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GENERATIVE ARTIFICIAL INTELLIGENCE AS A TOOL FOR PERSONALISING LANGUAGE LEARNING: ADAPTING MATERIALS TO LEARNERS' PROFICIENCY LEVELS AND INDIVIDUAL NEEDS

This article examines the use of generative artificial intelligence (GenAI) for adapting language learning materials to learners' proficiency levels and individual needs. Although personalisation has long been regarded as a desirable principle of instruction, its implementation has been limited by teachers' time and resources. The exploratory pilot study was conducted over six months with 92 students of the Faculty of Power Engineering and Electromechanics, and three cases were analysed in detail: level-based adaptation of technical texts, exercises targeting first-language interference, and formative feedback on writing. The findings suggest that adaptation is most reliable when prompts contain specific, operationalised parameters, whereas a general CEFR label may be interpreted only approximately, occasionally yielding lexis above the target level. Personalisation appears most productive when it responds to learners' actual difficulties rather than merely simplifying text. The study underlines the changing role of the teacher as designer of prompts and critical evaluator of machine-generated input. The conclusions are exploratory and define hypotheses for a controlled study. Keywords: generative artificial intelligence; personalised learning; language teaching; CEFR; first-language interference; teacher mediation.

Every language textbook is, in a sense, addressed to a person who does not exist: the "average learner", whose proficiency, interests, and difficulties conveniently coincide with the median of an imagined cohort. For decades, language pedagogy has acknowledged this fiction, yet it has lacked the means to resolve it, since the individualisation of materials has remained a labour-intensive craft available mainly to teachers with ample time and small groups. The emergence of generative artificial intelligence (GenAI) has altered this constraint in a fundamental way, as large language models can now rewrite a text, recalibrate its lexical and syntactic complexity, and produce tailored exercises within seconds. However, the speed and fluency of such output should not be mistaken for pedagogical validity: a text that is merely simplified is not necessarily a text that is appropriately adapted to a learner's zone of proximal development. This tension between technological capability and instructional soundness remains insufficiently theorised, particularly with regard to how proficiency descriptors, such as those of the CEFR, are operationalised in prompts and interpreted by models. The present article therefore examines GenAI-driven adaptation of learning materials as a distinct form of personalisation, in which the teacher's role shifts from author of content to designer and critical evaluator of machine-generated input. In doing so, it seeks to identify the conditions under which such adaptation genuinely responds to learners' needs rather than merely simulating individualisation.

Statement of the problem and its connection to scientific and practical tasks.

The central problem addressed in this study concerns the absence of a theoretically grounded and empirically verifiable framework for using generative artificial intelligence (GenAI) to adapt language learning materials to the

proficiency level and individual needs of the learner. Although personalisation has long been regarded [1] as a desirable principle of language instruction, its implementation has traditionally been constrained by the finite time and resources of teachers, which has led to the widespread reliance on standardised materials. GenAI appears to remove this constraint, since it enables [2] the rapid generation, simplification, and reformulation of texts and tasks for individual users. Nevertheless, the technical capacity to produce adapted content does not in itself guarantee that the adaptation is linguistically accurate, level-appropriate, or pedagogically productive. The problem is therefore twofold: it is necessary to determine, first, how reliably GenAI models interpret and reproduce proficiency criteria, such as the descriptors of the Common European Framework of Reference for Languages (CEFR), and, second, whether the resulting materials contribute to measurable learning gains.

This question is closely connected to several fundamental tasks of applied linguistics and educational theory, notably the operationalisation of the construct of text complexity and the refinement of models of learner-centred instruction. It also bears on the long-standing challenge of maintaining the principle of "comprehensible input" without placing an unsustainable workload on the practitioner. From a practical perspective, the problem is pertinent to the design of adaptive curricula, to the development of reliable procedures for the quality assurance of machine-generated materials, and to the professional preparation of teachers who must increasingly act as critical evaluators of such output. Its relevance is heightened in higher education, where groups are linguistically heterogeneous and where language competence directly affects academic mobility and participation in international research communities. Resolving this problem would thus contribute both to the theoretical understanding of AI-mediated personalisation and to the establishment of evidence-based standards for its responsible use in language teaching.

Analysis of the latest research and publications.

The integration of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) into personalized language learning represents a paradigm shift from static digital environments to dynamic, responsive instructional ecosystems. Historically, artificial intelligence in language acquisition [3] relied on predefined algorithmic pathways and rule-based systems to facilitate adaptive learning and basic vocabulary retention (Chen et al., 2021). However, the scholarly focus has recently transitioned toward the capacity of GenAI to autonomously generate, modify, and grade instructional materials in real time.

Contemporary frameworks emphasize [4] moving beyond generic content delivery to personalized ecosystems where LLMs provide adaptive feedback, generate contextualized linguistic exercises, and continuously align textual input with learners' evolving cognitive capacities (Jyothy et al., 2024). By acting as a scalable, adaptive tutor, GenAI initiates [5] a solution to the persistent challenge of providing individualized instruction without proportionately increasing educator workload (Ahmed et al., 2024). Current research underscores that LLMs can effectively modulate syntactic complexity and lexical density, thereby maintaining optimal cognitive load for learners across various proficiency tiers.

While recent publications establish the foundational viability of GenAI in language learning, significant gaps remain regarding its pedagogical optimization in specialized academic contexts. This article is devoted to addressing the following previously unsolved dimensions of the general problem:

- precision in domain-specific lexical adaptation. Current GenAI applications primarily target general conversational or academic language proficiency. There is a marked deficit [6, 7] in established cognitive-linguistic frameworks for adapting complex technical terminology and specialized discourse (e.g., English for Specific Purposes) to varying proficiency levels without compromising the factual and technical accuracy of the source material.
- methodological frameworks for prompt engineering in pedagogy. While LLMs possess inherent adaptive capabilities, the literature lacks standardized, evidence-based prompt engineering methodologies that educators can deploy to systematically calibrate learning materials for specific cognitive, translational, and linguistic objectives.
- transition from corrective feedback to heuristic scaffolding. Existing empirical studies predominantly utilize GenAI for immediate error correction in writing and translation tasks. The challenge of designing prompts that compel the AI to provide "clues before correction" – fostering metacognition, reflective analysis, and learner autonomy rather than over-reliance – remains critically underexplored.
- mitigation of algorithmic output degradation in specialized texts. Ensuring the structural and terminological integrity of AI-generated academic reading materials and technical translations requires robust validation protocols. The integration of GenAI as a reliable [8, 9] tool for Content and Language Integrated Learning (CLIL) necessitates safeguards against algorithmic hallucination that have not yet been fully formalized in applied linguistics literature.

Purpose of the article. This article aims to examine how generative AI can be used to adapt language learning materials to learners' proficiency levels and individual needs, and to determine the conditions under which such adaptation is both linguistically reliable and pedagogically effective, rather than merely appearing personalised.

Presentation of the main material (pilot study).

Design and ethics. The study was designed as an exploratory pilot and was conducted over six months with 92 students of the Faculty of Power Engineering and Electromechanics. All data were collected and processed confidentially; participation was voluntary, written informed consent was obtained from every student, including consent to the publication of aggregated and anonymised findings, and no personal data are disclosed in this article. Given the exploratory aim, the analysis is qualitative and case-based: it seeks to identify patterns, tensions, and hypotheses for subsequent controlled research rather than to establish statistically generalisable effects.

Procedure. The students, whose proficiency ranged from A2 to B2 on the CEFR scale, worked with discipline-specific materials adapted by a large language model in response to a structured prompt. The prompt specified the target level, the learner's first language (Ukrainian), the professional domain, and the intended skill. All outputs were reviewed by the instructor before classroom use, which made it possible to evaluate the quality of the adaptation separately from its pedagogical effect. Three representative cases were selected for detailed analysis, each corresponding to a distinct type of personalisation.

Case 1. Level-based adaptation of a technical text. The source sentence, taken from a textbook on electrical machines, read: "The rotating magnetic field produced by the stator windings induces an electromotive force in the rotor conductors, which in turn generates the torque that sets the rotor in motion." For B1 learners, the model produced: "The stator creates a magnetic field that rotates. This field produces an electric current in the rotor. The current and the field together make the rotor turn." The adapted version preserves the causal chain while reducing syntactic embedding and replacing low-frequency terms. However, in A2-level requests the model occasionally retained words such as dissipate and commutation, which lie above the target band. This suggests that the model's interpretation of a proficiency descriptor is approximate.

Case 2. Adaptation to first-language interference. When the prompt specified Ukrainian as the learners' first language, the model generated exercises on false friends in technical English, contrasting *tension* with *voltage* (Ukrainian *напруга*), *actual* with *current* (*актуальний*), and *accumulator* with *battery*. A typical learner error, *"The tension in the circuit is 220 V,"* was corrected together with a brief explanation of why *voltage* is the standard term. The case indicates that the model can target interference patterns when they are named in the prompt, although the extent to which this reduces such errors over time requires systematic measurement.

Case 3. Formative feedback on writing. A student drafted: *"The engine work with high efficiency in the nominal regime."* The model returned *"The motor operates at high efficiency under rated conditions,"* and explained three points: subject-verb agreement, the preference for *motor* over *engine* in the context of electrical machines, and the conventional collocation *rated conditions* in place of the calque *nominal regime* (*номінальний режим*). Combining correction with a rule-level explanation appears to support noticing, which is a precondition for uptake.

Table 1

Summary of the analysed cases

Case	Type of personalisation	Input to the model	Key feature of the output	Instructor's evaluation	Limitation identified
1	Level-based text adaptation	Textbook sentence; target level A2/B1	Shorter clauses, reduced embedding, simpler lexis; causal chain preserved	Appropriate at B1; partly inappropriate at A2	Occasional lexis above target level (*dissipate*, *commutation*)
2	L1-oriented exercises	Prompt specifying Ukrainian as L1 and technical domain	Exercises on false friends (*tension/voltage*, *actual/current*, *accumulator/battery*)	Relevant to observed interference patterns	Long-term effect not yet measured
3	Formative feedback on writing	Student sentence with grammatical and lexical errors	Corrected version with three-point rule-level explanation	Accurate and pedagogically useful	Dependence on the quality of the prompt and on teacher verification

Three tentative conclusions follow from the cases. First, adaptation was most successful where the prompt contained specific, operationalised parameters (the first language, the domain, the type of feedback), whereas reliance on a general level label such as "A2" produced less consistent results. Second, the benefit of personalisation appears to lie in its precision, that is, in the match between the material and the learner's actual difficulties, rather than in the mere volume of additional input. Third, the instances of lexical overshoot confirm that expert mediation is indispensable: GenAI functions [10] as an effective drafting tool for individualised materials only when its output is checked against explicit level criteria.

Conclusions and prospects for further research.

This pilot study set out to examine how generative AI can be used to adapt language learning materials to learners' proficiency levels and individual needs, and its findings, although exploratory, allow several conclusions to be drawn. First, GenAI proved capable of producing differentiated materials [11, 12] quickly and in a form that was, in most analysed cases, usable in the classroom; however, the adaptation was reliable only to the extent that the prompt contained specific, operationalised parameters. A general level label such as "A2" was interpreted approximately, and the occasional presence of lexis above the target band shows that the model's reading of proficiency descriptors cannot be taken for granted. Second, the most promising form of personalisation appeared to be that which responded to learners' actual difficulties, in particular first-language interference and domain-specific terminology, rather than that which merely simplified text. Third, feedback that combined correction with a rule-level explanation seemed to foster noticing, which is a precondition for learning. Finally, the study confirms that the teacher's role does not diminish but changes: from author of materials to designer of prompts and critical evaluator of machine-generated input.

Several directions for further research follow. A controlled study with pre- and post-testing is needed to determine whether the personalisation described here produces measurable learning gains. Independent measures of text level, such as vocabulary profiling and readability indices, should be used to test how accurately models reproduce CEFR descriptors. It would also be valuable to compare different models and prompt designs, to investigate learners' own perceptions and autonomy in working with adapted materials, and to examine longer-term effects on retention and transfer to authentic professional communication. Finally, the development of evidence-based guidelines for teacher training and for the quality assurance of machine-generated materials remains an important practical task, particularly in technical higher education, where language competence directly supports academic and professional mobility.

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