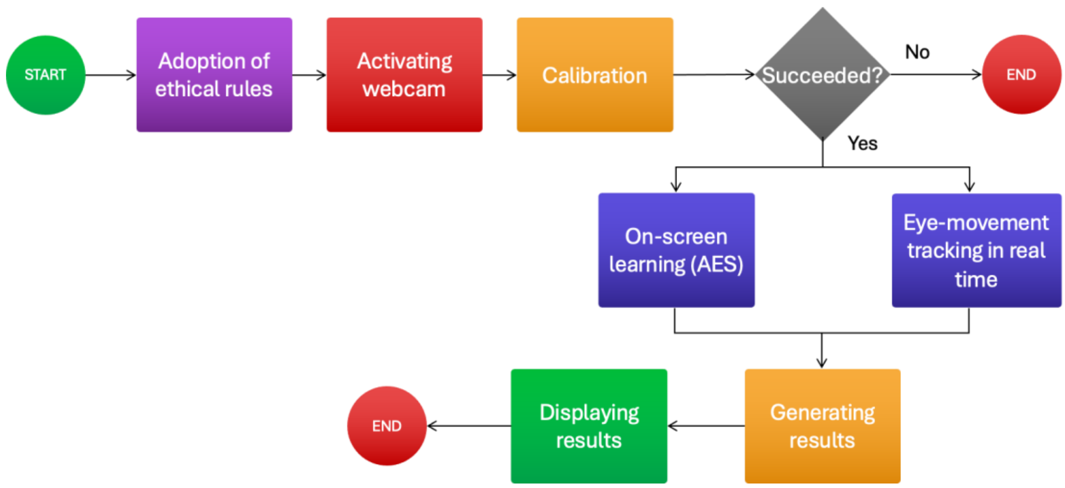

Fig. 3. Flowchart of the investigation (Own source)

4.2. Calibration

When the software is first started, a calibration process is required to accurately set up the eye movement tracking. The user must look at specific points on the screen while the software records the eye position. The calibration process helps the software link the eye position to the screen coordinates.

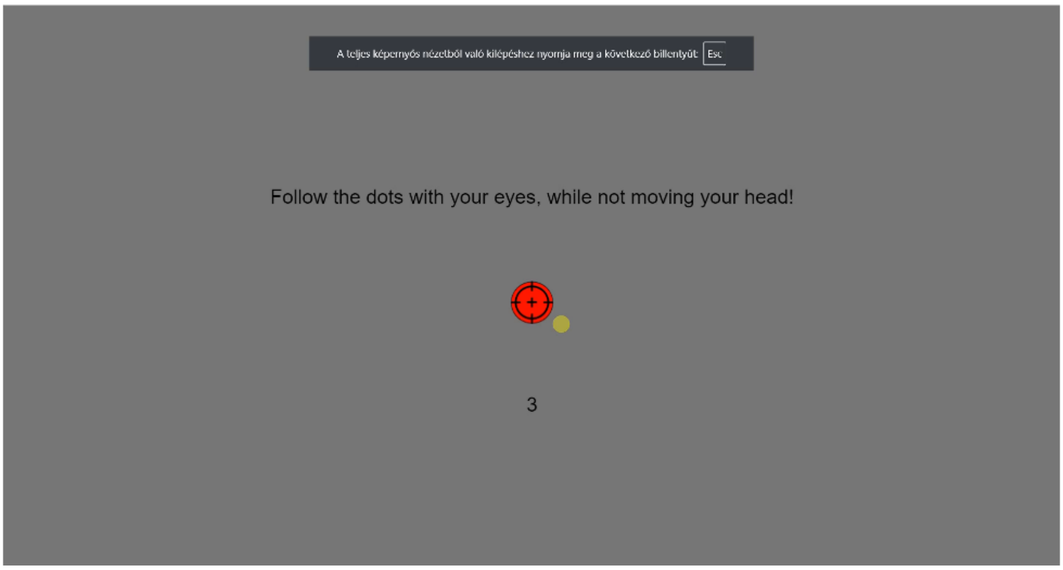

Fig. 4. Calibration start screen (Own source)

After the calibration is complete, the webcam continuously captures the user's face and eyes while using my adaptive e-learning system (Fig. 5), in our case for example while working through a course (Fig. 6). The software algorithms analyse the video images in real time and identify the position and movement of the eyes. Although the resolution and refresh rate of a webcam is generally lower than that of a dedicated infrared camera, modern image processing algorithms can provide reliable data.

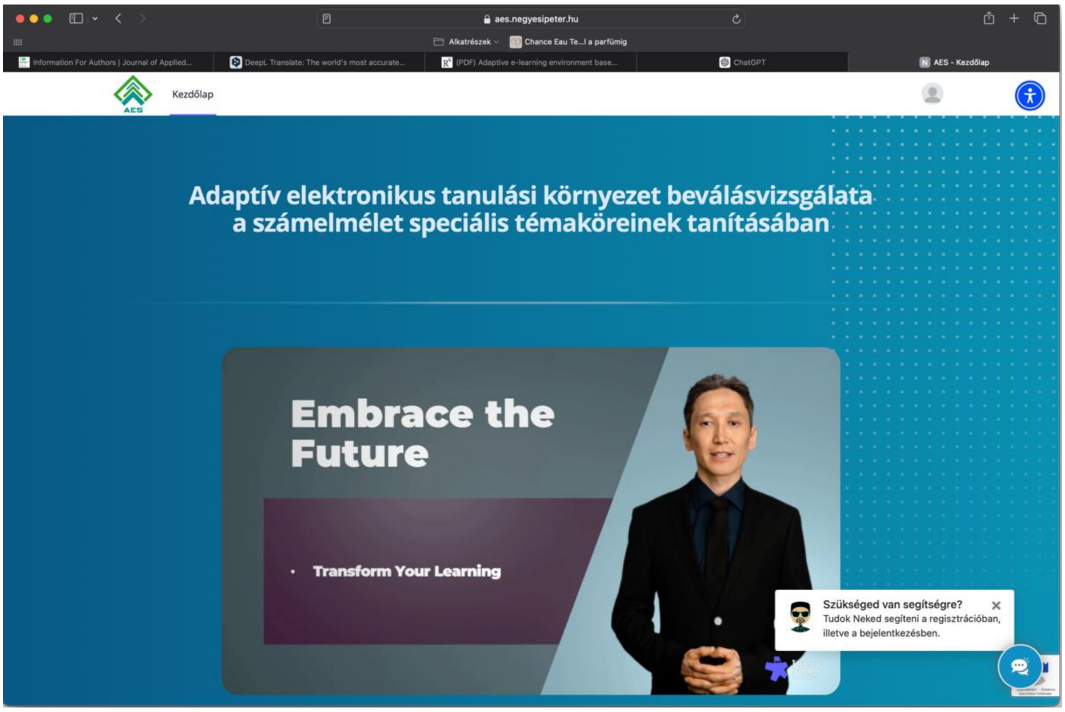

Fig. 5. AES home page (Own source)

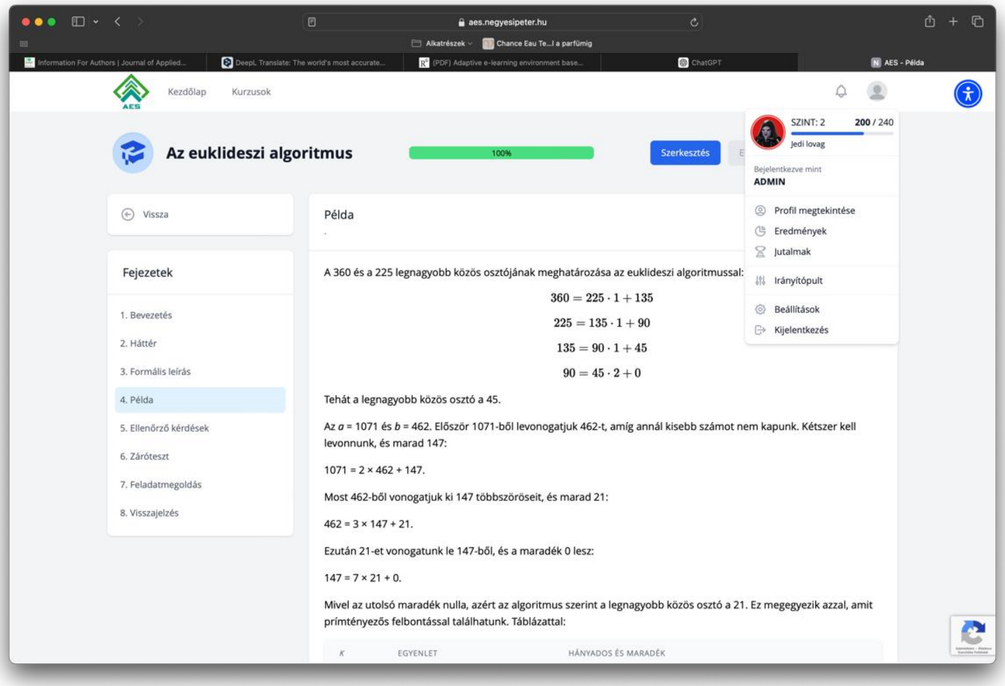

Fig. 6. The Euclidean algorithm course (Own source)

Gaze Recorder and similar eye-tracking software create heatmaps to show visually which parts of the screen users focus on most. The software first captures the user's eye movement using the webcam, monitoring which areas of the screen the user is looking at. Gaze Recorder records all eye movements as a single point. These points form the user's eye movement path. The software uses the recorded points to create a heat map. The heat map shows which areas of the screen the user has focused on. Frequently viewed areas are indicated by different colours (Fig. 7), where 'warmer' colours (e.g. red and orange) indicate that more attention has been paid to those areas, while 'cooler' colours (e.g. blue and green) indicate less attention.

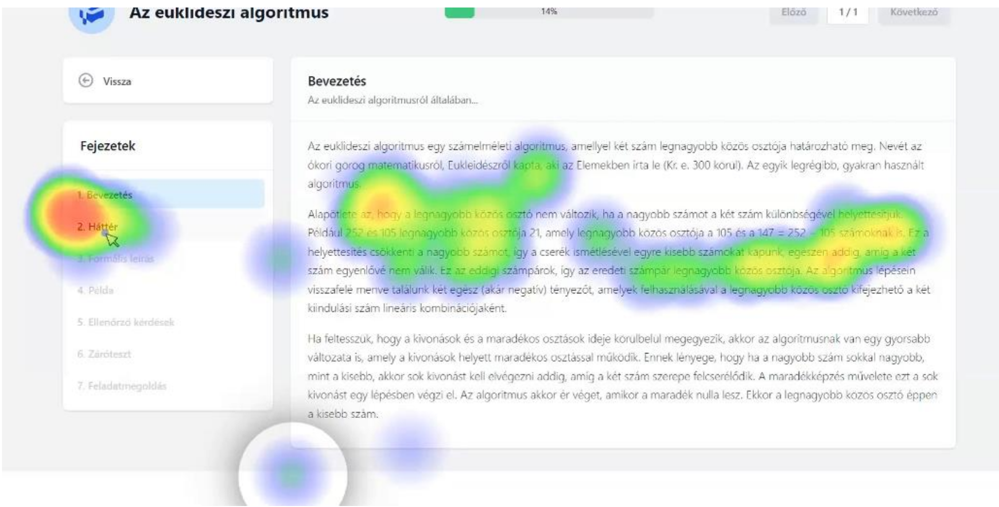

Fig. 7. Heatmap generation (Own source)

5. Results

When creating the heatmap cross-sections, I combined the heatmaps of the subjects to compare and analyse the differences in learning styles and learning styles between the different students. I exported the heatmaps at the same screen size and resolution to ensure an accurate match.

Using the programming language Python, the heatmaps were compared pixel by pixel using the packages NumPy and Matplotlib. It makes sense to handle multiple heat maps stored in a list or array, it is easy to calculate the common intersection of all heatmaps via the np.minimum.reduce function.

By analysing the resulting cross-sectional heat map, I have identified the areas of greatest or least overlap. The visual comparison of the final intersection heatmap display allowed a visual comparison, which proved to be crucial as it provided information on how different learners use the site, i.e. what learning style they represent.

The meta-analysis of the heatmaps for each user showed that there was a significant difference between visual and verbal learners. The cross-sectional heatmap in Figure 8 illustrates the viewpoints of students representing the verbal learning style, who spent most of their time looking at the textual part of the screen.

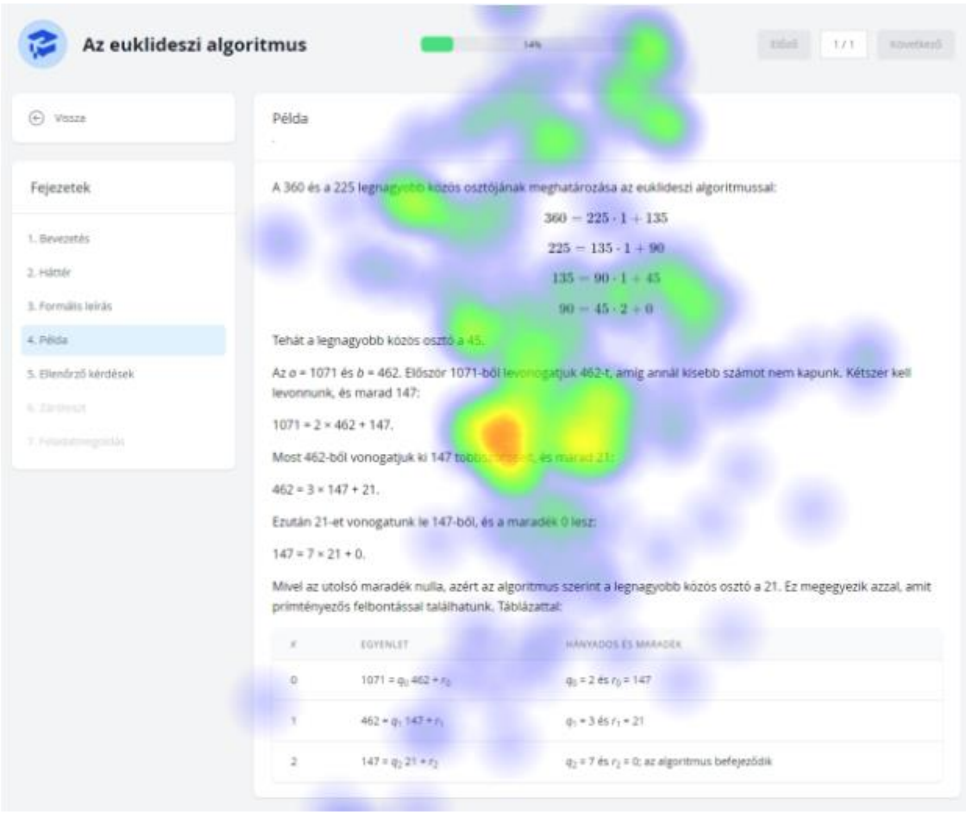

Fig. 8. Verbal learners' cross-sectional heatmap (Own source)

In Figure 9, we have a clear confirmation from the cross-sectional view of the visual learning style students, who spent more time looking at the graphical part of the screen. Moreover, the results show a high correlation between the Felder-Silverman learning style and the eye movements recorded during learning.

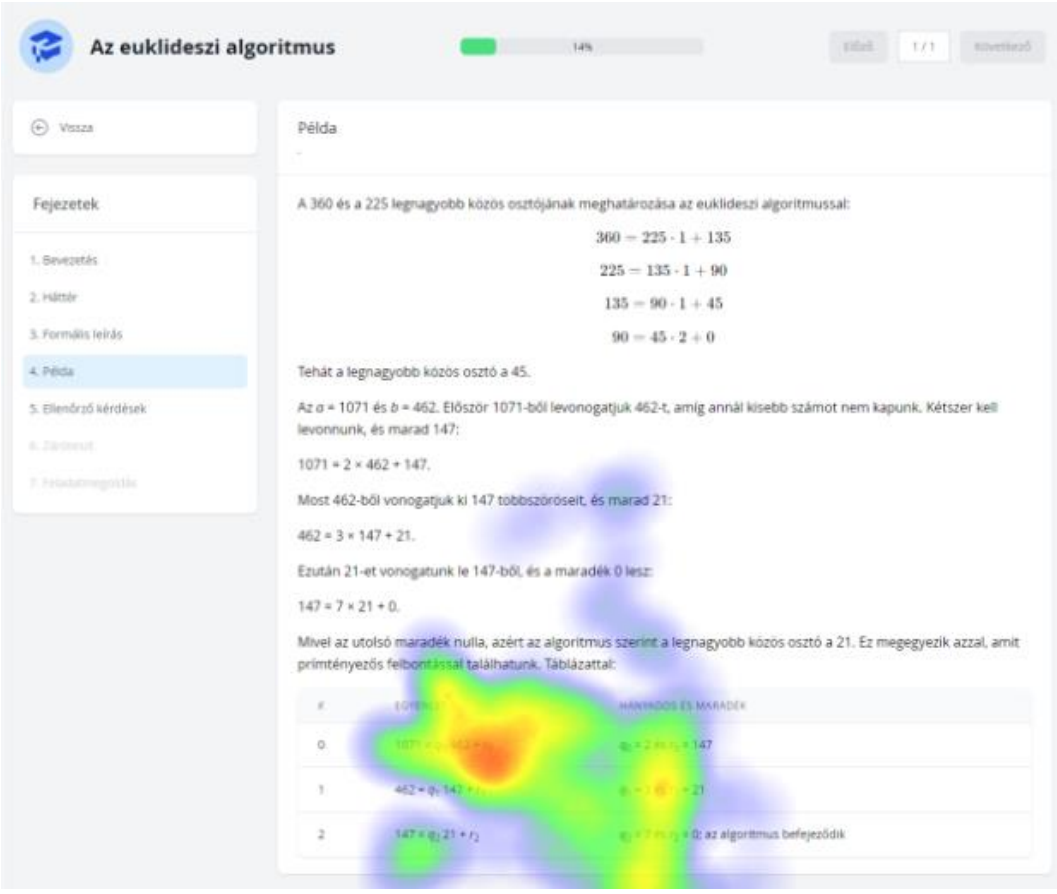

Fig. 9. Visual learners' cross-sectional heatmap (Own source)

6. Conclusions

In this study, we investigated online eye-tracking as a possible solution to identify learners' learning styles. For the study, the Gaze Recorder online eye movement tracking software was used on our new adaptive e-learning system to further develop it, as the identification of learning styles facilitates personalized learning. Based on the results of the study, the following conclusions were drawn:

- Length of gaze is one of the most important features for understanding human behaviour.
- Recording eye movements while reading is very important information in adaptive e-learning systems.

- Eye movement tracking can be used to identify learners with verbal and visual learning styles.
- There is a strong relationship between Felder-Silverman learning style and recorded eye movements.
- The way to improve accuracy is not clear from the results (suggestion: EEG).

To the author's knowledge, this study is one of the few studies that investigate the feasibility of identifying learning styles using eye-tracking technology in an adaptive e-learning system.

An important practical implication is the further development of the adaptive e-learning system under investigation, in which learners with visual and verbal learning styles can be quickly identified and given the learning materials that are most appropriate for them.

The limitations of this research are twofold. Firstly, the sample size (N = 204) is significantly reduced due to invalid data due to calibration problems; secondly, the results of this study can only answer the question of what learning styles learners can be identified by eye-tracking technology, without providing answers to what factors influence the results or how accuracy can be improved.

The author suggests future studies to investigate factors affecting identification accuracy, as well as more reliable recognition methods, such as studying brain electricity using electroencephalogram (EEG) (Emri et al., 2021; Alhasan et al., 2019).

The study may provide a solid basis for further eye movement tracking studies on a larger scale.

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