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USING AI-BASED TOOL MORPHCAST TO IMPROVE STUDENT ATTENTION AND ENGAGEMENT IN ASYNCHRONOUS LEARNING

Abstract. With online education's growing popularity, the quality assurance of the student learning process at a higher education institution has become particularly relevant. One of the key aspects of successful and effective online learning is maintaining a high level of student attention and engagement during various learning activities. This article explores the potential of exploring the possibilities of artificial intelligence (AI)-based tools to increase students' attention and engagement during asynchronous learning, namely by watching a video developed and integrated by the teacher into the e-learning course resources. In particular, the possibility of using the MorphCast AI tool to optimise pedagogical strategies in higher education to provide personalised feedback on students' attention levels and engagement during asynchronous learning. MorphCast AI, using artificial intelligence algorithms, analyses student behavioural data and provides teachers with valuable insights, such as emotional analytics, to improve the learning process. Such data allows teachers to promptly detect the general dynamics of decreasing student attention and engagement, as well as individual students who have particular difficulties with the perception of educational content, and provide them with personal support. The study was conducted as part of the academic practice in Information Technology for 1st-year students with a bachelor's degree in information technology, specialising in Software Engineering, Computer Science, Computer Engineering, Cybersecurity, Information Protection, Information Systems, and Technologies. As a result, it was concluded that the integration of MorphCast AI allows taking into account the emotional state of students, their attention and engagement in the learning process, providing a more individualised and adaptive educational experience for participants in the educational process.

Keywords: emotional state; attention; engagement; emotional analytics; MorphCast AI service; learning management systems (LMS)

1. INTRODUCTION

The problem statement. The rapid development of artificial intelligence technologies opens up new opportunities for optimising the learning process in asynchronous online courses. Artificial intelligence (AI) in online education has great potential to radically change the learning process and increase the productivity of participants in the educational process [1]. Asynchronous online courses are becoming increasingly widespread in higher education, which requires closer interaction between participants in the educational process [2]. O. Berestok [3] studied two main modes of e-learning - synchronous and asynchronous and compared their strategies, methods and goals. The author analysed the advantages and challenges of each approach, as well as the impact of these interaction formats on the effectiveness of the learning process. In this study, the author proposes using asynchronous learning in modern conditions as the primary type of learning, as it is more flexible and allows you to learn at a convenient time and anywhere. According to the study by M. Fadhilah et al. [4], both synchronous and asynchronous online learning methods have their advantages, but asynchronous learning promotes greater autonomy of students, provides flexibility and individualised pace of learning content. Providing fast and effective feedback through technical support based on interactive student content and improving communication are key aspects of asynchronous online interaction [5].

AI-based tools are essential in education, providing personalised learning experiences for students and automating routine tasks. Adaptive learning systems, such as Knewton, Smart Sparrow, etc., allow students to analyse their progress and adjust learning content to their needs, learning style, and level of knowledge. Voice assistants and AI tutors (Google Assistant, Alexa for Education, Squirrel AI) facilitate quick access to educational content and efficient organisation of the educational process. Among all AI tools used in education, systems for analysing the emotional state of students (iMotions, Viso Suite, MorphCast, Retorio, Affectiva, etc.) attract special attention as they help to personalise the learning process and increase their attention and engagement. One of these solutions is MorphCast, which allows you to track students' emotional reactions during synchronous and asynchronous interaction. However, despite its considerable potential, AI in education still needs to overcome several challenges related to student engagement, personalisation of learning, and effective interaction between participants in the educational process. The urgent need to integrate innovative AI-based tools that would overcome these challenges and increase the effectiveness of online learning is one of the most pressing tasks of modern education.

Analysis of recent studies and publications. In the context of rapid digitalisation, the global education system is adapting and exploring new technological innovations, such as artificial intelligence, the Internet of Things, and big data analytics, to improve educational systems. Classical education is transforming into distance education, given the conditions caused by the global pandemic and military operations in Ukraine [6, 7]. Today, there is a growing number of studies on automatic emotion recognition (AER) in the digital environment, as emotions play an essential role in students' learning process [8]. Personalised AI-based learning platforms, intelligent tutoring systems (ITS), and immersive virtual reality can improve student engagement and learning outcomes asynchronously [9].

One of the challenges for distance learning teachers is the ability to assess students' emotional reactions in learning management systems (LMS) [10]. B. Muzeyyen proposes a system that integrates a solution for recognising students' emotions with a learning management system [11]. According to L. Krithika and G. Lakshmi Priya [12], detected eye and head movements are essential for identifying students' emotional state and engagement during online learning. Computer vision allows us to analyse facial expressions, body posture, and hand gestures to assess participants' engagement levels in the educational process [13].

In the field of education, especially during the learning process in intelligent learning environments (ILEs), it is essential to take into account students' opinions (feedback) and emotional states to change and improve the content of learning [14]. Teachers do not interact directly with students during online learning, so most lose interest and eventually stop studying [15]. Existing online courses that provide the opportunity to create and deliver different types of learning content focus mainly on the development of student's knowledge and skills but do not take into account their individual needs and interests in the learning process and pay little attention to their satisfaction with education in modern conditions [16].

However, maintaining students' attention and engagement during asynchronous learning is a significant challenge for educators. Traditional approaches to teaching often do not consider students' individual needs, which can decrease their motivation and, accordingly, their academic performance. Accordingly, there is a need to use a tool that would allow you to track students' attention and engagement while organising various types of learning activities. One such tool is the MorphCast AI service. In [17], it investigated the criteria for assessing the effectiveness of such tools in the educational process. It explored the capabilities of the MorphCast tool for analysing students' attention and engagement during synchronous interaction.

The research goal. The study aims to determine the capabilities of the MorphCast AI tool to optimise pedagogical strategies in higher education by providing personalised feedback on students' attention and engagement levels during asynchronous learning.

2. RESEARCH METHODOLOGY

The study was conducted at the National University of Life and Environmental Sciences of Ukraine (NULES). The students' participation was not mandatory, and they were verbally asked to consent before the study. All students were briefed on its purpose, how an AI-based tool like MorphCast AI works, and the expected results. They explained that MorphCast AI analyses facial expressions in real-time to detect their emotions (joy, sadness, surprise, etc.) without storing video or identifying data. While watching the video, the system requested that students access their device's camera to read their emotions. If the consent was not confirmed, the student could watch the video content without reading emotions and their level of attention and engagement. They were also informed that the results of the emotion analysis did not affect their grade or academic performance. One hundred thirty-four first-year students of the Bachelor's degree program in Knowledge Area Information Technology, specialities Software Engineering, Computer Science, Computer Engineering, Cybersecurity and Information Protection, Information Systems and Technologies agreed to participate in the experiment. The experimental study was conducted as part of the educational practice in Information Technology.

The research results presented in the article are presented in the aggregate of the joint contribution of individual authors: idea and preparation of the draft article (O. Hlazunova); analysis of publications to substantiate the relevance of the research problem, international experience in recognising students' emotions (T. Sayapina); user story modelling of the process of creating interactive video content by the end user using an AI-based tool and using it in the organisation of the educational process (V. Korolchuk, O. Hlazunova), video development using the MorphCast AI tool, example of implementation and organisation of the experiment (T. Voloshyna, V. Korolchuk), analysis of the dynamics of changes in students' attention and engagement during asynchronous learning (V. Kravchenko).

3. RESEARCH RESULTS

Figure 1 shows the user story of the process of creating interactive video content by an end user (teacher) using an AI-based tool and its use in the organisation of the educational process. Tracking the emotional state of students while watching the recorded video allows the teacher to receive feedback and improve their attention and engagement.

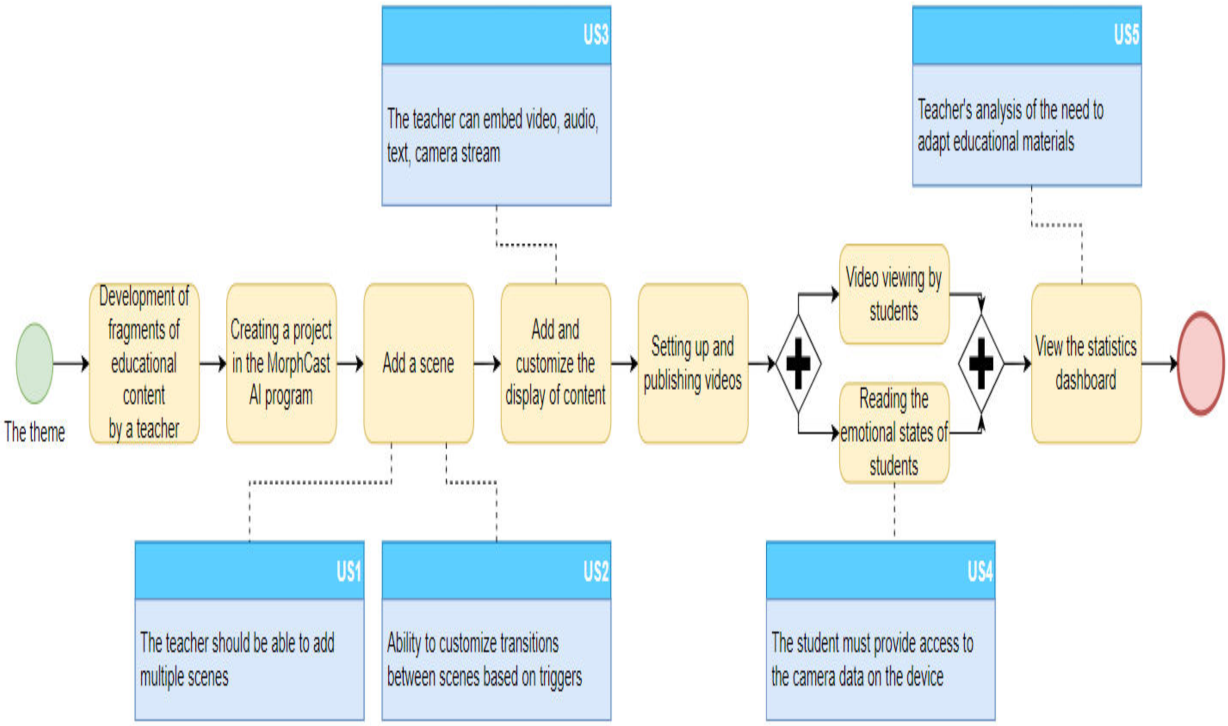

Figure 1. User story

At the initial stage, the teacher defines the topic for the training materials and develops the structure of such content, according to which the necessary video fragments are recorded. First, a new project is created in MorphCast AI, into which the developed educational content is imported. Within the project, the teacher creates different scenes filled with relevant content. Each of them can contain various types of academic content: video, audio, text, and images, which makes the lesson more interactive and engaging for students. The teacher can customise the content display according to students' attention, engagement, emotional states, or other triggers. After filling the scenes with relevant content, the teacher adjusts the order of the scene sequence, the transition conditions between them, and other parameters for displaying the educational video content. Accordingly, the content is shown to students based on the data obtained about their emotional state, attention, and engagement. This allows you to create an individual learning path for each student, considering their level of knowledge and learning style. Once the video content is created, the instructor sets up the display and embeds the video content into the e-learning course (eLearning) resources on the learning platform. In asynchronous mode, students can view the published content at their convenience and as often as needed. The tool records students' activity and interaction with the presented learning content during viewing. It reads the emotional state of students by analysing the video stream from the camera after they have given the appropriate permission to use it. The AI-powered tool determines the emotional state of students by analysing their facial expressions while watching video content.

All the data obtained about students' emotional state, attention, and engagement associated with a specific video viewing time and project fragments are saved. The data obtained is analysed and visualised by an AI-based tool and displayed on the corresponding project dashboard. This dashboard allows the teacher to view relevant visualisations about the students who viewed the content (age, gender), the emotional states of students while watching different fragments of video content, their attention and engagement, and identify moments when students had difficulty understanding the presented educational content or lose interest in viewing the material. Based on this analysis, the instructor can make changes to the content of the learning content or the way it is presented to students.

At the same time, the teacher should provide the functionality necessary to create videos and analyse the data obtained, such as student attention and engagement described in user stories (US1, US2, US3, US5), as well as student access to the data (US4).

US1: The instructor can add one or more initially defined scenes. This will make the learning process more interactive and control students' learning content based on their attention and engagement.

US2: The AI-based tool supports adaptive navigation through video content. This feature allows the teacher to simulate transitions from one piece of educational content (scene) to another sequentially and by taking into account the age, gender, attention, engagement, emotional state of students, or another trigger. The teacher pre-selects the triggers that will be used to make this transition between different scenes.

US3: The teacher can add different types of content to the video lesson. Such content can be pre-recorded video fragments, camera recordings, audio, text, or images. Other types of content allow not only to create diverse and interesting videos but also to present information in a way that is easy for the student to understand or to focus on the necessary details.

US4: A student can share the camera data of their device. When watching a video created in MorphCast AI, students will be prompted to turn on the camera and access the data. This way, when students watch a video, their attention level, engagement, and emotional states will be read. This feature can track the student's emotional state while watching video content and create more personalised recommendations.

US5: The teacher can analyse data on student interaction with the available video content and adapt learning materials to their needs. For each project the teacher creates, a separate dashboard is created, which will present visualised analytical data on the views of a particular video. On this dashboard, the teacher can track the total number of views, the level of attention and engagement of students, and their emotional states while watching the video, and analyse the data obtained both in general and by gender and age of students.

This study examined how students' attention and engagement changed during asynchronous interaction as part of an IT classroom practice. Teachers developed a video using the MorphCast AI tool (Figure 2), which was subsequently distributed to students; they could watch it at their convenience and in the amount they needed. Students watched the video 164 times during the three weeks of their internship.

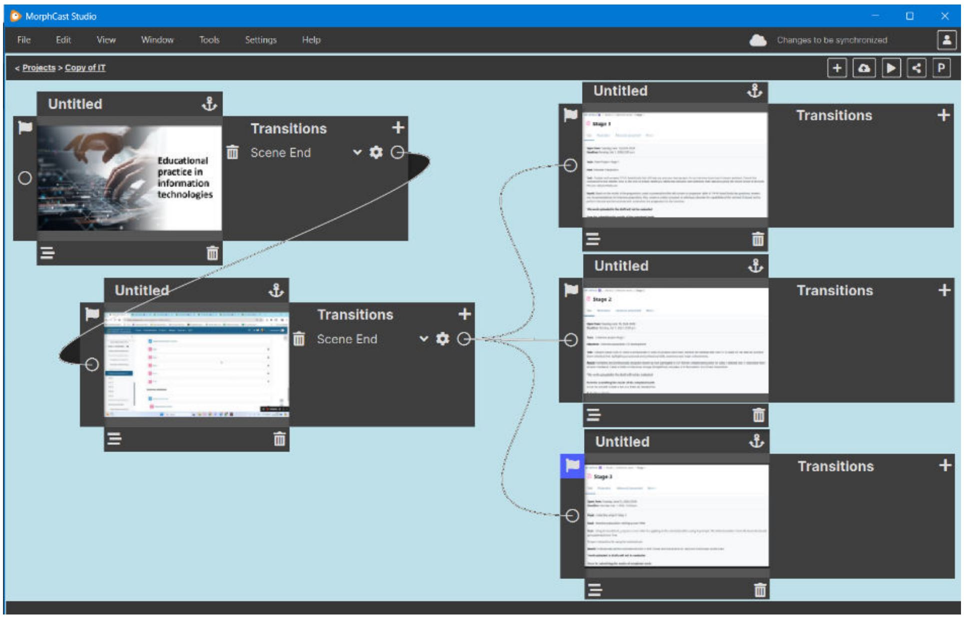

Figure 2. An example of using the MorphCast AI tool

If necessary, the teacher can monitor the level of attention and engagement and adapt the learning content in real time to student's needs, level of knowledge, and learning styles. For this purpose, appropriate triggers should be provided at the stage of its creation. For each video, you can add a trigger based on data received from the student's device or read from facial expressions while watching the content. Such triggers include Wish, Emotion, Affect, Age, Gender, Attention, Positivity, Presence, Feature, Head Pose, Date, Day, Month, Time, Position, Display Orientation, Device, Browser, Social. The teacher can configure the parameters for each trigger and what actions the tool should take depending on the data. For example, given the level of students' attention (above or below a certain threshold), the teacher can set up additional video viewing, click on a hyperlink to an additional resource, etc. Figure 3 demonstrates the ability to configure one of the triggers during video playback depending on the student's attention level.

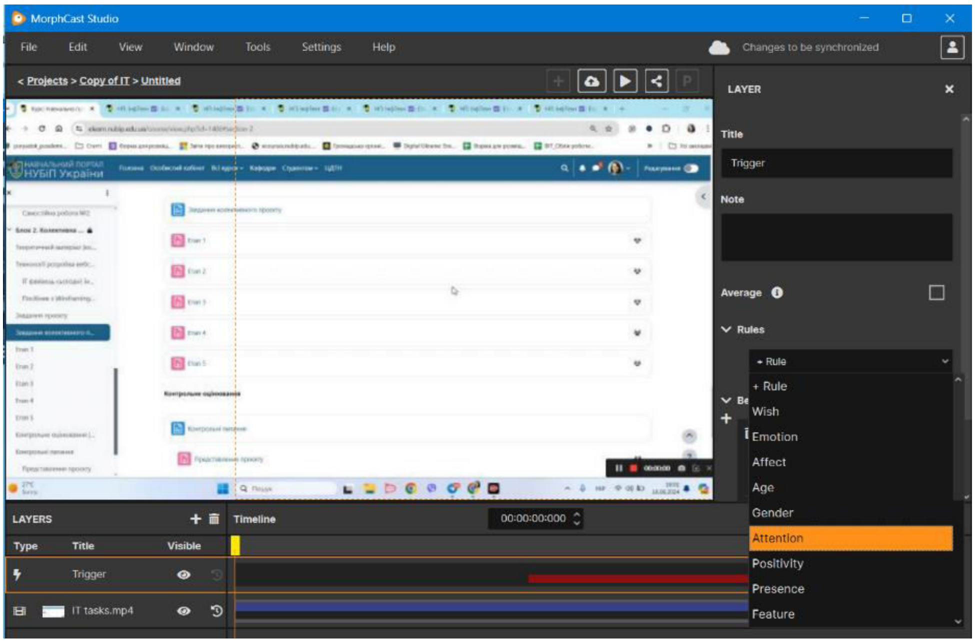

Figure 3. An example of setting up a trigger on the MorphCast AI tool

Over three weeks of practice, students watched the proposed video and agreed to have their emotions read. During these reviews, attention and engagement levels were measured from 0 to 100%, with 100% being the maximum.

Figure 4 shows the dynamics of attention changes throughout the entire period of video viewing by students. The graph shows significant fluctuations in attention measurements over time, indicating that students' attention levels constantly change during video viewing. Periodic highs in the measurements indicate moments of high attention, and lows indicate loss of attention or distraction during the video. The student's attention level was relatively high most of the time.

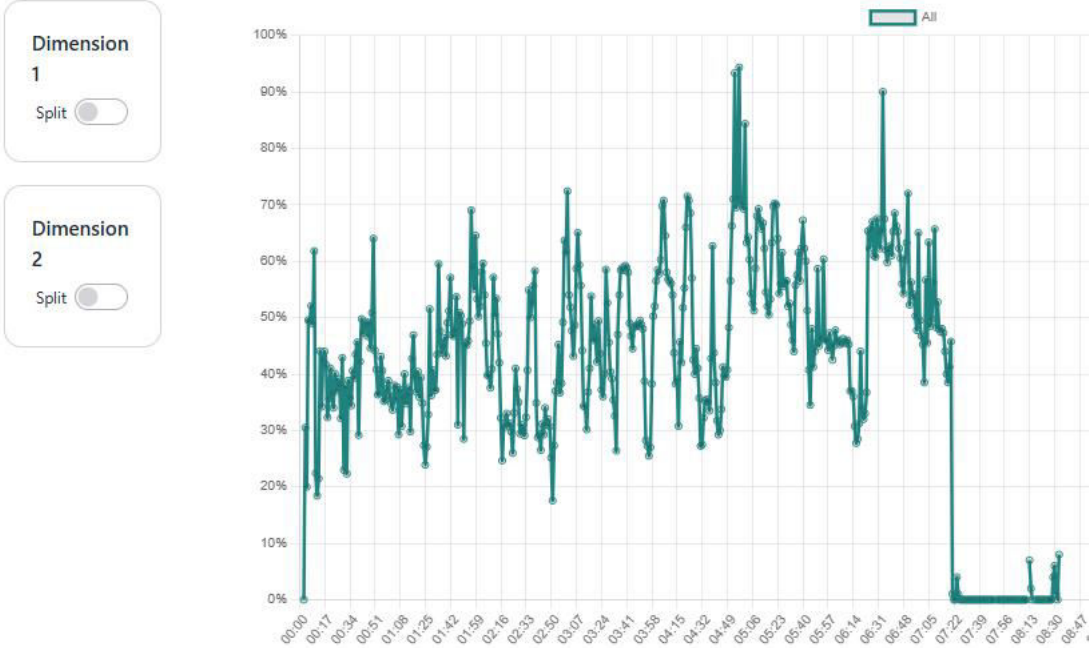

Figure 4. Dynamics of changes in student attention (according to MorphCast AI)

The graph shows significant fluctuations in the attention measurements over time, indicating that students' attention levels constantly change while watching the video. The periodic peaks in the measurements indicate moments of high attention (above 70%), and the lows indicate loss of attention or distraction during the video (less than 20%). Most of the time, students' attention levels were relatively high. This graph shows two peak periods of students' attention (over 90%) during the video, associated with the change in the type of content presentation.

Figure 5 shows the dynamics of changes in two dimensions over time for two groups of students: male students and female students. The data demonstrated are related to the level of students' attention when interacting with learning content in asynchronous mode. The level of attention in both groups is constantly changing, which is quite natural for any person performing tasks that require concentration. The graph clearly shows increased and decreased attention for both male students and female students. This could be due to various factors, such as the complexity of the material, external distractions, or individual student characteristics. A particular difference is observed in the dynamics of changes in the dimensions between male students' and female students' attention. This is because representatives of different genders have different strategies for interacting with learning content or different reactions to it. Since the MorphCast AI tool provides data on the level of attention and engagement of students by gender, it can become a tool that will allow you to implement a gender-oriented approach to learning.

Figure 5. Attention dynamics by gender (according to MorphCast AI)

As can be seen from the graph showing the level of students' attention in the context of the article, there are periodic peaks (increased attention) and troughs (decreased attention) in both groups. The average level of attention for male students was within 63%, and for female male students, the average value was 71%. This indicates that female students, on average, demonstrated slightly higher levels of attention while watching the video than male students. However, it should be noted that during specific periods of the video, male student's attention was higher than female students, especially in the second half.

The change in the level of students' engagement while watching an educational video is shown in Figure 6. A high level of student engagement is observed at the beginning of video viewing, possibly due to the novelty and relevance of the content and the student's interest in the proposed topic. Students' attention is stable during the first minutes of watching the video. Still, after a while, a gradual decrease in engagement may be due to their fatigue or decreased interest in the topic.

Figure 6. Dynamics of changes in student engagement (according to MorphCast AI)

Analysing the level of student engagement during the video, we noted its constant fluctuations. The graph shows increased (peaks) and decreased (dips) engagement periods. The level of engagement indicates the concentration of students while watching the video. The average level of student engagement was around 34%, and there was a drop in student engagement during certain parts of the video. Identifying the moments when students lose engagement allows you to change the training video to improve the effectiveness of interaction.

There is usually a drop in engagement and attention in the middle of a video, which is typical for long-form learning materials. However, engagement can temporarily increase by embedding interactive elements, visual cues, or student polls into the video. After these moments, interest may drop again, especially towards the end of the video. At the end of the video, there is usually another brief spike in engagement as students wait for the summary or conclusion and answers to their questions. The engagement dynamics generally reflect a typical ‘wave-like’ trend, with students' engagement decreasing in the middle and increasing at the beginning and end. This dynamic type is typical for medium-length (10-20 minutes) educational videos, where students maintain attention at the beginning, decrease it in the middle, but become more active again at the end. Optimising the footage by adding interactive elements or changing the pace of the material can improve the overall level of student engagement.

A description of the dynamics of student engagement while watching a video in the context of an article is presented in Figure 7.

Figure 7. Changes in engagement by gender (according to MorphCast AI)

The analysis of students' engagement in terms of gender allowed us to note that male students were more engaged at the beginning of the video. Female students showed higher engagement during the second half of the video. In general, male students' average level of engagement was about 29%, and female students was 41%.

According to the data presented in the graph, female students' engagement while watching the video is initially high, which may indicate their interest and attention to the new material. During the first minutes of the video, female students demonstrate a stable level of engagement, but then there is a gradual decline, especially in the middle. This may be due to fatigue or decreased interest in lengthy content. At the end of the video, especially if there are summaries or questions for reflection, female students' engagement increases again, indicating their readiness to absorb key information and summarise.

The dynamics of male students' engagement while watching a video differ from that of female students. At the beginning of the video, engagement is also high, but there is a rapid decline in attention compared to female students. In the middle of the video, male students show more significant fluctuations in engagement, which may be due to their response to specific elements of the video (e.g., new facts or interactive inserts). At the end of the video, male students' engagement increases. Still, this increase is less pronounced than for female students, which may indicate a less intense interest in the outcome or final moments of the video.

An analysis of changes in student engagement by gender shows that female students are more stable in maintaining attention throughout viewing but also tend to lose engagement in the middle of the content. Conversely, male students show sharper attention fluctuations and are more likely to be distracted but respond to interactive elements and content updates. Optimising your training video to account for these differences can help improve the overall learning experience for both groups.

4. DISCUSSION

It is worth noting that using artificial intelligence (AI)-based tools to increase students' attention and engagement in asynchronous learning is an essential trend in modern educational practice. AI capabilities can significantly change learning approaches by providing personalised and interactive learning environments that help increase student motivation and learning outcomes. Integrating artificial intelligence into the educational environment can serve as a basis for developing both the strategy of an academic institution and individual content training components of the educational program [18]. M. Yousuf et al. concluded [19] that modern web technologies and artificial intelligence technologies enable educators to create a personalised, interactive, and adaptive learning environment that significantly increases student engagement and, as a result, learning outcomes.

One of the challenges for teachers in distance learning is the ability to assess the emotional states of their students. A. Favareto et al. argue that modern learning management systems use formal language in the assessment process, such as questions, answers, etc. However, they cannot consider the emotional reactions expressed by the student during the assessment process [10].

AI-based tools can provide personalised learning, which is essential for increasing student engagement. For example, according to R. Sangarsu [9], platforms with intelligent learning systems and virtual reality can create interactive and individualised learning environments that promote active student engagement. In addition, AI can automatically assess student concentration in online courses, allowing teachers to intervene in time and adjust the learning process. M. Bulut studied the impact of combining student emotion recognition with a learning management system on student motivation and academic achievement [11].

Research by D. Duraes et al. has shown that using new tools related to student, teacher, content, technology, software, and communication leads to improved teaching methods in online learning. Students' academic emotions play an essential role in cognition, acquisition of new knowledge, and decision-making. Thus, they directly affect the perception, learning process, and the way of communication between participants in the educational process [20].

According to T. Wang et al. AI can significantly improve asynchronous learning by supporting students' cognitive and social presence. Systems based on generative AI can simulate learners, support multimodal interactions, and improve mental and social presence in asynchronous learning environments [21]. This will increase the effectiveness of the asynchronous approach to learning.

The ability of teachers to analyse and evaluate students' behaviour and emotional states during online learning is a key factor in ensuring the high quality of the educational process. Z. Trabelsi et al. determined that AI-based behavioural recognition methods can help assess students' attention and interest during classes [4]. In turn, S. Gupta et al. proved that student engagement is determined by automatically analysing facial emotions during online learning [22].

The gender gap in education favouring girls is a widely known phenomenon. Boys tend to have higher dropout rates, lower grades, and lower engagement. Support for autonomy and engagement partially mediate the relationship between gender and behavioural engagement. Support for independence was a protective factor for boys‘ engagement but not girls’[23].

E. Bru et al. studied gender differences in the relationship between perceived teacher support (emotional support, structuring of learning activities, support of the learning process) and student engagement (behavioural engagement, emotional engagement). According to the hypothesis, girls showed a higher level of behavioural engagement than boys. Interestingly, the relationship between structuring learning activities and engagement was more substantial for males, while the relationship between support for learning and emotional engagement was more substantial for females. These findings suggest that teachers may contribute to engagement differently for male and female students (providing structure) and facilitating a deeper understanding of subject material) [24]. The results also show no statistically significant differences in behavioural, emotional or cognitive subtypes of engagement related to gender and discipline. Learning strategies and student engagement are key to achieving the intended learning outcomes [25]. The available tools for determining the emotional state of students, their level of attention and engagement have several limitations related to objectivity, cost, and reading emotions from the face may not be accurate enough and do not consider the full range of their manifestation [26, 27]. Despite significant technological advances, improving tools requires achieving an optimal balance between accuracy, practicality and inclusiveness. This is a prerequisite for their effective integration into the digital learning environment of educational institutions.

Tools that use artificial intelligence algorithms have significant potential to improve both attention and engagement in asynchronous learning. Such tools can enhance student outcomes and provide personalised and interactive learning. However, data privacy issues must be considered before these technologies can successfully be integrated into the learning process.

5. CONCLUSIONS AND PROSPECTS FOR FURTHER RESEARCH

The MorphCast artificial intelligence tool in online education demonstrates significant potential to increase student engagement and learning efficiency in the modern environment. The results of the study confirm that analysing data on student behaviour can become a teacher's tool that will allow you to quickly identify difficulties in understanding different types of educational content and adapt the learning process to the individual needs of each student, their level of knowledge, learning style, etc. In addition, MorphCast contributes to a deeper understanding of the emotional state of students, which helps teachers avoid overloading them with educational content and reduce negative emotions during the learning process. The functionality of this tool also allows you to consider gender differences in the perception of academic content in asynchronous mode. However, these general trends, not absolute rules, must be considered when organising the educational process. Every student is an individual, and their level of attention and engagement depends on many factors, such as the type of learning material, time of day they watch the video, motivation, etc.

At the same time, there are certain limitations of MorphCast, namely the difficulty of determining a student's emotional state, as human emotions are multidimensional and may include mixed states that the system cannot accurately recognise. Dependence on video quality, poor camera quality, or insufficient lighting can significantly reduce the accuracy of the analysis. Introducing such tools creates a morpersonaliseded, interactive, and practical digital learning environment in higher education, improving teaching quality and student performance. Still, teachers must carefully approach them to avoid technical, ethical, and pedagogical challenges. Teachers must interpret the results of emotional analysis correctly and create conditions in which students do not feel uncomfortable or distrustful, thus helping to maintain trust between participants in the educational process and supporting academic integrity.

Further development of the study is planned in the direction of developing recommendations for the use of artificial intelligence tools to manage students' learning activities in synchronous and asynchronous learning, taking into account various educational components, forms of knowledge and levels of complexity of educational content presentation, as well as the introduction of methods for training teachers to use AI-based tools and further emotional analysis, which will help to build trust between participants in the educational process and ensure academic excellence.

REFERENCES (TRANSLATED AND TRANSLITERATED)

[1] E. Yousuf, A. Wahid & M. Khan. "Exploring the Effectiveness of AI Algorithms in Predicting and Enhancing Student Engagement in E-Learning." *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no 10, pp. 23–29, 2023. https://doi.org/10.17762/ijritcc.v11i10.8460. (in English).

[2] H. Yang & E. Romero-Hall. "A Pilot Study Exploring Interaction and Student Satisfaction in Asynchronous Courses in Higher Education". *Tech Trends*, vol. 68, pp. 761-770, 2024. https://doi.org/10.1007/s11528-024-00986-7. (in English).

[3] O. V. Berestok, "Synchronous and asynchronous e-learning modes: strategies, methods, objectives". *Engineering and Educational Technologies*, vol. 9, no 1, pp. 19-27, 2021. (in English).

[4] M. Fadhilah, S. Sutrisna, S. N. Muslimah, & M. T. Ihsan, (2021). "An Exploring Methods in Online Learning: Synchronous and Asynchronous". *Indonesian Journal of Research and Educational Review*, vol. 1, no 1, pp. 74-81. https://doi.org/10.51574/ijrer.v1i1.55. (in English).

[5] N. Ma, Y. Zhang, C. Liu, & L. Du. "The comparison of two automated feedback approaches based on automated analysis of the online asynchronous interaction: a case of massive online teacher training". *Interactive Learning Environments*, vol. 32, no. 7, pp. 3818–3839, 2023. https://doi.org/10.1080/10494820.2023.2191252. (in English).

[6] Z. Trabelsi, F. Alnajjar, M. Parambil, M. Gochoo, & L. Ali. "Real-Time Attention Monitoring System for Classroom: A Deep Learning Approach for Student's Behavior Recognition". *Big Data and Cognitive Computing*, vol. 7, no. 1, p. 48, 2023. https://doi.org/10.3390/bdcc7010048. (in English).

[7] O. G. Glazunova, A. M. Hurzhii, V. I. Korolchuk, and T. V. Voloshyna, "Selection of digital tools for organizing students' group work in distance education", Information Technologies and Learning Tools, vol. 94, №2, pp. 87-101, 2023. doi: https://doi.org/10.33407/itlt.v94i2.5211. (in English).

[8] Y. Shuzhen, A. Androsov, Y. Hanbing & Y. Chen. "Bridging computer and education sciences: A systematic review of automated emotion recognition in online learning environments". *Computers and Education*, vol. 220, no. 105111, 2024. https://doi.org/10.1016/j.compedu.2024.105111. (in English).

[9] R. Sangarsu. "Enhancing Student Engagement in Learning with Modern Web and AI Technologies". *International Journal of Science and Research (IJSR)*, vol.12, no.1, pp.1439–1442, 2023. https://doi.org/10.21275/sr231017100712. (in English).

[10] A.L. Favareto, L.A.L. Teixeira Jr., F. de Franco Rosa & R. Bonacin. "Integrated Solution for Evaluating Emotional Expressions in Learning Management Systems". *Lecture Notes in Computer Science*, vol. 14050, 2023. https://doi.org/10.1007/978-3-031-35891-3_3. (in English).

[11] B. Muzeyyen. "The effects of merging student emotion recognition with learning management systems on learners' motivation and academic achievements". *Computer Applications in Engineering Education*, vol. 26, no. 5, pp. 1862–1872, 2018. (in English).

[12] L. B. Krithika & G. G. Lakshmi Priya. "Student Emotion Recognition System (SERS) for e-learning improvement based on learner concentration metric". *Procedia Computer Science*, vol. 85, pp. 767–776, 2016. doi:10.1016/j.procs.2016.05.264. (in English).

[13] K. Sharma, M. Giannakos & P. Dillenbourg. "Eye-tracking and artificial intelligence to enhance motivation and learning". *Innovative Learning Environments*, vol. 7, no. 1, pp. 1–19, 2020. doi:10.1186/s40561-020-00122-x. (in English).

[14] M. L. B. Estrada, R. Z. Cabada, R. O. Bustillos & M. Graff. "Opinion mining and emotion recognition applied to learning environments". *Expert Systems with Applications*, vol. 150, p. 113265, 2020. https://doi.org/10.1016/j.eswa.2020.113265. (in English).

[15] A. Baqach & A. Battou. "A new sentiment analysis model to classify students' reviews on MOOCs". *Education and Information Technology*, vol. 29, no. 13, pp. 16813–16840, 2024. https://doi.org/10.1007/s10639-024-12526-0. (in English).

[16] O. Hlazunova, R. Schlauderer, V. Korolchuk, T. Voloshyna, T. Sayapina, I. Kostenko & R. Zolotukha. "Implementation of microlearning technology for economics students through online courses". *Information Technologies and Learning Tools*, vol. 100, no. 2, pp. 110–121, 2024. https://doi.org/10.33407/itlt.v100i2.5554. (in English).

[17] O. Glazunova, I. Savytska, V. Korolchuk, T. Voloshyna, and T. Saiapina. "Managing student engagement during the educational process using the MorphCast AI tool". V. Ermolayev et al. (Eds.): *ICTERI 2024*, CCIS 2359, pp. 1-13, 2025. https://doi.org/10.1007/978-3-031-81372-6_10. (in English).

[18] O. Kuklin, I. Ivanova & T. Borovyk. "Modelling artificial intelligence integration into the educational environment". *Information Technologies and Learning Tools*, vol. 103, no. 5, pp. 207-232, 2024. https://doi.org/10.33407/itlt.v103i5.5735. (in Ukrainian).

[19] M. Yousuf, A. Wahid & M. Y. Khan. "Exploring the Effectiveness of AI Algorithms in Predicting and Enhancing Student Engagement in E-Learning". *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 10, pp. 23–29, 2023. https://doi.org/10.17762/ijritcc.v11i10.8460. (in English).

[20] D. Duraes, R. Toala & P. Novais. "Emotion Analysis in Distance Learning". *Advances in Intelligent Systems and Computing*, vol. 1328, pp. 629–639, 2021. DOI:10.1007/978-3-030-68198-2_58. (in English).

[21] T. Wang, T. Wu, H. Liu, C. Brown & Y. Chen. "Generative Co-Learners: Enhancing Cognitive and Social Presence of Students in Asynchronous Learning with Generative AI", 2024. https://doi.org/10.48550/arXiv.2410.04365. (in English).

[22] S. Gupta, P. Kumar, & R. K. Tekchandani. "Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models". *Multimedia tools and applications*, vol. 82, no. 8, pp. 11365–11394, 2023. https://doi.org/10.1007/s11042-022-13558-9. (in English).

[23] S. Lietaert, D. Roorda, F. Laevers, K. Verschueren & B. De Fraine, "The gender gap in student engagement: The role of teachers' autonomy support, structure, and involvement". *The British journal of educational psychology*, vol. 85, no. 4, pp. 498-518, 2015. https://doi.org/10.1111/bjep.12095. (in English).

[24] E. Bru, T. Virtanen, V. Kjetilstad & C. Niemiec. "Gender Differences in the Strength of Association between Perceived Support from Teachers and Student Engagement". *Scandinavian Journal of Educational Research*, vol. 65, pp. 153-168, 2019. https://doi.org/10.1080/00313831.2019.1659404. (in English).

[25] M. Abulela & W. Bart. "Learning and study strategies and engagement among Egyptian undergraduates: do gender and discipline matter?". *Educational Psychology*, vol. 41, pp. 1160-1179, 2020. https://doi.org/10.1080/01443410.2020.1834076. (in English).

[26] E. Gottardo & A. Pimentel. "Inferring Students' Emotions Using a Hybrid Approach that Combine Cognitive and Physical Data". In: *Hammoudi, S., Śmiałek, M., Camp, O., Filipe, J. (eds) Enterprise Information Systems. ICEIS 2018. Lecture Notes in Business Information Processing*, vol. 363, pp. 283-302. Springer, Cham. https://doi.org/10.1007/978-3-030-26169-6_14. (in English).

[27] C. Llurba, G. Fretes & R. Palau. "Classroom Emotion Monitoring Based on Image Processing". *Sustainability*, vol. 16, no. 2, pp. 916, 2024. https://doi.org/10.3390/su16020916. (in English).

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ВИКОРИСТАННЯ ІНСТРУМЕНТУ НА ОСНОВІ ШТУЧНОГО ІНТЕЛЕКТУ MORPHCAST ДЛЯ ПОКРАЩЕННЯ УВАГИ ТА ЗАЛУЧЕНОСТІ СТУДЕНТІВ В АСИНХРОННОМУ НАВЧАННІ

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Анотація. Зі зростанням популярності онлайн-освіти особливої актуальності набуло питання якісного забезпечення процесу навчання студентів у закладі вищої освіти. Одним з ключових аспектів успішного та ефективного такого виду навчання є підтримка високого рівня уваги та залученості студентів під час різних видів навчальної діяльності. Дана стаття досліджує потенціал вивчення можливостей інструментів на основі штучного інтелекту (ШІ) для підвищення уваги та залученості студентів під час асинхронного навчання, а саме переглядаючи відео, розроблене та інтегроване викладачем у ресурси електронного навчального курсу. Зокрема можливості використання інструменту MorphCast AI для оптимізації педагогічних стратегій у сфері вищої освіти з метою забезпечення персоналізованого зворотного зв'язку щодо рівнів уваги та залученості студентів під час асинхронного навчання. MorphCast AI, використовуючи алгоритми штучного інтелекту, аналізує поведінкові дані студентів та надає викладачам цінні інсайти, а саме емоційну аналітику, для покращення навчального процесу. Такі дані дозволяють викладачам своєчасно виявляти загальну динаміку зменшення уваги та залученості студентів, які відчувають певні труднощі зі сприйняттям навчального контенту, та надавати їм індивідуальну підтримку. Дослідження було проведено в межах навчальної практики з дисципліни Інформаційні технології для студентів 1 курсу освітнього ступеня Бакалавр галузі знань Інформаційні технології спеціальностей Інженерія програмного забезпечення, Комп'ютерні науки, Комп'ютерна інженерія, Кібербезпека та захист інформації, Інформаційні системи та технології. У результаті був зроблений висновок, що інтеграція MorphCast AI дозволяє враховувати емоційний стан студентів, їхню увагу та залученість у процес навчання, забезпечуючи індивідуалізований та адаптивний освітній досвід учасників освітнього процесу.

Ключові слова: емоційний стан; увага; залученість; емоційна аналітика; ШІ-інструмент MorphCast; системи управління навчанням (LMS)