Title
Cognitive Modeling of Shogi: Effects of Relative Representations and Resource Constraints

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 48(0)

Authors
Muramatasu, Kimiya
Morita, Junya

Publication Date
2026

Cognitive Modeling of Shogi: Effects of Relative Representations and Resource Constraints

Kimiya Muramatsu (muramatsu.kimiya.22@shizuoka.ac.jp)[1] &
Junya Morita (j-morita@inf.shizuoka.ac.jp[1]
[1]Graduate School of Integrated Science and Technology, Shizuoka University, Japan

Abstract

We model shogi move selection in ACT-R to test how expertise depends on representation and cognitive resource constraints. The model integrates visual exploration, a capacity-limited imaginal stack, and declarative memory retrieval. Beyond absolute board encoding, we implement king-centered relative representations (3×3 local patterns) intended for endgame reasoning. Simulations crossed (i) relative representations on/off and (ii) imaginal capacity (9 vs. 18), while expertise was manipulated by storing expert vs. novice game records. Expert advantage was conditional: it was stable when relative representations were available, but collapsed (and sometimes reversed) when relative representations were absent under low capacity, accompanied by a sharp drop in retrieval use and earlier convergence of game states. Larger capacity partially compensated for missing relative representations. These results imply that expertise in this domain emerges from representation × resource coupling, not experience alone.

Keywords: ACT-R; shogi; cognitive modeling; expertise; resource management

Introduction

Board games provide controlled domains for studying human cognition under constraints of attention, memory, and decision making (Chase and Simon, 1973; Gobet and Jansen, 1994; Kawaji et al., 2023). Research on chess expertise shows that skilled players do not rely on exhaustive search but recognize meaningful configurations based on prior experience, enabling efficient move selection (Gobet, 2001). These findings indicate that strategic thinking is supported by perceptual and memory-based mechanisms rather than purely optimal computation.

However, focusing on a single game may obscure aspects of cognition related to how cognitive and material resources change over time. In chess, the number of pieces monotonically decreases and captured pieces are never reused, so global, absolute board representations remain effective throughout play. Many cognitive accounts of position understanding implicitly rely on this stability. It remains unclear whether such assumptions hold for games governed by different rule systems.

Shogi provides a contrasting case. Because captured pieces can be reused as pieces in hand, available resources change dynamically during play. Effective performance requires managing both board configurations and pieces in hand. Moreover, endgame situations often depend on local spatial relations centered on the opponent's king rather than the global board structure. These characteristics suggest that the usefulness of cognitive representations may shift as the game state evolves.

From this perspective, shogi serves as a theoretical test case for examining the scope of representation formats and search assumptions developed in prior board-game research. The reuse of captured pieces imposes cognitive demands on models that treat positions as fixed spatial configurations.

Addressing these issues requires a framework that explicitly represents constraints on attention and memory and can procedurally describe changes in representation use during play. Cognitive architectures provide such a framework by integrating visual attention, short-term memory, long-term memory, and action selection within a unified system (Kotseruba and Tsotsos, 2020). In this study, we build a shogi model in a cognitive architecture and examine how shogi-specific strategic conditions influence the use of representations and processing resources, with particular focus on endgame play.

Related Work

Board games have played a central role in cognitive science, particularly in studies of expertise and chunking. Research on chess shows that experts perceive positions as meaningful configurations rather than as isolated pieces (Chase and Simon, 1973; Gobet and Jansen, 1994; Simon and Chase, 1973). Similar findings have been reported in shogi: stronger players show superior memory for realistic positions but not for random ones (Ito et al., 2002; Matsubara and Ito, 2000), and individual differences in internal visual representations ("mental shogi boards") are associated with expertise (Yoshimoto and Nagai, 2022). These results suggest that position understanding in both chess and shogi relies on relationally structured memory rather than rote encoding of piece locations. In addition to pattern recognition, deeper search processes have also been shown to contribute to expertise in board games (Holding, 1985). More recent work has further investigated expertise using process-level computational modeling, showing that skilled players engage in deeper planning (van Opheusden et al., 2023).

In artificial intelligence, computational modeling of board games has increasingly prioritized performance over cognitive explanation. In shogi, systems such as Bonanza combined search with evaluation functions learned from human records (Hoki and Kaneko, 2014), and AlphaZero achieved superhuman performance through self-play reinforcement learning

In G. Boleda, I. Dautriche, M. Maldonado, C. Saldana and T. Torrent (Eds.), *Proceedings of the 48th Annual Conference of the Cognitive Science Society*

(Silver et al., 2017). While these approaches demonstrate that strong play can be realized computationally, cognitive science research has long focused on modeling the underlying processes of human decision-making. Prior work has modeled simple competitive games as dynamic systems in which behavior emerges from interactions between agents (**WestLebiere2001**), and has further shown that cognitive noise can systematically influence performance in such environments (West et al., 2005). Prior work has also explored decision-making in more complex game environments (**Sanner2000**). These approaches emphasize the importance of internal processes such as learning, memory, and interaction dynamics.

Cognitive architectures offer a framework for integrating these perspectives by modeling cognition under explicit resource constraints. Newell (1994) proposed that cognition should be explained through unified theories integrating perception, memory, and action selection. ACT-R is one such architecture, modeling visual attention, short-term (imaginal) representations, declarative memory, and production-based control (Anderson, 2007). It has been applied to a range of tasks, including game behavior, where both performance and internal processes are analyzed (Kawaji et al., 2023, 2025; Kotseruba and Tsotsos, 2020; Lebiere and West, 1999). However, to our knowledge, shogi has not been examined within an ACT-R framework, and how architectural resource constraints interact with shogi-specific representational demands remains unclear.

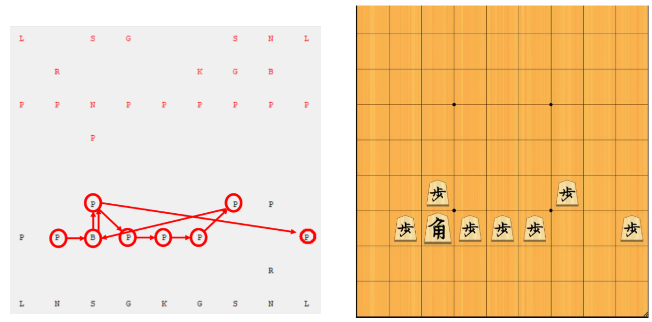
Objective

This study models shogi cognition within a cognitive architecture to clarify how expertise depends on representation format and cognitive resource constraints. Shogi differs from chess in allowing the reuse of captured pieces and in emphasizing local, king-centered relations in endgame situations. These characteristics suggest that global, absolute board representations may not always suffice.

We construct an ACT-R model that integrates visual exploration and memory-based move selection. The model employs both absolute board representations and relative, local representations, and we manipulate the availability of these representations as well as short-term memory capacity. By comparing models with expert and novice experience under these conditions, we examine when expertise advantages are preserved and when they degrade, thereby identifying how representation and resource constraints jointly shape skilled performance.

Model

The model is implemented in the ACT-R cognitive architecture to simulate human shogi move selection as a sequence of visual exploration, memory retrieval, and action selection. Two ACT-R agents interact through `python-shogi` (Gunyarakun, 2026), which enforces game rules and updates board states. The model produces moves based on internal cognitive processing, while legality checking is handled externally. We include cognitive processes related to detecting check but not those required to detect *nifu* (double pawn), thereby limiting the model to processes relevant to strategic reasoning.



(a) Board exploration through gaze transitions.

(b) Imaginal module representation of attended pieces (board image created using the Lishogi editor: https://lishogi.org/editor).

Figure 1: Perceptual exploration and short-term representation in the model.

The model integrates three functional components: (1) visual–imaginal processing for incremental board perception, (2) declarative memory retrieval of prior experiences, and (3) production-based control of information flow.

Perception and Short-Term Representation

The visual module acquires board information through sequential gaze shifts rather than full-board encoding. Attention is guided by stimulus saliency and local neighborhood exploration, approximating human eye-movement strategies (Figure 1a). Saliency was operationalized by assigning different stimulus strengths to piece types using an ACT-R technique in which multiple visual objects are overlaid at the same board location, with the number of overlays determining attentional priority. The relative weights assigned to pieces were informed by explanatory blog sources discussing typical attentional tendencies in shogi play (Lab, 2025); tactically critical pieces such as the king, *hisya*) (rook), and *kaku* (bishop) were assigned higher overlay counts than minor pieces. These values function as design assumptions to introduce attentional bias rather than as psychologically measured indices.

Attended pieces are encoded in the imaginal module, which functions as a capacity-limited short-term store, as shown in Table 1. The imaginal representation consists of symbolic labels combining side and piece type (e.g., `S-K`) and operates as a stack: newly attended items are pushed onto a fixed-capacity stack. When the capacity is exceeded, older items are displaced in a first-in-first-out manner. This mechanism captures resource-limited maintenance of local board information. Figure 1b illustrates board information corresponding to the eye movements shown in Figure 1a.

Table 1: Example update of stack contents in the imaginal module.

(a) During exploration

Stack	Piece
1	O-P
2	O-P
3	S-N
⋮	⋮
8	S-S
9	S-G

(b) After piece recognition

Stack	Piece
1	O-B
2	O-P
3	O-P
⋮	⋮
8	S-R
9	S-S

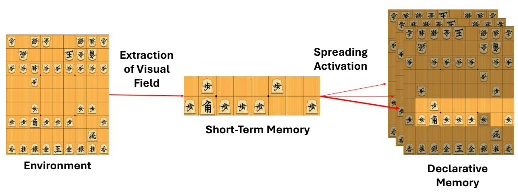


Figure 2: Schematic illustration of declarative memory retrieval based on spreading activation.

Declarative Memory and Representations

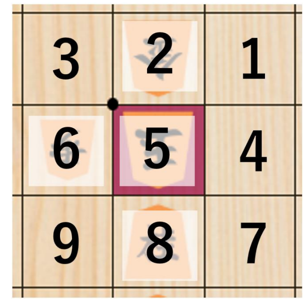
Declarative memory stores past positions and actions derived from game records. Retrieval is cue-driven from the contents of the imaginal module using ACT-R's spreading-activation mechanism (Anderson, 2007). Retrieved episodes serve as candidate moves, in contrast to evaluation-function approaches used in conventional game AI. Figure 2 schematically illustrates this retrieval process, showing how overlap between imaginal contents and stored chunks increases activation through spreading activation.

The model employs two representation formats. *Absolute representations* encode global board configurations and support matching based on overall spatial layout. In contrast, *relative representations* encode local 3×3 regions centered on the king, derived from *tsume-shogi* problems, capturing relational patterns that are particularly relevant in endgame situations. Figure 3 shows the king-centered 3×3 region used for relative encoding and its indexed coordinate system. Because these representations are defined relative to the king rather than to fixed board coordinates, they allow structurally similar positions to be matched.

Action Selection

The production system regulates the interaction among modules rather than performing explicit search. Processing alternates between exploration and retrieval, with transitions governed by ACT-R's standard utility-based conflict resolution. When the king is detected during exploration, memory retrieval is based on relative representations; otherwise, retrieval relies on absolute representations. Retrieved moves are validated and executed if legal, while invalid results return the model to the exploration phase. If processing fails to converge within a time threshold, the model switches to fallback random action generation. Figure 4 summarizes this overall processing cycle, illustrating transitions among exploration, retrieval, and action execution.

(a) A local 3×3 region.



(b) Indexing of the local region.

Figure 3: Example of a local region.

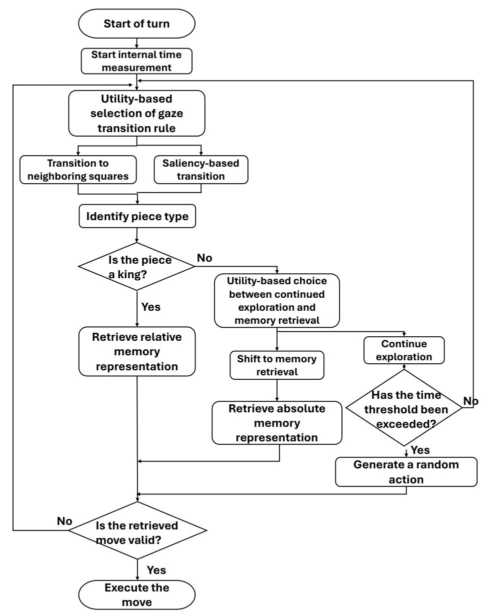


Figure 4: Overall processing flow of the model.

Subsymbolic Parameter Settings

All simulations used ACT-R's standard activation and utility-learning mechanisms. The utility learning rate (α) was set to 0.2. Exploration and retrieval productions were initialized with utilities $u_{\text{explore}} = 7$ and $u_{\text{retrieve}} = 4$, with a shared reward value of 3, so that exploration dominated early processing but gradually gave way to retrieval. For gaze control, saliency-based transitions were initialized with $u = 5$, neighborhood transitions with $u = 8$, both with reward = 4.

Base-level activation used decay parameter $d = 0.5$ and constant offset $\beta = 0.3$. Spreading activation used associative strength $S = 15$, and buffer weights were $W_j = 1/n$, where n

is the current number of items in the imaginal stack.

Theoretical Role of Relative Representations

From a cognitive perspective, relative representations can be interpreted as a form of context-sensitive relational encoding. Whereas absolute representations preserve global spatial layout, relative representations abstract spatial relations with respect to a task-relevant anchor (the king). Such anchoring reduces the need for maintaining globally consistent coordinates and instead supports relational matching based on local structural similarity.

This mechanism aligns with classical findings in expertise research. Studies of chess and other board games show that experts encode positions as meaningful relational structures (chunks) rather than as isolated absolute coordinates (Chase & Simon, 1973; Gobet, 2001; Gobet & Jansen, 1994). Relative representations in the present model instantiate a similar principle: they recode board states in terms of functionally organized local relations centered on a tactically critical piece.

Within ACT-R, this transformation changes the cue structure driving declarative retrieval (Anderson, 2007). Because spreading activation depends on overlap between working-memory contents and stored chunks, relationally encoded cues increase the likelihood of retrieving structurally similar episodes even when absolute board configurations differ. In this sense, relative representations do not merely add information; they reshape the representational geometry of the task space, shifting processing from coordinate-based matching toward relation-based retrieval.

Such a shift becomes especially important under resource constraints. When working-memory capacity is limited, maintaining a globally coherent absolute board representation is costly. Relative representations provide a more resource-efficient encoding that preserves task-relevant relational information, thereby supporting the emergence of expertise effects under bounded cognitive resources.

Simulation

Overview

We evaluated the model by having an expert-memory agent and a novice-memory agent play against each other within the same cognitive architecture. Expertise differences were implemented through the game records stored in declarative memory, while cognitive mechanisms remained identical.

Experimental Manipulations

Two factors were manipulated to examine how representation format and cognitive resources affect performance: (1) representational perspective (absolute only vs. absolute+relative) and (2) imaginal module capacity (stack size 9 vs. 18). These factors operationalize differences in representational availability and short-term memory resources associated with expertise.

Expertise was implemented through qualitative and quantitative differences in declarative memory:

- **Expert memory:** 20 most recent games of a top-ranked (6-dan) player in the Shogi Wars Dan–Kyu Championship standings in mid-January 2026,[1] with the number of games limited by ACT-R simulation cost.
- **Novice memory:** all available games (five in total) of a lowest-ranked (9-kyu) player from the same period.

Thus, expertise was operationalized as differences in stored experience, with quantity differences constrained by data availability and computational cost.

Game Procedure

Under each of the four resulting conditions, ten games were played with a maximum length of 150 turns. Games terminated upon decisive outcomes or when the turn limit was reached. Each move-selection had an upper time limit of 210 seconds. The expert model was always assigned as the first player. The expert model was consistently assigned as the first player to reduce variability across conditions.

Rule violations were treated differently depending on their type. Illegal candidate moves (e.g., double pawn or illegal pawn-drop mate) were rejected and led to continued exploration, whereas failure to respond to check resulted in immediate loss. This distinction reflects a separation between errors occurring during internal decision-making and those that determine actual game outcomes.

Evaluation Measures

Model behavior was evaluated using game outcome, termination reason, number of turns, number of checks delivered, number of pieces remaining on the board, and memory-retrieval rate, defined as the proportion of move selections driven by declarative memory retrieval rather than random action generation. Game outcome (win/loss) was treated as the primary performance measure, while the number of checks was included as a secondary measure to capture tactical activity rather than move quality.

Memory-retrieval rate was computed in 10-turn segments to capture temporal changes in reliance on declarative retrieval.

Results

We summarize the effects of representation format and memory capacity on game outcomes, game dynamics, and memory-retrieval behavior.

Game Outcomes and Termination

Win–loss distributions differed significantly across conditions ($\chi^2(3) = 14.40$, $p < .01$; Table 2). Expert advantage was stable when relative representations were available (9/1 wins under both stack sizes). However, under the relative-off, stack-9 condition, performance reversed and the novice model won more games (3/7). This pattern indicates that the absence of relative representations under limited memory capacity disrupts the typical advantage associated with expert memory.

[1] https://shogiwars.heroz.jp/

Table 2: Game outcomes under each condition (each cell shows "wins by the first player / wins by the second player").

	Stack 9	Stack 18
Relative on	9 / 1	9 / 1
Relative off	3 / 7	9 / 1

Table 3: Reasons for game termination under each condition (each cell shows "checkmate / failure to respond to check / 150-turn limit").

	Stack 9	Stack 18
Relative on	0 / 10 / 0	0 / 10 / 0
Relative off	2 / 8 / 0	0 / 10 / 0

Termination patterns mirrored this effect (Table 3) although the effect was not clearly observed ($\chi^2(3) = 6.316$, $.05 < p < .10$). Most games ended via failure to respond to check, which was treated as a terminal illegal move resulting in immediate loss. Checkmate terminations occurred only in the relative-off, stack-9 condition and always resulted in novice wins. This condition thus uniquely disrupted the usual expert advantage.

Game Progression

Neither representational perspective nor stack size affected game length (all $F < 1.2$, $p > .25$; Figure 5). However, game-state dynamics differed qualitatively. Only in the relative-off, stack-9 condition did the number of remaining pieces drop sharply after midgame, indicating earlier convergence of game states (Figure 6). This suggests that the absence of relative representations under constrained resources leads to simplified or prematurely resolved game trajectories.

Checks and Tactical Activity

Table 4 shows the mean number of checks delivered under each condition, with standard deviations. A three-way between-subjects ANOVA (perspective: relative on/off, stack size: 9/18, expertise level: expert/novice) revealed a strong main effect of expertise ($F(1, 72) = 22.68$, $p < .01$), with

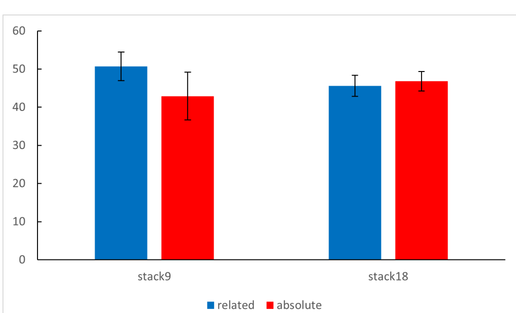


Figure 5: Mean number of turns until termination under each condition, Error bars indicate the standard error of the mean (SEM) for each condition.

Table 4: Mean number of checks under each condition (standard deviations in parentheses).

	Expert		Novice	
	Relative on	Relative off	Relative on	Relative off
Stack 9	1.10 (0.54)	0.40 (0.49)	0.20 (0.40)	0.80 (0.60)
Stack 18	1.00 (0.45)	1.00 (0.45)	0.10 (0.30)	0.30 (0.46)

expert-memory models producing more checks overall. As noted above, this measure reflects tactical activity rather than move quality.

Crucially, this advantage depended on representational and resource conditions (interactions among all three factors: $F(1, 72) = 6.22$, $p < .05$). Under the stack size 9 condition, the effect of representational perspective was significant ($F(1, 36) = 9.48$, $p < .01$), with the relative-on condition producing a higher number of checks than the relative-off condition ($M = 1.10$ vs. $M = 0.40$). In contrast, no difference between representational conditions was observed under the stack size 18 condition ($F(1, 36) = 0.00$, $p = 1.00$). Under the relative-off condition, the effect of stack size was significant ($F(1, 36) = 6.97$, $p < .01$), with the stack size 18 condition yielding more checks than the stack size 9 condition ($M = 1.00$ vs. $M = 0.40$).

For conditions using novice game records, the main effect of representational perspective was significant ($F(1, 36) = 4.74$, $p < .05$), with the relative-off condition producing a higher number of checks than the relative-on condition. The main effect of stack size was not significant ($F(1, 36) = 2.42$, $p = .129$).

The interaction between representational perspective and stack size was also significant ($F(1, 36) = 4.74$, $p < .05$). Simple main effects analyses indicated that under the stack size 9 condition, the relative-off condition produced significantly more checks, whereas no representational effect was observed under the stack size 18 condition. These results suggest that the effectiveness of representation format depends on available cognitive resources.

Number of Pieces Remaining on the Board

Figure 6 illustrates the changes in the number of pieces remaining on the board under each condition. Only under the condition without relative representations and with a stack size of 9 did the number of pieces decrease sharply after the middle phase of the game, indicating earlier convergence of game states compared to the other conditions. In contrast, under the remaining conditions, the number of pieces decreased more gradually, and the overall trajectories were similar across conditions.

Memory-Retrieval Behavior

Memory-retrieval rates declined gradually over time in most conditions. In contrast, the relative-off, stack-9 condition showed an abrupt drop around turn 30, after which retrieval remained consistently low (Figure 7). This collapse in re-

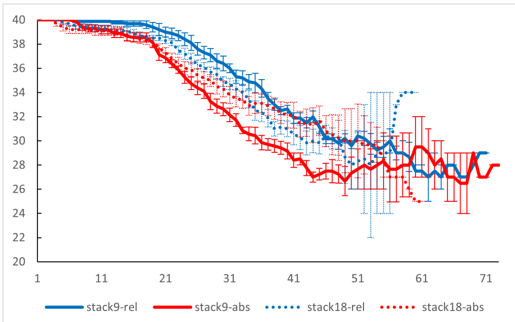


Figure 6: Change in the number of pieces remaining on the board under each condition. Error bars indicate the standard error of the mean (SEM) for each condition.

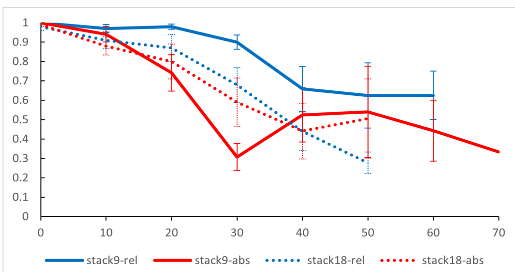


Figure 7: Memory usage rate over time (computed for every ten turns). Note: Error bars indicate the standard error of the mean (SEM) for each condition.

trieval coincided with the loss of expert advantage and earlier game convergence, suggesting that representational limitations disrupted sustained use of declarative memory.

Discussion

This study examined the conditions under which the performance advantage of an expert-memory model over a novice-memory model can be reproduced in a cognitive architecture. The results show that expertise effects were not uniformly expressed but depended critically on representation format and processing resource constraints.

Overall, the expert-memory model outperformed the novice-memory model, indicating that differences in experience were reflected in behavior. However, this advantage varied across conditions, demonstrating that experience alone is insufficient to guarantee expert performance.

Role of Processing Resources

Increasing stack length (18 vs. 9) supported more stable internal processing, reflected in higher memory-retrieval rates and smoother transitions in board-state dynamics. Larger capacity appeared to buffer against abrupt collapses of internal state, as seen in the condition where relative representations were unavailable. However, greater capacity did not consistently improve win rate, suggesting that additional resources do not automatically translate into more effective decision making.

Role of representation format

Relative representations generally supported the preservation of expert advantage, particularly in endgame situations where local king-centered relations are critical. Conditions with relative representations showed more gradual changes in board states, indicating sustained organization of local tactical interactions. These findings suggest that relative representations enable more effective use of stored experience when local relational structure dominates decision making.

Interaction Between Representation and Resources

The most distinctive result was that expert advantage broke down only when relative representations were absent and stack length was small. In this condition, memory-retrieval rates dropped sharply midgame, game states converged earlier, and the novice model frequently won. When stack length was larger, this deterioration did not occur, indicating that greater processing resources allowed absolute representations to partially compensate for the absence of relative representations. Conversely, relative representations appear to function as a resource-efficient format that supports effective use of experience under limited capacity.

Implications for Cognitive Modeling

These findings indicate that expertise does not emerge solely from experience quantity or quality. Instead, its manifestation depends on how knowledge is represented and how it is utilized under processing constraints. Reproducing expert performance in cognitive models therefore requires aligning representation format with architectural resource limitations. Relative representations act as a mechanism that enables efficient use of experience under constraint, highlighting the importance of representation–resource coupling in cognitive modeling.

Conclusion

We modeled shogi cognition in ACT-R and examined how expertise differences emerge as a function of experience, representation format, and processing resource constraints. While expert-memory models generally performed better, this advantage was conditional.

Performance degradation and reversals occurred only when relative representations were unavailable and processing capacity was limited. In contrast, when relative representations were available, expert advantage was preserved regardless of stack length. These results indicate that relative representations serve as a key mechanism for leveraging experience under resource constraints.

Thus, reproducing expertise in cognitive models requires not only differences in experience but also appropriate representational structures and alignment with processing resources. The findings underscore the importance of representation–resource coupling for modeling domain-specific cognition such as shogi.

References

Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* Oxford University Press.

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55–81.

Gobet, F. (2001). Chess expertise. In N. J. Smelser & P. B. Baltes (Eds.), *International encyclopedia of the social and behavioral sciences* (pp. 1663–1667, Vol. 3). Elsevier.

Gobet, F., & Jansen, P. (1994). Towards a chess program based on a model of human memory. *Advances in Computer Chess 7*, 35–60.

Gunyarakun. (2026). Python-shogi: A pure python shogi library [GitHub repository].

Hoki, K., & Kaneko, T. (2014). Large-scale optimization for evaluation functions with minimax search. *Journal of Artificial Intelligence Research*, *49*, 527–568.

Holding, D. H. (1985). *The psychology of chess skill*. Lawrence Erlbaum Associates.

Ito, T., Matsubara, H., & Grinbergen, L. (2002). Cognitive study of shogi (1): Analysis based on memory experiments. *IPSJ Journal*, *43*(10), 2998–3011.

Kawaji, R., Morita, J., & Osawa, H. (2023). Modeling cooperative behavior in the card game hanabi using act-r. *Proceedings of the International Conference on Human-Agent Interaction*.

Kawaji, R., Morita, J., & Osawa, H. (2025). Simulation of appropriate emotional states in cooperative learning using cognitive models. *Proceedings of the Annual Conference of the Japanese Society for Artificial Intelligence*.

Kotseruba, I., & Tsotsos, J. K. (2020). 40 years of cognitive architectures: Core cognitive abilities and practical applications. *Artificial Intelligence Review*, *53*, 17–94.

Lab, A. (2025). Piece values and visual saliency in shogi [Online article].

Lebiere, C., & West, R. L. (1999). A dynamic act-r model of simple games. *Proceedings of the Annual Meeting of the Cognitive Science Society*, 296–301.

Matsubara, H., & Ito, T. (2000). Cognitive study on memory for shogi positions (2). *Proceedings of the 61st Annual Convention of the Information Processing Society of Japan*, 37–38.

Newell, A. (1994). *Unified theories of cognition*. Harvard University Press.

Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., Lanctot, M., Sifre, L., Kumaran, D., Graepel, T., Lillicrap, T., Simonyan, K., & Hassabis, D. (2017). Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815*.

Simon, H. A., & Chase, W. G. (1973). Skill in chess. *American Scientist*, *61*(4), 394–403.

van Opheusden, B., Kuperwajs, I., Galbiati, G., Bnaya, Z., Li, Y., & Ma, W. J. (2023). Expertise increases planning depth in human gameplay. *Nature*, *618*, 1000–1006. https://doi.org/10.1038/s41586-023-06124-2

West, R. L., Stewart, T. C., Lebiere, C., & Chandrasekharan, S. (2005). Stochastic resonance in human cognition: Act-r versus game theory, associative neural networks, recursive neural networks, q-learning, and humans. *Proceedings of the 27th Annual Conference of the Cognitive Science Society*, 2353–2358.

Yoshimoto, Y., & Nagai, K. (2022). Individual differences in visual imagery of the mental shogi board. *Proceedings of the Annual Meeting of the Japanese Cognitive Psychology Society*.