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Original article

Odychess approach: a dialectical, constructivist and adaptive method for teaching chess with generative artificial intelligences

[*Enfoque Odychess: un método dialéctico, constructivista y adaptativo para la enseñanza del ajedrez con inteligencias artificiales generativas*]

[*Abordagem Odychess: Um Método Dialético, Construtivista e Adaptativo para o Ensino de Xadrez com Inteligências Artificiais Generativas*]

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ABSTRACT

Introduction: Chess teaching has evolved through different approaches, however, traditional methodologies, often based on memorization, contrast significantly with the new possibilities offered by generative artificial intelligence, a technology still little explored in this field.

Objective: To empirically validate the effectiveness of the Odychess approach in improving chess knowledge, strategic understanding, and metacognitive skills in students.

Materials and methods: A quasi-experimental study was conducted with a pretest/ posttest design and a control group (N=60). The experimental intervention implemented the Odychess approach , incorporating a Llama 3.3 language model that was specifically adapted using *Parameter-Efficient Fine- Tuning* (PEFT) techniques to act as a Socratic chess tutor. Quantitative assessment instruments were used to measure chess knowledge, strategic understanding, and metacognitive skills before and after the intervention.

Results: The results of the quasi-experimental study showed significant improvements in the experimental group compared to the control group in all three variables analyzed: chess knowledge, strategic understanding, and metacognitive skills. Complementary qualitative analysis revealed greater analytical depth, more developed dialectical reasoning, and higher intrinsic motivation in students participating in the Odychess - based intervention.

Conclusions: The Odychess approach represents an effective pedagogical methodology for teaching chess, demonstrating the potential of synergistic integration of constructivist and dialectical principles with generative artificial intelligence. The implications of this work are relevant for educators and institutions interested in adopting innovative pedagogical technologies and for researchers in the field of AI applied to education, highlighting the transferability of the language model adaptation methodology to other educational domains.

Keywords: educational chess, artificial intelligence in education, dialectical learning, adaptive tutoring.

RESUMEN

Introducción: la didáctica del ajedrez ha evolucionado a través de diferentes enfoques, sin embargo, las metodologías tradicionales, a menudo basadas en la memorización, contrastan significativamente con las nuevas posibilidades que ofrece la inteligencia artificial generativa, una tecnología aún poco explorada en este campo.

Objetivo: validar empíricamente la efectividad del enfoque Odychess en la mejora del conocimiento ajedrecístico, la comprensión estratégica y las habilidades metacognitivas en estudiantes.

Materiales y métodos: se llevó a cabo un estudio cuasiexperimental con un diseño pretest/post-test y un grupo control (N=60). La intervención experimental implementó el enfoque Odychess, incorporando un modelo de lenguaje Llama 3.3 que fue adaptado específicamente mediante técnicas de *Parameter-Efficient Fine-Tuning* (PEFT) para actuar como tutor ajedrecístico socrático. Se utilizaron instrumentos de evaluación cuantitativa para medir el conocimiento ajedrecístico, la comprensión estratégica y las habilidades metacognitivas antes y después de la intervención.

Resultados: los resultados del estudio cuasiexperimental mostraron mejoras significativas en el grupo experimental en comparación con el grupo control en las tres variables analizadas: conocimiento ajedrecístico, comprensión estratégica y habilidades metacognitivas. El análisis cualitativo complementario reveló una mayor profundidad analítica, un razonamiento dialéctico más desarrollado y una mayor motivación intrínseca en los estudiantes que participaron en la intervención basada en el método Odychess.

Conclusiones: el enfoque Odychess representa una metodología pedagógica eficaz para la enseñanza del ajedrez, demostrando el potencial de la integración sinérgica de principios constructivistas y dialécticos con la inteligencia artificial generativa. Las implicaciones de este trabajo son relevantes para educadores e instituciones interesadas en la adopción de tecnologías pedagógicas innovadoras y para investigadores en el campo de la IA aplicada a la educación, destacando la transferibilidad de la metodología de adaptación de modelos de lenguaje a otros dominios educativos.

Palabras clave: ajedrez educativo, inteligencia artificial en educación, aprendizaje dialéctico, tutoría adaptativa.

RESUMO

Introdução: O ensino do xadrez tem evoluído por meio de diferentes abordagens, porém, as metodologias tradicionais, muitas vezes baseadas na memorização, contrastam significativamente com as novas possibilidades oferecidas pela inteligência artificial generativa, tecnologia ainda pouco explorada neste campo.
Objetivo: Validar empiricamente a eficácia da Abordagem Odychess na melhoria do conhecimento de xadrez, compreensão estratégica e habilidades metacognitivas em alunos.
Materiais e métodos: Foi realizado um estudo quase-experimental com delineamento pré-teste/pós-teste e grupo controle (N=60). A intervenção experimental implementou a Abordagem Odychess, incorporando um modelo de linguagem Llama 3.3 que foi especificamente adaptado usando técnicas de Ajuste Fino Eficiente em Parâmetros (PEFT) para atuar como um tutor de xadrez socrático. Instrumentos de avaliação quantitativa foram usados para medir o conhecimento de xadrez, a compreensão estratégica e as habilidades metacognitivas antes e depois da intervenção.
Resultados: Os resultados do estudo quase experimental mostraram melhorias significativas no grupo experimental em comparação ao grupo controle nas três variáveis analisadas: conhecimento de xadrez, compreensão estratégica e habilidades metacognitivas. A análise qualitativa complementar revelou maior profundidade analítica, raciocínio dialético mais desenvolvido e maior motivação intrínseca nos alunos que participaram da intervenção baseada no Odychess.
Conclusões: A Abordagem Odychess representa uma metodologia pedagógica eficaz para o ensino de xadrez, demonstrando o potencial da integração sinérgica dos princípios construtivistas e dialéticos com a inteligência artificial generativa. As

implicações deste trabalho são relevantes para educadores e instituições interessadas em adotar tecnologias pedagógicas inovadoras e para pesquisadores na área de IA aplicada à educação, destacando a transferibilidade da metodologia de adaptação do modelo de linguagem para outros domínios educacionais.

Palavras-chave: xadrez educacional, inteligência artificial na educação, aprendizagem dialética, tutoria adaptativa.

INTRODUCTION

Several authors have addressed the teaching of chess, such as (Bueno, L., 2000; Ramírez, Bueno & Gordo, 2016), basing themselves primarily on pedagogical constructivism. This theory postulates the need to provide students with tools and temporary support (scaffolding) so that they can construct their own problem-solving procedures, modifying and adjusting their knowledge schemes based on experience. In essence, constructivism emphasizes active and reflective learning: students integrate new knowledge by relating it to their prior knowledge and reformulate their ideas when faced with challenges. This approach contrasts with traditional models focused on the passive transmission of content by the teacher, where the student assumes a more active role in their own learning.

In this way, the student builds his understanding by solving exercises, experimenting with ideas and discussing his reasoning, which is aligned with the constructivist principle of the "mutual construction of knowledge" between educator and learner (Coll *et al.,* 2006).

However, chess teaching often lacks strategies that promote an optimal teaching-learning process (Reyes-Joa *et al.,* 2020). In this sense, it is crucial to fully exploit dialectics through reflective conversations about chess positions. This encourages students to justify their moves, anticipate rebuttals, and compare alternative lines, training not only specific chess knowledge but also cognitive flexibility and openness to changing opinions in the face of evidence. These skills are inherent to dialectical thinking and essential for a competent chess player. In short, the dialectical dimension ensures that chess learning transcends rote memorization, becoming a process of critical inquiry where each concept is deeply understood by contrasting it with alternatives and resolving discrepancies that arise during reasoning.

In this context, the use of contemporary approaches such as Problem-Based Learning (PBL) and pattern acquisition in the chess domain become relevant. In general pedagogy, PBL (Problem-Based Learning) Learning (PBL) is defined as a teaching strategy focused on the presentation of complex and real problems as a driving force for learning key concepts, as opposed to the direct exposition of theoretical content (Barrows, 1986; Savery, 2006).

In today's educational landscape, the search for innovative methodologies that promote meaningful and in-depth learning is a constant priority (USFA, 2024). However, the effective application of these benefits to the field of chess requires pedagogical approaches that go beyond mere rote instruction.

In this scenario, this article introduces the Odychess approach, a pedagogical method for teaching chess that integrates dialectical and constructivist principles with generative artificial intelligence (AI) tools.

This methodological proposal emerges from the need to update chess teaching, traditionally focused on memorizing moves or one-way instruction, toward a more interactive, personalized, and student-centered model. Within Odychess , the learning process is conceived as a cognitive journey of discovery, where the student actively builds their chess knowledge through problem-solving, reflective dialogue, and the continuous adaptation of task difficulty.

This approach relies on advanced generative language models (such as Google's Gemini, Anthropic 's Claude, or Meta's Llama 3.3 model, used in our implementation) (

Grattafiori *et al.,* 2024) to provide personalized tutoring, guiding the student interactively and adjusting to their playing level.

From a didactic perspective, the Odychess method is justified by the convergence of several objectives: fostering meaningful chess learning (beyond the simple accumulation of openings or tactical patterns), developing students' critical and dialectical thinking through play, and harnessing the potential of generative artificial intelligence to offer large-scale individualized tutoring.

In parallel, Odychess emphasizes pattern-based teaching, recognizing that chess skill relies heavily on memory and the recognition of positional and tactical patterns. The cognitive science of chess has shown that elite masters do not necessarily calculate more deeply than less experienced players, but rather recognize familiar configurations that guide their thinking. In a classic study, Chase and Simon (1973) found that expert players possess an extensive catalog of patterns stored in long-term memory, allowing them to quickly recall and identify meaningful piece configurations, unlike novices. Indeed, chess mastery stems from internalizing increasingly sophisticated representations of the board and its characteristic patterns (De Groot, 1965; Gobet & Simon, 1996). Therefore, effective chess training often involves exposure to thousands of tactical problems and typical positions, so that the player develops an almost instantaneous "feel" for recognizing opportunities (e.g., a mating pattern, a structural weakness, etc.).

Odychess approach incorporates this idea through the systematic practice of patterns in a problem-solving context. Each problem or scenario presented is designed to highlight one or more specific strategic/tactical patterns. For example, one Decontextualized Problem-Based Learning (DPLLS) scenario might focus on the pinning pattern (a piece pinned in a line), another on a typical queen and knight mate, and another on a strategic motif such as an isolated pawn. By solving numerous cases, the student builds structured schemas in memory that can later be recalled during a real game. As Grandmaster Serper (2015) notes, "The more patterns you know, the easier it is to find good moves in your games."

The synergy between PBL and pattern-based learning in Odychess lies in the fact that the problems presented provide a meaningful context for pattern acquisition. Instead of studying a list of tactical topics in isolation, the student encounters them *in situ* by solving exercises. This led to deeper learning: the pattern ceases to be an abstract concept and becomes a concrete tool that allowed the student to overcome an obstacle. Furthermore, the variety of problems, many of them decontextualized from known sequences, prevents the student from relying on rote memorization; it forces them to analyze the essence of the position and transfer known principles to new contexts.

Thus, what Bueno (2016) discussed when proposing that the problems-patterns binomial ensures significant and transferable chess learning: students acquire repertoires of schemes (patterns) and also the ability to apply them flexibly, solving new situations.

The core objectives of the approach include improving students' strategic and tactical understanding, enhancing their problem-solving skills in novel chess contexts, and developing metacognitive skills (reflection on their own thinking processes) through interaction with an AI tutor.

Ultimately, Odychess aims to transform chess teaching into a more dynamic, adaptive, and formative process, serving as the basis for application manuals and guides for teachers who wish to incorporate this methodology into their practices. Therefore, the objective of this research is to empirically validate the effectiveness of the Odychess approach in improving chess knowledge, strategic understanding, and metacognitive skills in students.

MATERIALS AND METHODS

To evaluate the effectiveness of the Odychess approach, a quasi-experimental study was designed and executed with a pretest/ posttest design and non-equivalent control group.

- Participants: The sample consisted of 60 secondary school students (aged 13–15 years) from two schools with similar socioeconomic characteristics. Participants had a beginner-intermediate chess level (estimated ELO < 1200 FIDE) and were assigned to the conditions according to their pre-existing class groups (non-random assignment of intact groups): an experimental group (EG, n=30) that received instruction using the Odychess approach, and a control group (CG, n=30) that followed a traditional chess teaching method based on expository lessons and solving standard exercises. Informed consent was obtained from parents or legal guardians and assent from the students.
- Odychess- based chess program for one academic semester (16 weeks), with two 60-minute sessions per week. Sessions were led by a teacher trained in the Odychess approach and used the digital platform integrating the tutor " Odychess -Tutor". Students interacted with EAPBDs, participated in Socratic dialogues with the teacher and/or the AI, analyzed games, and maintained a digital portfolio. The CG received the same number of instructional hours but with a traditional method focused on the teacher explaining openings, middlegame, and endgames, followed by tactical problem-solving and practice games without the dialogic-adaptive component or the use of the dedicated AI tutor.

Data collection instruments:

- Chess Knowledge Test (CKT): a test composed of standardized tactical problems (calculation and pattern recognition assessment), questions on strategic principles, and position evaluation. It was administered at the beginning (pre-test) and at the end (post-test). Reliability, measured using Cronbach's alpha, was 0.83.
- Strategic Understanding Assessment (SCA): A task based on the written analysis of a complex position, assessing the ability to formulate plans, anticipate responses, and justify decisions. Graded using a rubric by two

independent evaluators with an inter-rater agreement index (kappa) > 0.85. Administered in the pre- and post-test.

- Chess Metacognitive Skills Scale (EHMA): A Likert-type questionnaire adapted to measure self-perceptions of planning, monitoring, and evaluating one's own thinking during play (based on Schraw and Dennison, 1994). Applied in pretest and posttest.
- Logging interactions with AI: For the GE, anonymized transcripts of dialogues with the Odychess tutor were qualitatively analyzed, looking for evidence of dialectical reasoning and reflection.
- Learning portfolios and teacher observation: qualitative analysis of the portfolios (commented items, reflections) and teacher observation notes on student participation and attitudes in both groups.
- Motivation and Engagement Questionnaire (MQE): a Likert scale measuring interest, enjoyment, and perceived usefulness of chess classes. Administered at the end of the study.

Procedure:

Following the administration of the pretests (PCA, ECE, EHMA), the intervention was implemented for 16 weeks. The EG teacher facilitated the Odychess sessions, while another teacher taught the traditional classes for the CG. Equivalence in experience and training between the two teachers was controlled to minimize this factor as an extraneous variable. At the end of the period, the posttests (PCA, ECE, EHMA) and the CMC were administered. Data on interactions with the AI and portfolios were collected for qualitative analysis.

Data analysis:

Student t-tests were used to compare posttest –pretest gains between GE and GC on quantitative measures (PCA, ECE, EHMA). Normality assumptions were pre-tested using the Shapiro–Wilk test and homogeneity of variances using the Levene test. Analysis of covariance (ANCOVA) was applied to control for potential initial differences

Ciencia y Deporte
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at pretest, using pretest scores as covariates (Miller and Chapman, 2001). For qualitative data (interactions with the AI, portfolios, observations), thematic analysis was performed using open and axial coding to identify patterns of thinking and attitudes (Braun and Clarke, 2006). CMC responses were compared using t-tests. Statistical significance was set at $p < 0.05$, and effect sizes were calculated using Cohen's d to determine the magnitude of the differences.

RESULTS AND DISCUSSION

Description of the adaptive dialectical cycle of teaching-learning

The teaching-learning process in Odychess develops through an iterative dialectical-adaptive cycle, which ensures both the dialogic construction of knowledge and continuous adaptation to the learner's level (Figure 1).

This cycle is repeated at different scales (from microinteraction on a single problem to planning over multiple sessions) and consists of several interrelated phases:

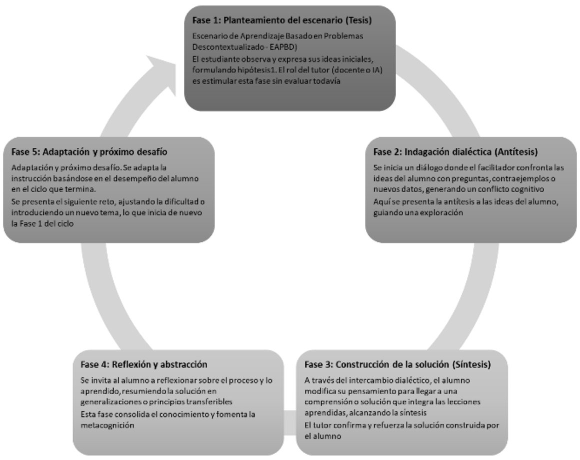

Fig. 1. - *Adaptive dialectical cycle of teaching-learning in the Odychess approach*

- Phase 1: Scenario Formulation (Thesis): The cycle begins with the presentation of a challenge or problem (usually a BDPE, as described above). Here, the thesis is presented, that is, the initial situation the student is confronted with. The student is given time to observe the position or statement and is invited to express their initial ideas: What do they interpret what is happening? What objective should they achieve? What relevant moves do they identify? In this phase, the student activates relevant prior knowledge, formulates solution hypotheses, or identifies what is problematic. The role of the teacher/RA is to stimulate this phase by asking: "What element catches your attention?" or "What do you consider to be the problem to be solved?", but without yet evaluating or correcting; the aim is for the student to commit to an initial idea (their thesis).
- Phase 2: Dialectical Inquiry (Antithesis): This is where the actual dialectical dialogue begins. The facilitator (human or AI) confronts the student's ideas with questions, counterexamples, or new data, generating a cognitive conflict. If the student proposed a flawed or incomplete solution, the antithesis is presented here. For example: "I understand your plan for a mate with the rook down the file, but what would happen if the enemy king escapes through the dark squares?" Or "You claim that exchanging queens solves the problem; can you prove that this ending is a winning one?" Even if the student didn't propose anything, the tutor introduces the antithesis in the form of challenging clues: "It seems difficult to attack down the file. Is there another weakness in the position that I could exploit?" This phase is essentially guided exploration: the student mentally tests their hypotheses against the tutor's questions.
- Phase 3: Solution Construction (Synthesis): Through dialectical exchange, the student (with guidance) modifies their thinking until they reach a synthesis, that is, an understanding or solution that overcomes initial limitations by integrating the lessons learned during the inquiry. In practical terms, this is the phase in which the solution to the problem or the sought-after concept is reached. It can occur gradually, with the tutor guiding the student step by step. "Exactly, the king would escape through black." So how do we prevent that? "Maybe I need a bishop on those diagonals." "Okay, and do you have a bishop?" — Yes, but it's

blocked..." Finally, the student may conclude, for example: "So first I have to redirect my bishop to that diagonal, and then the rook will mate" – thus achieving synthesis, combining their original idea with the newly discovered element (the role of the bishop). In other cases, the synthesis emerges as a moment of sudden understanding where the student, after relating the elements, announces the correct answer. The important thing is that this solution was constructed through effort on the part of the student; it was not directly delivered. At this stage, the tutor confirms and reinforces: "Correct! The key was to include the bishop to close the escape route, and so your rook plan works." Details are also clarified or the concept is formalized in technical language. "You have applied a well-known mating motif: the rook-bishop battery that confines the king," giving a name to the synthesis achieved.

- Phase 4: Reflection and Abstraction: Once the immediate challenge has been resolved, the cycle continues with a metacognition stage. Here, the student is invited to reflect on what happened: "Why wasn't your first idea sufficient? What did we learn from this problem?" They are encouraged to summarize the solution in generalizations. "Whenever the king has escape squares, it is necessary to block them before mate"—extracting a principle. Or "This problem taught us that an attack plan may require the collaboration of several pieces; one is not enough." This phase consolidates the synthesis, elevating it to transferable knowledge. It also allows the student to become aware of their own process: "At first, I rushed to attack without seeing my opponent's defense; now I understand that I must verify my opponent's responses; that is important." The facilitator complements, links with formal theory (if applicable), or corrects any conceptualizations if necessary. This is the ideal opportunity to record your findings in a log or portfolio, since expressing the lesson learned in writing (or verbally in class) cements the learning better.
- Phase 5: Adaptation and Next Challenge: The final phase closes the current cycle and prepares for the next. It involves adapting instruction based on the performance observed in the concluding cycle and proposing the next challenge accordingly. If the student achieved the synthesis with relative ease, the

facilitator may decide to increase the difficulty or complexity of the next EAPBD, perhaps introducing a new topic or a problem with a combined pattern. If, on the other hand, the student needed significant assistance or remains unsure, the same topic will be reinforced with another similar exercise or more basic components will be reviewed before moving forward.

Once the adjustment is made, the next problematic scenario presents itself, beginning phase 1 of the cycle again with the new thesis to address. Thus, the process is cyclical and cumulative: each turn of the dialectical-adaptive cycle builds on the previous ones, with increasing sophistication. Over several iterations, the student acquires knowledge (patterns, principles) through successive syntheses and, in parallel, improves learning strategies (learning to dialogue better, to anticipate antitheses themselves, to reflect more deeply).

This dialectical-adaptive cycle is inspired by classic experiential learning models, but integrates the essence of the teacher-student dialectic and individualized adaptation. In some ways, it is also reminiscent of the continuous formative assessment approach, where the idea is to teach something, observe progress, provide feedback, adjust teaching, and reteach something new in a constant cycle. However, here the feedback is highly interactive, and the "new teaching" arises from problem-solving. The dialectical component ensures quality in the understanding of each cycle; the adaptive component guarantees optimal progression through the cycles.

In classroom practice, a teacher applying Odychess will orchestrate this cycle with one or more students simultaneously. For example, in a group class, a general EAPBD could be presented, everyone could be allowed to think (individual phase 1), then a discussion could be moderated where several student proposals emerge (multiple theses) and compared among themselves and with the teacher (group phase 2), the solution could be collectively constructed (phase 3, where different students may contribute elements of the synthesis), then a student could be asked to summarize the idea (group phase 4), and finally, depending on how the teacher perceived the group, another more complex position could be proposed or subconcepts clarified (adaptation phase 5). In a one-to-one setting (e.g., a student practicing with the AI platform), the same cycle occurs, but the interaction is student vs. virtual tutor; the AI asks the dialectical questions, the student answers, etc., and the AI decides the next task based on the student's performance.

The cyclical and iterative nature of this process ensures that learning never stagnates. Even after mastering a subject, students are always faced with a new challenge that once again tests and expands their skills, maintaining interest and continuous improvement. Furthermore, the dialectical-adaptive approach is inherently inclusive: each student goes through the cycles at their own pace, receiving the necessary encouragement and support at each step. This minimizes both the frustration of those who progress more slowly (because they adjust to it) and the boredom of those who advance more quickly (because they are challenged more). In short, the dialectical-adaptive cycle is the backbone of the Odychess method, practically combining theoretical principles (dialectics, constructivism, scaffolding, PBL, adaptability) into a dynamic chess learning process.

Adaptation of the Llama 3.3 language model through specific adaptation for personalized chess tutoring

To maximize the effectiveness of the AI tutor within the Odychess approach, a *fine-tuning* process of the Llama 3.3 base language model was performed. Fine-tuning is a transfer learning technique in natural language processing where a large-scale pre-trained model (trained on vast general text corpora to acquire linguistic understanding and knowledge of the world) is further trained on a dataset more specific to the target domain or task (Ruder, 2021). Unlike pre-training, which requires enormous computational resources, fine-tuning adjusts the parameters (weights) of the pre-existing model to specialize it.

In our implementation, Llama 3.3, specifically the version with 70 billion (70B) parameters, was selected as the base model due to its proven ability to reason and follow complex instructions, as well as its potentially open architecture that facilitates customization (Touvron The objective of the specific adaptation was twofold: first, to provide the model with accurate and reliable chess knowledge, ensuring the understanding of rules, notation (PGN, FEN), tactical and strategic concepts, and the correct evaluation of basic positions, minimizing incorrect or inconsistent generations; second, to instill the Odychess pedagogical style , training it to prioritize the Socratic method, adapt the difficulty, and maintain an appropriate tone.

The specific adaptation process was carried out using *Parameter-Efficient Fine- Tuning* (PEFT) techniques, which are particularly suitable for adapting large models such as Llama 3.3 in environments with limited computational resources (Houlsby *et al.*, 2019). Specifically, the Low-Rank Adaptation (LoRA) methodology was used (Hu The choice of LoRA was strategic: it drastically reduces memory requirements by training only a small subset of adaptive parameters (introducing low-rank matrices into the transformer layers *and freezing* most of the pre-trained weights), which is crucial for working with memory-limited GPUs (typically 12-16 GB) available on accessible platforms such as Google Colab. Furthermore, LoRA significantly speeds up training time compared to full *fine- tuning* and generates small adapters (on the order of megabytes instead of gigabytes), facilitating their storage and deployment. Crucially, this technique helps preserve the vast general knowledge of the base model (avoiding catastrophic forgetting) while efficiently specializing it to the desired task, achieving performance comparable to full fine-tuning for specific domains such as our chess methodology.

The practical implementation was carried out in a cloud-based environment, specifically Google Colab, taking advantage of its GPU-equipped instances (accelerators such as T4 or P100 were used) and configuring execution environments with high RAM availability. To efficiently manage memory, quantization techniques were applied, using libraries such as *bitsandbytes*, which allow the model to be loaded and operated with lower numerical precision (for example, with 4-bit or 8-bit representations) without a significant performance loss for the adaptive inference and training task. Likewise, gradient accumulation was used to simulate batch sizes *larger than those that would be allowed by the GPU memory, thus stabilizing the training process. The entire process was orchestrated using the* Hugging tool ecosystem. Face, including the *transformers* libraries for model management, *peft for* LoRA implementation, and *datasets* for managing the training corpus (Wolf *et al.,* 2020).

Generating the training corpus was a critical and multifaceted step, designed to capture the essence of the Odychess approach (Figure 2). Although PEFT techniques can work with relatively small datasets (on the order of hundreds of high-quality examples), to ensure the desired pedagogical depth and chess robustness, a large corpus of approximately 50,000 examples was compiled. This corpus included:

1. Odychess principles for guided solving of EAPBDs, position analysis, and concept explanation, tagged by difficulty and skill.
2. Commented games with a dialectical approach: PGN games enriched with commentary simulating Odychess interactions (reflective questions, exploration of alternatives), tactically verified with engines such as Stockfish but with a pedagogical discursive emphasis.
3. Supervised Synthetic Generation: Additional data generated using an advanced foundational model (such as GPT-4o or Claude 3 Opus) instructed to act as an " Odychess Tutor ", rigorously filtered and reviewed by human experts.

Ciencia y Deporte
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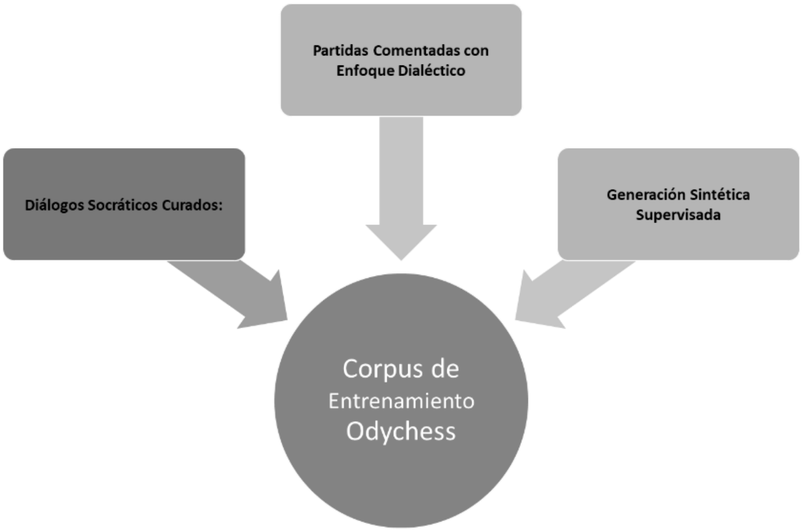

Fig. 2. - Components of the training corpus for the Odychess - tutor

All of these data were unified into a consistent format (instruction-response or continuous dialogue) suitable for *Supervised Fine- Tuning* (SFT). Training was performed over several epochs, monitoring the loss metric (loss*)* on a validation set and periodically evaluating model performance both with automatic metrics (perplexity*,* BLEU) and through expert human evaluation (Raffel Key hyperparameters such as learning rate, effective batch size (using gradient accumulation), and LoRA-specific parameters (r , *alpha)* were tuned until satisfactory performance was achieved. The final evaluation included specific tests to measure the model's ability to apply the Odychess methodology to solve novel chess problems not present in the training set.

General objectives and skills to be developed

Odychess approach pursues a set of general educational objectives that guide its curricular and teaching design. These objectives translate into specific competencies that students must develop throughout the program. The most relevant objectives and competencies are highlighted below:

- Develop strategic thinking and long-term planning.

- Enhance problem-solving and tactical creativity.
- Promote pattern recognition and structured chess memory.
- Cultivate metacognitive reflection and self-criticism.
- Strengthen decision-making under uncertainty and emotional management.
- Incorporate the ethical and effective use of technology as a learning tool.

These objectives and competencies are operationalized in the Odychess methodology through specific activities and content.

Decontextualized Problem-Based Learning (DPL) scenarios – core didactic component

The didactic core of Odychess is decontextualized problem-based learning (DPL) scenarios. This concept refers to learning situations designed in the form of specific chess problems or challenges, deliberately presented outside the context of a complete conventional game, in order to focus the student's attention on certain cognitive or conceptual aspects. Unlike a traditional chess problem (e.g., "mate in 2" taken from a known endgame), Odychess DPLs can be positions, exercises, or even chess minigames that do not necessarily come from real games, or whose narrative environment has been abstracted, to focus learning on pure problem-solving.

Statistical analyses revealed significant differences in favor of the experimental group (Odychess) (Table 1).

Table 1vs. *control group comparison)*

Variable evaluated	Statistics and p-value	Effect size
PCA (Total Chess Knowledge)	$t(58) = 4.82$, $p < 0.001$	$d = 0.79$
ECE (Strategic Understanding)	$F(1, 57) = 15.6$, $p < 0.001$	Partial $\eta^2 = 0.22$
EHMA (Metacognitive Skills)	$t(58) = 3.91$, $p < 0.001$	$d = 0.64$
CMC (Motivation and Commitment)	$t(58) = 5.25$, $p < 0.001$	$d = 0.85$

The EG showed significantly greater gains than the CG in the Total Chess Knowledge Test $(t\,(58)\ = 4{,}82, p\ <\ 0{,}001, d\ =\ 0{,}79)$, and specifically in the Strategic Understanding subscale assessed by the ECE $(F\ (1, 57)\ = 15{,}6, p\ <\ 0{,}001, \eta^2\ parcial\ =$ $0{,}22$, controlling for the *pre-test*). Significant differences were also found in the Metacognitive Skills Scale $(t\,(58)\ = 3{,}91, p\ <\ 0{,}001, d\ =\ 0{,}64)$, indicating greater development of reflection on one's own learning in the Odychess group. The qualitative analysis of the interactions with the Odychess tutor and the EG portfolios evidenced a frequent use of dialectical reasoning (considering alternatives, justifying moves, responding to counterarguments) and a greater depth in game analysis compared to the CG's work. Finally, the EG reported significantly higher levels of intrinsic motivation and perceived engagement in the CMC $(t\,(58)\ = 5{,}25, p\ <\ 0{,}001, d\ =\ 0{,}85)$.

- Ethical Considerations: Participant confidentiality and anonymity were guaranteed in accordance with the ethical principles of educational research (BERA, 2018). Data were stored securely following data protection protocols and used exclusively for research purposes. Participants were informed that they could withdraw from the study at any time without penalty. At the end of the study, the control group was given access to introductory materials on the Odychess approach to ensure equitable learning opportunities.

These results suggest that the implementation of the Odychess approach, mediated by a facilitator teacher and a specialized AI tutor (Odychess -tutor), was more effective than traditional teaching in improving not only chess knowledge and skill (especially strategic understanding), but also in developing metacognitive competencies and fostering greater motivation and engagement. It is important to note, however, that the study's limitations, such as the lack of random assignment and the moderate sample size, suggest the need for further research to confirm the generalizability of these findings.

In short, assessment in Odychess is a rich, dynamic, and learning-centered process: it informs the student of their journey, informs the teacher for better guidance, and informs the curriculum for further development. Because it is a natural part of each session (and not a separate event often perceived as punitive), students take it on naturally and even with interest, seeing it as a tool to become better players and learners, not a static judgment about themselves. This contributes to an environment where the focus is on individual and collective progress, and where every achievement—be it a new strategy mastered or an improved attitude toward defeat—is recognized as valuable.

CONCLUSIONS

Odychess approach emerges as an original and solidly grounded pedagogical proposal, integrating cutting-edge educational theory with the significant possibilities offered by generative artificial intelligence to transform chess teaching. Throughout this article, its methodological and didactic design has been detailed, and the results of applied research that empirically validates its effectiveness have been presented. The convergence of constructivist principles, Socratic dialectics, problem- and pattern-based learning, and adaptive personalization facilitated by a specialized LLM (Odychess tutor) has proven highly beneficial.

The originality of Odychess lies in its integrative synthesis of key elements: it draws on well-established pedagogical foundations, such as constructivism and the formative power of critical dialogue, articulating them in a contemporary context where advanced AIs act as supportive educational agents. Applied research confirms that this articulation, in which the student has an intelligent virtual tutor under the guidance of an expert teacher, provides a personalized, highly interactive, and feedback-rich learning experience, surpassing traditional methods in crucial aspects. This reveals considerable potential for democratizing and elevating the level of chess education by bringing quality, almost individualized teaching to a greater number of students.

The applicability of the approach, now supported by empirical evidence, is projected to be broad. Its principles are transferable to other knowledge domains that value guided discovery learning and personalization. In the specific field of chess, Odychess has proven viable and effective in school programs for the development of transversal skills, and its usefulness in high-performance academies or online platforms is emerging. The technical feasibility of specifically adapting models like Llama 3.3, using efficient techniques like LoRA on accessible platforms, was demonstrated during the preparation of the study, and its positive impact on learning was significant.

The dialectical and adaptive nature of Odychess suggests that future implementations and action-research cycles will continue to refine the method, the EAPBDs, and the AI tutor itself, progressively optimizing its robustness and effectiveness. Odychess is therefore presented not as a static method, but as a flexible and validated framework that invites informed adoption and adaptation.

In conclusion, the Odychess approach is distinguished by its integrative and synergistic conception of pedagogy and technology, supported by empirical evidence; its effective focus on developing strategic and metacognitive thinking, beyond mere chess instruction; its proven adaptability to different levels within the range studied, thanks to progressive scaffolding and artificial intelligence; and its transformative nature, evidenced by the study's results, which support the vision of "one tutor for every student" as a promising way to redefine education.

The successful implementation of this approach in the studio suggests the possibility of training a new generation of chess learners who not only improve their game but also develop deeper and more reflective thinking.

The potential impact of Odychess goes beyond the 64-square board, contributing to the ideal of AI-enabled education that enhances, rather than replaces, human creativity and intellect. This article, enriched with the research methodology and results, provides a solid foundation for the development of application manuals and teaching guides, inviting future research and applications to continue exploring and refining this promising approach.

BIBLIOGRAPHIC REFERENCES

Barrows, H. S. (1986). A taxonomy of problem-based learning methods. Medical Education, 20(6), 481-486. https://pubmed.ncbi.nlm.nih.gov/3796328/

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101. https://www.tandfonline.com/doi/abs/10.1191/1478088706qp063oa

Bueno Pérez, L. A. (2000). Modelo para la enseñanza-aprendizaje del ajedrez en la universidad. Tesis de Doctorado (Doctorado en Ciencias Pedagógicas). Santiago de Cuba, Universidad de Oriente. Centro de Estudios de la Educación Superior "Manuel F. Gran".

Bueno, L. (2015). Ajedrez juego ciencia y conciencia. Editorial Academia. La Habana, Cuba. https://www.libreriavirtual.cu/libreria/ajedrez-juego-ciencia-y-conciencia

Chase, W. G., & Simon, H. A. (1973). Perception in chess. Cognitive Psychology, 4(1), 55-81. https://www.sciencedirect.com/science/article/abs/pii/0010028573900042

Coll, C., Martín, E., Mauri, T., Miras, M., Onrubia, J., Solé, I., & Zabala, A. (2006). El constructivismo en el aula. Graó. https://books.google.com.cu/books/about/El_constructivismo_en_el_aula.html?id=si5frgEACAAJ&source=kp_book_description&redir_esc=y

De Groot, A. D. (1965). Thought and choice in chess. Mouton. https://www.jstor.org/stable/j.ctt46n0r2

Gobet, F., & Simon, H. A. (1996). Templates in chess memory: A mechanism for recalling several boards. Cognitive Psychology, 31(1), 1-40. www.sciencedirect.com/science/article/abs/pii/S0010028596900110

Grattafiori, A., Dubey, A., Jauhri, A., Pandey, A., Kadian, A., Al-Dahle, A., & Vasic, P. (2024). The llama 3 herd of models. arXiv preprint arXiv:2407.21783. https://arxiv.org/abs/2407.21783.

Ramírez-Guerra, D. M., Bueno-Pérez, L. A., & Gordo-Gómez, Y. M. (2016). La capacitación en el proceso de masificación del ajedrez en las comunidades urbanas. Ciencia y Deporte, 1(2), 56-71. https://dialnet.unirioja.es/servlet/articulo?codigo=8100881

Reyes-Joa, H. M., Ramírez-Guerra, D. M., & Bueno-Pérez, L. A. (2020). El perfeccionamiento del proceso de enseñanza-aprendizaje del Ajedrez de la categoría 10-11 años. Ciencia y Deporte, 5(1), 19-31. https://dialnet.unirioja.es/servlet/articulo?codigo=8111228

Savery, J. R. (2006). Overview of problem-based learning: Definitions and distinctions. Interdisciplinary Journal of Problem-Based Learning, 1(1), 9-20. https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=1002&context=ijpbl

Serper, G. (2015). Patterns, patterns everywhere! Chess.com. https://www.chess.com/article/view/chess-patterns-patterns-everywhere

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., et al. (2020). Transformers: State-of-the-art natural language processing. Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, 38-45. https://aclanthology.org/2020.emnlp-demos.6/

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