INTEGRATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES INTO THE PROCESS OF FOREIGN LANGUAGE LEARNING IN HIGHER MILITARY EDUCATIONAL INSTITUTIONS: AN ANALYTICAL OVERVIEW

ІНТЕГРАЦІЯ ТЕХНОЛОГІЙ ШТУЧНОГО ІНТЕЛЕКТУ В ПРОЦЕС ВИВЧЕННЯ ІНОЗЕМНИХ МОВ У ВИЩИХ ВІЙСЬКОВИХ НАВЧАЛЬНИХ ЗАКЛАДАХ: АНАЛІТИЧНИЙ ОГЛЯД

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Computer-Assisted Language Learning (CALL) is an interdisciplinary field of research and practice that integrates linguistics, pedagogy, learning psychology, and information technology. CALL encompasses the use of computers, mobile devices, digital platforms, and artificial intelligence to support the process of foreign language teaching and learning. Its primary objective is to create an interactive, adaptive, and efficient learning environment that fosters the development of foreign language professional communicative competence.

The article explores the potential of artificial intelligence technologies to enhance language training for cadets in higher military educational institutions. Under conditions of limited instructor time and an increasing demand for high-quality professional communication in a foreign language, CALL technologies provide flexibility, personalized learning, and immediate feedback.

CALL becomes particularly relevant in wartime conditions, when the importance of distance and blended learning increases, along with the need for rapid adaptation to new tasks and the maintenance of a continuous educational process. Modern CALL systems include various modules, ranging from automated task and test generation to performance analytics, error diagnostics, and the provision of individualized recommendations. Through the integration of AI, such systems can dynamically adapt learning content to each cadet's level and learning pace.

Although most current solutions remain at the prototype or partial implementation stage, advances in artificial intelligence open new perspectives for the development of CALL in military education. This includes the implementation of adaptive language learning, intelligent instructor support, and educational data analytics. The article summarizes current approaches to the integration of AI into CALL environments in military educational institutions and proposes directions for interdisciplinary collaboration aimed at improving the effectiveness of language training for future officers.

Key words: *Computer-Assisted Language Learning (CALL), Artificial Intelligence (AI), language learning, Intelligent Tutoring Systems (ITS), Zone of Proximal Development (ZPD), Generative AI for Education (GAIED), Automated Essay Scoring (AES).*

*Комп'ютеризоване вивчення мов (**CALL, Computer-Assisted Language Learning**) – це міждисциплінарна галузь досліджень і практики, що поєднує лінгвістику, педагогіку, психологію навчання та інформаційні технології. CALL охоплює використання комп'ютерів, мобільних пристроїв, цифрових платформ та штучного інтелекту для підтримки процесу викладання й вивчення іноземних мов. Його основна мета – створення інтерактивного, адаптивного та ефективного навчального середовища, яке сприяє розвитку іншомовної комунікативної компетентності.*

У статті розглядається потенціал застосування технологій штучного інтелекту для удосконалення мовної підготовки курсантів у вищих військових навчальних закладах. В умовах обмеженого часу викладача та зростання потреби у високоякісній професійній комунікації іноземною мовою, CALL-технології забезпечують гнучкість, персоналізацію навчання й оперативний зворотний зв'язок.

Особливої актуальності CALL набуває у військовий час, коли зростає роль дистанційного та змішаного навчання, необхідність швидкої адаптації до нових завдань і підтримки безперервного освітнього процесу. Сучасні CALL-системи включають різні модулі: від автоматизованої генерації навчальних завдань і тестів до аналітики результатів, діагностики помилок і надання індивідуальних рекомендацій. Завдяки впровадженню ШІ такі системи можуть динамічно адаптувати навчальний контент до рівня й темпу засвоєння кожного курсанта.

Попри те, що більшість сучасних рішень перебувають на стадії прототипів або часткової реалізації, досягнення у сфері штучного інтелекту відкривають нові перспективи розвитку CALL у військовій освіті. Зокрема, це стосується впровадження адаптивного мовного навчання, інтелектуальної підтримки викладача та аналітики освітніх даних. Стаття узагальнює сучасні підходи до інтеграції ШІ в CALL-середовище військових закладів освіти й пропонує напрями міждисциплінарної співпраці для підвищення ефективності мовної підготовки майбутніх офіцерів.

Ключові слова: *Computer-Assisted Language Learning (CALL), Artificial Intelligence (AI), language learning, Intelligent Tutoring Systems (ITS), Zone of Proximal Development (ZPD), Generative AI for Education (GAIED), Automated Essay Scoring (AES).*

Introduction. Innovative technological support in foreign language teaching and learning remains a crucial scientific and practical challenge, particularly in higher military educational institutions. *Computer-Assisted Language Learning* (CALL) is an interdisciplinary field that integrates artificial intelligence, machine learning, language technologies, educational analytics, applied linguistics, and teaching methodology [1]. A key factor in this process is the quality of software tools, as an intuitive and user-friendly interface sustains cadets' motivation and promotes regular engagement with CALL systems.

The concept of using computers for language learning originated approximately half a century ago.

For many years, the field of CALL was dominated by the paradigm of the "computer as tutor," which allowed not only the delivery of learning materials but also adaptive responses to individual learner progress. One of the earliest examples was the *PLATO* system (1970s) [2], which laid the groundwork for the development of modern *Intelligent Tutoring Systems* (ITS). These systems combine adaptability, performance assessment, and personalized feedback.

In various educational domains–such as mathematics, natural sciences, and management–ITS have proven their effectiveness. In the field of language education, well-known examples include *ETutor*, *TAGARELA*, and *Robo-Sensei*. These systems demonstrate diverse approaches, ranging from adaptive learning models to fixed task sequences. However, all of them have shown that even a partial replication of instructor functions (10–15%) can significantly reduce human workload and enhance learning outcomes.

The architecture of an ITS typically encompasses three primary components:

• **Domain Model** – representing the knowledge structure of the subject area;

• **Student Model** – describing the learner's knowledge, skills, and progress;

• **Instruction (Tutoring) Model** – determining pedagogical strategies and feedback mechanisms.

Modern systems also include a **User Interface Model**, which ensures effective interaction between the learner and the system. This architecture enables the integration of several key functionalities:

1) generation of exercises of varying complexity and focus (productive and receptive skills);

2) assessment of learner proficiency and content difficulty;

3) provision of personalized feedback;

4) educational analytics for both cadets and instructors.

In military education, these aspects hold particular importance, as the level of cadets' language proficiency directly influences their ability to perform service-related tasks in international environments. Effective CALL and ITS strategies must therefore take into account learners' initial proficiency levels and their specific professional language needs [3].

The structure of the paper is organized as follows: **Section 2** outlines the architecture of the tutoring system; **Section 3** discusses its key functions and potential integration into military language education; and **Section 4** presents conclusions and directions for further research.

1. System Structure

The literature on *Intelligent Tutoring Systems* (ITS) emphasizes that in order to emulate an effective instructor, a system must possess knowledge of:

• the **subject domain**,

• the **learner's current level and cognitive state**, and

• an appropriate **set of tasks or exercises** that best match the learner's needs and promote gradual development of *foreign language professional communicative competence* [4].

These requirements directly correspond to the three classical components of an ITS: the **Domain Model**, the **Student Model**, and the **Instruction (Tutoring) Model**. Additionally, the system must include a **User Interface Model** that ensures interaction with the learner–presenting tasks, explanations, and feedback in an accessible form, maintaining motivation, and fostering trust in the technology.

1.1. Domain Model

The *Domain Model* represents the structure of knowledge within a particular academic discipline. It encompasses both **declarative knowledge** (facts, rules, concepts) and **procedural knowledge** (the ability to apply rules in practical contexts) [5]. In the context of language education, this model may include:

• vocabulary and synonymy (e.g., distinctions in usage between *retain* and *keep*);

• grammatical rules ("uncountable nouns do not take the indefinite article" → *a sand*),

• word formation and irregular verb conjugation,

• syntactic relations,

• fixed expressions, collocations, and idioms.

In this paper, the term **construct** is used to denote all elements that constitute the Domain Model in the context of language learning.

Knowledge representation within this model may take various forms – from **semantic networks** to **ontologies** [6]. In most cases, the core data originate from grammars, dictionaries, or textbooks developed by domain experts. However, modern ITS are capable of refining the Domain Model through **educational data mining**: by analyzing patterns in learners' responses (both correct and incorrect), the system identifies hidden dependencies among linguistic constructions and potential learning trajectories.

A comprehensive overview of the application of this approach to second language acquisition is provided in the study by Bravo *et al.*

1.2. Specific Features for Military Education

In military higher education institutions, the construction of a **Domain Model** involves a number of distinctive tasks. Cadets must acquire not only general English proficiency but also master **military terminology**, command structures, and **standardized communicative formulas** (for example, those used in radio communication or during multinational operations). This becomes particularly significant in wartime, when **speed, accuracy, and mutual understanding** among service members from different NATO countries are critical for the successful execution of combat missions.

Therefore, the **Domain Model** in a military CALL (Computer-Assisted Language Learning) environment should encompass:

• **Tactical vocabulary** (e.g., terms related to logistics, medicine, command, and control);

• **Modules for emergency situations** (commands, warnings, safety protocols);

• **Contextualization of knowledge** within realistic combat scenarios (briefings, negotiations, coordination with allies);

• **Adaptability** to wartime learning conditions (e.g., short intensive exercises that can be performed in the field).

Thus, the structure of an ITS designed for military cadets not only reproduces the classical CALL framework but also provides a foundation for the development of **foreign language professional communicative competence**, which directly contributes to the **combat readiness and operational efficiency** of military units.

1.3. Student Model

The **Student Model** represents the predicted "state" of a learner's knowledge, skills, and competences at any point in the learning process. It accounts for both **static** and **dynamic** characteristics.

• **Static characteristics** include the learner's native language, previously studied foreign languages, level of prior training, and other individual background data.

• **Dynamic characteristics** involve real-time indicators such as current proficiency level, task performance results, common errors, response time, content preferences, and learning styles [7].

This model captures all individual traits that distinguish one learner from another, thereby enabling **personalized learning**. It interacts closely with the **Domain Model**, mapping which constructs have been mastered and which require further practice or revision.

In the context of **military education**, the model must also account for **operational learning conditions** during wartime. Cadets may study in field environments, during mission preparation, or within constrained timeframes. The Student Model should therefore incorporate not only linguistic progress but also factors influencing learning efficiency – **stress level, time limitations**, and the **need to prioritize critical terminology** (e.g., orders, commands, signals). This approach ensures cadets' **practical readiness for real-life communication** in combat or high-pressure situations.

1.4. Instruction (Tutor) Model

The **Instruction Model** performs a pedagogical function: it determines **what to teach, when to teach, and how to teach**. It operates based on data from both the Student Model and the Domain Model. Essentially, this model organizes the **selection and sequencing of constructs and tasks**, adapting the learning process to each learner's individual needs.

The functioning of the Instruction Model is closely aligned with the educational concept of the **Zone of Proximal Development (ZPD)** [8]. This zone represents the range of tasks a learner can accomplish at the next stage of learning with appropriate guidance. For each cadet, certain tasks may be too difficult, while others may be too simple and thus fail to promote development. Following the ZPD principle means selecting "optimal" tasks-challenging enough to sustain interest and cognitive engagement, yet not so difficult as to cause frustration.

In **military education**, this model assumes particular importance. The system must dynamically determine not only grammatical or lexical constructs but also **professionally oriented tasks** aligned with operational needs–such as practicing standard commands, preparing for English-language briefings, or interacting with foreign units. During wartime, this allows cadets to rapidly acquire **mission-critical linguistic units** for specific purposes, such as conducting radio exchanges, giving medical instructions, or coordinating logistical operations.

Thus, the **Instruction Model** functions as a **dynamic and adaptive component** of the ITS: it not only selects exercises based on the learner's knowledge analysis but also **adjusts them to the conditions of military training**, ensuring **practice-oriented and operationally relevant learning**, even in complex and high-stress environments.

2. System Functions

This section explores the application of artificial intelligence for the automatic generation of grammatical and communicative exercises, as well as reading, listening, and speaking tasks tailored to cadets' needs. Special attention is given to automated assessment and feedback generation, particularly in evaluating written work (essays, military documents) and oral performance (briefings, reports).

2.1. Exercise Generation

The most common types of automatically generated exercises in military language training include:

• **Wh-questions** (short-answer questions based on a source sentence or military situation);

• **Gap-filling exercises** based on instructional texts or military documents;

• **Multiple-choice questions**.

These exercises may vary in complexity-from basic (vocabulary and grammar) to professionally oriented (NATO terminology, translation of orders, analysis of authentic combat reports).

The main objectives of automatically generated exercises are to:

• develop comprehension skills for authentic texts (e.g., military briefings or reports);

• consolidate professional military vocabulary and terminology;

• form grammatical accuracy within the context of military communication (e.g., correct use of modal verbs in orders or prepositions in radio exchanges).

Modern neural network approaches are used to create such tasks, including:

• **Transformer models and Large Language Models (LLMs)** (e.g., GPT-based architectures) that identify relevant words and generate blanks in texts;

• **Ranking algorithms** for selecting distractors based on common cadet errors;

• **Machine translation methods** to create complex alternative answers through linguistic transformations of military texts.

AI-based systems can account for the individual proficiency level of each cadet by automatically adjusting task complexity. For example:

• at the beginner level, basic vocabulary and grammar exercises are proposed;

• at the advanced level, exercises involve translating orders, analyzing combat reports, or practicing communication in multinational units.

Several platforms – such as **REAP**, **Lärka**, and **Revita** – demonstrate the integration of authentic texts into the exercise generation process. For military higher education institutions, this implies the use of combat manuals, real radio communication samples, and authentic articles from military journals as training materials.

Thus, through the automatic generation of exercises, AI enables:

• rapid preparation of training materials that reflect military specificity;

• personalization of tasks according to the cadet's proficiency level;

• the use of authentic materials to develop **foreign language professional communicative competence** under wartime conditions.

2.2. Reading

Reading comprehension tasks – such as answering content questions, verifying statement accuracy, or identifying key information – are an essential component of CALL systems for cadet training in higher military institutions. Experimental research indicates that automatically generated questions enhance text comprehension and retention [9]. Heilman demonstrated the effectiveness of automatic question generation for beginner and intermediate learners, which is particularly relevant for cadets who have limited time for independent study under wartime conditions.

Before the advent of neural networks, question generation relied on **lexical and syntactic transformations**, **template-based methods**, or **keyword substitution**. Later studies shifted toward exercises focused on grammatical and linguistic structures, assessing both understanding and functional use of specific constructions.

Contemporary question generation approaches employ **neural networks**, including **attention mechanisms**, **pointer networks**, and **Transformer architectures**. These methods allow for the creation of longer, semantically richer questions similar to those used in reading comprehension tests. Research by **Gao et al.** and **Stasaski et al.** confirms the effectiveness of such models for exam preparation and testing.

Recent advances in **large language models (LLMs)** – such as **GPT-3**, **GPT-4**, **Llama**, **Gemini**, and **Mixtral** – demonstrate the capability to generate high-quality educational materials in **zero-shot** or **few-shot** modes. Conversational systems such as **ChatGPT** can automatically produce comprehension questions, generate summaries, explain complex vocabulary, and adapt tasks to the cadet's language proficiency level [10].

Xiao et al. implemented a system that generates English reading passages and corresponding questions for Chinese students. The resulting materials demonstrated high quality, in some cases surpassing those produced by human teachers. Such systems can be adapted for cadets, particularly for use with authentic military texts and documents.

Säuberli and Clematide explored the application of LLMs for creating and evaluating multiple-choice questions. Using **Llama 2** and **GPT-4** enabled automation of the labor-intensive process of developing high-quality test items. This opens opportunities for rapid material development even for low-resource languages, which is valuable in military English training.

Despite their advantages, several challenges remain: the risk of factual inaccuracies, limited personalization, data bias, unauthorized content reuse, and ethical concerns [11]. However, the academic community is actively addressing these issues. An example is the **Generative AI for Education (GAIED)** workshop at the **NeurIPS** conference, dedicated to the pedagogical use of LLMs.

For cadets in military higher education institutions, the integration of LLMs into reading comprehension tasks can not only accelerate instructional material creation but also enhance **interactivity and adaptability** in learning – both crucial under wartime conditions that require flexible and efficient training.

2.3. Listening and Speaking

The development of listening skills among cadets of higher military educational institutions (HMEIs) is of critical importance, as the ability to comprehend oral commands, instructions, or reports in English promptly constitutes a component of operational readiness. Artificial intelligence (AI) opens new possibilities for improving auditory competence through the integration of authentic audio materials and interactive platforms. Synchronized subtitles in educational videos or audio content enable cadets to internalize vocabulary more effectively and enhance their ability to comprehend speech in real time.

Although services such as **YouTube**, **Spotify**, or voice assistants like **Siri** and **Alexa** can partially support listening comprehension practice, they are not specifically designed for pedagogical objectives. Research indicates that **Computer-Assisted Language Learning (CALL)** systems are considerably more effective in developing selective listening and training learners to grasp the meaning of audio texts, as they allow instructors to account for individual learners' needs. For instance, **Duolingo** exercises require cadets to reproduce what they hear or complete post-listening tasks that assess factual comprehension. Such tools foster the discipline of *active listening*, essential during radio communications or military briefings.

The new generation of **Large Language Model (LLM)**-based systems integrates automatic speech recognition (ASR) and speech generation technologies, thereby enabling the creation of conversational simulators. These systems imitate real communicative situations, providing cadets with unlimited opportunities to practice response speed, repeat identical scenarios, and overcome the psychological barrier to speaking. Studies demonstrate that interaction with dialogue-based systems reduces anxiety, enhances self-confidence, and contributes to the expansion of both active and receptive vocabulary.

Recent developments, such as **FunAudioLLM** and **Comuniqa**, illustrate the potential of AI in establishing natural voice-based interaction with users, including the simulation of dialogues in military contexts. Although such systems still fall short of human instructors in terms of feedback flexibility and empathy, they offer promising prospects for scalable language learning. The integration of LLM technologies with situational dialogue models enables cadets to practice communication in conditions closely resembling authentic combat or operational scenarios – from patrol duties and checkpoint procedures to multinational staff interactions.

Thus, the combination of **CALL applications** and **AI-driven dialogue systems** creates a novel learning environment for cadets of HMEIs, where listening and speaking skills are developed in a comprehensive and purposeful manner, enhancing their readiness for practical use of English in professional military activities.

2.4 Assessment and Feedback

The assessment of a learner's performance is closely connected with the **Student Model** and the **Instructional Model**. The Student Model is continuously updated based on the learner's history of correct and incorrect responses, while the Instructional Model uses these data to determine subsequent developmental steps, generate individualized feedback, and guide the progression of skills and topics.

Various methods may be applied in the assessment process, including **pattern matching**, **rule-based approaches**, and **statistical models**. Pattern matching is effective for multiple-choice tasks, which typically involve a single correct answer. However, exercises such as gap-filling or sentence rearrangement often allow several acceptable responses, necessitating more flexible models capable of evaluating grammatical accuracy.

Grammatical Error Detection (GED) is crucial for assessing both written and spoken texts, as it affects not only scoring but also the quality of feedback. Accurate error identification provides deeper insights into the learner's understanding of specific grammatical constructions, which directly informs the subsequent selection of exercises within the Instructional Model.

A distinct line of research is **Automated Essay Scoring (AES)**, which dates back to the 1960s AES is a complex task encompassing grammar, spelling, semantics, discourse, and pragmatics assessment. Contemporary studies emphasize two major aspects:

- **Holistic evaluation**, reflecting the overall quality of a learner's written output;
- **Multidimensional evaluation**, assigning separate scores to distinct parameters.

Research in AES explores stylistic features (e.g., orthography, text length), content and coherence, as well as multi-feature integration [12]. A comprehensive review of key AES approaches is presented by **Lim et al.** While some AES systems are publicly accessible (e.g., the **Automated Writing Placement System**, integrated into **Cambridge English Write & Improve™**), most remain commercial products such as **Project Essay Grader (PEG)**, **Intelligent Essay Assessor (IEA)**, **IntelliMetric**, and **E-rater**. For instance, **SAGE** evaluates text coherence through lexical diversity analysis, while **Revision Assistant** automatically identifies sentences requiring improvement. A broader overview of AES systems and methods is provided by **Ramesh et al.** However, to date, no AES system has been directly integrated into a CALL environment.

According to **Bibauw et al.**, dialogue-based CALL systems can be classified into several categories:

- **Intelligent Tutoring Systems (ITS)**, which assess learners' speech and generate adaptive feedback;
- **Computer-Assisted Pronunciation Training (CAPT)** systems;
- **Spoken Dialogue Systems (SDS)** or **Conversational Agents (CA)**;
- **Chatbots**, primarily text-based, designed to produce reactive responses.

Automated **spoken language assessment** has also emerged as an independent research area. Initially, it focused on evaluating pronunciation quality by comparing learners' prepared responses with native-speaker reference samples. Subsequently, attention shifted toward spontaneous speech, where researchers now analyze grammatical errors, pronunciation, lexical inaccuracies, accent features, and off-topic responses [13].

A practical example is **SpeechRaterSM** – operational since 2006 – which pioneered the assessment of spontaneous English responses by non-native speakers. It integrates **ASR** and **NLP** technologies to filter out off-topic or non-English responses and provides detailed feedback on prosody, pronunciation, vocabulary, and grammar.

Recent studies employ **LLMs** for speech evaluation. **Fu et al.** developed a model analyzing speech accuracy and fluency by aligning learner utterances with contextual features, while **Wang et al.** investigated prosodic characteristics, including pauses in L2 English speech, using both pre-trained models and LLM-based systems.

Challenges in delivering **instant and personalized feedback** in spoken language assessment are comparable to those encountered in AES. The effectiveness of such feedback depends on several factors, including:

- The **degree of specificity** (direct vs. indirect comments);
- The **accuracy of error detection**;
- The **consideration of individual learner variables**, such as L2 proficiency and educational background.

Conclusions and Directions for Future Research. This article has provided an overview of contemporary artificial intelligence tools that can be integrated into foreign language learning, particularly within military institutions of higher education. Special attention has been given to the interrelation between the structural components of Intelligent Tutoring Systems (ITS) and their key functional capabilities, such as automatic exercise generation, assessment, and personalized feedback. The approaches examined demonstrate the significant potential of AI to enhance the efficiency of language skill formation among future officers.

However, despite the existence of successful practical implementations, there remains a lack of coherent and comprehensive theories concerning the intelligent support of foreign language learning. This highlights the need for further research aimed at developing holistic frameworks for the application of AI in military pedagogy.

Future research should focus on the following areas:

- **Adaptive learning:** developing systems that take into account the learner's proficiency level–from beginner to advanced user–as well as the specific characteristics of the military context.
- **Material complexity assessment:** creating algorithms for the automatic determination of readability and relevance of instructional texts used in cadet training.
- **Text simplification:** designing systems capable of generating authentic yet level-appropriate learning materials.
- **Crowdsourced resources:** building corpora of cadets' spoken and written language to serve as a foundation for the improvement of educational platforms.
- **Comparative analysis:** conducting systematic studies of the effectiveness of commercial and academic CALL/ITS systems in military settings.

In conclusion, the application of artificial intelligence in foreign language education for cadets of military higher education institutions opens wide prospects. It not only enhances the quality of professional training but also ensures flexibility and personalization of the learning process–features that are particularly vital in wartime conditions.

REFERENCES:

1. Meurers, D.: Natural Language Processing and Language Learning. In: Encyclopedia of Applied Linguistics, pp. 4193–4205. Blackwell Oxford, UK (2012)
2. Chapelle, C., Jamieson, J.: Language Lessons on the PLATO IV System. System 11(1), 13–20 (1983)
3. Slavuj, V., Kovaˇciˊc, B., Jugo, I.: Intelligent Tutoring Systems for Language Learning. In: Proceedings of the 38th International Convention on Information and Communication Technology, Electronics and Microelectronics, pp. 814–819 (2015). IEEE
4. Albacete, P., Jordan, P., Katz, S., Chounta, I.-A., McLaren, B.M.: The Impact of Student Model Updates on Contingent Scaffolding in a Natural-language Tutoring System. In: Proceedings of the 20th International Conference on Artificial Intelligence in Education, pp. 37–47 (2019). Springer
5. Anderson, J.R., Boyle, C.F., Corbett, A.T., Lewis, M.W.: Cognitive modeling and intelligent tutoring. Artificial Intelligence 42(1), 7–49 (1990).
6. Chang, M., D'Aniello, G., Gaeta, M., Orciuoli, F., Sampson, D., Simonelli, C.: Building Ontology-driven Tutoring Models for Intelligent Tutoring Systems Using Data Mining. IEEE Access 8, 48151–48162 (2020)
7. Bravo-Agapito, J., Bonilla, C.F., Seoane, I.: Data Mining in Foreign Language Learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 10(1), 1287 (2020)
8. Alkhatlan, A., Kalita, J.: Intelligent Tutoring Systems: A Comprehensive Historical Survey with Recent Developments. International Journal of Computer Applications 181(43), 1–20 (2019)
9. Shabani, K., Khatib, M., Ebadi, S.: Vygotsky's Zone of Proximal Development: Instructional Implications and Teachers' Professional Development. English language teaching 3(4), 237–248 (2010)
10. Steuer, T., Filighera, A., Tregel, T., Miede, A.: Educational Automatic Question Generation Improves Reading Comprehension in Non-native Speakers: A Learner-Centric Case Study. Frontiers in Artificial Intelligence 5 (2022)
11. Kohnke, L., Moorhouse, B.L., Zou, D.: ChatGPT for Language Teaching and Learning. RELC Journal 52, 537–550 (2023)
12. Caines, A., Benedetto, L., Taslimipoor, S., Davis, C., Gao, Y., Andersen, O., Yuan, Z., Elliott, M., Moore, R., Bryant, C., Rei, M., Yannakoudakis, H., Mullooly, A., Nicholls, D., Buttery, P.: On the Application of Large Language Models for Language Teaching and Assessment Technology. arXiv preprint arXiv:2307.08393 (2023)
13. Lee, C.M., Yoon, S.-Y., Wang, X., Mulholland, M., Choi, I., Evanini, K.: Off-Topic Spoken Response Detection Using Siamese Convolutional Neural Networks. In: Proceedings of the 18th Annual Conference of the International Speech Communication Association, pp. 1427–1431 (2017)

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