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CAN AI RESIGN AT THE RIGHT TIME IN A GAME OF SHOGI?

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ABSTRACT

This study introduces an innovative resignation mechanism to enhance shogi AI's decision-making by identifying the optimal moment to resign. Through 300 self-play games per skill level, data on game length and branching factor were collected and analysed using game refinement theory and motion in mind techniques. The resignation threshold, defined as the maximum score of the losing player's advantageous position plus a small value, prompts AI resignation when further alteration of the game's outcome is improbable. Results indicate that implementing this mechanism significantly reduces game length compared to without AI, bringing AI performance closer to human-level proficiency. Specifically, the average game length at skill level 20 decreased from 165.66 to 110 moves, while at skill levels 15, 10, and 5, the lengths reduced from 141.18, 133.97, and 121.17 to 112, 116, and 121 moves, respectively. Notably, gameplay speed, measured as the number of moves per unit time, also increased significantly after applying the resignation mechanism. Before its application, speed decreased with higher AI ability; however, post-application, speed increased with AI ability, underscoring the mechanism's effectiveness in accelerating gameplay. The primary objective of this research is to enhance shogi AI's decision-making capabilities, thus improving overall performance. By integrating the resignation mechanism, reliable data can be obtained for comparison with human players, contributing to advancements in game theory. In conclusion, introducing a resignation mechanism in shogi AI leads to smarter decision-making and more efficient gameplay. The findings of this study highlight the potential for improving AI performance in various board games and offer valuable insights into both AI decision-making processes and human gameplay strategies.

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Introduction

Since the dawn of human civilisation, games have been a means of pursuing excitement and happiness. As a form of play, games have been central to human culture, fostering complex activities such as organisation, language, philosophy, war, and art [1]. Artificial intelligence (AI) has become increasingly sophisticated, equalling and surpassing peak human performance in a growing number of domains [2, 3]. With the advent of AI engines, more players are using AI for training. These engines can play against humans and analyse their weaknesses. Among these AI engines, those designed for board games are particularly popular, as they cater to both professional players and beginners. One of the oldest board games in the world is shogi, which originated in Japan. However, strong AI self-play in shogi often results in long game durations, as the AI may exhibit suboptimal behaviour in losing positions due to its inability to determine an appropriate time to resign. This study seeks to explore a new approach that enables AI to resign at the optimal moment.

The objective of this paper is to explore an innovative approach for implementing a resignation mechanism in shogi AI. With such a mechanism, AI can identify the most appropriate time to resign, addressing a significant limitation in its decision-making process. While AI has reached superhuman levels in two-player, complete information games such as chess, shogi, and Go, it often exhibits suboptimal behaviour in losing positions due to its inability to determine the right moment to resign. This paper proposes an innovative approach for identifying the optimal resignation time and obtaining reliable data on truly intelligent AI behaviour.

The structure of the paper is as follows: Section 2 presents the methodology and application of game refinement theory to shogi. Section 3 presents and discusses the results. Section 4 concludes the paper.

Literature Review

Several studies have addressed the concept of AI resigning at appropriate positions to mimic human behaviour. Reid *et al*. developed a new deep neural network chess engine, inspired by AlphaZero, which learns from billions of online games to simulate human behaviour rather than relying on traditional self-play training [4]. While their approach involved training AI using human data, this study focuses on utilising self-play AI to explore the resignation mechanism.

Bhatt *et al*. introduced the concept of algorithmic resignation, which involves strategically disengaging or limiting AI assistance in specific scenarios [5]. This approach goes beyond merely avoiding AI usage by incorporating governance mechanisms within AI systems to guide their appropriate utilisation, taking into account system performance and user preferences. Algorithmic resignation safeguards organisations from potential AI misuse or dependency and can be implemented through methods such as restricting AI access or providing explicit guidance.

Wirth *et al*. investigated the use of expert feedback from annotated chess games to automatically construct an evaluation function [6]. While annotations provide valuable insights, the study highlights limitations and recommends enhancing training data with artificial preferences to improve the quality of the learned function. They propose hybrid approaches and future research directions, including integrating novice annotations and modelling positions with similar evaluations.

Methodology

This study employs an open-source completion engine called Suisho5 as the primary method for evaluating shogi games. Simultaneously, game refinement theory is applied to the collected data to quantify game length, the number of strategies per round, and the acceleration change trends in shogi gameplay. The evaluation method is formulated based on the game length of the shogi board game and the score variations of possible legal moves in each round, with particular focus on the score of the losing AI players.

Game Refinement Theory

Game refinement (GR) theory is a logistical model of game progression, interpreted from the perspective of the game designer [7, 8] and was first formally proposed by Iida *et al*. [9].

Information about a game's outcome is an increasing function of time t (i.e., the number of moves in a board game). In this case, it is defined as the amount of information obtained (or uncertainty resolved) $x(t)$, as shown in Equation (1). The parameter n (where $1 \leq n \in N$) is the number of all possible options, $x(0) = 0$ and $x(T) = 1$.

$$x'(t) = n/t \cdot x\,(t) \tag{1}$$

Here, $x(T)$ represents the normalised amount of solved uncertainty. Note that $0 \leq t \leq T$, $0 \leq x(t) \leq 1$. The rate of increase in solution information, $x'(t)$ is directly proportional to $x(t)$ and inversely proportional to t, as shown in Equation (1). By solving Equation (1), Equation (2) is obtained under the assumption that the information $x(t)$ to be solved for is twice differentiable at $t \in [0, T]$. The acceleration of uncertainty resolution throughout the game is represented by the second derivative of Equation (2), as shown in Equation (3). This acceleration of velocity implies differences in the rate of information acquisition during the game process. The square root of the resulting second derivative is used as a measure of game refinement, as given in Equation (4).

$$x(t) = \ (t/T)^n \tag{2}$$

$$x''(t) = [n(n-1)/T^n]t^{n-2}|_{t=T} = n(n-1)/T^2 \tag{3}$$

$$GR = \sqrt{n(n-1)}/T \tag{4}$$

A skilled board game player will consider a set of less reasonable candidate moves (say b) from all legal possible moves (say *B*) to find a move that can be made. The stochastic game model assumes that each of the *b* candidates has an equal probability of selection. The number of possible legal moves *b* corresponds to the parameter *n* in Equation (4), leading to the approximation $n \simeq \sqrt{B}$. Therefore, for a game with branching factor *B* and length *D*, GR can be approximated as shown in Equation (5). Similar GR measurements have also been conducted to analyse chess and mahjong [10].

$$GR \approx \sqrt{B}/D \tag{5}$$

The complexity of games was found to have degrees of information acceleration, with all FR values falling within the range *GR* ∈ [0.07, 0.08], as detailed in Table 1.

Table 1: Measures of game refinement for board games using human data [8, 9]

	B	**D**	**GR**
Chess	35	80	0.074
Shogi	80	115	0.078
Go	250	208	0.076

Let represent the length of a given game. The uncertainty $y(t)$ is then solved as shown in Equation (6). Complex games assume an appropriate game length for resolving uncertainty while obtaining the necessary information to determine a winner. A game length or total score that is too long or too short can make a game boring or unfair.

$$y(t) = vt \tag{6}$$

GR measurements reflect the sensation of information acceleration encoded and transmitted in our brains, potentially aligning with physical forces and laws. By applying the Equations (4) and (6), an intersection point t_0 can be identified between $y(t) = vt$ and $y(t) = \frac{1}{2}GR^2t^2$, which is equals to $2v/GR^2$. In the analysed game, t_0 signifies the optimal balance between skill and chance achieved through the acceleration of information. Consequently, Equation (7) can be derived, representing the level of complexity that satisfies fairness, a gamified experience, and comfortable stimulation.

$$v = 1/2 \cdot B/D \tag{7}$$

Suisho5-YaneuraOu Engine for Shogi

To generate game data for AI self-play, the Suisho5-YaneuraOu engine is used. YaneuraOu, developed by Japanese programmer Hiroshi Yamashita, is a renowned Shogi engine that has become an important player in the Shogi world. Its strength lies in the application of deep learning technology, enabling it to compete with top human players in Shogi games and achieve excellent results on various websites and platforms. Additionally, its source code is often used by researchers to explore AI and machine learning in shogi. The emergence of YaneuraOu marks a major advancement in computer Shogi and has garnered widespread attention and discussion within the field.

YaneuraOu is an open-source project initially released in 2015. It builds upon the success of AlphaGo and advancements in deep learning technologies, particularly the application of algorithms such as deep residual convolutional neural networks and Monte Carlo tree search (MCTS). Originally rooted in statistical physics to approximate intractable integrals, MCTS has been widely adopted in various fields, including games research [11]. In Suisho5, MCTS is implemented in close alignment with the algorithm described in the AlphaZero paper [11]. Suisho5 is notable for its speed in generating strategies and its robust performance. Through systematic evaluations of player strength, the game intensity of Suisho5 used in this study was rated R4500, surpassing the performance of grandmaster players.

Since the engine lacks a built-in graphical user interface, the software ShogiGUI is used for visualisation. ShogiGUI displays various game information, including move scores and board visualisation.

CShogi Engine

The CShogi engine, developed using C++, significantly improves running speed compared with python-based shogi engines. It can calculate all possible legal moves for each shogi turn, regardless of their quality. After a game is completed, the average number of moves is calculated, providing accurate data that can be applied to game refinement theory.

Results and Discussion

The experiment was conducted in two parts. First, four different skill levels were set: 20, 15, 10, and 5. In simple terms, the lower the skill level, the higher the probability that the second and subsequent moves in the strategy will be selected. However, extremely poor moves will not be accepted. This ensures that the impact of lowering skill levels of AI players remains within a reasonable range, and there will be no particularly bad moves. AI player performance decreases as skill level decreases. Two AI players with the same skill level competed against each other over 300 rounds at each skill level. During a game, the AI player resigns only when the winning probability reaches 99.99%, meaning it cannot resign before that point. The game was then analysed, and a score was assigned to each step.

The data collected in the experiment are shown in Table 2, which illustrates the performance of AI players without resignation. At skill level 20, the average branching factor and game length exceed the human master data of 80 and 115, respectively. As the skill level decreases, the average branching factor approaches that of a human master, but the game length remains significantly higher.

Table 2: Results of self-play experiments with shogi AI at different skill levels

Skill Level	B	D
20	92.41	165.66
15	82.31	141.18
10	81.39	133.97
5	78.74	121.17

After conducting a thorough analysis, a resignation mechanism was developed to determine when a player should concede. This mechanism hinges upon the losing player reaching a point where they have no viable means to alter the course of the game. In essence, the mechanism is determined by the maximum advantage score ever achieved by the losing side. Once the disadvantage score of the losing side surpasses the maximum advantage score they attained in the game, they may opt to resign.

To establish a reasonable maximum value for the losing side in 300 games of varying difficulty levels, the data was analysed. It was observed that the scores obtained by AI players varied significantly depending on their skill levels. Notably, as the skill level of the AI player increased, the advantage scores they achieved diminished. Conversely, lower skill levels necessitated larger advantage scores to prevent the disadvantaged side from having a chance to reverse the game's outcome. This led us to conclude that the baseline value for resignation must be determined based on the maximum advantage score attained by the loser when the AI makes no errors. Prior to conducting the experiments, it was hypothesised that more powerful AIs should be able to end the game more quickly after applying the resignation mechanism. Based on this hypothesis, experiments were conducted at different skill levels to analyse the impact of the resignation mechanism on game length.

During the analysis, instances were observed where the losing side's moves were accompanied by exceptionally high ratings. Upon investigation, these inflated ratings were attributed to mistakes made by the AI or to the adoption of suboptimal strategies. Such errors often led to a complete turnaround, with the player who initially held a winning advantage ultimately losing the game. As a result, it became evident that a sensible resignation threshold should be established at the maximum advantage score achieved by the losing side under the assumption that the AI executes flawlessly. By integrating this hypothesis and conducting thorough experiments, the goal was to verify whether higher-level AIs could significantly shorten game length with the resignation mechanism, thereby improving overall game efficiency.

Table 3: The resignation threshold and game length

Skill Level	Threshold	Game Length
20	850	110
15	2950	112
10	6450	116
5	9999	121

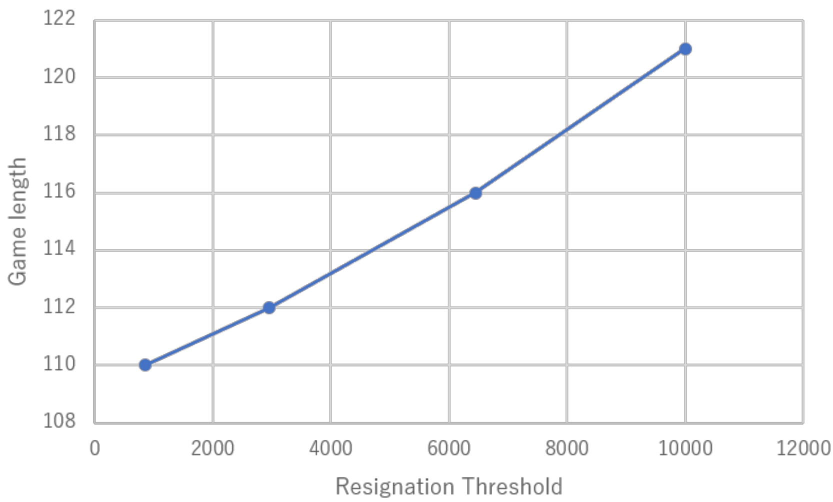

Figure 1: The relationship between the resignation threshold and skill level

In 300 games at skill level 20, a resignation threshold was defined when the score advantage exceeds 850 points, at which point the AI player should resign. For skill levels 15 and 10, the thresholds were set at 2950 and 6450, respectively, while the threshold for skill level 5 was 9999. The relationship between skill level and score is shown in Figure 1, indicating that higher AI performance corresponds to a lower score needed to determine when the AI should resign. After applying the resignation mechanism, as shown in Table 3, the game length was significantly reduced, resulting in faster gameplay. Specifically, at skill level 20, the average game length was reduced to 110 moves, compared with 112, 116, and 121 moves at skill levels 15, 10, and 5, respectively. This demonstrates that the resignation mechanism effectively shortens game duration across different skill levels.

After applying the resignation mechanism, as shown in Table 4, game length was significantly reduced, and the speed of gameplay increased. Specifically, at skill level 20, the average game length decreased from 165.66 moves to 110 moves, while at skill levels 15, 10, and 5, the average game lengths were reduced from 141.18, 133.97, and 121.17 moves to 112, 116, and 121 moves, respectively. In each game, the advantage of the players was evaluated. If a player had a sufficient advantage, meaning the score was greater than or equal to the resignation threshold, the game concluded at that point. The analysis of the gaming data revealed a clear correlation between a player's skill level and the number of branching factors encountered during the game.

Table 4: Comparison of game length and speed before and after applying the resignation mechanism

Skill Level	B	D	D'	V	V'	Threshold
20	92.41	165.66	110	0.28	0.42	850
15	82.31	141.18	112	0.29	0.37	2950
10	81.39	133.97	116	0.30	0.35	6450
5	78.74	121.17	121	0.33	0.33	9999

Figure 2 shows that as player skill decreases, the complexity of decision points also diminishes, leading to fewer branching factors for less skilled players. This trend suggests that less skilled players face a more limited set of options at each decision point compared with their more skilled counterparts. One plausible explanation for this is the narrower understanding of game mechanics and strategies among less skilled players, which may result in oversights of potential moves or a failure to recognise all available options, thereby reducing the complexity of decision trees. Understanding this trend is crucial for both game design and player experience. Game developers can use this insight to tailor gameplay to different skill levels, creating more engaging and accessible gaming experiences. Additionally, this correlation can inform strategies for player education and skill development, helping less skilled players expand their awareness of available options and improve their decision-making abilities. Notably, skill levels 20 and 15 exceed the capabilities of human masters, level 10 is comparable to that of human masters, and level 5 represents intermediate and novice players.

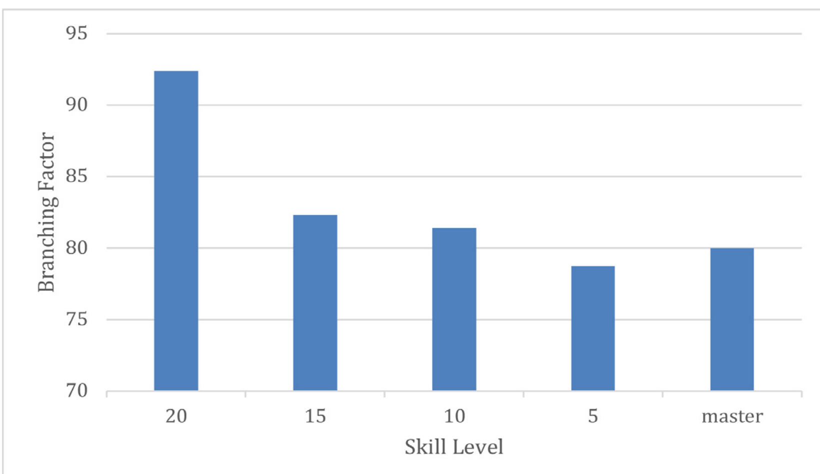

Figure 2: The relationship between the branching factor and skill level compared with human masters

Figure 3 illustrates the changes in game speed (velocity) before and after applying the resignation mechanism. Prior to its application, game speed (V) decreased as the AI player's skill level increased. However, after the mechanism was applied, the game speed (V') increased with the AI player's skill level, suggesting that higher-skilled AI players concluded games more quickly. Specifically, before applying the mechanism, the speeds for skill levels 20, 15, 10, and 5 were 0.27, 0.29, 0.30, and 0.32, respectively. After its application, the speeds increased to 0.42, 0.37, 0.35, and 0.33, respectively. This demonstrates the effectiveness of the resignation mechanism in accelerating the game conclusion for more skilled AI players.

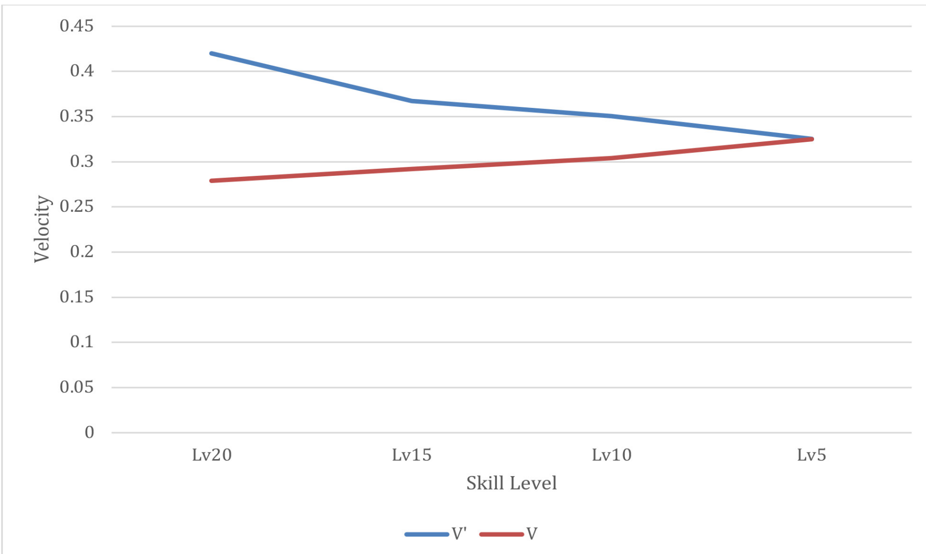

Figure 3: The relationship between game velocity and skill level

This finding suggests that the impact of the resignation mechanism on game length is more significant among higher-skilled players. The observed correlation between skill level and the extent of game length reduction highlights the varied effects of the mechanism on gameplay dynamics. It implies that more skilled players can better leverage the resignation mechanism strategically, leading to more substantial reductions in game duration. In contrast, less skilled players may not fully utilise the mechanism, resulting in comparatively smaller decreases in game length. These findings have significant implications for game design and player experience. The resignation mechanism proves to be a promising tool for modulating the pace of gameplay, particularly for more skilled players who may benefit most from its implementation. By facilitating faster decision-making and streamlining gameplay, the mechanism contributes to a more dynamic and engaging gaming experience across different skill levels.

Furthermore, the implementation of the resignation mechanism has led to a noticeable increase in game speed. This acceleration in gameplay suggests that the resignation mechanism not only shortens the duration of individual games, but also improves the overall tempo of gameplay sessions. Based on the average number of branching factors for a human master, which is 80, it can be inferred that the skill level of a human master falls within the range of 5 to 10. This deduction is based on the premise that lower skill levels correspond to fewer branching factors, while higher skill levels involve a greater number of potential moves to consider at each decision point.

Given this information, it can be reasonably concluded that a human master likely possesses a skill level ranging between 5 and 10 in the context of the analysed games. This estimation aligns with the observed average number of branching factors and offers valuable insights into the proficiency level of human players within the game environment.

Conclusions

This study introduces the concept of a resignation threshold, defined as the maximum advantageous score of the losing player plus a small increment. The threshold is based on the idea that resignation occurs when the losing side has no viable means of altering the outcome of the game. Experimental findings show that in most games, the maximum advantageous score of the losing player remains relatively small, with only a few games exhibiting larger scores. As a result, the resignation threshold is set slightly above the maximum advantageous score of the losing player.

The experiments revealed an interesting phenomenon: After AI players with different skill levels were equipped with a resignation mechanism, the average game time decreased slightly as the skill level decreased. Higher-level players reduce game length more significantly, indicating that they recognised the option to concede earlier. The primary objective of this study is to integrate the resignation mechanism into shogi AI, thereby significantly enhancing its intelligence. Utilising such an advanced AI facilitates the collection of data pertinent to target games, including game length and branching factor. This data serves as valuable input for game refinement theory and comparisons of cognitive depth between human and AI players.

In conclusion, the findings demonstrate that incorporating a resignation mechanism into AI systems not only enhances their intelligence, but also ensures the reliability of AI-generated data. Moreover, this mechanism can be readily adapted for implementation in other board games, highlighting its versatility and applicability across various gaming domains.

Future research will involve different game engines to conduct experiments and analyse the performance of the resignation mechanism across various games. This will facilitate the development of more generalised models and conclusions that can be applied to a wider range of board games. By testing the mechanism in diverse gaming environments, its impact on different game dynamics and decision-making processes can be better understood. This research will contribute to refining the resignation mechanism and enhancing its applicability, ultimately contributing to the development of more intelligent and efficient AI systems in various gaming contexts.

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Conflict of Interest Statement

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

References

[1] Huizinga, J. (2014). Homo ludens ILS 86. In Routledge eBook. https://doi.org/10.4324/9781315824161

[2] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115-118. https://doi.org/10.1038/nature21056

[3] 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. (2018). A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science*, *362*(6419), 1140-1144. https://doi.org/10.1126/science.aar6404

[4] McIlroy-Young, R., Sen, S., Kleinberg, J., & Anderson, A. (2020). Aligning superhuman ai with human behaviour: Chess as a model system. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1677-1687).

[5] Bhatt, U., & Sargeant, H. (2024). When Should Algorithms Resign? *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2402.18326

[6] Wirth, C., & Fürnkranz, J. (2014). On learning from game annotations. *IEEE Transactions on Computational Intelligence and AI in Games*, *7*(3), 304-316. https://doi.org/10.1109/tciaig.2014.2332442

[7] Iida, H. (2003). *A logistic model of game's refinement* (Technical Report). Department of Computer Science, Shizuoka University.

[8] Sutiono, A. P., Purwarianti, A., & Iida, H. (2014). A mathematical model of game refinement. In *International Conference on Intelligent Technologies for Interactive Entertainment*, pp. 148-151.

[9] Iida, H., Takahara, K., Nagashima, J., Kajihara, Y., & Hashimoto, T. (2004). An application of game-refinement theory to mahjong. In *International Conference on Entertainment Computing*, pp. 333-338.

[10] Yicong, W., Aung, H. P. P., Khalid, M. N. A. & Iida, H. (2019). Evolution of games towards the discovery of noble uncertainty. In *2019 International Conference on Advanced Information Technologies (ICAIT)*, pp. 72-77.

[11] Browne, C. B., Powley, E., Whitehouse, D., Lucas, S. M., Cowling, P. I., Rohlfshagen, P., Tavener, S., Perez, D., Samothrakis, S., & Colton, S. (2012). A survey of monte carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in Games*, *4*(1), 1-43.