Towards Interactive Chess Textbooks: Utilizing Human-Crafted Strategic Knowledge

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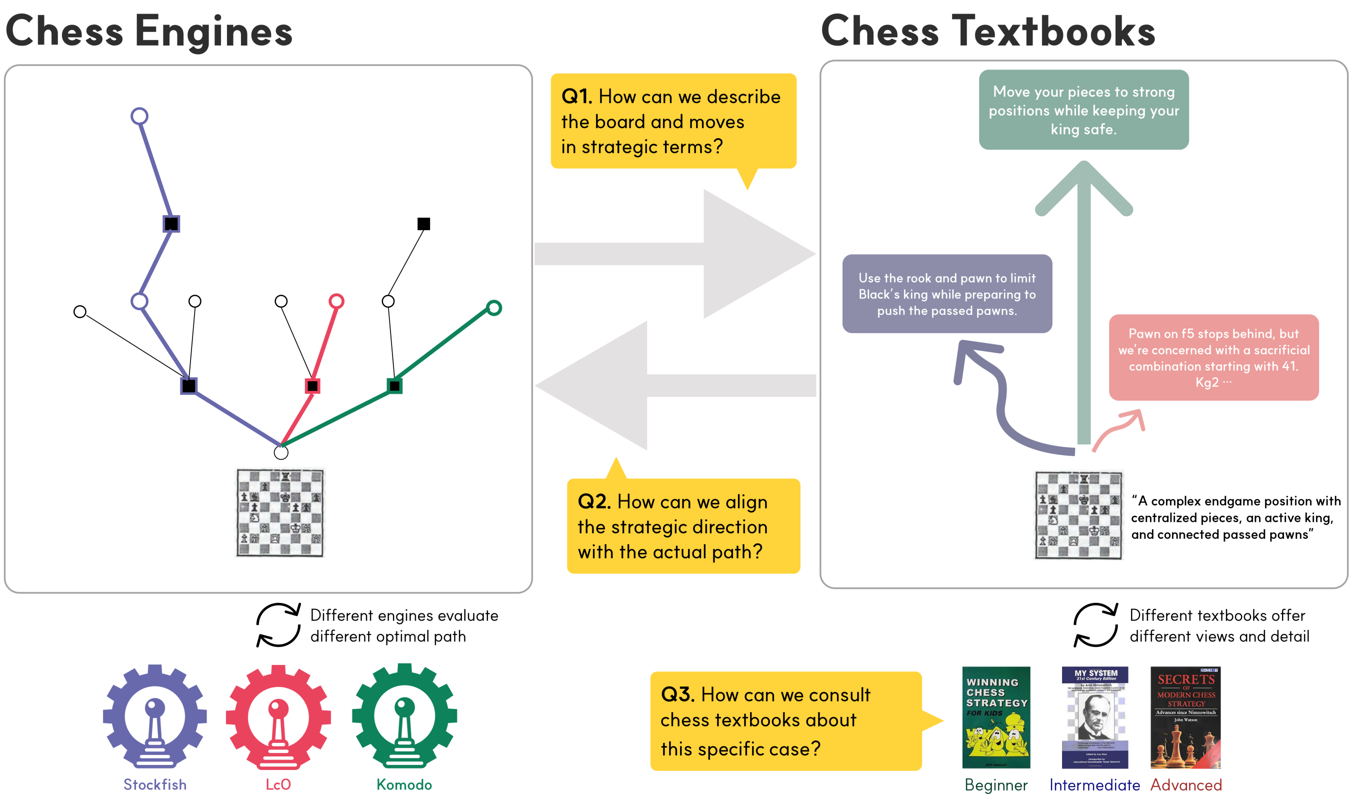


Figure 1: An overview of our approach: chess engines on the left explore the game space computationally, while the textbooks on the right provide strategic guidance. The yellow boxes highlight our central questions on (Q1) describing board states and moves in strategic terms, (Q2) aligning abstract strategic direction with concrete move execution, and (Q3) consulting textbook knowledge for specific cases.

ABSTRACT

Chess engines have surpassed human capabilities in calculating moves, yet strategy textbooks remain crucial for human learners who need conceptual guidance and explanations beyond raw computation. In this paper, we propose perspectives on transforming traditional chess strategy textbooks into interactive tutorials through language model capabilities. Key challenges include aligning board states with textbook principles, retrieving relevant content, and guiding users toward strategic move sequences. We discuss the broader role of human-crafted knowledge as an interpretable and adaptable resource amid AI's growing capabilities.

CCS CONCEPTS

• **Applied computing → Interactive learning environments**; • **Human-centered computing → Hypertext / hypermedia**.

KEYWORDS

Chess, Interactive Learning, Large Language Model

1 INTRODUCTION

Chess remains a popular board game with major competitions, including the World Championship held annually. Online platforms host hundreds of thousands of active players, and many creators produce chess-related content, ranging from educational videos to entertainment. Despite computers surpassing human players as early as the 1970s, chess continues to be valued as both an intellectual sport and a form of cultural entertainment.

As a turn-based game, chess requires players to analyze possible sequences of moves and select the best option. Many well-known chess anecdotes involve seemingly illogical moves, such as sacrificing high-value pieces, that ultimately lead to advantages through meticulously calculated combinations. This boosts the idea that chess is all about cognitive ability, and those who think deeply across many possibilities come out on top.

However, chess mastery extends beyond calculation. Strong players recognize abstract board patterns and aim for favorable positions based on these structures. This approach, known as positional play, gained recognition in the late 19th century when players focused on exhaustive calculation were consistently defeated by those who prioritized positional understanding. The chess community distinguishes these two skills as *"tactics"* (short-term sequences that gain immediate advantage) and *"strategy"* (long-term planning based on positional factors), both of which are essential for modern players.

Chess strategy is primarily documented in textbooks, and few systems provide interactive feedback. Because many people play chess on online platforms, interactive tutorial systems can support a wide range of users by offering immediate feedback on game positions. For tactical play, many platforms already employ chess engines to indicate whether the most recent move was suboptimal and, if so, how that mistake could unfold. However, unlike tactics, which can be confirmed through short sequences of moves, strategic knowledge is abstract and difficult to formalize. While recent research has examined the potential of large language models (LLMs) to capture and explain strategic concepts [7], explicit and extensive integration of textbook knowledge remains limited.

This work explores the idea of converting chess textbooks into interactive tutorials that seamlessly integrate with specific chess board context. We examine the problem, identify gaps in current practice, and propose potential solutions. We discuss broader implications, including the role of human-crafted knowledge as an interpretable and adaptable resource as AI increasingly matches or surpasses human performance across various domains.

2 WHAT IS CHESS STRATEGY?

2.1 Human Perspective

In the chess community, strategy generally refers to higher-level, long-term planning that accounts for positional elements, such as controlling more space, establishing a solid defensive structure, and ensuring the king's safety. In contrast, tactics concern short-term sequences of moves aimed at producing immediate outcomes, often by attacking multiple pieces at once or leveraging other tactical motifs.

Chess strategy follows a hierarchical structure, where fundamental principles support more advanced concepts. At the basic level, principles such as central control, piece development, and king safety provide the foundation. Building on these, more specific ideas emerge, such as exploiting weaknesses or controlling key squares and files. At a higher level, strategic understanding extends to how particular piece structures create long-term advantages.

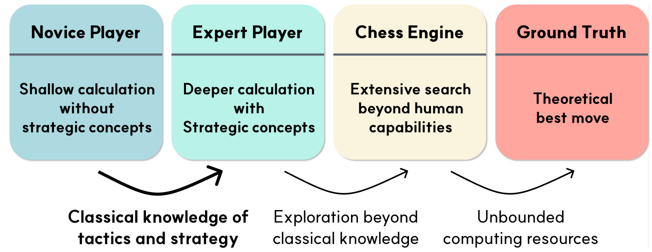


Figure 2: Illustration of hierarchy in chess skill levels. Classical knowledge of tactics and strategy serves as a bridge for novice players to improve their skills.

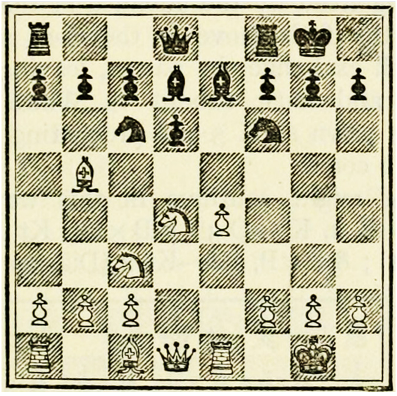
Figure 3 presents an excerpt from a chess strategy textbook [10], illustrating how strategic concepts apply to specific board positions. It identifies key pieces (*e.g.,* KP, King's file) and strategic objectives (*e.g.,* Black's abandonment of KP, White's pressure on KP, attacking chances along the King's file, and Black's efforts to resolve piece development constraints). The specific move sequences in the excerpt analyze how these objectives can be sought or compromised. Underlying these strategic ideas are core principles, including piece development, space control, piece coordination, and the use of open lines.

2.2 Computational Perspective

Chess, like Go and Shogi, is a perfect-information, turn-based game, theoretically represented as a finite-state graph traversed by two players, where an optimal solution necessarily exists [5]. However, chess has an enormous game tree complexity as large as 10^{120} [12], making an exact solution computationally infeasible. Both humans and chess engines rely on abstractions to manage this complexity. While humans use positional intuition, computational engines apply pruning techniques in tree-based search and value networks in reinforcement learning. In all cases, strategy emerges as an abstraction derived from necessary simplifications. Prior research has identified similarities between human-developed heuristics and AI-learned patterns in chess [11]. From a computational perspective, human-crafted strategy provides useful insights, but it is not the only possible outcome of data-driven simplification. As both humans and AI continues to advance, established knowledge may evolve, making prior strategic principles less certain.

2.3 Role of Strategy in Chess Skill Hierarchy

The concept of chess skill can be understood as a continuum, ranging from beginner-level play to advanced human performance, engine-level analysis, and, in theory, an optimal solution (Figure 2). At the level of chess engines, the distinction between tactics and strategy becomes less meaningful in practical terms, as search depth and evaluation functions integrate both into a unified process. At the highest level of human play, elite competitors apply



In the second main line of defence, of which I shall treat now, Black renounces the maintenance of his KP, and makes an attempt to find compensation by attacking White's King's Pawn. The King's file, opened by the disappearance of the Black pawn, offers opportunities for that purpose. After the first few moves we arrive at the following position, which may be reached thus: 3. B-Kt5, P-Q3; 4. P-Q4, B-Q2; 5. Kt-B3, Kt- B3; 6. Castles, B-K2; 7. R-K1, PxP; 8. KtxP, Castles. The exchange on the seventh move is compulsory, because the loss of a pawn after BxKt is in effect threatened, now that the White KP is supported by the Rook.

Black's intention of exerting pressure on the KP is now difficult of execution, because his pieces are very cramped and hinder one another in a restricted area. The KB in particular cannot be brought into action without great difficulty, for instance by: R- K1, B-KB1, P-KKt3, and B-Kt2. It is therefore advisable for White to develop his QB at Kt2 instead of at Kt5, in order not to give Black a chance of exchanging his troublesome Bishop. (In a game Bernstein-Emanuel Lasker, Moscow, 1914, there happened 9. BxKt, PxB; 10. B-Kt5, P-KR3; 11. B-R4, Kt-R2; 12. BxB, QxB with a good game for Black.)

The defence has a totally different trend, if Black gives up his own KP, but captures the White KP at once. I have already pointed out that White would not mind his KP being taken, in view of the attack on the open King's file. Let us now consider in which way this attack can be planned. There are two essentially different lines, according to whether Black interpolates P-QR3 or not.

Figure 3: Excerpt from a chess strategy textbook [10], illustrating how strategic concepts apply to specific board positions, highlighting strategic objectives and move sequences.

strategic principles but increasingly rely on AI-assisted preparation, analyzing numerous variations—some of which may appear unintuitive or purely memorized from a human perspective [1, 8]. In this context, classical strategic concepts remain relevant but may seem less distinct, as the range of viable moves extends beyond conventional human understanding.

By contrast, classical strategic principles provide significant educational value for players progressing from beginner to advanced levels. Beginners lack the ability to calculate deeply or assess positions intuitively, so structured instruction on development, pawn structure, open files, and piece coordination can improve their decision-making. In this sense, traditional strategic education remains a key tool for building foundational skills.

3 CHESS STRATEGY TEXTBOOKS

Chess strategy textbooks have long provided systematic instruction based on human-defined concepts. They offer educational value by presenting material in a way that aligns with human cognition, giving novices and intermediate players the vocabulary and frameworks to discuss and analyze positions.

However, the limitations of textbooks are also evident. They are static, non-interactive, and can be overwhelming for casual learners. In contrast to tactical training websites—where users receive immediate feedback and can practice specific motifs—strategy discussions in books often require readers to carefully study large amounts of text before applying ideas in a real game. Some online platforms do provide "digitized" strategy lessons, yet most simply replicate textbook-like content with limited room for exploration.

Existing work in Natural Language Processing (NLP) has explored the potential of adding interactivity to chess textbooks. Prior studies have constructed datasets and trained models to pair chess positions with strategic descriptions [6, 13]. More recent research [3, 7] has leveraged large language models (LLMs) to enhance position evaluation and explanation generation. While these approaches demonstrate the potential of language models in chess education, they introduce new challenges. By integrating human knowledge into complex models, they reduce interpretability and do not preserve the original educational structure of chess textbooks. For example, interactive explanations should align with the intended audience of the book, whether beginners or advanced players, but current methods do not account for these distinctions.

Another key challenge is linking abstract strategic concepts to specific board moves. For example, the excerpt in Figure 3 describes both general strategic aims and the specific moves that achieve them. Although language models exhibit some capacity to approximate these formal operations [3, 14], they do not natively support them [9] and thus remain less effective than dedicated chess engines. Directly inputting textbook content into a language model will not guarantee a dynamic, interactive system with a deep understanding of strategic concepts, board geometry, and the causal relationships between moves.

4 TOWARDS INTERACTIVE CHESS TEXTBOOKS

Chess strategy textbooks remain valuable for human learning, distinguishing them from highly accurate but non-explainable engine solutions. Given language models' ability to flexibly transform knowledge formats, we envision an advanced role for chess textbooks that integrates with the chessboard and provides immediate feedback.

The key challenges in achieving this are outlined in Figure 1. Chess engines and human-crafted strategies serve distinct but complementary roles. Textbooks act as a compass, offering contextualized guidance and stable strategic principles that are easier for humans to follow. By abstracting away precise calculations, they reduce cognitive load and support long-term planning. However, this abstraction makes it difficult to translate strategic insights into concrete moves. In contrast, chess engines function as navigators, systematically searching for optimal moves. While effective in computation, they fail to capture the conceptual nuances humans use to understand chess and do not align with a user's focus when the goal is to learn strategy rather than maximize winning chances. Bridging the gap between these approaches requires addressing three key questions.

Q. How can we consult chess textbooks about specific cases? To preserve the conceptual structures curated by textbook authors, it is crucial to reference the textbook text in its original form, locating the sections most relevant to each query. A retrieval-augmented generation (RAG) pipeline integrated with a large language model (LLM) [4] can facilitate this process, provided it is coupled with strong grounding checks to ensure fidelity to the textbook content. Moreover, the system's feedback should retain the textbook's organizational elements—such as section hierarchies, key concepts, and thematic groupings—so that learners can progressively learn the book's conceptual framework. Effective interface design is equally important, presenting this framework-related information without distracting from the broader flow of learning.

Q. How can we describe the chessboard and moves in strategic terms? Chess textbooks typically present strategic knowledge in layered natural language, building complex ideas upon foundational principles. While LLMs can translate raw board states and moves, generating natural language descriptions about a board state that align with a textbook's conceptual framework would improve response quality. One approach is to build on existing commentary-generation systems [6, 7, 11], which integrate commentary databases, chess engine evaluations, and annotated resources to produce explanatory text. However, these systems often focus on single-move commentary rather than extended sequences. A possible method to construct a cohesive narrative across multiple moves is to recursively incorporate textbook content, ensuring that generated explanations remain grounded in established principles.

Q. How can we align strategic direction with the actual path? This problem is the reverse of the second one. A direct but impractical approach would be to annotate every possible node in the game tree with a natural language description and allow an LLM to navigate toward nodes that align with a chosen strategic framework. However, the exponential growth of move possibilities makes this infeasible. A more effective method is to use chess engines to reduce the search space by eliminating moves with little strategic value. Annotations and explanations can then be generated for the remaining set of meaningful moves.

5 DISCUSSION

5.1 Opportunities on Interactive Textbooks

Recent advances in large language models (LLMs) allow vast textual content to be freely transformed and restructured into diverse formats. This development suggests that special knowledge, traditionally locked into lengthy and dense textbooks, need not remain fixed in a single form but can be reorganized or reinterpreted in response to situational needs. Notably, many such comprehensive textbooks address extensive domains of human expertise beyond chess. Historically, only those who had undertaken a thorough reading and developed a holistic understanding could fully utilize the specialist knowledge contained therein. Now, however, interactive approaches can enable *learning by doing* rather than mere *doing by learning*, letting even non-experts progressively explore targeted concepts and receive contextual explanations as needed. Moreover, by "flexibilizing" textbook content, learners can consult multiple sources—like plug-and-play game cartridges—choosing the material or perspective most relevant to their current goals. While high-stakes areas such as medicine, therapy, or policy may demand caution for the risks of misapplication, there remain plenty of domains in which these interactive, exploratory methods can be profoundly beneficial. For instance, one could draw on different philosophical texts to reflect on personal beliefs, or refer to various economics and business texts to obtain tailored feedback on financial planning or management strategies.

5.2 Significance of Human-Crafted Knowledge

As chess engines surpass human abilities, similar advances in other fields seem likely, illustrated by the recent *o3* model achieving a high ranking in competitive algorithmic programming contests, placing it among the top 200 competitors [2]. As AI continues to grow in capability, some may question whether human-crafted knowledge is becoming outdated. Yet, just as chess books' explanations of why and how remain essential for beginners, human-centered knowledge across different fields should remain important. Even if AI can find the best solution, true learning requires people to understand the core ideas and reasoning behind it, which depend on knowledge structures built by and for humans. Returning to the algorithm programming example, even if AI outperforms human programmers, concepts like complexity analysis, dynamic programming, and recursive modeling remain key foundations for computational thinking.

Moreover, complementary roles of chess engines and textbooks show that an AI-optimized solution may not always provide the best human experience. This gap appears in many areas beyond chess; for instance, a GPS may suggest the fastest route, yet travelers often take detours for more meaningful experiences. In such cases, a travel guidebook can act as a kind of natural language constraint on pure optimization, anchoring route planning in human context and preference. Our broader goal is to explore how human-centered, text-based knowledge can be integrated into formal, logic-driven systems, expanding what is considered optimal to better align with human needs and values.

5.3 Comparison with Adjacent Fields

The core challenge of interactive chess strategy lies in the relationship between abstract strategic ideas and formal operations. This concept also applies to other fields, such as mathematics and programming, which blend conceptual structures with precise symbolic operations. How do chess strategies compare to those in math? One key difference is that chess is purely structured: valid moves form a well-defined game tree. The chess domain has proven that the patterns identified by AI align with the strategic principles developed by humans, and smaller advantageous patterns combine in a linear way to create stronger positions. Whether this kind of linearity and consistency holds in fields with greater flexibility or fewer formal rules remains uncertain. As less rigid disciplines begin to integrate human-authored knowledge with AI-generated insights, we may discover both unexpected synergies and new challenges in preserving coherence between abstract principles and formal operations.

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