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A practical based determination of preheating temperature of high strength steels welding

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Abstract: *This study introduces a straightforward method for calculating preheating temperature in steel welding, combining hardness testing with graphical representations of cooling time. The approach begins with hardness tests on welded joints, providing essential insights into material behavior under different cooling conditions. Graphical diagrams are then created to illustrate the relationship between hardness values and cooling times. These diagrams facilitate the selection of optimal cooling times for desired hardness levels. By integrating these diagrams with an existing C++ program, preheating temperature can be easily determined based on the chosen cooling time. This streamlined approach enhances the accuracy of preheating temperature calculations, ultimately improving weld quality and structural integrity.*

Keywords: *Preheating temperature, Hardness testing, Steel welding, Cooling time analysis, Graphical representations, Simplified methodology.*

1. Introduction

This paper discusses the possibility of having a serious defect in the welding which is the Cold cracking, or hydrogen-induced cracking, generally occurs at temperatures below 200℃. It is also called “delayed cracking” due to the incubation time required for crack development. It is generally accepted that cold cracking will occur when the following factors are present simultaneously: diffusible hydrogen in the weld metal, a susceptible microstructure, and residual stress. In the past, cold cracking was most commonly observed in the heat affected zone (HAZ) of high-strength steels, and for avoiding the cold cracking, some have proposed the use of a carbon equivalent as a steel weldability indicator, with the principal aim being the determination of the minimum necessary preheating temperature for welding high-strength structural steels, because the most reliable and fail-safe measure to avoid cold cracking is preheating, it is able to allow a low cooling rate to obtain a lower hardness value for the HAZ. The known principal factors influencing cold cracking in weld metal are the strength of the weld metal, hydrogen level, microstructure, restraint, and weld cooling rate. (Kou, 1987), (Yurioka, 2001), (Yurioka & Kasuya, 1995) (Sun & Dilger 2023) (Kvackaj et al 2021).

The aim from this paper is to give new findings regarding calculating the preheating temperature by using a simple C++ program that takes in a map representing the chemical composition of the steel (carbon and manganese content), as well as the thickness and welding speed as parameters. The program then calculates the preheating temperature using predetermined coefficients and returns the result, (Dale & Weems 2004) (Hubbard, 2021), (Abdulkareem & Abboud, 2021).

Additionally, the paper presents new graphs according to my results during testing the hardness after the Gleeble 3500 simulation, I included thermo-mechanically treated steels in the thermal process modeling, namely S355MC, S500MC, S700MC, S960MC, and S1100MC. The cooling time was set to 5 seconds, 10 seconds, 15 seconds, and 20 seconds within the temperature range of 800°C to 500°C.

The created graphs present the relation between the hardness values and the cooling time, which will be helpful to determine the preheating temperature as well.

2. Determining the critical cooling time

According to welding heat input theories, which describe the heat process occurring at different points of the welded joint, for example, Rosenthal and Rykallin theories (Yurioka, 2001), the heat cycle typically formed at a specific point can be described. The heat cycle based on physical principles is shown in Figure 1.

The notations used in the figure are as follows:

- [T] temperature,
- [t] time,
- [Tmax] maximum temperature,
- [Tcrit] critical temperature,
- [W(T)] cooling rate measured at a given temperature (T),
- [Th] overheating time, the time spent above the Tcrit temperature,
- [T1] upper temperature at which the cooling time is measured (in our case, 850°C),
- [T2] lower temperature until which the cooling time is measured (in our case, 500°C),
- [Δt8/5] cooling time between 850 and 500 °C, critical cooling time,
- [ΔtT1-T2] cooling time between temperatures T1 and T2.

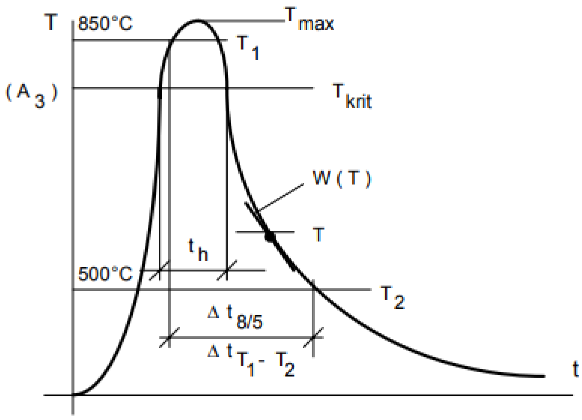

Fig. 1. Welding heat cycle [1]

The critical cooling time (measured in s) depends on the mode of heat conduction. In the case of three-dimensional heat dissipation, according to equation (1), the cooling time does not depend on the plate thickness (represented by "s" and measured in meters) (Yurioka, 2001):

$$\Delta t_{850-500} = \frac{(q/v)_{eff}}{2\pi\lambda}\left(\frac{1}{500-T_0} - \frac{1}{850-T_0}\right) \qquad (1)$$

For two-dimensional cooling, equation (2) gives the critical cooling time [2]:

$$\Delta t_{850-500} = \frac{(q/v)_{eff}^{2}}{4\pi\lambda c\rho s^2}\left(\frac{1}{(500-T_0)^2} - \frac{1}{(850-T_0)^2}\right) \qquad (2)$$

According to equation (2), the cooling rate depends on the plate thickness. Whether the heat conduction is 2D or 3D depends on the critical plate thickness (s_{crit}, measured in meters) and is given by equation (3) (Yurioka, 2001):

$$s_{krit} = \sqrt{\frac{(q/v)_{eff}}{2c\rho}\left(\frac{1}{850-T_0} + \frac{1}{500-T_0}\right)} \qquad (3)$$

If the plate thickness (s) is greater than the critical plate thickness (s_{crit}), then the heat dissipation is 3D.

In the equations, [("q/v") _"eff"] represents the effective specific heat input (J/m), and it can be determined using equation (4) (Yurioka, 2001):

$$(q/v)_{eff} = \frac{UI\eta_{eff}}{v_{heg}} \qquad (4)$$

In the equations,

λ is the thermal conductivity coefficient (for steels, λ = 37…42 W/m°C),

T_0 is the preheating temperature (measured in °C),

cρ is the volumetric heat capacity (for steels, cρ = (5…5.2)10^6 J/m^3°C).

Regarding the equations, it should be noted that they are written for a point located in the plane of the weld, at the centre of the weld cross-section (Yurioka & Kasuya, 1995). In real cases, lower cooling rates occur, so deviating from the application of these equations provides a safety direction.

Analysing the equations, it can be observed that the critical cooling time becomes longer with an increase in the specific heat input, the application of preheating, and a thinner plate.

From equations (1) and (2), the expression for [("q/v") _"eff"] can be derived. This means that for a given critical cooling time, the specific heat input can be determined such that the smallest critical cooling time is achieved. Therefore, a cooling rate faster than the cooling rate corresponding to the critical cooling time does not occur. It also follows that if the critical cooling time is prescribed based on a mechanical criterion, such as hardness, when applying the calculated required specific heat input (or a higher heat input), a hardness greater than the prescribed hardness in the heat-affected zone will not be achieved.

Next, the paper reviews how the critical cooling time can be determined and what criteria can be used to specify its value.

The method for determining the required specific heat input and preheating temperature based on the critical cooling time was already included in the MSZ 6280 standard which equivalent to ISO 3834 (Palotás, 2015) (MSZ 6280 – 82, 1985). This standard contained the correlation between the carbon equivalent (C_e) associated with different hardness levels and the critical cooling time (Δt_{HV}) (Figure 3), as well as the determination of the specific heat input in the form of nomograms. Although the nomograms in the mentioned standard appendix were not accurate, they represented pioneering work as they were based on fundamental principles and introduced a new way of thinking, proving practical usability.

The equations describing the individual curves were also provided in the form of (Yurioka, 2001):

$$[\Delta tHV = a\ (Ce - C0)b] \qquad (5)$$

given at a 95% confidence level. The carbon equivalent is determined based on the recommendation of the IIW using a commonly known correlation (Yurioka, 2001):

$$Ce = C + Mn/(6) + (Cr+Mo+V)/5 + (Ni+Cu)/15 \qquad (6)$$

The constants corresponding to different hardness levels are as follows:

300 HV10 in the case of heat-affected zone hardness levels a= 432.5; b =1.87; C0 = 0.225

350 HV10 in the case of heat-affected zone hardness levels a = 291.5; b =1.66; C0 = 0.275

375 HV10 in the case of heat-affected zone hardness levels a = 283.9; b =1.56; C0 = 0.300

400 HV10 in the case of heat-affected zone hardness levels a = 214.1; b =1.40; C0 = 0.350.

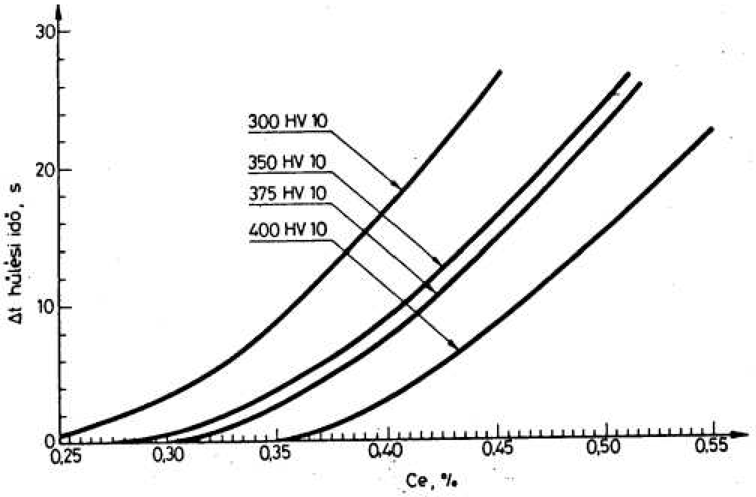

Fig. 2. Correlation between the critical cooling time and carbon equivalent at different hardness levels (Yurioka & Kasuya, 1995)

In Figure 2, these relationships are applicable only up to 0.50% carbon equivalent and up to a maximum of 0.55% even in the case of the highest hardness. This means that these relationships can only be applied to conventional, easily weldable steels (such as normalized steels with yield strengths of 235 MPa, 275 MPa, 355 MPa, 420 MPa, and 460 MPa). They are not applicable to the high-strength steels used today.

There is a need to establish relationships that can prescribe the maximum allowable hardness for various high-strength steels. The application of continuous cooling transformation diagrams taken for weldable steels seems suitable for this purpose. Examples of such diagrams are presented in Figure 3 and 4 (Bödök, 1997).

If we assume that we do not want martensitic microstructure in the heat-affected zone, based on the diagrams, we can determine the critical cooling time that can be prescribed. For KL 7 steel (currently designated as P355_), this value is 10 s, for 52D steel (S355J2+N) it is 7 s, for 12H1MF steel (low-alloy creep-resistant steel) it is 9 s, for 10 CrMo 9-10 steel (alloy creep-resistant steel) it is 25 s, and for H5M steel it is 18 s (this steel is a moderately alloyed creep-resistant steel with C = 0.14%, Cr ≈ 4.5%, Mo ≈ 0.5%). Beyond these estimated cooling times, other microstructures besides martensite start to form. The faster heating curves were considered in the analysis (Stroetmann et al 2018).

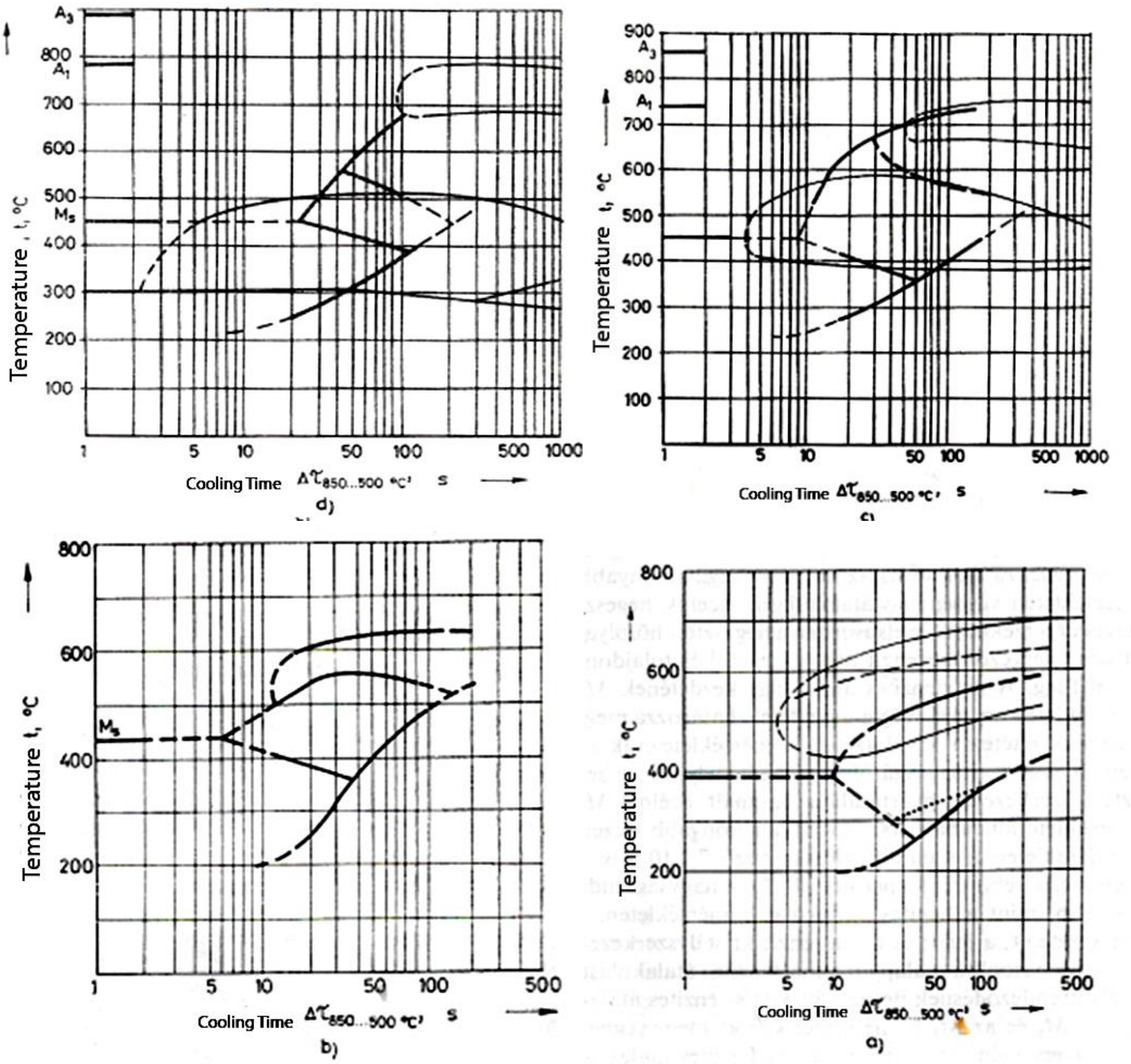

Fig.3. Transformation diagrams obtained through welding (Part 1) a. KL 7 steel b. 52D steel c. 12 H 1 MF steel d. 10 CrMo 9 10 steel (Thick line: [Wheat] = 250 °C/s, [tmax] = 1375 °C, [τ] = 0; Thin line: [Wheat] = 7 °C/s, [tmax] = 900 °C, [τ] = 300 s)

The presented correlations cannot be applied to the increasingly prevalent hardened and tempered steels (indicated by the supplementary letter Q, e.g., S690Q). They are also not applicable to steels produced through thermomechanical treatment (e.g., S960Msteel). If the critical cooling time for a specific steel is known, the presented equations (1), (2), (3), and (4) can be applied to determine the specific heat input that ensures crack-free welding, or if that cannot be achieved, the necessary preheating value. If we had access to continuous cooling diagrams for welding (like Figure 4, i.e., critical cooling time and corresponding temperature values along with the resulting microstructures), the critical cooling time could be determined, as shown earlier. However, recording transformation diagrams would require numerous measurements. Therefore, finding a simpler method for determining the critical cooling time would offer several technical and economic advantages.

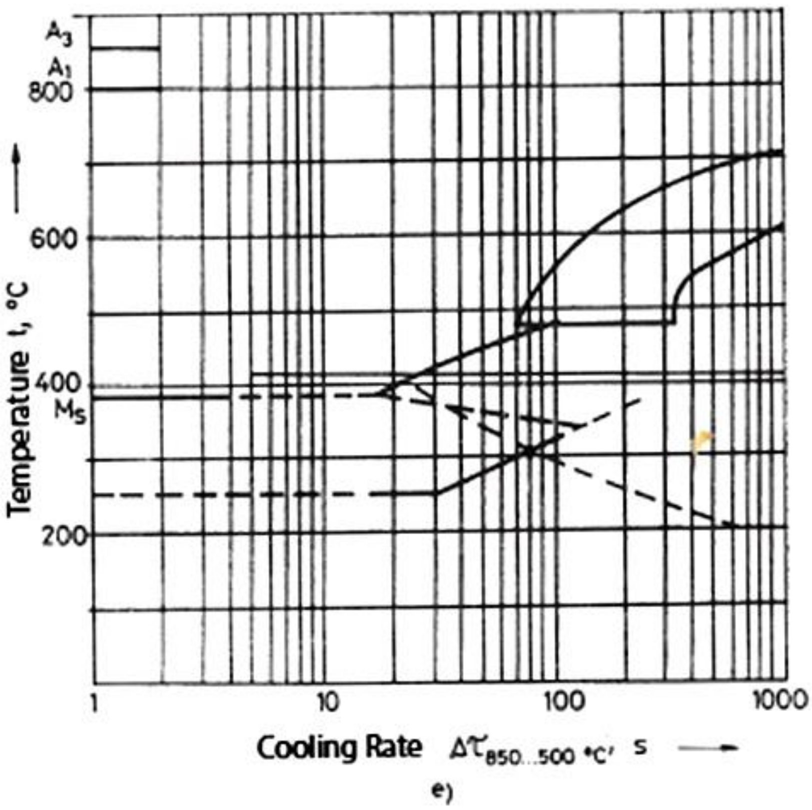

Fig.4. Transformation diagrams obtained by welding (Part 2)

e. H5M steel (Thick line: [Wheat] = 250 °C/s, [tmax] = 1375 °C, [τ] = 0; Thin line: [Wheat] = 7°C/s, [tmax] = 900 °C, [τ] = 300 s)

3. Determining the critical cooling time through measurement

I recommend using GLEEBLE physical simulators for determining the critical cooling time. The simulator can simulate identical thermal cycles throughout the entire cross-section of a test specimen, either in a vacuum or in a shielding gas environment. Both heating and cooling rates can be adjusted over a wide range. The simulator and the test specimen setup are illustrated in Figure 5 (Radaj, 1992).

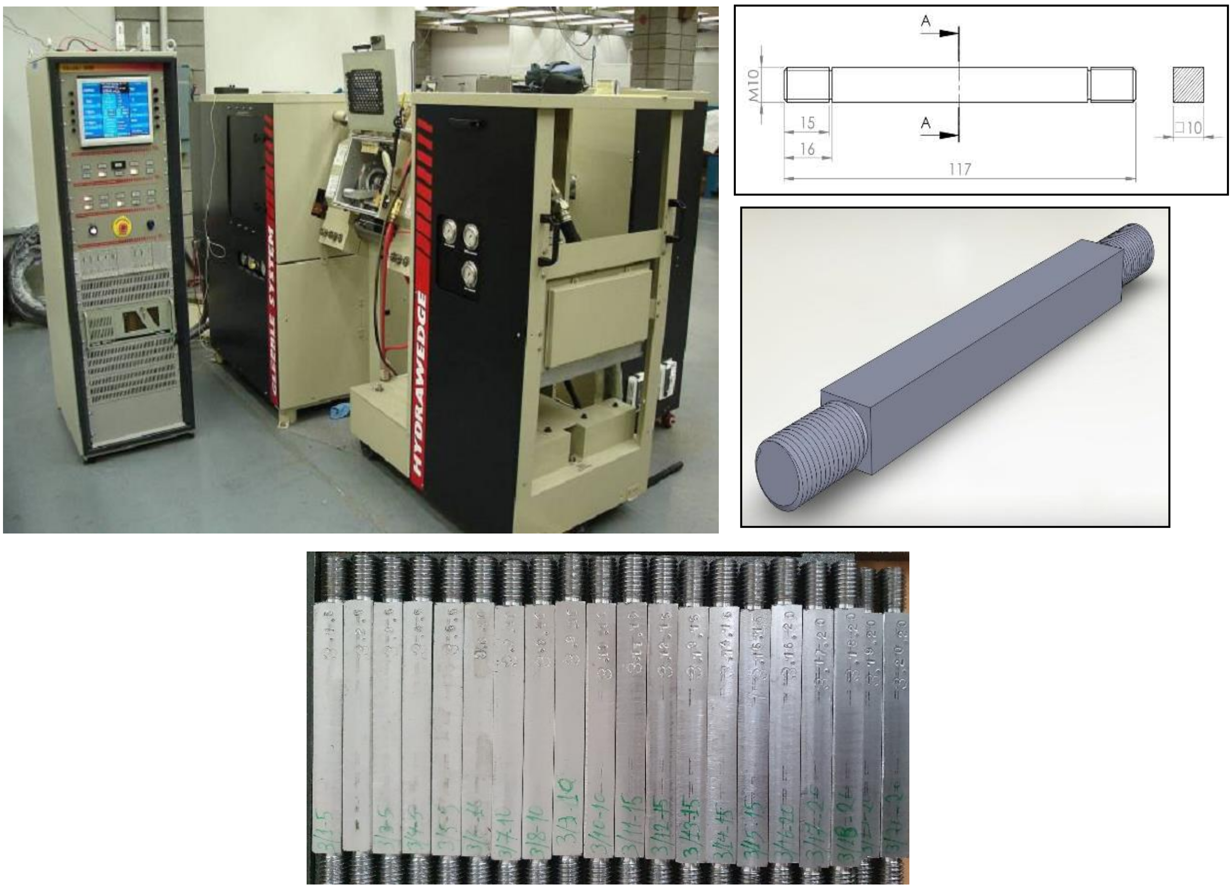

Fig.5. Image of the thermal process simulator and the test specimen and the prepared samples

I included thermo-mechanically treated steels in the thermal process modeling, namely S355MC, S500MC, S700MC, S960MC, and S1100MC. The cooling time was set to 5 s, 10 seconds, 15 seconds, and 20 seconds within the temperature range of 800°C to 500°C. The test specimens were rapidly heated to the austenitizing temperature (950°C ±20°C). Temperature regulation was performed using a thermocouple welded onto the center of the test specimen. The modeling was conducted using a GLEEBLE 3500 physical simulator located at the University of Miskolc. After that the Gleeble 3800 in university of Dunaújváros was repaired and I could repeat the simulation for two grades of my samples which were (S960MC, S1100MC) (Palotás, 2017). The applied thermal cycle is presented in Figure 6.

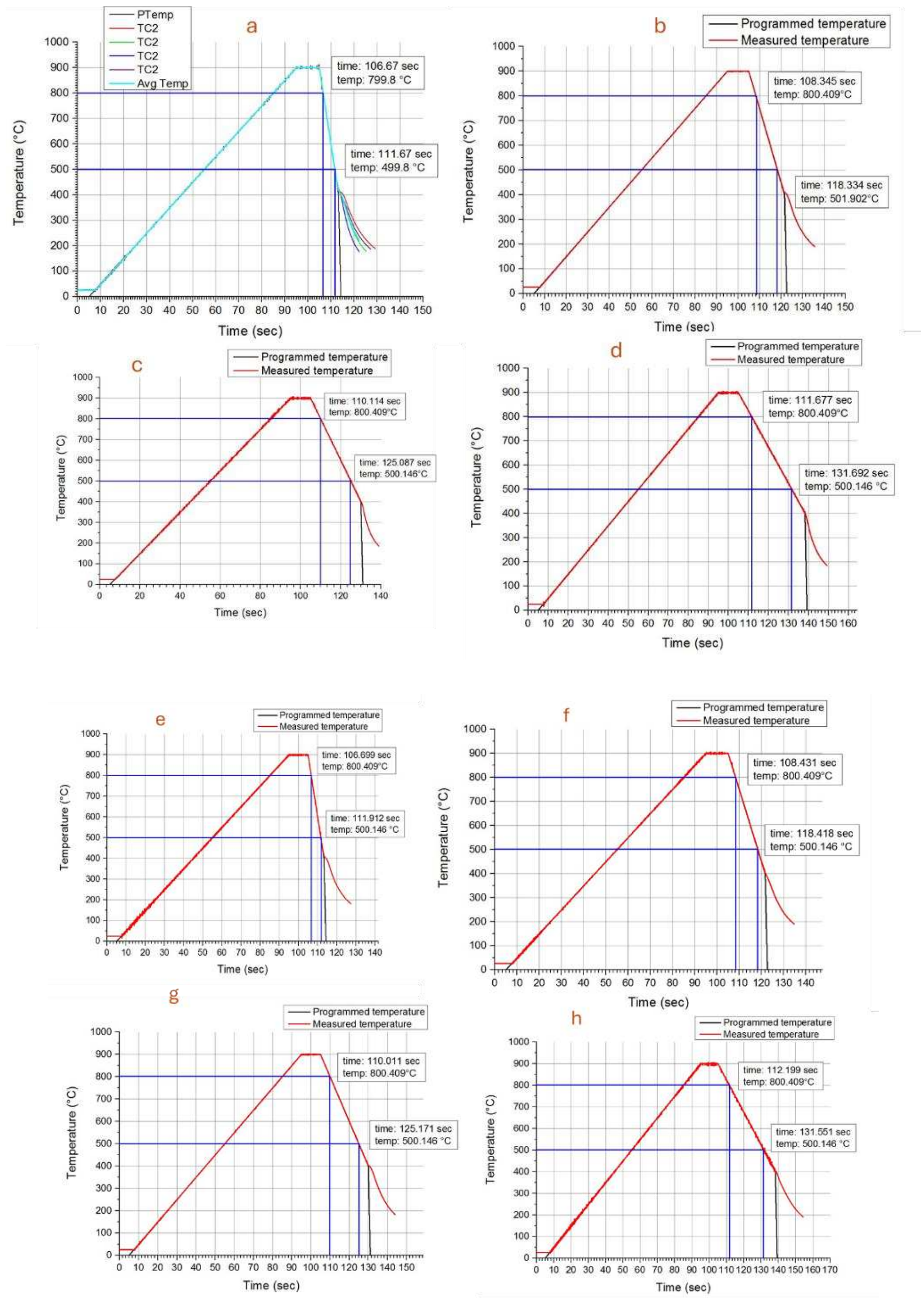

Fig.6. a: the applied thermal cycle in case of S960MC, 5sec summary for the five samples,

b: the applied thermal cycle in case of S960MC, 10Sec,

c: the applied thermal cycle in case of S960MC, 15sec,

d: the applied thermal cycle in case of S960MC, 20 sec

e: the applied thermal cycle in case of S1100MC,5sec,

f: the applied thermal cycle in case of S1100MC,10sec,

g: the applied thermal cycle in case of S1100MC,15sec,

h the applied thermal cycle in case of S1100MC,20sec

I chose the shape of the test specimen used for modeling in such a way that hardness measurements (at the center of the specimen on each plane) could be performed, and there was also the possibility of measuring impact energy. We had five test specimens made from each material and for each cooling time. With approximately 100 test specimens, a reliable evaluation can be carried out. The results of hardness measurements are illustrated in Figure 7. Results show the steel S355MC did not quenched no cases (this result is coherent with result found in (Palotás, 2017).

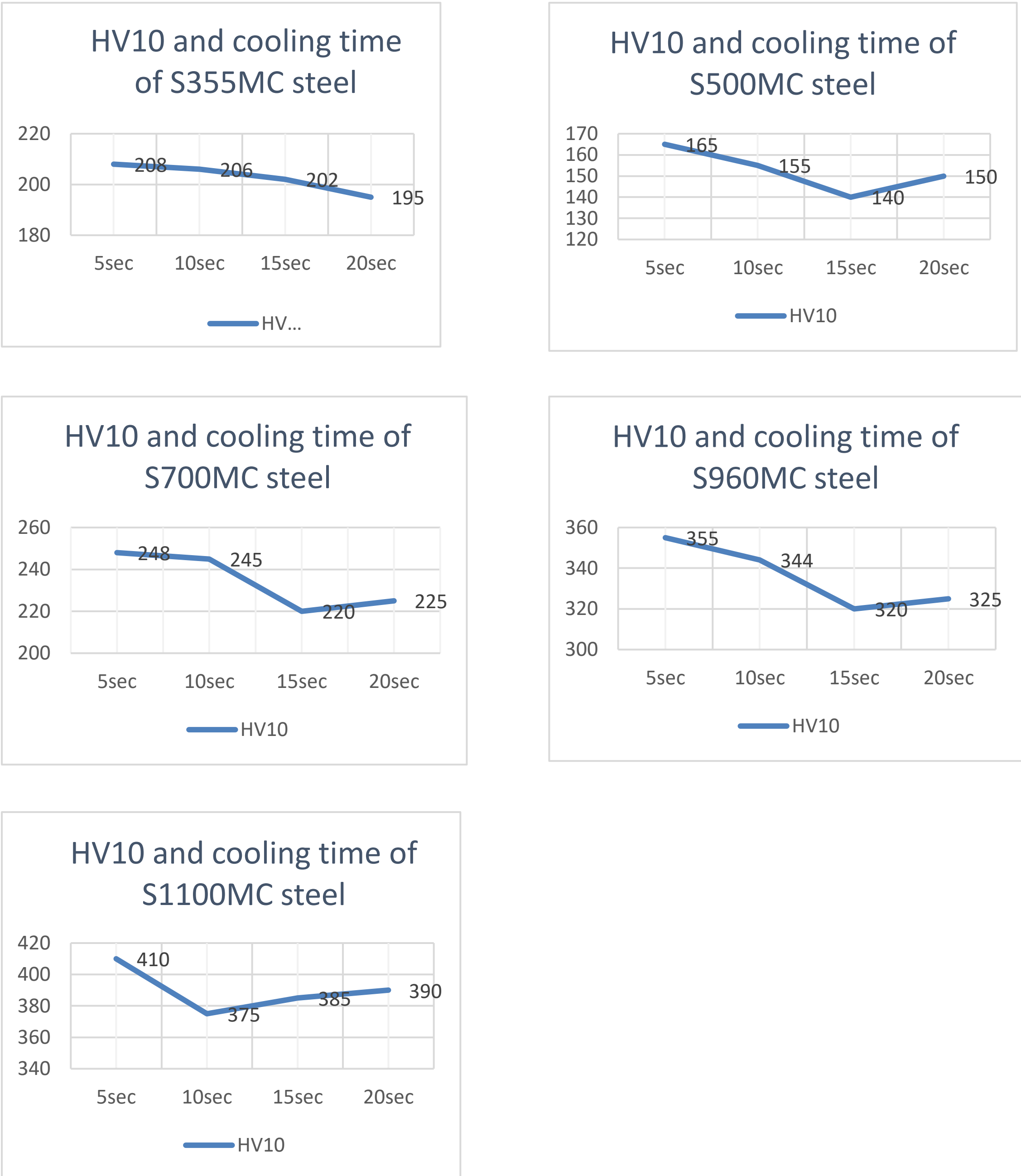

Fig.7. the relation between the cooling time and the hardness results for all the grades materials

Based on these diagrams, we can determine the required cooling time based on my findings. This information is crucial for accurately determining the preheting temperature for materials such as S355MC, S500MC, S700MC, S960MC, and S1100MC. By extracting the cooling time value from the graph and integrating it into the equations mentioned earlier, we can ascertain the appropriate preheating temperature for these materials.

To make the calculation more accurate I create a C++ program to give the preheating temperature according to the carbon content and the cooling time.

This program takes input for cooling time (in seconds) and carbon content (in percentage), calculates the preheating temperature based on the provided formula, and outputs the result. You can use this program directly without any modification. However, please note that you may need to adjust the constants in the formula (constant1 and constant2) based on the specific formula you are using for preheating temperature calculation. See the Appendix A.

4. Conclusion

The study focuses on a practical method for determining the preheating temperature in steel welding through hardness testing and graphical representations of cooling time. Cold cracking in welding is a serious defect that can be avoided by preheating high-strength steels. The use of a carbon equivalent as a weldability indicator is proposed, with preheating being the most effective way to prevent cold cracking. The study introduces a simplified methodology using a C++ program that calculates preheating temperature based on specific parameters. By conducting tests on various thermal process models of high-strength steels and analyzing hardness values at different cooling times, the study provides insights into determining the optimal preheating temperature for welding. The critical cooling time can be determined using specialized equipment like the GLEEBLE simulator, and the results can be used to calculate the required preheating temperature accurately. By developing a C++ program, the study offers a practical tool for welders to determine the preheating temperature based on the carbon content and cooling time, enhancing the quality and integrity of welds.

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About Authors

Lama Mkanna received her M. Sc. degree in Mechanical Engineering from University of Dunaújváros in 2020 and currently a PhD student in Széchenyi István University, Doctoral School of Multidisciplinary Engineering Sciences, Transportation and vehicle engineering. She is a teacher assistant at University of Dunaújváros, she is giving lectures and supervising the students with their thesis. Her research interests include weldability and avoiding the cold cracking for the HSS, the importance of the HSS in the vehicle industry.

Appendix A

```
#include <iostream>
using namespace std;

// Function to calculate preheating temperature
double calculatePreheatingTemperature(double coolingTime, double carbonContent) {
   // Constants for calculation
   const double constant1 = 50;  // Modify this constant based on your formula
   const double constant2 = 0.8;  // Modify this constant based on your formula

   // Convert cooling time from seconds to minutes
   coolingTime /= 60.0;

   // Formula for calculating preheating temperature
   double preheatingTemperature = constant1 * coolingTime + constant2 * carbonContent;
   return preheatingTemperature;
}

int main() {
   // Input parameters
   double coolingTimeInSeconds; // Cooling time in seconds
   double carbonContent;        // Carbon content in the steel (percentage)

   // Get user input
```



```
    cout << "Enter cooling time (seconds): ";
    cin >> coolingTimeInSeconds;
    cout << "Enter carbon content (%): ";
    cin >> carbonContent;

    // Calculate preheating temperature
    double preheatingTemperature = calculatePreheatingTemperature(coolingTimeInSeconds,
carbonContent);

    // Output result
    cout << "Preheating temperature for welding HSS: " << preheatingTemperature << " °C" <<
endl;
    return 0;
}
```


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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).

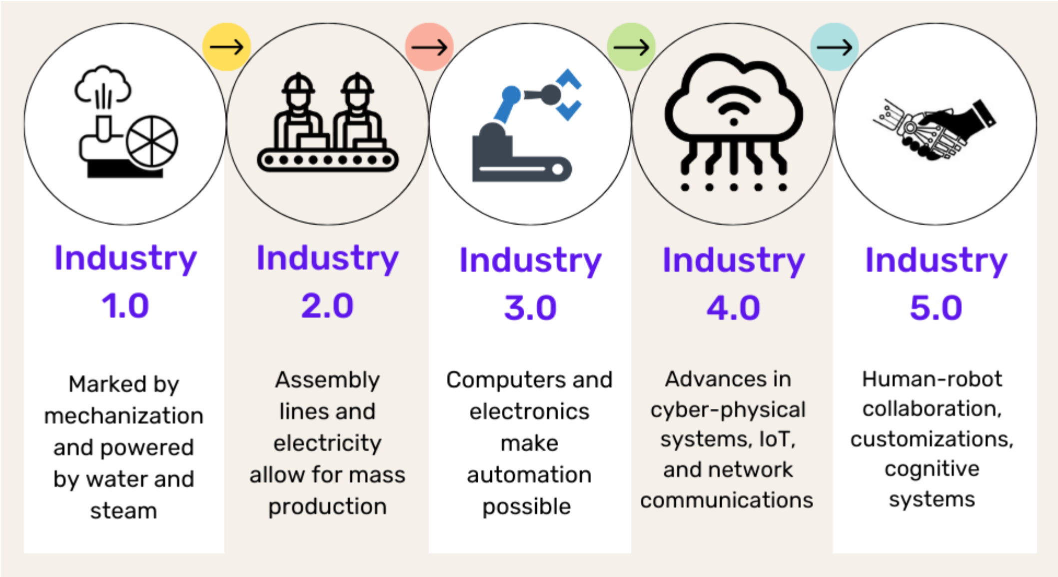

Fig. 1. Industrial revolutions (Source[1])

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.

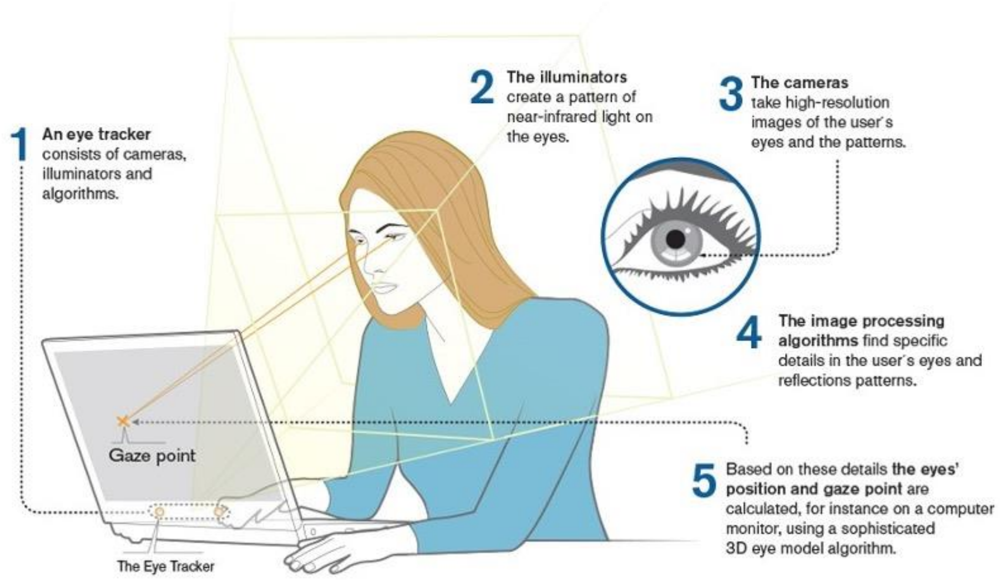

Fig. 2. The principle of eye movement tracking (Source[2])

[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.

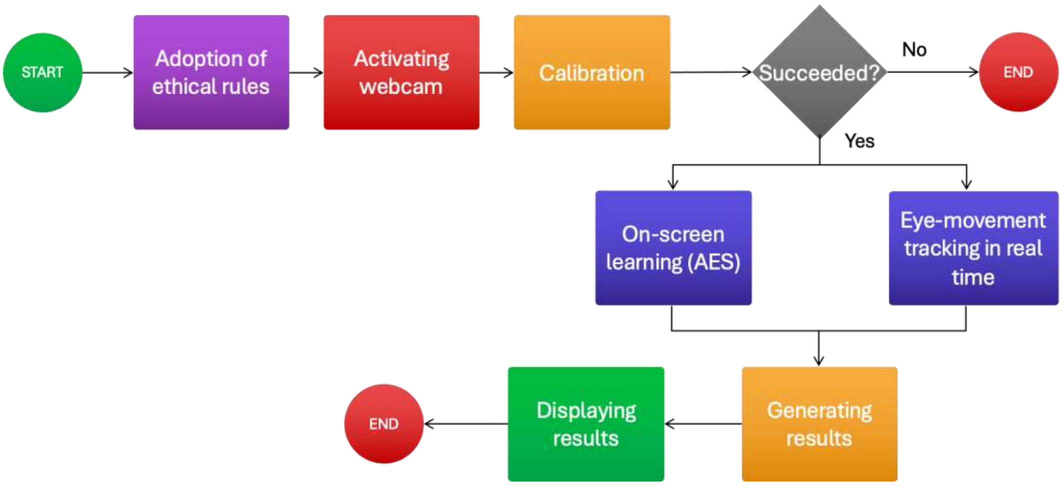

Fig. 3. Flowchart of the investigation (Own source)

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.

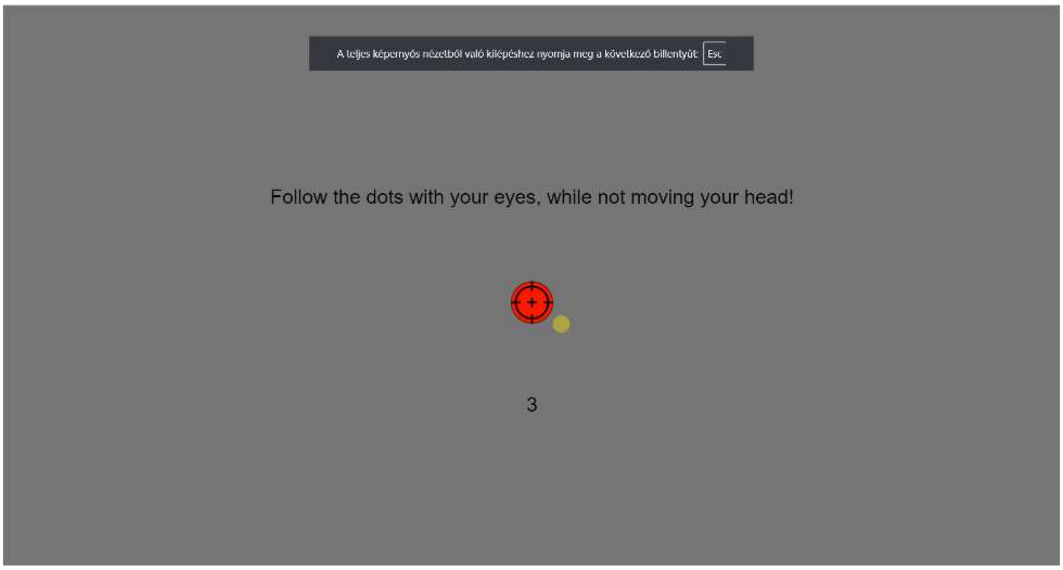

Fig. 4. Calibration start screen (Own source)

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.

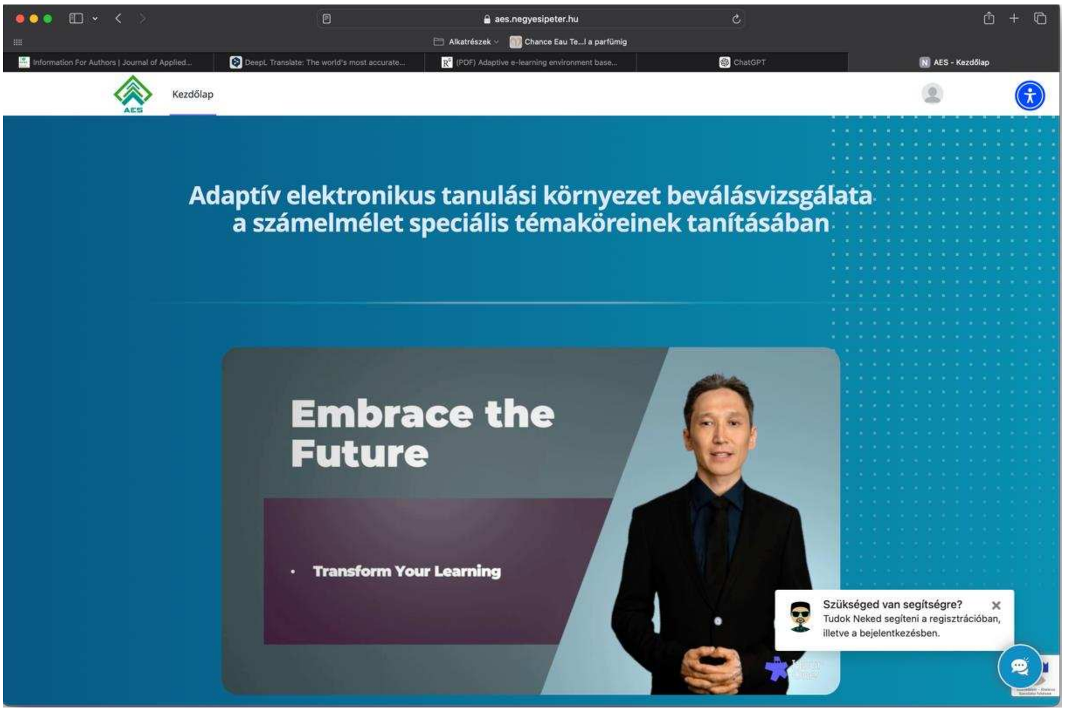

Fig. 5. AES home page (Own source)

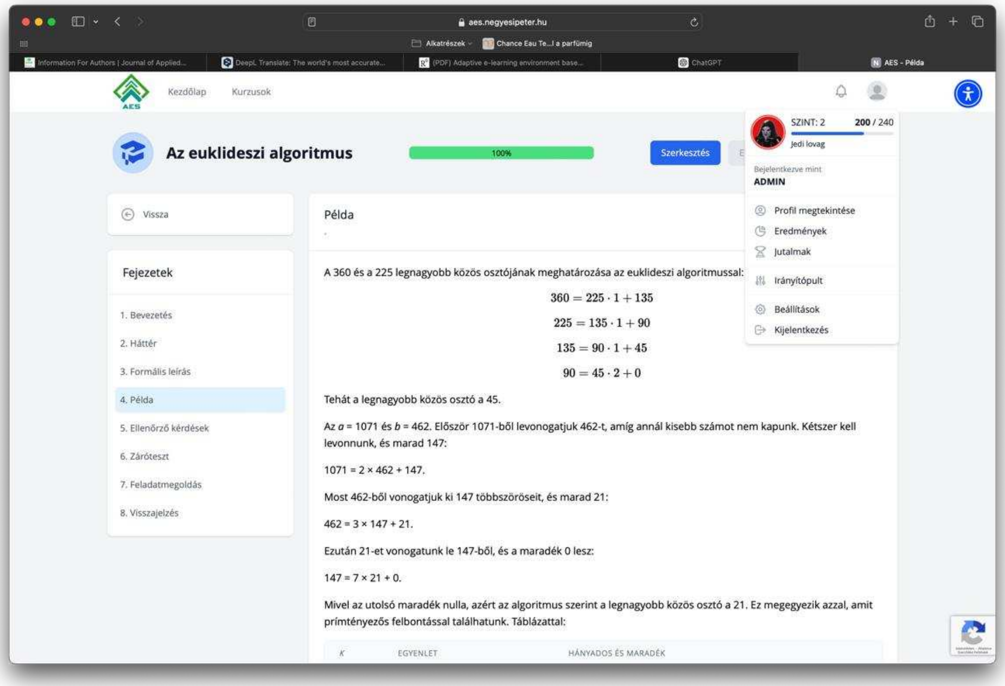

Fig. 6. The Euclidean algorithm course (Own source)

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.

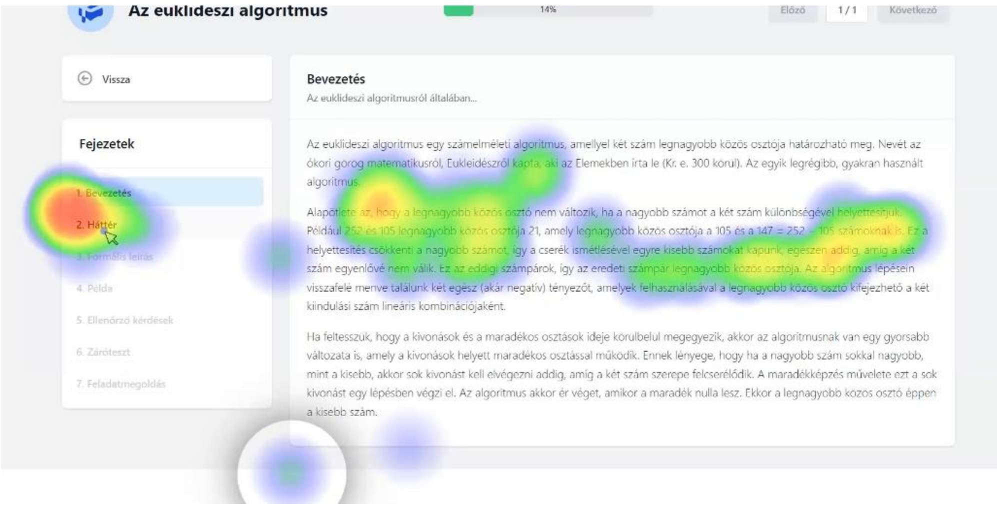

Fig. 7. Heatmap generation (Own source)

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.

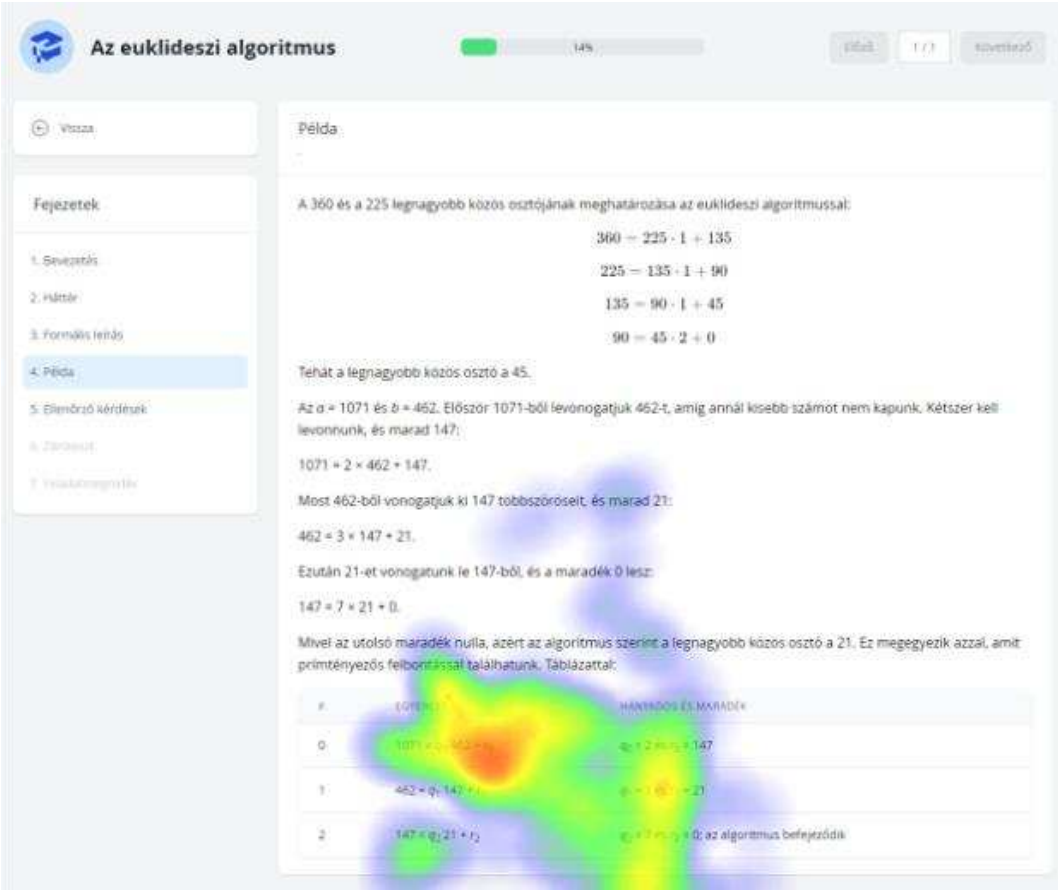

Fig. 9. Visual learners' cross-sectional heatmap (Own source)

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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The Role of AI-based Adaptive Learning Systems in Digital Education

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Abstract: *The application of AI-based adaptive learning systems is an important innovation in educational technology offering efficient and personalized learning experiences. The potential advantages of learning with AI support are significant besides the various challenges and limitations that should also be considered. The future of this new wave in education is promising, as it can transform and improve learning outcomes for students. As technology progresses, these systems will become more sophisticated, possibly offering more extensive opportunities for personalized education. This research gives an overview of the implementation of AI-based adaptive learning systems focusing on the advantages. The paper foresees the visualized practical use of AI in the process of learning and teaching as a helpful tool in digital education and discusses the key aspects of its use.*

Keywords: *Artificial Intelligence; adaptive learning; AI-based adaptive learning; digital education; machine learning*

1. Introduction

Digital education has rapidly become a significant and now an indispensable methodological feature of current educational procedures and the concept is referred to as the new paradigm in education. (Kilicoglu & Kilicoglu, 2020), (Mhlanga 2023) According to Szűts, digital pedagogy simultaneously states the relation to technique, communication, media, and pedagogy. In his interpretation, digital pedagogy is a unit of classroom or distance learning methodologies, ways of thinking, organizational processes, and forms of work based on info-communication devices, screens, databases and digital content. (Szűts, 2020) In the comprehensive view by Lengsfeld, digital education is the formation of an individual in the sense of a comprehensive and holistic spiritual, physical, social, and cultural development into a reflected person aware of every side of his or her being as a human in a digital world and is able to draw conclusions for the shaping of his or her life in the digital age based on this. The term 'digital education' is also instrumentally used in his approach. In this respect, digital education is seen as a process of education that is supported, made possible, or shaped by the use of digital information and communication technologies. (Lengsfeld, 2019) Leveraging technology to the classroom, digital pedagogy extends the limitations of traditional education with flexibility, accessibility and opportunities for personalized learning. From online courses and virtual classes to interactive educational applications and multimedia resources, digital education includes a wide range of tools and platforms that create new opportunities to make learning and teaching enhanced. It is a transformative way of education, as it not only caters to different learning styles and paces, but also removes geographical barriers leading to the access to quality education worldwide. As the result of the continuous advancement of digital education, learning has become democratic, lifelong, and the skills from digital learning enabled students to thrive in the progressively digital world.

In recent years, Artificial Intelligence (AI) has emerged in and revolutionized various sectors of our lives including the field of education, too. The appearance of AI in digital education manifests in different forms and applications, changing the way of learning and teaching, i. e. the role of the student and the teacher in the learning process. These AI-based learning systems have emerged as potent tools in digital education with innovative solutions to improve teaching and learning experience. These systems basically work on advanced algorithms and are able to perform data analysis to provide a personalized learning experience, automate administrative tasks and insights into student performance. AI-based learning systems adapt to individual learning styles and needs and dramatically change traditional educational paradigms creating a more inclusive, efficient and engaging learning environment. (Tuomi, 2020)

2. AI-based adaptive learning systems

AI-based adaptive learning systems refer to those educational technologies that use artificial intelligence to personalize learning experience considering the needs of individual students. The systems collect and analyse information related to student performance, learning preferences and progress to create personalized learning pathways. Therefore, in modern education, adaptive learning is of paramount importance addressing students' diversified needs, keeping learners engaged and improving learning results. The basic premise of adaptive learning systems lies in their ability to capture a huge volume of data on student performance, behaviour, preference and interactions with the material. The measured data is analysed based on advanced analytics techniques to help understand and draw conclusions about the learning process. At the core of adaptive learning systems, machine learning algorithms can be found. These algorithms can analyse the received data, detect patterns, predict future performance and recognise the most effective way in which each individual student learns. The use of machine learning ensures that the efficiency of the system can continuously be enhanced as it adapts to the changing needs of students. Based on the gained data insights, adaptive learning systems create personal learning pathways for each student. This would then ensure that both the content and pace are ideally designed to suit the individual learning preferences and abilities for a more efficient and interesting learning experience. One of the significant advantages of adaptive learning systems is real-time feedback that students receive based on their performance in order to give information about their strengths and weaknesses, thus allowing for correction in learning strategies when needed. This constant feedback is crucial, as it cultivates self-directed learning and self-improvement. (Ezzaim et al, 2022), (Arroub et al, 2020), (Chen et al, 2020)

There are other important benefits of adaptive learning systems. Catering to the individual needs of each student by providing personalized learning experience is a key feature as well, which can evoke better understanding and application of knowledge. Adaptive learning systems can engage and motivate students by providing relevant and appropriately challenging content. The attention and motivation of students can be kept continuously throughout their studies when the learning content is adaptive to their level of performance and interest. Research has shown that adaptive learning can lead to tremendous improvement in learning results. The adaptive learning systems can help close the learning gaps and ensure each student reaches the best of their potential by focusing on the specific needs of individual students. Besides, AI-based adaptive learning systems can cater for a large number of students, making quality education available for those in need. (Verdú Pérez et al, 2008), (Contrino et al, 2024), (Chen et al, 2020)

Scalability makes these systems crucial for addressing educational disparities and providing access to personalized learning opportunities for students. Another significant advantage includes catering to a differentiated kind of instruction, which is rare in the usual classroom settings. Differentiated instruction is an approach where teachers adjust their teaching approaches and materials to suit the various styles, abilities and interests found among students. Adaptive learning systems automate this process by continually assessing the progress of a student and dynamically changing the instructional content. This proceeding can help both teachers and students, especially in a diverse class where the prior knowledge and learning speed of students are different. (Wang & Hannafin, 2005), (Chen et al, 2020), (Bakhshinategh, 2018)

Furthermore, adaptive learning systems provide information for teachers about student performance, and they can use the received data to identify students who may be lagging behind and in need of support, or to recognize students who are excelling and need more challenging content. This saves instructional time, hence achieving more within a limited period. Adaptive learning systems not only enhance the individual learning outcome but also forms collaboration among learners. Through the identification of students with the same learning needs or those whose skills are complementary, these systems can enable group activities and further peer learning. Working in groups not only enhances one's understanding through discussion and interaction, but also aids in developing the soft skills of students such as communication, teamwork and problem solving. (Steenbergen & Cooper, 2014), (Chen et al, 2020), (Bakhshinategh, 2018)

Though they have promising advantages, there are some challenges faced by AI adaptive learning systems, too. Apart from the emerging questions of its ethical use, one major concern is the possibility of creating technological dependence if both students and teachers become too reliant on adaptive systems to the detriment of other forms of learning and basic elements of critical thinking. There must be a balance between the use of technology and other instructional techniques so that students receive a comprehensive education. In addition, though adaptive learning systems can offer individualized instruction, they sometimes lack the sophistication of human teaching. Factors such as the emotional and social dimensions of learning, which play an important role in student engagement and motivation, cannot be easily measured and incorporated into adaptive algorithms. This makes integration with holistic educational practice very important because the wider context of student development also needs to be considered. (Verdú Pérez et al, 2008), (Contrino et al, 2024)

Another area of concern is the digital divide, the gap between technology and internet access for some and a lack of such for others. These inequality reasons are what might probably render it impossible for students in underprivileged or rural areas to access to any adaptive learning system, hence creating more division in educational outcomes. This factor requires some level of responsibility from policymakers, educational institutions, and stakeholders who provide technologies to ensure that there is equitable access to digital learning resources. The advantages and disadvantages of an adaptive learning system can be maximized and minimized, respectively, through research and development. Further advancements in machine learning algorithms make them less biased with increased data privacy, security and incorporating friendly interfaces for both educators and students. In addition, there must be a culture of continuous improvement and feedback in learning institutions as part and parcel of integrating adaptive learning systems. (Ezzaim et al, 2022), (Arroub et al, 2020)

The introduction of adaptive learning systems requires adequate technical infrastructure and expertise. The implementation of such systems may be difficult for educational institutions due to the cost of acquiring the resources and training the staff to support their use. Traditional educational institutions may be conservative in terms of adapting to new technologies and changing established practices in teaching. The way of overcoming possible resistance include provisions for the value and effectiveness of the adaptive learning systems and support for educators during implementation. AI-based adaptive learning systems has the potential to revolutionize education technology. These systems could really enhance student outcomes and engagement by personalizing the learning experience through real-time feedback. However, it will become imperative to meet challenges related to data privacy, bias and access to technology for systems of adaptive learning implementation to actually work effectively and fairly.

3. The key features of the presence of AI in digital education

Some of the major aspects of AI in digital education are advanced personalized learning environments, intelligent tutoring systems, content creation and curation, advanced engagement tools, language processing tools, accessibility and inclusion, and teacher support systems.

1. Personalized learning environments

- Adaptive learning platforms: The use of AI technologies to change the level of difficulty and even genre of content based on the performance level and speed of learning of a particular student. In most cases, there is a provision for an interface with which the student can interact through the lessons and quizzes that are meant for independent learning as well as actual practice.
- Learning analytics dashboards: Graphical displays of students' progress such as their strengths and areas that need improvement. Mostly, these visual displays are in the form of graphs and charts for clear understanding.

2. Intelligent tutoring systems

- Virtual teachers and assistants: AI tutors are used to provide one-on-one support, answer questions, and make explanations on various topics. They normally appear as chatbots or animated characters.
- Automated feedback and grading: It is provided for systems that offer instant feedback on tests and performance by pointing out the mistakes and indicating how student achievement can be improved.

3. Content creation and curation

- AI-generated content: Systems that produce learning items, such as practice questions, flashcards and summaries from the curriculum data.
- Smart resource recommendations: The algorithms suggest more or better sources of learning materials and resources that is adjusted to the level, need and interest of students.

4. Engagement tools

- Gamification tools: Game-based, AI-driven learning platforms have potential to engage and motivate students, where they can score some points, win badges, and get into a leaderboard ranking system.
- Interactive simulations and virtual labs: AI-powered environments which enable students to perform experiments and simulations that will allow them to virtually experience a hands-on learning process.

5. Language processing tools

- Language translation and transcription: AI tools that perform the translation of the educational content into different languages and its real-time transcription in delivering lectures and discussions.
- Natural language processing for writing support: Using NLP technologies in enhancing a student's writing by suggesting the corrections made in grammar, style, or plagiarism.

6. Accessibility and inclusion

- Speech-to-Text and Text-to-Speech: AI technology that interprets spoken language into text and vice versa, thereby helping students with disabilities.
- Adaptive earning interfaces: These programs adjust the size of fonts, colour contrasts and layouts for each student with respect to their learning needs, whether in visual or cognitive terms.

7. Teacher support systems

- Professional development: AI-driven platforms offering personalized learning paths for teachers to develop new skills and stay updated with educational trends.
- Classroom management tools: The AI-related tools that would be of major importance in assisting a teacher's activities would include tracking attendance and monitoring students' activities, behaviour and interaction.

4. The possible visualization of AI in digital education

A picture of a new kind of classroom, where artificial intelligence is embedded in digital education, includes an efficient learning atmosphere that is dynamic, inclusive and supportive. The possible visualization of the image of the application of AI support might feature students interacting with tablets or laptops using an adaptive learning platform with the screen showing personalized lessons that each student receives, based on performance data, preferences and progress on an individual learning path. The AI-based virtual tutor avatar will guide students through complex topics with explanations and instant feedback. This virtual tutor changes its teaching style according to the engagement of students for an even more effective and interesting experience. (Popenici & Kerr, 2017)

The classroom is itself a centre of smart technology. Smartboards are used instead of old chalkboards and show dynamic information that the teachers may control on time to support or portray lessons more clearly. Many connected devices are alternately available in classrooms for students and teachers to get access to digital resources. This is not just limited to tablets and laptops but includes VR headsets for an immersive learning experience and IoT devices that make the lessons interactive.

Teachers can monitor the real-time progress of students by using AI-driven dashboards containing data from sources offering clear insights to performance. They bring into relief the areas that students are good in and areas that might need improvement and, therefore, enable teachers to intervene effectively and in time. Such insights happen in real-time; this assures timely learning interventions based on the very latest data. (Persico & Pozzi, 2015)

In this image, we see a varied group of students, each using different AI tools that cater to their specific learning needs and interests. Some students use language-translation apps to break the language barrier and be able to consider learning contexts. Others have virtual labs where they can do experiments and explore scientific concepts in a controlled, simulated setting. The interactive games, which are also part of the lesson, capture the attention of students by making a relatively dull activity interesting or are used as checking for understanding or practice.

The realization of this image would require in-service trainings for teachers on how to use AI tools for improving their teaching methods, making their lessons engaging and keeping students motivated. Such tools empower teachers with personalized learning pathways and resources that continually assist in revolutionizing their educational strategies. The AI analytics help teachers understand the impact of their practices and those areas where they can change for improvement.

This image clearly illustrates the broad adoption of AI technologies in education. This illustrates how AI personalizes the learning experience not only for the students, but also for teachers with high-quality teaching. The classroom is a place where traditional teaching methods are spiked with state-of-the-art technology, hence striking the proper balance of paying respect to the foundations of education and pushing the boundaries. In other words, AI images in digital education lean towards a learning atmosphere created with the integration of technology into human creativity in an adaptive, inclusive and very effective learning environment. All of these visualized features can benefit learners and at the same time empower teachers to make the journey through education a more collaborative and personalized experience. (Khosravi & Cooper, 2017)

5. The AI-based adaptive learning systems framework

According to the above presented study, the framework of the AI-based adaptive learning systems can be established based on the advantages as shown in Figure 1.

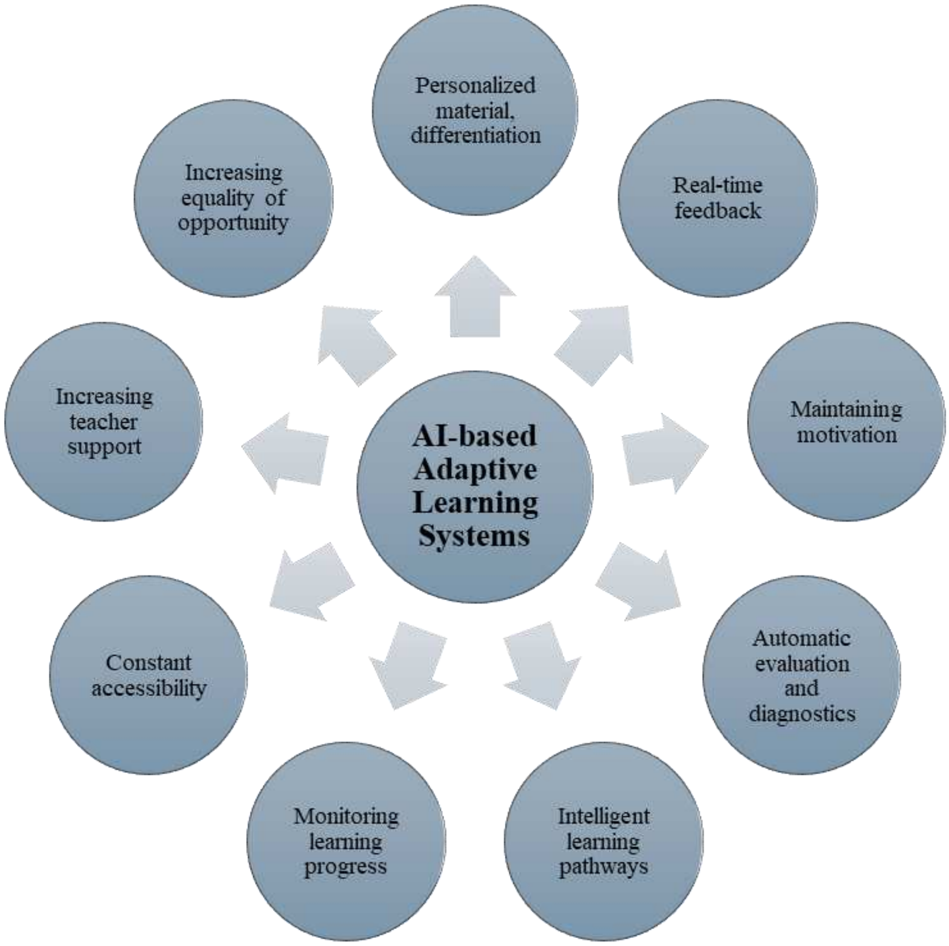

Figure 1. The AI-based adaptive learning systems framework

1. Personalized material or learning and differentiation: through AI the customization of educational content and learning approaches in a way that is more in tune with the preferences and needs of individual learners can be achieved. Differentiated groups can be better detected in regard to learning styles, strengths, weaknesses, and preferences, focusing on closer, more effective and personal learning experiences.

2. Real-time feedback: AI can provide instant feedback to students, which could help them realize errors and learn from them immediately. This would allow teachers to be able to offer interventions and support on time.

3. Maintaining motivation: AI can be used to create engaging, personalized and supportive learning experiences that keep students motivated. Techniques and tools that aim to leverage AI to keep motivation include personalized learning paths, gamification, real-time feedback and rewards, adaptive assessment, interactive content, social learning and collaboration, goal setting and progress tracking.

4. Automatic evaluation and diagnostics: AI in education is implemented to automatically assess and diagnose student performance, provide feedback, and spot learning gaps or areas of imperfection. AI can grade and assess automatically, leaving the teacher more time for other duties and providing the students with immediate feedback.

5. Intelligent learning pathways: ILP, with the help of AI and data analytics, will dynamically be able to adapt the content, pacing, and style of learning materials to optimize learning results. These pathways offering personalized learning experiences that are capable of significantly enhancing engagement and thus, effectiveness, are essential in today's education and corporate training environments.

6. Monitoring learning progress: Teachers can monitor learning progress by leveraging the data analytical skills, pattern recognition and predictive analysis into student performance provided by AI and thus, they can customize learning experiences. This would enable the learning progress to be monitored in real time and continuously, allowing for interventions or student support to be put in place.

7. Constant accessibility: Students can have continuous support, learning material and opportunities due to the constant accessibility ensured by AI without regard to time or location. AI, unlike human teachers, is always available for students and can be constantly productive.

8. Increasing teacher support: AI might be used to enhance teacher support, without any claim to completeness, including administrative duties, lesson plans, managing classroom behaviour, automatic grading and testing. Thanks to the AI-based support, teachers can focus more on other important factors of their profession, for example, giving students the personal touch or building community in the classroom.

9. Increasing equality of opportunity: AI could be used in increasing equality of opportunity in education as it would help solve existing disparities in access, learning experiences and support by personalizing the learning experience for all students.

6. Summary

AI-based adaptive learning systems can be integrated with traditional learning environments to support teaching and learning in the educational experience. In this hybrid approach, the maintenance of the structure and social benefits of traditional classroom settings would be combined with the AI-supported personalized learning. The field of adaptive learning is rapidly evolving, with emerging new trends and technologies. These include bringing forward advanced natural language processing to evoke improvements in interaction, the inclusion of virtual and augmented reality to create more immersive learning experiences and developing more sophisticated algorithms to increase personalization. Further developments of artificial intelligence tools and machine learning will probably continue to transform adaptive learning systems. Advancements in data analytics, predictive modelling and personalization algorithms will lead to a more efficient and engaging learning experience. Although AI-based adaptive learning is spreading, the role of educators, who adapt to new technologies and utilize them during teaching, remains crucial. Teachers have an important role in guiding and supporting students in the process of education, where technology facilitates rather than replaces human interaction and mentorship.

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