ISSN 2413-3833 (Online), ISSN 1681-4886 (Print)

І Н Ф О Р М А Ц І Й Н О – К Е Р У Ю Ч І С И С Т Е М И Н А З А Л І З Н И Ч Н О М У Т Р А Н С П О Р Т І

УДК 004.93:004.5:364.4 DOI: https://doi.org/10.18664/ikszt.v31i1.357674

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Model and algorithm for neural network-based gaze fixation duration determination for dynamic content adaptation in inclusive learning

Abstract.. *The relevance of this study stems from the fact that most existing inclusive educational technologies provide only basic access to content but do not ensure its effective mastery. In practice, they rely on static personalization grounded in a pre-defined user profile (e.g., impairment type). The key shortcoming of this approach is its blindness to the dynamics of the actual learning process: the system cannot recognize when a learner experiences an immediate spike in cognitive load or encounters difficulty understanding a specific term or formula. This creates a barrier that leads to frustration, loss of motivation, and ultimately superficial learning.*

The objective of the work is to develop and substantiate an innovative mechanism for real-time dynamic adaptation of educational content that responds to learners' cognitive difficulties as they occur.

The study is based on designing a system that uses eye-tracking to monitor user interaction with digital instructional materials. The primary biometric indicator is the fixation duration on specific semantic units (text fragments, images, formulas).

This work is the first to propose an adaptation mechanism grounded in the hypothesis that prolonged gaze fixation is a reliable marker of comprehension difficulty or elevated cognitive load. Upon detection of an extended fixation, the system automatically triggers an adaptive scenario and offers targeted, context-specific support (e.g., term definitions, simplified explanations, visual examples) precisely for the unit that elicited difficulty. This approach enables a shift from macro-personalization (profile-level) to micro-personalization (real-time), thereby creating a more responsive and effective inclusive learning environment.

Keywords: *multimodal systems, assistive technologies, context-aware interaction, people with disabilities, personalized interfaces.*

Introduction

Education is a fundamental right of every person. Modern technologies open up new opportunities for inclusive learning. However, digital content often contains significant barriers. These barriers make it impossible for people with disabilities and special educational needs to effectively perceive information. The existing classification of impairments clearly indicates this diversity of needs. It covers visual, hearing, motor and cognitive impairments. Effective design requires «deficit-agnostic» design. This means that functional limitations and environmental barriers must be taken into account. The main requirements of inclusive technologies include the appropriateness of presentation formats (vision, hearing, tactile) and control of cognitive load. Adaptive selection of control methods (voice, gaze, switches) is also necessary. Despite these requirements, existing adaptive systems often rely on subjective assessments or manual settings. They do not take into account the real process of content perception.

Cognitive impairments are one of the most challenging categories to accommodate. These include dyslexia, ADHD, and ASD. These impairments directly affect the ability to concentrate and process visual information. Assessing cognitive load is key to ensuring effective learning. In this context, eye movement is a direct indicator of cognitive activity. Analysis of visual fixation time allows for an objective measurement of attention and complexity of perception. This method provides accurate data on which content elements cause the greatest difficulties.

The paper proposes the use of eye tracking data as the main criterion for automatically adjusting the complexity and presentation of information. The results of the work will contribute to the creation of inclusive and personalized learning environments.

Analysis of the latest research and publications

Inclusion is the creation of conditions under which people with diverse abilities have equal access to resources, services, and participation in social life. In the technical) context, inclusion refers to designing and implementing information technologies that reduce barriers in interaction with the environment, information, and other people.

An analysis of recent systematic reviews and research articles shows that contemporary studies in the field of inclusive technologies focus on three pillars: the philosophical justification of inclusion, improving basic accessibility through assistive technologies (AT), and macro-personalization driven by AI.

However, a key challenge remains unresolved: the creation of systems capable of responding not to a user's profile, but to their current cognitive state. There is a significant gap in the development of mechanisms that would use biometric data-such as eye-movement patterns-to detect moments of cognitive load or misunderstanding during the learning process itself.

This is precisely what makes the present study relevant. It proposes a new adaptation mechanism based on analyzing gaze-fixation time, intended to fill this gap by shifting from static adaptation toward dynamic adaptation that is sensitive to the user's cognitive state.

There is a substantial body of work dedicated to systematic reviews of existing assistive technologies (AT). In the work [1] the authors confirm that AT effectively improve accessibility, yet they also identify barriers such as insufficient teacher training and a general lack of awareness. In the work [2] the types, tools and characteristics of existing technologies. These reviews capture the current state of technological development. They clearly show which tools are available (for example, screen readers and text-to-speech applications), yet they simultaneously highlight a significant "gap": the vast majority of AT focus on providing access to content rather than adapting that content based on the learner's understanding.

Another group of studies explores the potential of artificial intelligence (AI) for personalizing learning. In the review [3] it examines how AI can create personalized learning pathways. In [4] it also reviews systems that AI offers for students with special needs. The study [5] highlights the role of machine learning–based voice and speech processing methods in educational technologies, particularly when working with groups of younger school-age children. This line of research is the most closely related to our topic, yet it also most clearly delineates the existing limitations. The personalization discussed in these reviews is generally at a macro level. It is based on:

1. Static profiles. The systems adapt to a pre-determined diagnosis (e.g., dyslexia) or type of impairment.
2. Outcome-based. Adaptation occurs after the student has failed a test or answered a question incorrectly.

None of the reviewed studies identified a substantial number of investigations dedicated to dynamic micro-adaptation - that is, systems capable of detecting the moment difficulties arise in real time, before the student makes an error.

The key idea of this study is the use of two types of multimodal data to develop a context-adaptive system for supporting people with disabilities, incorporating dynamic micro-adaptation:

- human-centered data;
- environmental data.

The relevance of support technologies for people with disabilities in the modern world is driven by a number of powerful factors that span all areas of social life (Fig. 1).

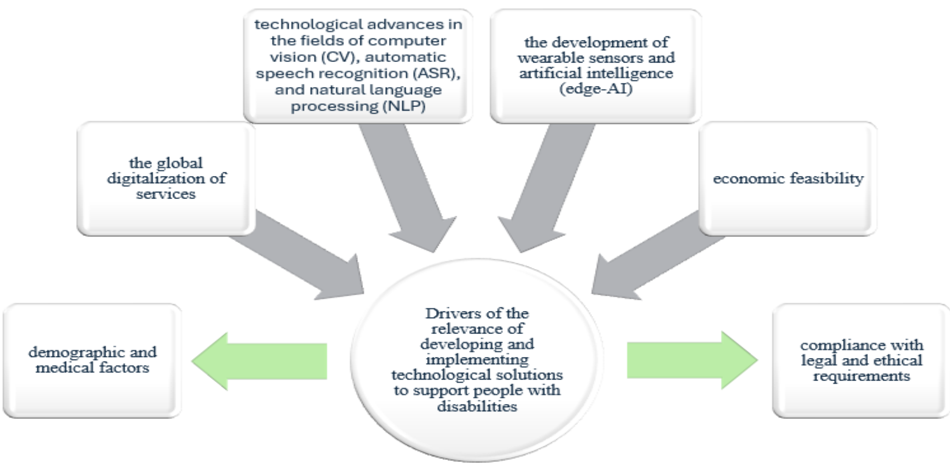

Fig. 1. Drivers of the relevance of the chosen topic

First, these are demographic and medical factors: global population aging, an increasing share of people with temporary and permanent impairments, as well as the widespread consequences of armed conflicts, manifested in injuries and PTSD, which significantly expand the circle of those in need. Second, the global digitalization of services (from government services to education and healthcare) simultaneously opens new opportunities and creates a high risk of digital exclusion for those without access to adaptive interfaces. Third, technological advances in computer vision (CV), automatic speech recognition (ASR), natural language processing (NLP), as well as the development of wearable sensors and artificial intelligence (edge-AI), provide an unprecedented opportunity for the creation of autonomous solutions; however, without the principles of inclusive design, the technologies themselves can reproduce and even reinforce existing social barriers.

These factors are inextricably linked to economic feasibility, as social inclusion increases participation in the labor market, reduces long-term social costs, and expands the talent pool for the economy, as well as to legal and ethical requirements stemming from international standards, the «design for all» concept, and data security considerations. Ensuring urban mobility and safety presents a separate challenge, where navigation in complex spaces requires the development of intelligent multimodal assistive systems.

To identify priority directions for the development and implementation of support technologies, the first step is to determine the areas of life where barriers for people with disabilities are most significant and where technological intervention can have the greatest social impact. Social inclusion is not an abstract concept; it is realized through full participation in specific activities. Accordingly, the relevance of support technologies is primarily determined by the need to overcome obstacles in key segments, as illustrated in Fig. 2.

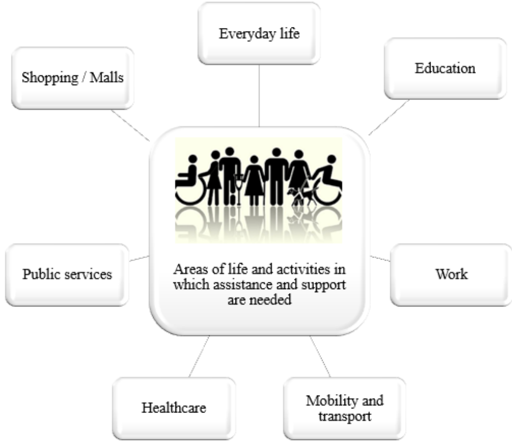

Fig. 2. Key areas of life requiring technological support for people with disabilities

For example, in education, users aim to access materials without barriers, participate in exams and laboratory sessions, and interact within learning management systems (LMS) and during video lectures. Critical barriers include the absence of alternative content formats (such as audio versions, subtitles, and audio descriptions of images), inaccessible learning platforms, and non-compliance with accessibility principles. These needs can be addressed through automatic subtitles and audio descriptions, content adaptation to the user's needs, support for keyboard navigation and screen reader compatibility, as well as personalized settings for contrast and fonts.

Formulation of the purpose of the research

The aim of this study is to develop and substantiate a mechanism for dynamic adaptation of educational content based on the analysis of gaze fixation time as an objective indicator of cognitive difficulties, in order to enhance the effectiveness of content acquisition for individuals with special educational needs.

To achieve this goal, the following tasks need to be addressed:

- conduct an analysis of existing approaches to educational content adaptation and identify the limitations of static personalization based on user profiles;
- justify the use of gaze fixation time as a key biometric indicator for detecting cognitive difficulties in real time;
- develop a conceptual model and algorithm for a dynamic adaptation mechanism that triggers the provision of supportive materials when fixation time exceeds a threshold on a difficult content fragment;
- experimentally investigate and compare the effectiveness of deep learning models (VGGNet, ResNet) for reliable gaze direction detection under various conditions (lighting, distance, angle), which serves as the

technological foundation for implementing the proposed mechanism.

Materials and methods

Based on the conducted analysis, there arises a task of further improving and adapting educational materials to the needs of users with disabilities and special needs by creating an adaptive ergonomic engine for content presentation. This engine would adjust, in real time, font size, contrast, line thickness, information density, and output modality, taking into account the type of impairment, assessed distance to the screen, actual viewing conditions (lux/DPI/glare), cognitive load, and interaction history, while forming an individual «ergonomic user profile» (based on impairment type, cognitive load, and interaction history). A key enhancement is adaptive alternative control rather than static design: support for gaze-based input and authentication (including «gaze-passwords»), selection of responses/commands via gestures or switches, voice input (ASR) with tactile or visual feedback confirmation, and text-to-speech (TTS) with adjustable speech rate, voice, and offline mode. The engine should contextually select and duplicate input-output channels (visual/audio/haptic) according to the principle of minimizing the risk of perception errors, ensure offline-first processing (privacy by design), and automatically update the user profile based on proxy metrics of accuracy, time, and effort.

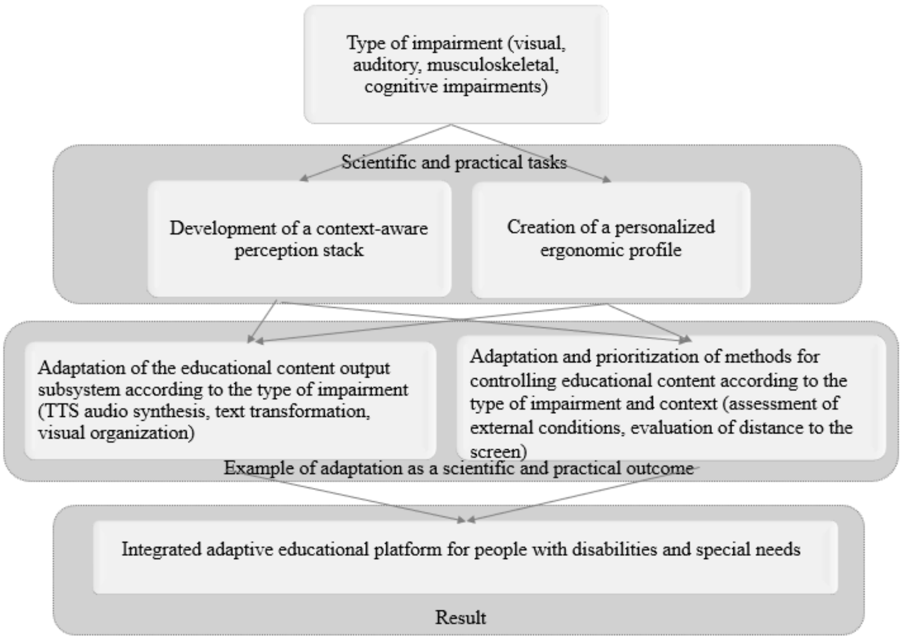

Fig. 3. Mechanisms of adaptive interaction between the context-aware core and the personal ergonomic profile within an inclusive educational system for people with disabilities and special needs

Thus, the study proposes a mechanism for the interaction of subsystems within a unified inclusive education system, combining adaptive design, machine learning, and neuroergonomics, which implements:

- dynamic visual adaptation (taking into account load parameters, viewing conditions, and the individual ergonomic profile);
- adaptive alternative control, input, and authentication (via gaze, gestures, or voice);
- intelligent communication (contextual selection and duplication of channels).

The implementation of the proposed solution will achieve a comprehensive positive effect: enhancing accessibility to educational content by removing traditional barriers for students of all categories; eliminating technical limitations through adaptive control and offline functionality; optimizing ergonomics by creating individualized interaction profiles that account for user characteristics; and significantly reducing cognitive load through intelligent, context-aware selection of communication channels and adaptation of content difficulty. Altogether, these measures will provide a qualitatively new level of inclusive educational interaction.

This diagram illustrates the architecture of an adaptive educational platform that dynamically adjusts both the educational content and the methods of interaction with it. The goal of the system is to create a flexible and effective learning environment that accommodates the individual needs of students and the conditions in which they are situated.

The concept is based on two key scientific and practical tasks:

1. Creation of a context-aware core: The system analyzes the learning environment (noise level, lighting, distance to the screen, type of device).

2. Creation of a personalized ergonomic profile: Depending on the type of impairment (visual, auditory, cognitive) and the user's learning preferences, a unique profile is created.

The system's adaptation layer uses the above data to implement bidirectional adaptation:

- adaptation of content output, i.e., transforming the material into the most accessible form (for example, converting text to speech, increasing contrast, simplifying vocabulary);
- adaptation of control methods, i.e., dynamically changing and prioritizing ways of interacting with the platform (for example, activating voice control if the user is far from the screen).

Thus, the proposed interaction mechanisms provide comprehensive adaptation not only of the content but also of the methods of interacting with it. Unlike traditional platforms that merely offer alternative content formats, this system proactively modifies the control interface itself, making it convenient for each specific situation.

This is achieved by the mechanism's dynamic selection of the optimal pair (presentation method, control method): the ergonomic profile determines what the user needs (for example, «requires audio support»), while the context-aware core determines how best to implement it at the moment (for example, «via headphones because the environment is noisy»).

Thus, the system does not merely vocalize the text but does so at an optimal volume, considering microphone data on the surrounding noise. The operation of the system can be described as an adaptation function A, which, for an ergonomic profile P_E and the current context Ctx_t selects the optimal pair consisting of an output modality (M_{out} and a control method C_{in}:

$$(M_{out}, C_{in}) = A\,(P_E, Ctx_t),$$

Where P_E - a vector of ergonomic profile parameters, including sensory, cognitive, and learning characteristics: $P_E = \{p_{congitive}, p_{vision}, p_{hearing} \cdots\}$, where $p_{cognitive}, p_{vision}, p_{hearing}$ represent the presence of cognitive features, visual acuity, and hearing ability, respectively;

Ctx_t - a vector of context parameters at time t: $Ctx_t = \{c_{distance}, c_{device}, c_{noise} \dots\}$, where $c_{distance}, c_{device}, c_{noise}$ correspond to the distance from the monitor screen, the type of device, and the ambient noise level, respectively.

The adaptation function A aims to maximize a utility function U, which evaluates the effectiveness of each possible pair (M_{out}, C_{in}):

$$A\,(P_E, Ctx_t) = \arg\max_{(M_{out}, C_{in})} U\,(M_{out}, C_{in} | P_E, Ctx_t)$$

.

As an example, consider the following situation: if the profile indicates poor vision ($p_{vision} < threshold$), the utility of the output modality $M_{out} = 'TTS'$ (text-to-speech) will be high. If the context shows a large distance to the screen ($c_{distance} > threshold$), the utility of the control method $C_{in} = 'voice\_control'$ increases. However, if the ambient noise level is high ($c_{noise} > threshold$), the utility of $C_{in} = 'voice\_control'$ decreases, and the system may suggest gesture-based control or interaction via a mobile application.

To implement the user gaze evaluation module, we create a sequence of operations necessary to transform images into the required data. The diagram of these operations is shown in Fig. 4.

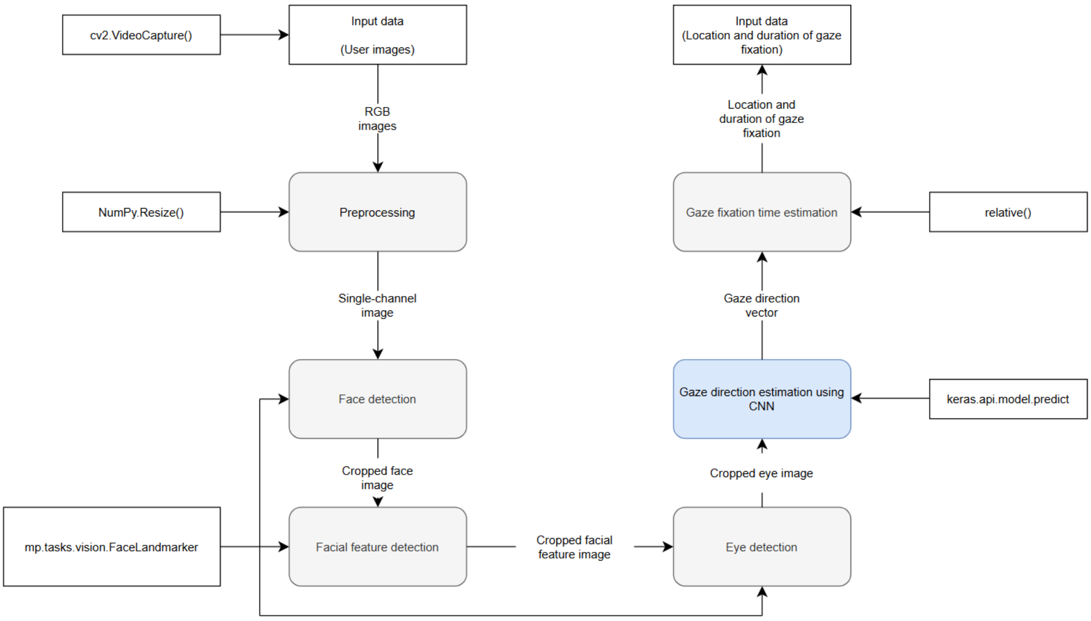

Fig. 4. Sequence of transforming input images into gaze localization coordinates

This model takes user images as input, which are converted into single-channel images using the NumPy library (via the resize function). This choice is motivated by the efficiency of this function for tasks involving image feature transformation. Facial features are then detected, and the eyes are located using Mediapipe tools, specifically the built-in facial landmark detection module. The extracted eye images are fed into a convolutional neural network, which computes a gaze vector based on the image.

The next stage involves determining the gaze fixation point, i.e., identifying the location on the screen where the user is looking. This task is typically performed through a series of transformations using NumPy and OpenCV tools. To measure fixation duration, the Time library is additionally used.

The system outputs the coordinates of the gaze localization point and the duration of the gaze fixation.

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Results and discussions

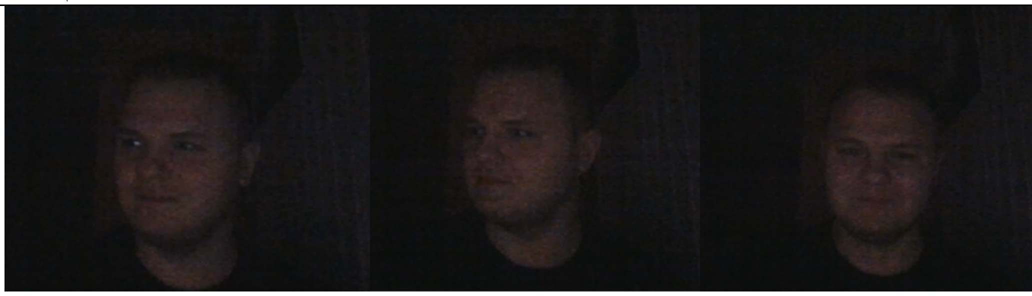
Based on the results presented in [6, 7], it can be concluded that the highest test accuracy for gaze direction detection and the lowest loss value are achieved using the ResNet architecture with 25 training epochs and the combination of the Swish activation function and the AdamW optimizer. Under these conditions, the maximum accuracy approaches 85%, while the minimum loss value reaches 15.4 %.

Regarding the VGGNet architecture, with 25 training epochs and the combination of the GELU activation function and the SGD optimizer, the maximum accuracy also approaches 85 %, with the minimum loss value at 15.3 %.

The outcome of the conducted research in this study is an assessment of the adaptation of the trained neural network model to changes in external parameters, such as head tilt angle, distance from the camera, and lighting conditions.

For this purpose, the two aforementioned models, which provide the best results, are selected and tested on real images captured under varying environmental conditions-camera distance and lighting (Fig. 5). The model evaluation results are presented in Tables 1, 2.

a



b

Fig. 5. Demonstration of research conditions: a - under good lighting; b - under poor lighting

The first model uses the VGGNet architecture and has the following parameters:

- number of epochs: 25;
- number of epochs: 25;
- optimizer: SGD;
- activation function: GELU;
- dataset split: 70 % : 15 % : 15 %.

Evaluation results of the VGGNet model based on real image

Good lighting (300 lumens/m²)						
	Distance from camera = 30			Distance from camera = 100		
	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°
Accuracy, %	0.8151	0.8134	0.7913	0.7818	0.7282	0.7139
Loss value, %	0.1813	0.1884	0.2017	0.1961	0.2184	0.2131
Evaluation time, c	471	464	473	484	467	472
Poor lighting (30 lumens/m²)						
	Distance from camera = 30			Distance from camera = 100		
	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°
Accuracy, %	0.7951	0.7814	0.7847	0.6713	0.6927	0.6876
Loss value, %	0.2004	0.1916	0.1932	0.2532	0.2476	0.2580
Evaluation time, c	481	462	475	468	469	474

The next stage is the evaluation of the model with the ResNet architecture with the following parameters:

- Number of epochs: 25;
- Batch size: 16;
- Optimizer: AdamW;
- Activation function: Swish;
- Dataset split: 70 % : 15 % : 15 %.

The evaluation results of this model are presented in Table 2.

Evaluation results of the ResNet model based on real images

Good lighting (300 lumens/m²)						
	Distance from camera = 30			Distance from camera = 100		
	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°	Tilt angle = 0°	Tilt angle = 15°	Tilt angle = 30°
Accuracy, %	0.8380	0.8264	0.8209	0.8063	0.7937	0.7962
Loss value, %	0.1726	0.1791	0.1786	0.1916	0.1986	0.1949
Evaluation time, sec	532	561	568	541	545	559
Poor lighting (30 lumens/m²)						
	Distance from camera = 30			Distance from camera = 100		
	Tilt	Tilt	Tilt	Tilt	Tilt	Tilt

	angle = 0°	angle = 15°	angle = 30°	angle = 0°	angle = 15°	angle = 30°
Accuracy, %	0.8184	0.7931	0.7946	0.7631	0.7541	0.7591
Loss value, %	0.1801	0.1935	0.1985	0.2153	0.2236	0.2209
Evaluation time, sec	553	548	561	543	575	550

Summarizing the obtained results, it can be concluded that the two parameters with the greatest impact on gaze direction detection quality are lighting and distance to the camera. Accuracy decreases particularly sharply when both parameters are suboptimal simultaneously. The least influential parameter turned out to be head rotation.

The implementation of these results is carried out by a separate module within the learning management system. Based on prolonged gaze fixation, a specific semantic block (text, image, formulas) that causes the highest cognitive load is identified (Fig. 6) and therefore requires more in-depth study.

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Fig. 6. Identification of a semantic block (green circle) in the educational content that generates the highest cognitive load

When prolonged gaze fixation is detected, the system automatically activates an adaptive scenario, offering the user additional, targeted information (e.g., definitions of terms, simplified explanations, visual examples) specifically related to the block that caused difficulty.

C onclusions

The study develops a conceptual model and a dynamic adaptation algorithm, where the gaze fixation duration - determined using the proposed ANN - acts as a trigger for providing supportive materials. Unlike existing approaches, it responds not to a static user profile but to the user's actual psychophysiological state-specifically, cognitive difficulties during learning.

It was established that a key indicator of difficulty in understanding material is gaze fixation time, which significantly exceeds the individual's baseline reading pace. When such a deviation is detected, the mechanism automatically triggers the provision of targeted supplementary information.

To provide the technological foundation for this mechanism, a comparative analysis of VGGNet and ResNet models for gaze direction detection was conducted. Experimentally, it was demonstrated that the ResNet model shows higher accuracy and stability under various conditions (e.g., 0.8380 vs. 0.8151 for ResNet and VGGNet, respectively, under good lighting and a 30 cm distance).

Critical factors affecting system reliability were identified: the greatest drop in gaze detection accuracy (down to 0.75–0.76 for ResNet) occurs under poor lighting (below 30 lumens) and increased distance from the camera (over 1 m). These factors must be considered when designing real-world inclusive systems.

The proposed approach enables a transition from static macro-personalization (adaptation based on the type of impairment) to dynamic micro-personalization (adaptation to a specific misunderstood term or formula), significantly enhancing the potential for effective learning.

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МОДЕЛЬ ТА АЛГОРИТМ НЕЙРОМЕРЕЖЕВОГО ВИЗНАЧЕННЯ ТРИВАЛОСТІ ФІКСАЦІЇ ПОГЛЯДУ ДЛЯ ДИНАМІЧНОЇ АДАПТАЦІЇ КОНТЕНТУ В ІНКЛЮЗИВНОМУ НАВЧАННІ

Актуальність дослідження зумовлена тим, що переважна більшість існуючих інклюзивних освітніх технологій забезпечує лише базовий доступ до контенту, але не гарантує його ефективного засвоєння. Вони здебільшого пропонують статичну персоналізацію, що базована на заздалегідь визначеному профілі користувача (наприклад тип порушення). Основний недолік такого підходу – «сліпота» щодо динаміки реального навчального процесу. Система не здатна розпізнати, коли саме користувач стикається з миттєвим когнітивним перевантаженням або труднощами розуміння конкретного терміна чи формули. Це створює бар'єр, що призводить до фрустрації учня, втрати *мотивації та, як наслідок, поверхневого засвоєння матеріалу.*

Метою роботи є розроблення та обґрунтування інноваційного механізму динамічної адаптації навчального контенту, який реагує на когнітивні труднощі користувача в режимі реального часу.

В основі дослідження лежить розроблення системи, що використовує технологію відстеження погляду (eye-tracking) для моніторингу взаємодії користувача з цифровим навчальним контентом. Важливим біометричним індикатором є час фіксації погляду на певних семантичних блоках (текст, зображення, формули).

У роботі вперше запропоновано механізм адаптації, що базований на такій гіпотезі: тривалість фіксації погляду є достовірним маркером виникнення труднощів із розумінням або підвищеного когнітивного навантаження. Із детектуванням тривалої фіксації система автоматично активує адаптивний сценарій - пропонує користувачеві додаткову, таргетовану інформацію (наприклад визначення термінів, спрощені пояснення, візуальні приклади), що стосується саме того блока, який викликав труднощі. Цей підхід дає змогу перейти від макроперсоналізації (на рівні профілю) до мікроперсоналізації (на рівні реального часу), створюючи більш чутливе та ефективне інклюзивне навчальне середовище.

Ключові слова: *мультимодальні системи, асистивні технології, контекстно-залежна взаємодія, люди з інвалідністю, персоналізовані інтерфейси.*

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Стаття надійшла 23.11.25
Стаття прийнята до друку після рецензування 14.01.26
Стаття опублікована (оприлюднена) 27.04.26