ARTIFICIAL INTELLIGENCE AND EDUCATIONAL TECHNOLOGIES: AN EMOTIONAL APPROACH TO ADAPTIVE LEARNING

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To cite this article: Sysoiev, O. (2024). Artificial intelligence and educational technologies: an emotional approach to adaptive learning. *Education: Modern Discourses, 7*, 114–120. https://doi.org/10.37472/2617-3107-2024-7-11

Abstract. *Modern education requires innovative approaches that consider both cognitive and emotional aspects of learning. This paper presents the concept of an adaptive educational platform that utilizes artificial intelligence technologies for analysing students' emotional states and integrating an emotional approach into the educational process. The platform is based on advanced machine learning methods, including convolutional and recurrent neural networks, as well as ensemble learning algorithms. Special attention is paid to data protection and ethics, emphasizing developers' responsibility to all participants in the educational process. The author concluded that for further development it is necessary to strengthen interdisciplinary collaboration between artificial intelligence experts and educational researchers, enhance educators' competencies in artificial intelligence and educational technologies, and develop ethical standards governing data use. The implementation of the described technological and methodological solutions will enable the development of a functional educational platform prototype and conduct comprehensive most effective use of digital tools and platforms.*

Keywords: *emotional approach; artificial intelligence; adaptive learning; emotional intelligence; personalization; educational technologies; convolutional neural networks; recurrent neural networks; emotion analysis; ethics.*

INTRODUCTION, PROBLEM STATEMENT

The rapid development of artificial intelligence (AI) technologies opens new possibilities in education, enabling the creation of personalized educational trajectories and adaptive learning systems. Such approaches not only increase the flexibility of the educational process but also ensure improved student engagement through consideration of their emotional state. According to research, the emotional component of learning plays a key role in students' cognitive development, contributing to a 23–30 % increase in material retention efficiency (Santos-Guevara & Rincon-Flores, 2023; Stracqualursi & Agati, 2023; Zapotichna, 2024).

The integration of emotional approaches into adaptive educational systems requires a comprehensive understanding of the relationship between emotions, cognitive processes, and technologies. Fredrickson (2002) emphasizes that positive emotions expand cognitive abilities, including attention, memory, and problem-solving, which is confirmed by research in digital education. The implementation of technologies such as gamification and adaptive learning helps reduce stress and create a favourable emotional environment for effective learning (Micheal & Marjadi, 2023; Pereira & de Lima, 2023).

Current research shows that the use of AI in education contributes to creating personalized approaches that adapt to students' emotional states. These technologies include emotional data analysis through computer vision, speech analysis, and biometric indicators, allowing for dynamic changes in material complexity and information delivery formats (Kashyap et al., 2024). This approach ensures improved academic performance and the formation of sustainable self-learning skills.

THEORETICAL FOUNDATIONS AND CURRENT STATE OF THE RESEARCH

With the development of artificial intelligence and its integration into education, there has been a significant increase in publications in this field, especially after 2016. According to bibliometric analysis conducted by Pan et al. (2021), the main contributing countries are the USA (72 publications), China (50 publications), England and Spain (21 publications each). Despite this, bibliometric analysis also shows that the potential of AI technologies has not been fully realized in higher education. This may be related to the knowledge gap between AI experts and educational researchers.

The effectiveness of educational strategies remains a subject of intensive research. The emotional approach in education, involving conscious perception, processing, and expression of emotions, significantly improves educational outcomes. Ryan & Deci's (2000) self-determination theory emphasizes that satisfying basic needs for autonomy, competence, and relatedness creates the foundation for intrinsic motivation. The growth mindset proposed by Dweck (2006) proves that students' belief in their ability to develop their capabilities reduces their fear of mistakes and maintains engagement.

Fredrickson's research shows that positive emotions substantially enhance cognitive flexibility and learning effectiveness. When positive emotions are integrated into the educational process, there is an increase in motivation and student resilience to difficulties (Fredrickson, 2002).

Current research confirms the significance of the emotional component in technology-mediated learning. Santos-Guevara & Rincon-Flores (2023) demonstrate that the implementation of gamification elements contributes to reducing negative emotions and strengthening positive emotional states, especially in complex subject areas such as mathematics. This is supported by research from Pereira & de Lima (2023), showing that innovative gamification technologies improve educational outcomes through creating a positive emotional background. In the context of professional education, Micheal & Marjadi (2023) found that the use of gamification and interactive learning methods in medical schools improves knowledge retention due to students' positive emotional response. Stracqualursi & Agati (2023) emphasize the effectiveness of adaptive learning and gamification in creating a favourable emotional learning environment.

Research by Stanton et al. (2000) shows that emotional processing includes active exploration of meanings and understanding of one's emotions, while emotional expression is realized through writing, creativity, and social interactions. The influence of emotions on attention, memory, and decision-making has been empirically proven, confirming their key role in cognitive and emotional adaptation.

The fundamental understanding of the relationship between emotions and cognitive processes is supported by research (Paul et al., 2005), which emphasizes the multicomponent nature of emotions, including physiological, behavioural, cognitive, and subjective elements. Their work demonstrates that cognitive processes play a key role in generating emotional states, while emotional states influence cognitive functioning, causing biases in attention, memory, and judgment.

Purpose of this study is to develop the foundations of an AI integration model in the educational process, taking into account the emotional component of learning, and to analyse its effectiveness in the context of higher education. The study examines modern approaches to adaptive learning, methods of emotional state recognition, and practical aspects of implementing emotionally adaptive systems based on experimental research results.

MAIN RESULTS

Technical Aspects of the Platform

Creating an adaptive educational platform requires a combination of advanced machine learning technologies and flexible architecture. The data analysis module processes information using a combination of convolutional (CNN) and recurrent (RNN) neural networks. CNNs extract visual and audio features, such as facial expressions or voice tonality (Goodfellow et al., 2016), while RNNs analyse temporal dependencies in student behaviour (Hochreiter & Schmidhuber, 1997).

As noted by Brusilovsky & Peylo (2003), adaptive and intelligent web-based learning systems can be classified into five main technological groups:

- Adaptive hypermedia technologies (adaptive navigation and presentation);
- Intelligent tutoring technologies (course sequencing, solution analysis);
- Adaptive information filtering;
- Intelligent class monitoring;
- Intelligent collaborative learning support.

In modern practice, three main directions of AI application in education are distinguished (Pan et al., 2021):

- Various AI technologies: utilizing machine learning, deep learning, and natural language processing;
- Intelligent learning systems: supporting students through intelligent tutoring systems (ITS);
- Educational data mining and learning analytics: analysing big data to optimize educational processes.

Predictive analytics, according to Baker & Yacef (2009) research, plays a key role in modern educational systems, allowing the prediction of academic performance based on behavioural and emotional patterns. Romero & Ventura (2020) emphasize the importance of identifying potential learning difficulties in early stages and optimizing the distribution of educational resources. Of particular significance, as noted by Hernández-Leo et al. (2019), is the integration of predictive models with real-time systems, ensuring dynamic adaptation of educational content and delivery methods.

The combination of intelligent tutoring systems (ITS) and adaptive intelligent web-based educational systems (AIWBES) can lead to the creation of a powerful learning platform that combines the best qualities of both technologies. The advantages of such integration include personalization of learning: ITS provides individualized instruction, adapting to the needs and knowledge level of each student, and in combination with the adaptive capabilities of AIWBES, this allows for creating learning paths that maximally correspond to individual needs. Accessibility and scalability are also improved, as AIWBES operate through a web interface, and the combined system will be accessible from anywhere in the world at any time, increasing reach and convenience for users. Interactivity and engagement are enhanced because intelligent tutoring systems can use advanced interaction methods, including virtual assistants and interactive assignments, which, combined with web technologies, improves student engagement. Analytics and feedback become more precise through the joint use of data on student performance and behaviour, allowing for more accurate assessment of progress and providing timely feedback. Content flexibility is ensured by the fact that the combined system can dynamically change educational material in real-time, adapting it to changes in the student's level of understanding and interests.

Cognitive-Emotional Mechanisms of the Platform

Based on the work of Salovey, Mayer, & Caruso on emotional intelligence, the platform model includes modules for:

- Assessment and development of students' emotional intelligence;
- Monitoring stress levels and adapting material complexity;
- Development of emotional self-regulation skills.

Building on Stanton et al.'s (2000) research, the platform model includes tools for written emotional expression. A meta-analysis of 13 studies showed that such practice improves psychological health, immune function, and social adaptation of students. The system takes into account gender differences in emotional processing, as women more frequently and effectively use emotional processing and expression strategies, which is associated with better psychological adaptation and increased self-esteem (Stanton et al., 2000).

The development of the platform model is based on contemporary understanding of the relationship between cognitive and emotional processes. According to Paul et al. (2005), emotional states significantly modify cognitive processes such as attention and memory, which provides important advantages in the learning process. The platform model considers these relationships through:

- An emotional state monitoring system that tracks potential cognitive biases;
- Adaptive mechanisms that adjust material delivery considering the student's emotional state;
- Tools for assessing the impact of emotions on perception, memory, and decision-making in educational contexts.

Historically, the development of adaptive educational systems has gone through several evolutionary stages: from computer-assisted instruction (CAI) through intelligent computer-assisted instruction (ICAI) to intelligent tutoring systems (ITS) and modern adaptive web-based systems AIWBES (Brusilovsky & Peylo, 2003). Each stage brought new opportunities for learning personalization and consideration of individual student characteristics.

According to Stanton's research (Stanton et al., 2000), emotional awareness directly affects academic performance. The system uses this data to create personalized learning strategies that take into account students' emotional states.

Modern neuroscience research (Immordino-Yang & Damasio, 2007) demonstrates the close connection between emotional and cognitive processes in learning. Pekrun et al. (2017) show that emotional state significantly affects memory and attention processes, while emotional context plays an important role in forming new neural connections. Tyng et al. (2017) confirm that the interaction between emotional regulation systems and cognitive control determines learning effectiveness.

The integration of emotional approaches into the combined system of intelligent tutoring systems (ITS) and adaptive intelligent web-based educational systems (AIWBES) can significantly improve learning effectiveness and student satisfaction. By considering students' emotional states, such a system can provide more relevant and engaging content, enhancing motivation and interest in learning. Furthermore, the inclusion of tasks and scenarios aimed at developing emotional intelligence – such as empathy, self-regulation, and social interaction — contributes to personal growth. Personalized support is achieved through adapting information delivery methods and feedback in response to students' emotional reactions, making learning more effective. By recognizing signs of stress or anxiety, the system can provide resources for their management or adjust task complexity.

The integration of social-emotional learning (SEL) in educational technologies, researched by Durlak et al. (2011), represents an important development direction. This approach, according to Weissberg et al. (2015), includes the development of self-awareness and self-management skills. Jones & Kahn (2017) emphasize the importance of developing social awareness and relationship-building skills, as well as the ability to make responsible decisions.

Ethics and Data Protection

The implementation of AI in the educational process requires strict adherence to ethical principles. All collected information is encrypted and stored on secure servers that comply with modern security standards (Binns, 2018). Regular model evaluations for fairness and equity are conducted to minimize algorithmic bias.

The experience of developing early adaptive web systems has demonstrated the necessity of a comprehensive approach to security. As noted in the research by Brusilovsky and Peylo (2003), special attention should be paid not only to personal data protection but also to ensuring fair access to educational resources.

Particular attention should be given to the ethical aspects of using educational big data. As education becomes increasingly data-intensive, the importance of developing ethical policies that define the boundaries of AI use and data generated during the learning process grows.

Special emphasis is placed on ensuring algorithm transparency and the explainability of system decisions (Rudin, 2019). This is achieved through the development of interpretable machine learning models and the creation of user-comprehensible explanations for system decisions (Molnar, 2020). Holstein et al. (2019) emphasize the importance of considering cultural diversity and ensuring inclusivity through content adaptation to various cultural contexts.

CONCLUSIONS

The integration of emotional approaches into educational platforms with artificial intelligence elements forms a new paradigm in learning. The use of neural network technologies and ensemble learning algorithms allows for creating an adaptive system that considers individual student characteristics. Special attention to ethical aspects and data protection ensures the system's sustainability and responsibility to all participants in the educational process.

A promising direction for platform development is the integration of augmented reality (AR) technologies for emotional intelligence development within adaptive learning. Research by Osadchyi et al. (2021) shows that combining psychological-pedagogical approaches with AR technologies significantly increases the effectiveness of developing intrapersonal and interpersonal components of students' emotional intelligence. Dede (2009) also notes the importance of expanded use of virtual and augmented reality, while Roll & Wylie (2016) emphasize the significance of natural language recognition systems and multimodal interfaces. Research by Zawacki-Richter et al. (2019) demonstrates the development of pedagogical approaches, including gamification methods and peer-to-peer learning systems.

For further development, it is necessary to strengthen interdisciplinary collaboration between AI experts and educational researchers, enhance educators' competencies in AI and educational technologies, and develop ethical standards governing data use. The implementation of the described technological and methodological solutions will enable the development of a functional educational platform prototype and conduct comprehensive most effective use of digital tools and platforms.

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