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Integrating Explainable AI in Chess Coaching Systems for Beginners.

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An incredible journey will begin, with one of the most ancient and respected games of kings entering the modern era of artificial intelligence. An experience that places the impossible reason of a machine in a sage-like mentor role. We may be at the very beginning of a new era for chess education, where technology can do more than show the best moves; it helps to illuminate the building blocks of the strategy behind chess. Education is no longer about winning. Education is about understanding.

Abstract:

While today's AI chess programs are extremely capable, they do a poor job of teaching new chess players. These systems often provide a player with the best action to take but rarely explain its relevance or how it was determined. By providing the best move without context, these new players cannot take away the important foundational learning that should occur while they are improving their game. This paper introduces a new chess coaching system that utilizes Explainable AI (XAI) to solve this issue. Our intelligent coaching system is capable of providing a simple, understandable explanation for the complex reasoning done by a chess engine for both expert and novice players: for a beginner on a novice chess platform, the intelligent coaching system would not only tell the player to move their knight forward but also inform them that it was a good action because it 'develops' the knight, placing it into a better position, while allowing for future options to control the centre of the board, being on an open file, and creating a threat to their opponent's rook. In this paper we provide a description of how the coaching system was designed, offer examples of the explanations that would be provided, and explore how this approach enables AI to be much more than an analysis tool but also a mentor. This work is designed to explore how AI-enabled learning could be made more affordable and feasible for new learners interested in playing chess.

I. INTRODUCTION:

The use of artificial intelligence (AI) in chess has led to the creation of extremely highly advanced engines such as Stockfish and AlphaZero that can beat the world's top players. While such technologies are good tools for detailed analysis, they are of little educational use to new players. Modern chess engines are "black boxes" that provide suggestions on moves without showing the strategy or reasoning used in arriving at them. This is thus hindering new players from understanding the reasoning of good moves and thus hindering them from getting an understanding of basic chess principles.

This paper provides a solution to the aforementioned problem by integrating Explainable AI (XAI) into a coaching system for chess beginners. The objective is to transform the AI from a passive analysis system to an efficient coach. The proposed system is designed to translate the complex outputs of a chess computer into simple, easy-to-understand natural language explanations. For example, instead of simply suggesting a move, the system will inform you why, saying, "This move places your knight on a strategically better central square" or "This move protects your king from threats."

This paper presents a framework for an XAI-based system and its architecture along with the approach used in explanation generation. The approach is aimed at easing the learning process for beginners by providing simple and comprehensible explanations and making AI-based learning more efficient and accessible. The structure of this paper is as follows: Section II presents the review of related literature, Section III presents the proposed system and Methodology, Section IV presents the Results, Section V represents the discussion of the research, and Section VI represents the conclusion of the research.

II. LITERATURE REVIEW:

This section describes the early work in AI, chess, and intelligent tutoring systems as a foundation to establish the context for our work and identify the research gap. The literature identifies significant contributions in each discipline but also that there is an essential, unfilled need: to develop a pedagogically focused, explainable AI system for novice chess players.

A. AI in Chess

AI in chess history is characterized by the pursuit of optimum play, with a well-defined progression from symbolic, rule-based approaches to contemporary, self-improving networks. Early programs such as IBM's Deep Blue based their performance on huge computational resources and hand-coded evaluation functions, calculating billions of positions per second [1]. These utilized minimax and alpha-beta pruning to explore the game tree, prioritizing brute-force calculation over strategic insight [2].

The advent of deep learning changed everything. Google's AlphaZero and its open-source cousin, Leela Chess Zero (LC Zero), demonstrated a new paradigm by learning the game from scratch with self-play [3]. The engines use deep neural networks to evaluate board positions and guide a Monte Carlo Tree Search (MCTS), achieving superhuman strength without human-provided opening books or positional knowledge [4].

While these new engines are powerful, their inherent limitation for learning is that they are "black boxes." Their mechanism for determining how to make a move, through activations of complex neural networks and millions of game simulations, is not accessible to an observer. The outcome is an extremely accurate move and an assessment score (e.g., +1.5), with no idea of the strategic or tactical rationale of the move [5]. This makes them unsuitable as a stand-alone learning tool for beginners, who require knowledge on why a move is good.

B. Explainable AI (XAI)
Explainable AI aims at making AI model choices more understandable and transparent to human intelligence. The XAI area is primarily divided into two types of methods:

Intrinsically Interpretable Models: These models, such as decision trees or linear regression, are clear-cut in nature. Their own logic is simple and intuitive to think about [6]. These models are not likely to have the complexity required to keep up with today's chess engines, however.

Post-Hoc Explanations: These techniques are employed after a complex "black box" model has made a prediction in order to explain its output. Methods like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (Shapley Additive Explanations) provide insight into the particular features that were most determinant for a single prediction [7]. For example, in an image classification model, SHAP is able to determine the pixels that were most important for the model's decision [8]. These methods are powerful, but it is difficult to use them in the dynamic, multi-step environment of a game of chess.

C. AI in Tutoring and Education Systems
Extensive usage of AI has been made in Intelligent Tutoring Systems (ITS) to personalize learning and provide adaptive feedback [9]. Research has shown that AI can also be a powerful tool to accelerate skill acquisition by providing tailor-made practice and highlighting the weaknesses of a learner. There have been attempts to create chess tutors that decompose the concept into easier-to-understand ideas or emulate playing strategies to become more human-like [10]. These sites, like Decode-Chess, have achieved this by translating the output of engines into positional and tactical explanations [11].

However, existing systems generally sacrifice play strength for ease or provide generic, pre-composed explanations with the complexity of a full engine analysis missing. There is an evident gap in the literature for one that can combine the brute-force precision of the world's top chess engine with an adaptable, dynamic XAI element to provide genuinely pedagogical explanations for beginners.

D. Research Gap
The literature surveyed clearly identifies a research gap. Superhuman AI chess software does exist, but its outputs are impenetrable to novices. On the other hand, although XAI techniques and intelligent tutoring systems have been explored, no work has effectively combined a robust, high-performance chess engine with an advanced XAI system to offer focused, natural-language descriptions of its moves to novices. Our paper attempts to bridge this gap by outlining and suggesting such a system.

III. PROPOSED SYSTEM AND METHODOLOGY:

This chapter describes the proposed system of chess coaching and the research methodology applied to carry out the included user survey. The two-part structure contains both the theoretical framework of the project as well as the empirical basis for supporting its fundamental principles.

A. System Architecture
The system proposed works to give insightful, real-time explanations to novice chess players by closing the gap between a strong AI engine's incomprehensible analysis and a human learner's intuitive feedback requirements.

Component 1: The AI Chess Engine: The analytical heart of the system is a chess engine, like Stockfish, that is optimized to perform at high speed and outputs a numerical assessment of the board position, along with the best string of moves. The component is the source of raw data for the explanations.

Component 2: The XAI Translator Module: This is the main innovation of the system. The module takes the raw engine output (e.g., evaluation score, principal variation) and converts it into natural-language explanations according to a pre-specified set of chess rules and patterns. The module recognizes important aspects of the board state, e.g., tactical threats, positional weaknesses, piece development, or king safety, and creates a simple, easy-to-read explanation for the suggested move.

Component 3:
The User Interface: The UI is made for ease of understanding and usability. The explanations produced are given to the user by way of a simple, user-friendly design, perhaps with visual indications on the chessboard (e.g., underlining pieces or squares) to supplement the textual feedback.

B. Survey Methodology
A quantitative survey among users was conducted to find empirical evidence about issues associated with novice players of chess and their willingness to use an explainable AI coaching system.

Research Design: The study employed a descriptive research design using an online survey tool to gather information regarding participant demographics, playing behaviour, perceived issues, and attitudes toward AI learning systems.
Participants: The survey focused on casual and beginner-level chess players. Recruitment took place online, such as through social media and chess forums, to reach a general pool of self-identified learners. 15 full responses were gathered for analysis.

Survey Instrument: The survey questionnaire was a set of questions, ranging from multiple-choice to Likert scale to open-ended questions. Questions were framed such that they

would address a few broad areas: 1) participant demographics (age, gender, education level), 2) habits of playing chess (skill level, amount of time spent playing), 3) self-reported difficulties in learning to play chess, and 4) comments on the hypothetical use of an AI-based coaching tool with features of explainability.

Data Analysis: The data gathered was analysed for dominant trends, percentages, and themes. The statistical data was utilized to generate the charts and graphs contained in the Results section, and the qualitative feedback added meaning and distinct viewpoints.

IV. RESULTS:

This section presents the findings from the survey, providing empirical evidence to support the claims made in this paper. The results are divided into three subsections: first, an overview of the participants' demographics and playing profiles; second, an analysis of the common challenges and prior AI usage; and third, an evaluation of the perceived value of an AI coach with explainable features.

A. Participant Demographics and Profile

The survey received 15 completed responses from a target audience of beginner and casual chess players. The demographic data reveals young, educated people with limited experience in the game. A significant majority of respondents (93.3%) were aged between 18 and 24, with the remainder falling into the "Under 18" category (**Fig. 01**).

Age distribution of survey respondents.

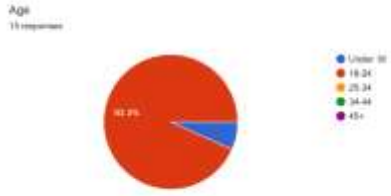

Fig. 01

In terms of gender, two-thirds of the participants were male (66.7%), while one-third were female (33.3%) (**Fig. 02**).

Gender distribution of survey respondents.

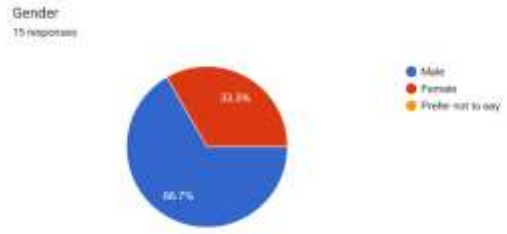

Fig. 02

The education level of the respondents was also high, with 64.3% having completed an undergraduate degree (**Fig. 03**).

Highest education level completed by respondents.

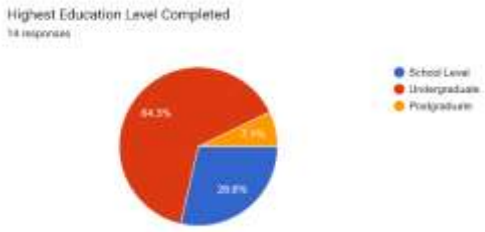

Fig. 03

The participants' playing habits reinforce their status as casual or beginner players. While 40% of respondents play chess regularly or occasionally, another 40% know the rules but do not play at all, and 13.3% have never played (**Fig.04)**

Current chess playing status.

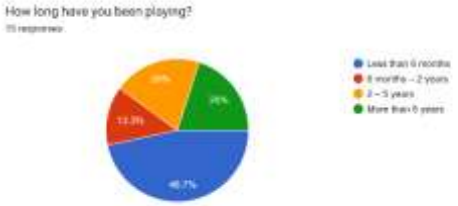

Fig. 04

A key finding is the limited time commitment to the game; a vast majority (86.7%) reported spending less than one hour per week on chess, with the most common duration of play being less than six months (46.7%) **(Fig. 05)**.

Average time spent playing chess per week.

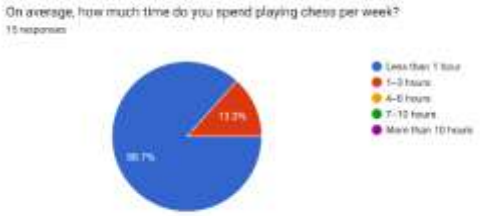

Fig. 05

Over half of the respondents (53.3%) self-identified as a “Beginner” skill level, while 40% considered themselves “Intermediate” (**Fig. 06**).

Current self-identified skill level.

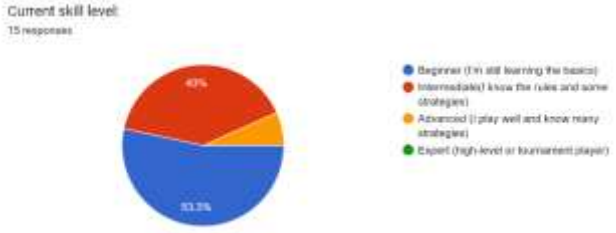

Fig. 06

B. Common Challenges and Prior AI Usage

The survey results highlight a strong need for improved learning tools, as participants face significant challenges in their chess journey. As illustrated in **Fig. 07**, the most commonly reported issues were a “Lack of confidence in my moves” and “Forgetting strategies during play,” each selected by 46.7% of respondents. Another major challenge was “Struggling to understand the rules/strategies” (40%). For those who do not play chess, the primary reason was a “lack of time” (40%), followed by a feeling of “nervousness playing against others” (33.3%) (**Fig. 07).**

Common issues/challenges you face while playing chess:

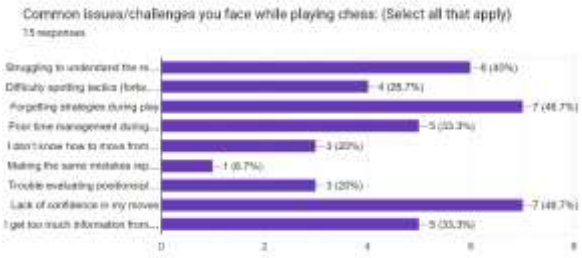

Fig. 07

A crucial finding that directly supports the premise of this paper is the limited prior exposure to AI tools. A striking 80% of respondents reported having **never** used a chess engine or online coach before (**Fig. 08)**.

Prior usage of chess engines/online coaches.

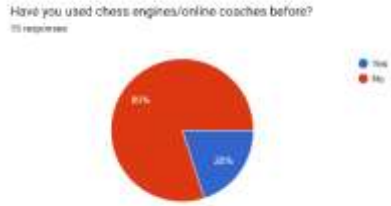

Fig. 08

C. Perceived Value of an AI Coach and Desired Features

The second section of the survey also helped shed light on how this target audience would view an AI-powered coaching system. While opinions were somewhat mixed, as a whole they welcomed the idea of an AI coach. Overall a higher percentage of respondents were "Neutral" (53.3%) about using the tool however 40% were at least "Somewhat Easy" or "Very Easy"(**Fig. 09)**.

Perceived ease of use of the AI tool.

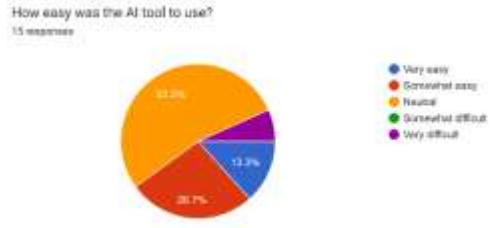

Fig. 09

Similarly, the clarity of the explanations was met with neutrality, with 60% of respondents selecting "Neutral," while a combined 33.3% found them "Clear" or "Very Clear"(**Fig. 10).**

Perceived clarity of the AI's explanations.

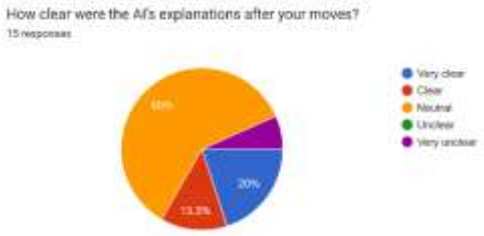

Fig. 10

Despite these neutral ratings, the feedback on the AI's impact on learning was encouraging. A combined 40% of participants felt the AI helped them understand *why* a move was good or bad to some degree, and a combined 46.6% found the feedback "Helpful" or "Always Helpful" (**Fig. 11**).

Did the AI help you understand *why* certain moves were good or bad?

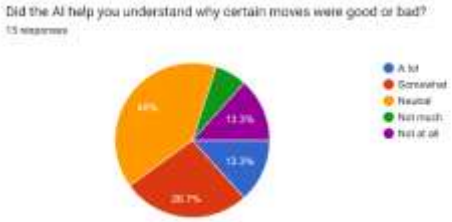

Fig. 11

The AI tool also had a favourable effect on enjoyment and confidence; as a group, 60% of respondents reported that the AI made chess "A little more fun" or "Much more fun" (**Fig. 12**), and 60% felt "A little more confident" or "Much more confident" in their moves after using the tool (**Fig. 13**).

Did the AI make chess more fun?

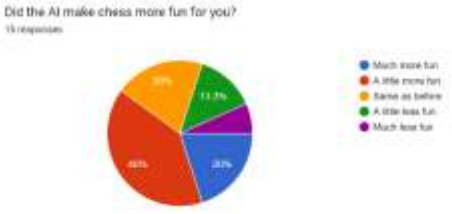

Fig. 12

Did confidence in your moves change after using the AI?

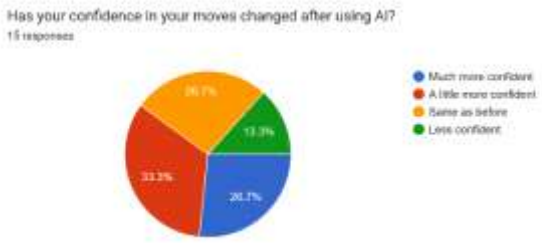

Fig. 13

There was a significant request for personalized and simple explanations. The majority (60%) felt that the explanations should match their experience level (**Fig. 14**) and that "Short & simple" was the preferred style of explanation (53.3%); however, "Detailed & in-depth" and "With diagrams" were also found to be very preferred (**Fig. 15**).

Should the explanations match your skill level?

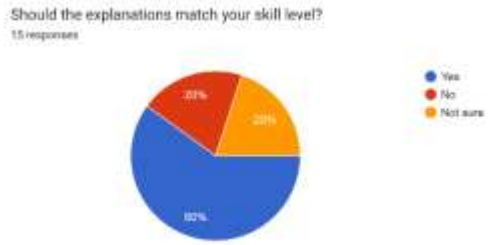

Fig. 14

Preferred style of explanation.

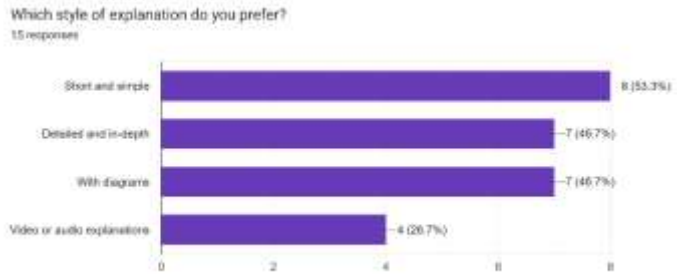

Fig. 15

The most helpful types of explanations were classified as "Tactical tips" and "Strategy tips" based on responses of all participants who had used the tool (**Fig. 16**). There was also considerable interest in further use of the tool. When asked if they would use the AI tool to play more, a total of 66.7% answered "Yes, definitely" or "Yes, maybe" (**Fig. 17**).

Most helpful types of explanations.

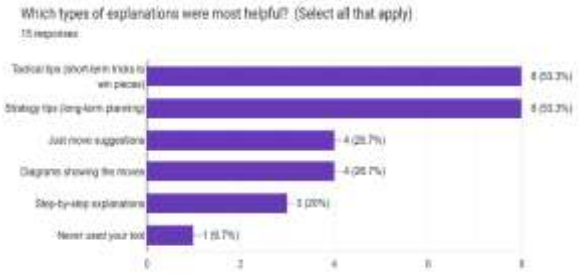

Fig. 16

Willingness to play more using the AI tool.

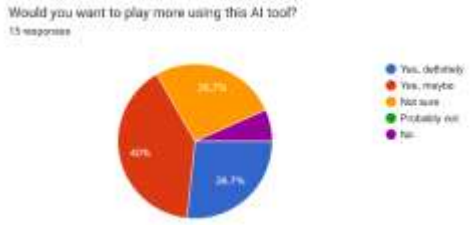

Fig. 17

The average satisfaction reported toward the AI coach was quite favourable, as one-third of respondents indicated they were either "Satisfied" or "Very Satisfied" for a combined total of 66.7% (**Fig. 18**). Similarly strong support was indicated with respect to their willingness to recommend this tool, where a combined 73.4% said they would "Yes, definitely" or "Yes, maybe" recommend this to other learners (**Fig. 19**). The most requested feature included "Practice exercises after mistakes" (60%) and "Short lessons on the topic" (46.7%), which indicates participants desired a comprehensive learning environment (**Fig. 20**).

Overall satisfaction with the AI coach.

Fig. 18

Willingness to recommend the tool to other learners.

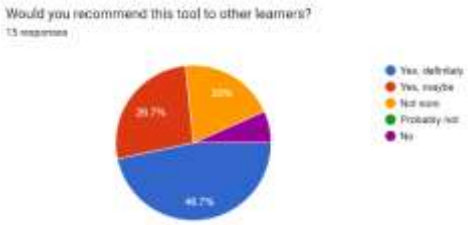

Fig. 19

Most desired extra features.

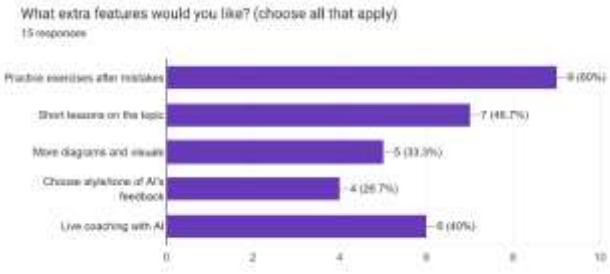

Fig. 20

V. DISCUSSION:

The findings from our survey provide strong evidence supporting the main idea of this paper: there is a significant, unmet need for a user-friendly, explainable AI coaching system for beginner chess players. The results directly highlight the research gap noted in the literature, which points out the difference between the exceptional abilities of modern chess engines and their limited teaching value for novices.

The demographic data shows that our target audience consists of young, educated individuals who are new to chess. Most have less than a year of experience and spend very little time on the game. This profile of a casual learner, who is both pressed for time and new to the sport, fits well with a tool that offers quick, intuitive, and effective learning without extensive study or in-depth analysis.

The data on common challenges further supports our argument. The two main issues identified by respondents were a lack of confidence in their moves and forgetting strategies while playing. These problems arise from the "black box" nature of traditional AI tools. Without understanding the reasons behind a move, a learner's confidence cannot grow, and their strategic memory remains weak. A significant 80% of participants had never used a chess engine before, highlighting the limited use of these complex tools by the beginner community and reinforcing the market opportunity for a more accessible solution.

The feedback on our proposed system was mostly positive and provides strong evidence that users would welcome a system with explainable features. While there was some neutrality regarding initial ease of use, a combined 60% of participants felt more confident in their moves after using the tool, and another 60% found it more enjoyable. This is important validation: the system's ability to offer context seems to directly address the main psychological barriers—lack of confidence and nervousness—that the players reported. The high overall satisfaction, with 66.7% feeling satisfied or very satisfied, and the strong likelihood of recommendation, with 73.4% willing to recommend it, further confirm the system's potential as a valuable learning aid.

The specific features and explanation styles preferred by the participants fit well with our proposed XAI framework. A preference for short, simple explanations and a desire for lessons and practice exercises highlights the need for a system that does more than just provide raw data. The high demand for tactical tips and strategy advice shows that beginners seek conceptual understanding and guidance, not just move data.

In conclusion, the survey results support the theoretical framework of our paper. They show that the issues we aim to solve are real and widely felt by our target audience. The overwhelmingly positive response to the proposed system confirms the hypothesis that an explainable AI approach can make AI an effective and engaging tool for chess education. Although the study's sample size is a limitation, the findings present a strong case for developing such a system and its potential to change how beginners learn to play chess.

VI. CONCLUSION:

This paper has examined the significant gap in AI-based chess education. The power of modern engines does not match their ability to teach beginners. We identified the main problem as the "black box" nature of these systems, which provide the best moves but do not offer the strategic or tactical reasoning learners need.

To address this issue, we proposed a new chess coaching system that combines a strong engine with an Explainable AI (XAI) module. The framework we describe aims to turn complex AI decisions into clear and simple explanations. This transforms the AI from a passive analysis tool into an active teaching mentor.

Our research, based on a user survey, provided strong evidence supporting this approach. The findings showed that the target audience—young, casual, and inexperienced players—faces challenges related to a lack of confidence and strategic understanding. Additionally, the survey results confirmed the proposed system's advantages. There is a strong connection between understandable explanations and increased user confidence, engagement, and overall satisfaction.

The main contributions of this work are twofold: first, providing empirical proof of the need for an XAI-based chess coach for beginners, and second, suggesting a modular framework for such a system.

Future work should focus on creating a functional prototype of the proposed system for more in-depth study. A larger, long-term experiment could assess the system's impact on a learner's skill gain over time, providing measurable proof of its educational effectiveness. The XAI framework could also expand to other complex strategic games, increasing the potential of AI as a tool for accessible and engaging education.

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