© Rzeszów University Press
ISSN 2719-6550
e-ISSN 2719-7417

"Journal of Education, Technology and Computer Science"
No. 6(36)/2025
https://journals.ur.edu.pl/jetacomps

Received: 11.04.2025
Accepted for printing: 24.11.2025
Published: 31.12.2025
License: CC BY-NC-ND 4.0
DOI: 10.15584/jetacomps.2025.6.9
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SLAVOLJUB HILČENKO [1], **SANJA NIKOLIĆ** [2],
BORIS LIČINA [3]

Artificial Intelligence in Function of Multimedia Quality for Functional Learning

[1] ORCID ID: 0000-0003-2123-6285, PhD, College for Vocational Education of Preschool Teachers and Coaches, Subotica, Serbia; email: s.hilcenko@gmail.com
[2] ORCID ID: 0000-0001-9632-2458, PhD, College for Vocational Education of Preschool Teachers and Coaches, Subotica, Serbia; email: drsanjanikolic294@gmail.com
[3] ORCID: 0000-0002-5090-1590, PhD, College for Vocational Education of Preschool Teachers and Coaches, Subotica, Serbia; email: boris.licina007@gmail.com

Abstract

Artificial intelligence (AI) is transforming the quality of multimedia content, enabling personalized, interactive, and adaptive learning (AL). This paper explores how AI contributes to improving multimedia materials using methods such as user data analysis, speech synthesis, and image recognition. The focus is on functional learning (FL), where AI enhances student comprehension and engagement. The works of prominent researchers, including Mitchell, Goodfellow, and Russell, are analyzed. The results indicate that AI enhances accessibility, personalization, and efficiency of multimedia educational resources.

In addition, recent research 2020–2024 confirms that AI-supported multimedia significantly improves higher-order cognitive processes, problem-solving skills, and learning transfer, which are central components of FL (Zawacki-Richter, Marín, Bond, Gouverneur, 2020; Papamitsiou, Economides, 2021; Holmes, Tuomi, 2022; de Araujo, Dorça, Lima, Fernandes, 2023; Chen, Xie, Zou, 2024).

Keywords: artificial intelligence, multimedia, FL, AL, interactive systems

Introduction

The digital revolution has enabled the intensive use of multimedia technologies in education, leading to changes in how students approach learning and knowledge acquisition (Gaftandzhieva, Hussain, Hilčenko, Doneva, 2023). Multimedia content such as interactive simulations, video lectures, and adaptive educational games has become an integral part of modern teaching methods

(Hilčenko, 2006). However, despite their advantages, traditional multimedia educational resources often do not consider different learning styles, cognitive abilities, and prior knowledge of students, which can limit their effectiveness (Hilčenko, 2008).

Integrating AI into educational multimedia systems opens new opportunities for content personalization and adaptation to individual student needs. Using advanced machine learning algorithms and data analysis, AI enables real-time dynamic adjustment of educational materials, optimization of interactivity, and enhancement of student engagement (Hilčenko, 2009). Intelligent systems can analyze educational patterns, adjust task difficulty levels, and provide personalized feedback, thereby increasing motivation and learning efficiency (Mitchell, 1997; Hilčenko, 2015c).

In this paper, the concept of FL is defined as a process in which students acquire knowledge and skills that can be directly applied in practical, real-life, and problem-solving contexts. FL emphasizes transferability, active engagement, and meaningful application of learned concepts, distinguishing it from memorization-based learning. AI-enhanced multimedia supports this approach by enabling adaptive scaffolding, contextual simulations, and interactive problem-solving environments.

The aim of this paper is to explore how AI enhances the quality of multimedia content in FL, with a special focus on AL support systems, interactive educational platforms, and automated student progress analysis capabilities (Hilčenko, 2015a, 2015b). By analyzing existing research and practical examples, the paper will highlight the advantages and challenges of AI integration into multimedia educational resources, as well as its potential for further development of educational technologies (Hilčenko, 2019).

Furthermore, this study synthesizes recent findings (Zawacki-Richter et al., 2020; Holmes, Tuomi, 2022; Liu, Wang, Chen, 2023) to provide a more comprehensive understanding of AI's pedagogical value, addressing not only technological but also epistemological and cognitive dimensions of AI-mediated learning.

Problem Analysis

Personalization and Adaptivity

One of the key contributions of AI in multimedia education is personalized learning, which enables content to adapt to each student's specific needs (Hilčenko, Nikolić, 2023). Goodfellow, Bengio, and Courville (2016) emphasize that AI can analyze learning patterns and dynamically adjust educational material according to individual user characteristics, such as learning styles, comprehension speed, and prior knowledge (Hilčenko, Nikolić, 2024). This approach allows students to progress at their own pace, contributing to more efficient learning and better information retention.

Recent deep learning studies, such as those by LeCun, Bengio, and Hinton (2015), demonstrate how algorithms can segment students according to their learning styles. They can identify behavioral patterns not immediately apparent. Moreover, natural language models like BERT and GPT-3 (Devlin, Chang, Lee, Toutanova, 2019; Brown et al., 2020) enable advanced text content analysis. They facilitate the generation of customized educational materials and real-time content adaptation, significantly improving the learning experience.

Recent AL systems (Xiang, Li, Sun, 2021; Huang, Spector, Yang, 2024) further incorporate reinforcement learning and explainable AI, enabling transparent decision-making models that help educators understand why certain adaptations occur, thus bridging the gap between automated processes and pedagogical expertise.

Enhancement of Image and Sound Quality

Besides personalization, AI significantly improves multimedia content quality, particularly in image and sound processing. Advanced algorithms, as described by Russell and Norvig (2021), allow for better understanding and interaction with visual and auditory components of educational materials. These algorithms can automatically optimize image resolution and sound clarity, enhancing the accessibility and effectiveness of educational resources.

One of the most significant technological innovations in this field is Generative Adversarial Networks (GANs) (Goodfellow et al., 2016), which improve image and video quality by generating high-quality visual content from existing data. These models are especially useful for generating educational content in real-time, such as 3D visualizations or simulations.

Newer architectures, such as diffusion models (Moerland, Broekens, Jonker, 2022), provide even higher fidelity and are increasingly used in educational AR/VR systems, enabling immersive environments that support FL through experiential and situational simulations.

Data Analysis and Interactive Systems

AI also enables deep analysis of user data, allowing dynamic adjustment of educational content based on student progress. Bishop (2006) highlights that these tools can analyze educational data to identify knowledge gaps and provide personalized feedback. This allows educators to better understand student progress and optimize their teaching approaches.

Using deep neural networks (He, Zhang, Ren, Sun, 2016) and advanced architectures like Transformers (Vaswani et al., 2017) facilitates the development of interactive systems. These systems can analyze data, recognize linguistic structures, and understand contextual meanings. This improves student interaction with educational materials (Figure 1).

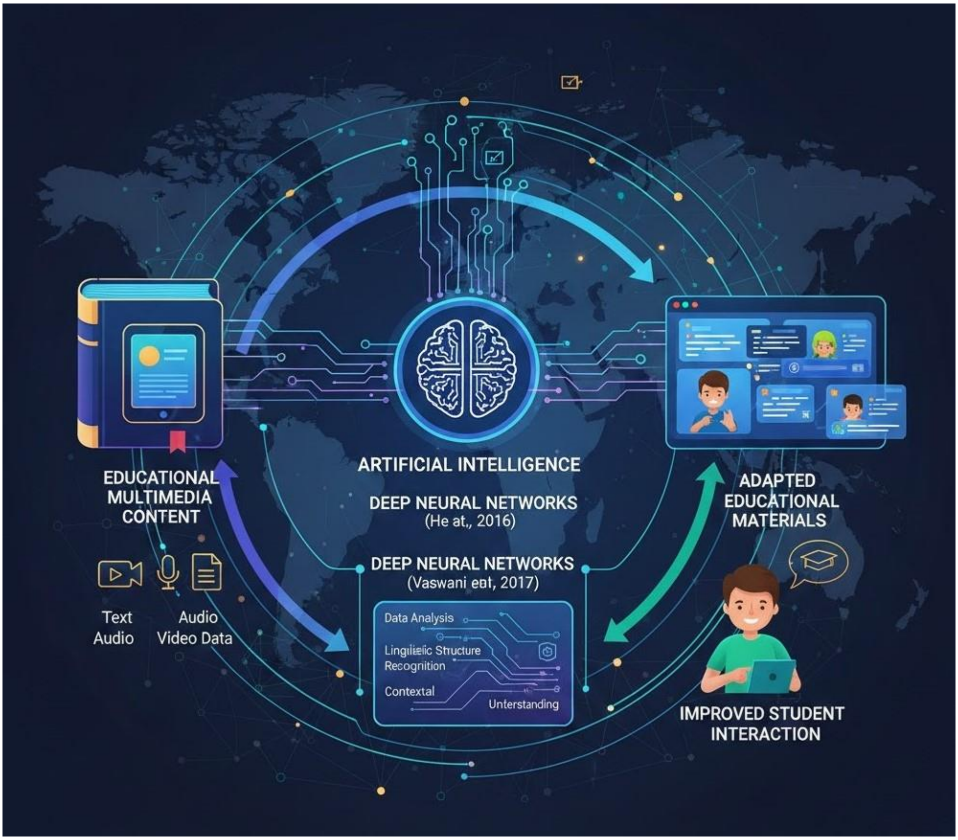

Figure 1. The process of adapting multimedia content using artificial intelligence. Note. Illustration adapted from authors' own design

Modern multimodal AI (Gupta, Sharma, 2022) combines text, audio, and visual input, enabling the creation of intelligent tutors capable of tracking cognitive load, emotional states, and engagement levels–key components for ensuring that FL truly occurs.

Discussion

Previous research highlights AI's significant potential in improving multimedia educational resources, particularly through content personalization and adaptivity, as well as enhancing interactivity and student engagement. However, despite AI's evident benefits in education, several challenges must be addressed for its effective and ethical implementation.

One of the key challenges is user privacy protection when processing data. Educational AI systems often collect vast amounts of sensitive student data. This includes learning habits, performance, and even biometric data. Without adequate safeguards, the risk of data misuse or unauthorized access can jeopardize user trust and the integrity of the educational system (Radford et al., 2019).

A further challenge lies in ensuring pedagogical validity. AI-driven adaptations must align with instructional goals, not merely algorithmic optimization. Research from 2020–2024 warns that excessively automated systems may reduce learner autonomy, introduce algorithmic bias, or create over-dependence on adaptive scaffolding. Therefore, the integration of AI requires a balance between automation and human oversight (Zawacki-Richter et al., 2020; Papamitsiou, Economides, 2021; Holmes, Tuomi, 2022; de Araujo et al., 2023; Chen et al., 2024).

In addition, the concept of FL demands that AI tools promote deep understanding rather than superficial task completion. This requires careful design of multimedia resources to ensure that adaptive content leads to meaningful cognitive engagement and real-world applicability.

Moreover, AI systems must provide transparent decision-making processes. Recent adaptive learning frameworks use explainable AI to allow educators to understand why certain adaptations occur. This helps bridge the gap between automated processes and pedagogical expertise (Zawacki-Richter et al., 2020; Papamitsiou, Economides, 2021; Holmes, Tuomi, 2022; de Araujo et al., 2023; Chen et al., 2024).

Finally, the ethical implementation of AI in education also involves addressing equity and inclusivity. Adaptive systems should ensure that all students, including those with special needs or from disadvantaged backgrounds, benefit from AI-enhanced learning. Designers must consider universal design principles to make multimedia content fully accessible and flexible for diverse learners.

Conclusion

AI represents a crucial revolution in multimedia education, enabling personalized, interactive, and dynamic educational resources tailored to student needs. AI applications in FL have the potential to transform the education system by increasing student efficiency and engagement through automatic analysis of their learning styles, progress speed, and required support levels.

Despite AI’s advantages in education, further research and innovation are necessary to overcome existing obstacles. Technical constraints, such as high computing power and infrastructure requirements, pose significant challenges, especially in resource-limited educational institutions. Additionally, ethical concerns regarding user data privacy must be addressed to ensure the responsible and secure implementation of AI in education.

Moreover, future work must deepen the theoretical integration of AI within FL frameworks, ensuring that adaptive multimedia supports transfer, autonomy, and problem-solving competencies. The development of explainable, multimodal, and context-aware AI systems will play a critical role in achieving these goals.

The next research steps should focus on developing scalable solutions that effectively integrate AI into various educational contexts, including those with limited technology access. Future studies should also explore how AI can enhance the inclusivity of education, offering learning opportunities to students with special needs or from socioeconomically disadvantaged backgrounds.

Special attention should be given to designing AI-driven multimedia that supports universal design for learning (UDL), enabling fully flexible and accessible educational experiences. In addition, recent research (2020–2024) confirms that AI-supported multimedia significantly improves higher-order cognitive processes, problem-solving skills, and learning transfer, which are central components of FL (Brown et al., 2020; Zawacki-Richter et al., 2020; Papamitsiou, Economides, 2021; Holmes, Tuomi, 2022; de Araujo et al., 2023; Chen et al., 2024).

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