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Doctoral Dissertation

The Role of AI and Games Towards Discovering Fairness

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Abstract

Game playing is widely regarded as a mentally stimulating activity. It has long served as not only entertainment but also test beds and benchmarks for artificial intelligence. Major milestones in the development of computer programs capable of playing chess over the last 60 years, to some extent, lead to the major development history of artificial intelligence (AI). In the transition from traditional games to games with AI players, it is hard to keep fairness when AI becomes stronger than human experts. Fairness stems from a respect for local goals and a desire to learn what the rules of the game are for them in that setting from individuals at different levels. In different cultures, fairness presents an interesting problem because local perceptions of fairness vary and every civilization has distinct ideas about what is fair and what is unfair. Fairness in games affects not only how a game is played, but also how the game is experienced. Previous works have interpreted the importance of fairness, called advantage of initiative (AoI), which had been previously discussed and proved through a conclusive and elegant theorem on first-player wins over second-player wins, but there have been no clear links among those interpretations. Observing the effect of the advantage of initiative in the game leads to addressing the challenge of not only keeping fairness but also maintaining the balance between competitiveness and entertainment. Inspired by classical physics, the motion in mind model was developed and adopted to better define the user experience in game-playing, where its relations in the social context were investigated from the historical development of games. The Gini coefficient g is an indicator used to quantify unfairness in n-person cooperative games (i.e., economics in society). In this thesis, the measurements of fairness and comfort, which are derived from the motion in mind concept and Gini coefficient, were used to analyze how the evolutionary trends of different games are changed to maintain the fairness and various elements of games. This thesis focuses on understanding the advantage of initiative along with its impact on game outcome and exploring the concept of play comfort, social comfort, and their culture with consideration of fairness. To achieve it, we are guided by three purposes: (1) To characterize the advantage of initiative and its impact on the evolution of game rules and game outcome, and (2) To define the gamified experience and notion of fairness (3) To develop the fairness measurement that indicates the balance between competitiveness and entertainment and establish the link between play, culture, and society. Using the motion in mind model as a measurement of fairness and comfort based on the 2-person game contexts demonstrates that it can show the link between play comfort and play culture. Furthermore, the measurement is expanded into n-person cooperative games that show social comfort which is related to play culture. For comparison, fairness indicators in n-person games with a focus on the Gini coefficient in economics were adopted in which similarities were found, prompting the revisiting of Huizinga's Homo Ludens that identify a link between play, culture, and society decades prior. In both competitive two-person games and society, it was found that the trend of unfairness was reduced, while some enhancements to maintain fairness in classical board games and economics were discussed.

Keywords: *fairness, game progress pattern, motion in mind, Gini coefficient, economy*

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Chapter 1

Introduction

1.1 Chapter Introduction

In this chapter, we first introduce the history of the game as test-beds for Artificial Intelligence (AI) and discuss how the growth of AI affects the original game rules and outcome. As the major interest of this thesis lies in analyzing the advantage of initiative and generalizing the notion of fairness with the evolution of games and culture from the entertainment perspective, we overview the general inequality indicators in the economic field. Finally, we summarize our contributions and outline the contents of this thesis.

1.2 Background

The experience and effects of playing digital games have been studied in great detail theoretically and empirically and described as a multidimensional and multilayered construct [62, 72]. Playing is a good practice or informative to learn how to maintain fairness in such complicated situations concerning their culture and economics. The perspective of fairness is cultivated in the playing context, which might be translated into the social context, i.e., society is influenced by the such perspective of fair playing. People are conscious of the fairness of decisions made or treatment given in everyday life. The perceived fairness of process and treatment is as significant as outcomes when engaging employees, stakeholders, or the public [25]. Fairness stems from a respect for local goals and a desire to learn what the rules of the game are for them in that setting from individuals at different levels. In different cultures, fairness presents an interesting problem because local perceptions of fairness vary and every civilization has distinct ideas about what is fair and what is unfair. However, these ideas can and do differ from one community to the next.

The concept of fairness in a game context had been discussed by Van Den Herik [117], which is as follows: a game is a fair game if its game-theoretic value is a draw and both players have roughly an equal probability of making a mistake. Another definition of fairness is observed in terms of the evolution of games [55]. Prior work had investigated the definition of fairness, the nature of Scrabble, its fairness mechanism, and its evolution in gameplay, using game refinement theory to discover the underlying process of fairness [14, 15, 16]. The critical idea of fairness in economics refers to equal life chances, to provide all populations with an essential and equal minimum of income, goods, and services. Unfairness has significantly increased in recent decades, possibly driven by the process of economic globalization, economic liberalization, and integration [66]. The increase of unfairness as an issue has explicitly been severe in the economic context of high-income countries and emerging market economies, where it has been associated with social recession and distress, before being linked more often to political populism [63, 41].

The concept of the position and region of the game in culture and society has been one of the essential issues of philosophical evaluation since ancient instances, that are described in the writings of ancient thinkers and scientists. Any cultural phenomenon is not only historical and cultural but also ethnocultural. While maintaining the essential characteristics of general game phenomenon and even the existence of certain game kinds in each culture of more or less distinctive ethnic groups, the game can have ethnic and cultural specificity [114]. The idea of the role and place of the game in culture has been one of the important problems of philosophical analysis since ancient times, which is described in the writings of ancient thinkers and scientists.

Interestingly, both fairness and engagement tend to be essential elements that are perceived to manifest in well-balanced and popular games [76]. In other words, the game is perceived to be less motivating by the player to begin the play if they believe it to be unfair. Also, if fairness and engagement are not sustained, they will not continue the play. As such, fairness may be a crucial element alongside engagement for a holistic understanding of process dynamics in both games and non-game contexts.

In this thesis, the aim of adopting specific mechanics in games as the main tool for the experimentation of this study involves determining the impact of player initiatives. The first is the impact of fairness in games while the latter is the impact of unfairness in society. Based on such a discussion, the link between play, culture, and society can be established.

1.3 Statement of Research Questions

This thesis focuses on understanding the advantage of initiative in games as well as its impact on game entertainment from a fairness perspective. To achieve it, we have defined specific objectives that must be attained: (1) To find the impact of the advantage of initiative over different performance levels and changes in the search space, (2) To define the gamified experience and notion of fairness and (3) To identify the link between play, culture, and society by proposing the new measurement of fairness and comfort.

1.4 Structure of The Thesis

This thesis comprises six main chapters, given as follows:

- **Chapter 1: Introduction**

  This chapter's objective is to introduce the big picture of the research, such as its definitions, how each of the keywords relates to each other in the research, as well as a brief historical overview of the domain considered. It serves to explain the main problem that the research aims to solve. The Introduction chapter also includes the statement of the research questions, as well as the goal and significance of the research. At the end of this chapter, the structure of the dissertation will be stated.

- **Chapter 2: Literature Review**

  The chapter serves as a review of the theoretical background related to this research as well as presenting state-of-the-art research in the field. The first section of this chapter is a review of AI and games which indicates fairness in game evolution, revealing a glimpse of what human intelligence from different parts of the world sought throughout history in all games: thrilling and fair play. The second section covers the review of three masters model that reveals that the attractiveness of games highly relates to harmony between fairness, judges, and thrill in games. They correspond to each of the three important characteristics that games possess: competitiveness, entertainment, and communication. The third section of the Literature Review covers the research related to the inequality indicators which are reviewed historically. The last section includes the Uncertainty in Entertainment with Game Refinement Theory and Motion in Mind model. At the end of the chapter, a conclusion that leads to the justification of the research carried out in the dissertation will be presented.

- **Chapter 3: Characterizing the Advantage of Initiative and Notion of Fairness**

  The third chapter of the dissertation covers the result of research that leads to the advantage of initiative using Scrabble as a test bed. Recently, the list of solved two-person zero-sum games with perfect information has increased. Among them, most of the games are a win for the first player (i.e., the advantage of initiative), some are draws, and only a few games are a win for the second player. Self-play experiments using Scrabble AIs were performed in this study. The results show that the player who established an advantage in the early opening took a higher win expectancy. This implies that the advantage of initiative should be reconsidered to apply to all levels including nearly perfect players. Thus, we meet a new challenge to improve the rules of a game to maintain fairness. The game of Scrabble gives an interesting example while giving a randomized initial position. This chapter will start with the basic overview of Scrabble and the early work of Scrabble, followed by the advantage of initiative from AI's perspective. Following that, the methodology of the research will be presented as well as the result and discussion. Experimental evidence on playing Scrabble by AI will be presented and the traits of the advantage of initiative will be included in its conclusion, which also leads to the following chapter.

- **Chapter 4: Finding the Critical Aspect of Fairness in Games**

The fourth chapter of the dissertation covers the research carried out related to the notion of fairness and proposes the concept of *dynamic* komi in Scrabble. The compensation system called komi has been used in scoring games such as Go. In Go, White (the second player) is at a disadvantage because Black gets to move first, giving that player an advantage; indeed, the winning percentage for Black is higher. The perceived value of komi has been re-evaluated over the years to maintain fairness. However, this implies that this *static* komi is not a sufficiently sophisticated solution. We leveraged existing komi methods in Go to study the evolution of fairness in board games and to generalize the concept of fairness in other contexts. This work revisits the notion of fairness and proposes the concept of *dynamic* komi Scrabble. We introduce two approaches, *static* and *dynamic* komi, in Scrabble to mitigate the advantage of initiative (AoI) issue and to improve fairness. We found that implementing the *dynamic* komi made the game attractive and provided direct real-time feedback, which is useful for the training of novice players and maintaining fairness for skilled players. A possible interpretation of physics-in-mind is also discussed for enhancing game refinement theory concerning fairness in games. At the end of this chapter, the effectiveness of implementing the proposed *dynamic* komi idea for different performance levels will be presented as a conclusion.

- **Chapter 5: Huizinga's Homo Ludens Revisited: A New Perspective from Motion in Mind Approach**

  The fifth chapter of the dissertation covers research concerning fundamental quantities of fairness in two different contexts: two-person games and n-person games, where the two aspects of fairness framework in a game context for both objective and subjective sense are formalized. In this chapter, the notion of fairness related to the motion-in-mind model and the new measurement of fairness in the domain of two-person competitive games will be included. It is then followed by the notion of fairness in the domains of n-person games related to economic inequality. Following that, an overview of Huizinga's Homo Ludens Revisited and the current related findings for the link between play, society, and culture and the evolutionary changes from a fairness perspective will be presented as well as the result and discussion. The link between play, society, and culture will serve as the conclusion of this chapter.

- **Chapter 6: Conclusion**

  The last chapter is the conclusion of the dissertation. It concludes the whole dissertation relative to the main aim and objectives of the dissertation. Some potential future works are also outlined.

Chapter 2

Literature Review

2.1 Chapter Introduction

The chapter serves as a review of the theoretical background related to this research as well as presenting state-of-the-art research in the field. The first section of this chapter is a review of AI and games which indicates fairness in game evolution, revealing a glimpse of what human intelligence from different parts of the world sought throughout history in all games: thrilling and fair play.

The second section covers the review of three masters model that reveals that the attractiveness of games highly relates to harmony between fairness, judges, and thrill in games. They correspond to each of the three important characteristics that games possess: competitiveness, entertainment, and communication. The perspective of fairness is cultivated in the playing context, which might be translated into the social context, i.e., society is influenced by the such perspective of fair playing. People are conscious of the fairness of decisions made or treatment given in everyday life. The third section covers the research related to the inequality indicators which are reviewed historically. The idea of inequality indicators serves as the main inspiration behind Gini Coefficient, as well as our new proposed measurement, both being important keywords of this thesis. Although the Gini coefficient is a popular index in economics, it can theoretically be applied in any science field that considers a distribution. Thus, it is important to review the historical importance of those indicators. The last section of the Literature Review includes the measurement of Uncertainty in Entertainment with the Game Refinement Theory and

Motion in Mind model.

2.2 AI and Games

Game playing is generally regarded as an intelligent activity. In the year after the Dartmouth Symposium [75], there was worldwide research into computer chess games that could play against human professional players. Major milestones over the past 60 years in the development of computer programs that could play chess, to some extent, leads to the major development history of artificial intelligence (AI).

From the perspective of AI, a match between a machine versus a human, or a robot competition is an efficient way for scientists to demonstrate AI. Computers can perform as intelligent agents to solve the real world's problems that are very similar to playing chess games. A computer player that could play against a human player has some advantages such as reasoning, speed, and logical thinking; while the human brain may work differently. On the other hand, human expert players could improve their strategies and methods by cooperating with machines and figuring out the weak points of intelligent computers. To some extent, the rivalry between humans and machines is an endless process.

In recent years, AI had achieved performance that rivals human performance by a large margin [3]. For such a case, fairness is a very important criterion of the game. If a game loses fairness and equality, then it cannot survive for a long time [119, 15]. This situation can be compounded further when considering the state of the current knowledge where many games are a win for the first player, some games are draws, and only a few games are a win for the second player (called advantage of initiative or AoI for short) [14]. Maintaining fairness is difficult when a game was created, whereas most games with a long historical background had survived by changing the rules to seek fairness and become more attractive. The *Komi* or *komidashi*, is a compensation system, widely used in the board game of Go, where the Black (first player) needs to subsidize some value to White, to address the AoI issue [119].

2.3 Fairness in Games

The experience and effects of playing digital games have been studied in great detail theoretically and empirically and described as a multidimensional and multilayered construct [62, 72]. People are conscious of the fairness of decisions made or treatment given in everyday life. The perceived fairness of process and treatment is as significant as outcomes when engaging employees, stakeholders, or the public [25]. Several issues had been raised based on different dimensions of fairness (input, output, experience, knowledge, compute, psychological, and common sense) when a human plays versus a computer agent[24]. Currently, agent ability has featured the propensity of the wealth of information (e.g., look-up tables for opening and endgame) and massive state space simulations (e.g., usage of a forward model), associated with *knowledge* fairness and *compute* fairness, respectively. Inferring human-level intelligence implies an entirely fair competition achievable with an artificial system that is essentially equivalent to a flesh and blood human. With the pervasive of machine learning models and approaches, discrimination against sensitive attributes becomes a critical agenda, where biases need to be detected and guarantee fairness instead of those attributes' importance for prediction [30].

Fairness is essential for many multi-agent systems and human society and contributes to both stability and productivity. The concept of fairness emerges in various contexts, such as telecommunication networks, operating systems, and the economy [45, 73], when a limited amount of resources is to be concurrently shared among several individuals. Recent work has shown that fairness is becoming increasingly critical with the rapid increase in the use of machine learning software for important decision-making because of the black-box nature of this technology [11, 26, 38, 9, 34]. The potential for advanced machine learning systems amplifies social inequity and unfairness, which are receiving increasing popular interest and academic attention [49]. Measuring the fairness of machine learning models has been studied from different perspectives with the aims of mitigating the bias in complex environments and supporting developers in building fairer models [18, 28, 39, 74, 37, 78]. In the field of intelligent communication, throughput fairness was improved by a novel user cooperation method in a wireless powered communication network (WPCN) [50].

Fairness is one of the most important aspects of a good game, but it is rarely straightforward. It is also an essential element to attract more people to play the target game. If a game loses fairness and equality, then it cannot survive for a long time [14]. The various stakeholders of society define fairness, in which fair play gives games the characteristic of beauty [19]. The evolution of fairness was studied under an assortative matching rule in the ultimatum game[99]. In the domain of two-player perfect information board games such as chess and Go, the definition has been given that a game is fair if and only if the winning ratio for White and Black is statistically equal or nearly so [55].

Artificial intelligence (AI) is typically achieved by a collection of techniques to simulate human decision-making skills. Since the 1950s, AI has played an essential role in the game industry as an ideal domain to evaluate the potential of AI applications. AI strives to build intelligent agents that can perceive and act rationally to accomplish goals. In recent years, AI researchers have developed programs capable of defeating the strongest human players in the world. Superhuman-performance programs exist for popular board games such as chess, shogi, Go (AlphaZero [107]), checkers (Chinook [95]), Othello (Logistello [22]), and Scrabble (Maven [97]).

Although superhuman-performance programs have been achieved, the question of what makes a game good and fair is still actively debated [24, 67]. While a game's rules might be balanced, the player may feel that the experience is not fair, which is a source of design tension. The concept of fairness in games was first studied by Van Den Herik [117]. Meanwhile, fairness in game evolution was discussed, revealing a glimpse of what human intelligence from different parts of the world sought throughout history in all games: thrilling and fair play[53].

Some board games have persisted in popularity despite the changing entertainment opportunities afforded to consumers by rapidly changing technology. Scrabble is one of the brilliantly engineered board games that remain unique to the contemporary game community. Scrabble is a popular crossword game and a board game that is interesting from an AI perspective because the information is gradually revealed to the player during gameplay. Scrabble has been sold in 121 countries (approximately 150 million sets have been sold worldwide); it is available in 29 languages, is played in approximately 4000 Scrabble clubs, and is owned by roughly one-third of American and half of the British households. Scrabble is a type of scoring game that is played on physical or virtual board space. Scrabble AI programs have achieved a level of performance that exceeds that of the strongest human players [97].

2.3.1 Three Masters Model

The original concept of the three masters model reveals that the attractiveness of games highly relates to harmony between fairness, judges, and thrill in games[56].In games, a balance of skill and chance was employed, resulting in evolutionary changes in noble uncertainty. Three distinct master aspects: the Master of Winning (M/W), the Master of Playing (M/P), and the Master of Understanding (M/U) were explored.

The Master of Understanding was studied from solving a game to knowing its true color. A better understanding of a game necessitates the selection of the best initial state from among several plausible candidates. The quality of the initial state would be highly dependent on the game creators' intelligence or sense of art.

The Master of Playing was observed where thrilling sense is derived from the second derivative. A logistic model of outcome uncertainty based on the principle of seesaw games or late chance was proposed as shown in Figure 2-2. This model has been developed in order to establish game-refinement theory based on outcome uncertainty. A good dynamic seesaw game in which the outcome is unpredictable in the final moves of the endgame stage corresponds to a high value of the second derivative at $t = T$. This implies that a game is more exciting, intriguing, and entertaining when this value is larger. We expect this property to be the most important feature of an exciting game.

The Master of Winning indicates the noble uncertainty and mind state of vanity. Choosing between a few best candidates is a thrilling task Namely, the skill of game playing enables to the transformation of a game with many possibilities (superficial freedom) into a stochastic game with fewer possibilities (essential freedom), as shown in Figure 2-3. Therefore, an attractive game requires a balance of judges, fairness, and thrill. For some games, a draw has served as a link between judges and compassion.

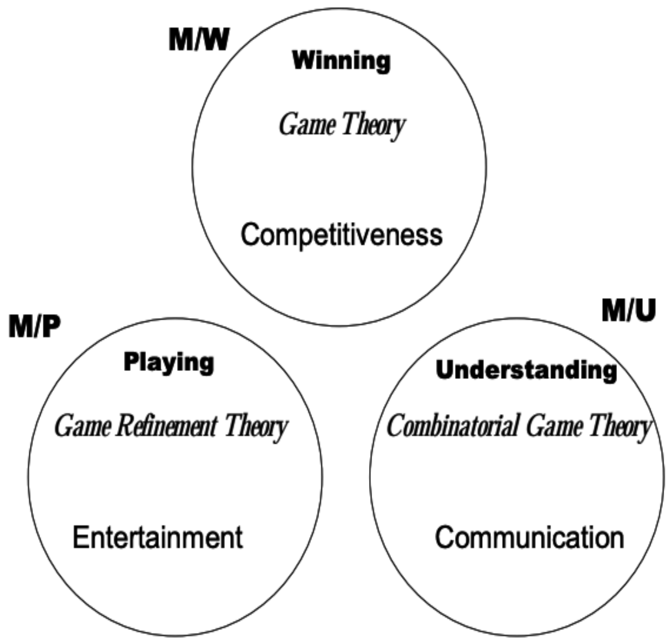


Figure 2-1: A model of three masters[56]

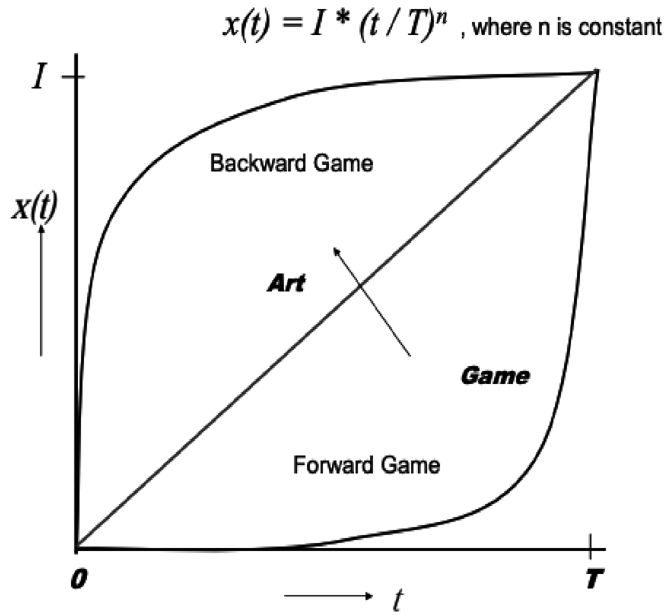


Figure 2-2: A logistic model of game-outcome uncertainty: from game to art

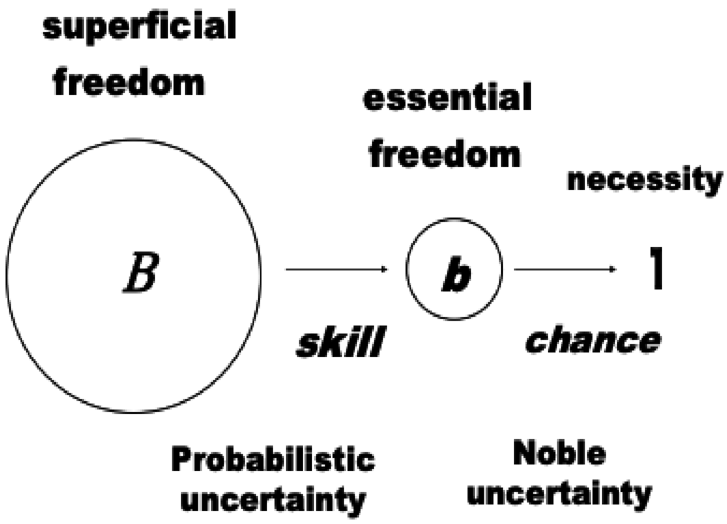


Figure 2-3: A model of noble uncertainty

2.4 Economic Inequality and Its Indicators

The critical idea of fairness in economics refers to equal life chances, to provide all populations with an essential and equal minimum of income, goods, and services. Inequality has significantly increased in recent decades, possibly driven by globalization's worldwide economic processes, economic liberalization, and integration [66]. The increase of inequality as an issue has explicitly been severe in the economic context of high-income countries and emerging market economies, where it has been associated with social recession and distress, before being linked more often to political populism [63, 41].

A study suggests that inequality increases risk-taking because individuals selectively make upward social comparisons, independent of their resources and relative standing [88]. It has been shown that inequality reflects structural economic forces and behavioral responses to unequal economic contexts where inequality in outcomes becomes self-perpetuating due to preference over high-risk options (i.e., significant gains for a few individuals but losses for most). The effect of one's income also determines the level of happiness because of their comparison to others in the same gender-ethnic group, highlighting the importance of social comparison [77]. It was previously established that social comparison effects are consequential when one's referents are those close in social, structural, and physical distance, especially when inequality is greater. Another empirical study had shown that people tolerate more income inequality in countries with more actual inequality, where high-inequality countries accept almost four times more income inequality than otherwise similar low-inequality countries [96]. The interpretation of economic inequality has been derived from the conventional outcome-oriented aspect, where inequality of outcomes occurs when individuals do not possess the same level of material wealth or overall living economic conditions or proxy for prosperity (i.e., income/wealth, education, health, and nutrition) [8]. The opportunity-oriented perspective acknowledges that circumstances of birth are essential to life outcomes and that equality of opportunity requires a fair starting point. This framework depends on contingent circumstances, such as personal (age, gender, family background, and disability), social, climatic conditions, societal conditions (health care, education systems, prevalence of crime, community relationships), or customs convention.

2.4.1 Gini Coefficient

In welfare economics, the Pigou–Dalton principle (PDP) is a principle related to the condition of social welfare functions, which defines that when all other things are equal, a social welfare function should prefer allocations that are more equitable [91, 35]. This is related to an inequality measure to rise (or at least not fall) in response to a mean-preserving spread [64]. In other words, a transfer of some defined variable (for example, utility or income) from the rich to the poor is desirable, as long as it does not bring the rich to a more impoverished situation than the poor. Most measures in the literature, including the Generalized Entropy class (GE), the Atkinson class, and the Gini coefficient, satisfy this principle with the main exception of the logarithmic variance (LV) [33].

The Gini coefficient's closely related economic indicators were the decomposition analysis such as the mean logarithmic deviation (MLD), and the squared coefficient of variation (SCV). A decomposition analysis involves calculating income source based on the proportion of total inequality associated with different income sources (i.e., earnings, property income, public, and private transfers, and taxes), where the proportion is a function of its inequality index, of its share of disposable income and its correlation with disposable income. The MLD and SCV are the decomposition indicators by population groups and by income sources, respectively [64]. Those decomposition formulae of the MLD and SCV were first developed and yield a ranking consistent with the Gini coefficients [83, 100, 101].

Gini coefficient (G), also known as the Gini index or Gini ratio, was proposed by Corrado Gini, a famous Italian economist, statistician, and sociologist, as a comprehensive investigation of statistical dispersion intended to represent the income inequality or wealth inequality, [44], in which since then has been an essential international analysis indicator [118]. The G coefficient is a popular inequality index mostly associated with the descriptive approach to inequality measurement.

2.4.2 Theil Index

The Theil index is a metric for measuring economic inequality. The Theil index measures the population's entropic distance from the ideal egalitarian state in which everyone has the same income [87]. The numerical result is expressed in terms of negative entropy, with a higher number indicating more order and a lower number indicating maximum disorder. By formulating the index to represent negative entropy rather than entropy, it can be used to measure inequality rather than equality.

2.4.3 Atkinson Index

The Atkinson index (also known as the Atkinson measure or Atkinson inequality measure) was developed by British economist Anthony Barnes Atkinson as a measure of income inequality. The metric is useful for determining which end of the distribution is most responsible for the observed inequality[87].

By imposing a coefficient to weight incomes, the index can be transformed into a normative measure. Changes in a specific portion of the income distribution can be given more weight by appropriately adjusting the level of "inequality aversion." As it approaches 1, the Atkinson index becomes more sensitive to changes at the lower end of the income distribution. In contrast, as the level of inequality aversion decreases (that is, approaches zero), Atkinson becomes more sensitive to changes in the upper bound.

2.5 Uncertainty in Entertainment

In this section, the theories and mathematical models based on the concept of uncertainty of game outcome will be introduced as uncertainty is an important element of gameplay that is widely believed to be a prerequisite to the gaming experience.

2.5.1 Game Refinement Theory

The game refinement theory plays an essential role in quantifying game sophistication by determining the rate of solved uncertainty along the game length where fairness, excitement, and thrills were identified [60, 59]. When a game is perceived as fair to the player, the player's experience is considered a sense of entertainment. It has been investigated based on the uncertainty of game outcome [79, 59, 61]. It has been studied not only in fun-game domains such as video games [126, 122], board games [59], and sports [112, 111], but also in non-game domains such as education and business [127, 52]. The tendency of game refinement value typically converges towards a comfortable zone ($GR \in [0.07, 0.08]$), which is associated with the measures of game entertainment and sophistication involving a balance between the level of skill and chance in the game [57, 123].

The information on the game's result is an increasing function of time (i.e., the number of moves in board games) t, which corresponds to the amount of solved uncertainty (or information obtained) $x(t)$, as given by (2.1). The parameter n (where $1 \leq n \in N$) is the number of possible options and $x(0) = 0$ and $x(T) = 1$.

$$x'(t) = \frac{n}{t}\, x(t) \tag{2.1}$$

$x(T)$ stands for the normalized amount of solved uncertainty. Note that $0 \leq t \leq T$, $0 \leq x(t) \leq 1$. The rate of increase in the solved information $x'(t)$ is proportional to $x(t)$ and inversely proportional to t, which is given as (2.1). By solving (2.1), (2.2) is obtained. It is assumed that the solved information $x(t)$ is twice derivable at $t \in [0, T]$. The accelerated velocity of the solved uncertainty along the game progress is given by the second derivative of (2.2), which is given by (2.3). The acceleration of velocity implies the difference of the rate of acquired information during game progress. Then, a measure of game refinement (GR) is obtained as the square root of the second derivative which is given by (2.4).

$$x(t) = \left(\frac{t}{T}\right)^n \tag{2.2}$$

$$x''(t) = \frac{n\ (n-1)}{T^n}\ t^{n-2}\ |_{t=T} \quad = \frac{n\ (n-1)}{T^2} \tag{2.3}$$

$$GR = \frac{\sqrt{n\ (n-1)}}{T} \tag{2.4}$$

A skillful player would consider a set of fewer plausible candidates (b) among all possible moves (B) to find a move to play. The core part of a stochastic game assumes that each among b candidates may be equally selected. Knowing that the parameter n in (2.4) stands for the number of plausible moves b, $n \simeq \sqrt{B}$ is obtained. Thus, for a game with branching factor B and length D, the GR can be approximated as in (2.5).

$$GR \approx \frac{\sqrt{B}}{D} \tag{2.5}$$

A sophisticated game postulates an appropriate game length to solve uncertainty while gaining the necessary information to identify the winner [59]. The cross-point area between $y(t) = vt$ and $y(t) = \frac{1}{2}at^2$ where $a = \frac{B}{D^2}$ is indicated with noble uncertainty zone of GR $(= \sqrt{a}) \in [0.07, 0.08]$ [58]. It meets fairness, gamified experience, and the sense of comfortable thrill, as depicted in Figure 2-4.

2.5.2 Motion in Mind

The game refinement theory plays an essential role in quantifying game sophistication by determining the rate of solved uncertainty along the game length where fairness, excitement, and thrills were identified [60, 59]. When a game is perceived as fair to the player, the player's experience is considered a sense of entertainment. Such a concept is explored further via the "motion in mind", which analogously defines the mind's subjective law of motions to the natural law of physics [58]. Such an analogical link between motion in mind and the motion in natural physics is given in Table 2.1.

The definition for each analogy is as follows [58]:

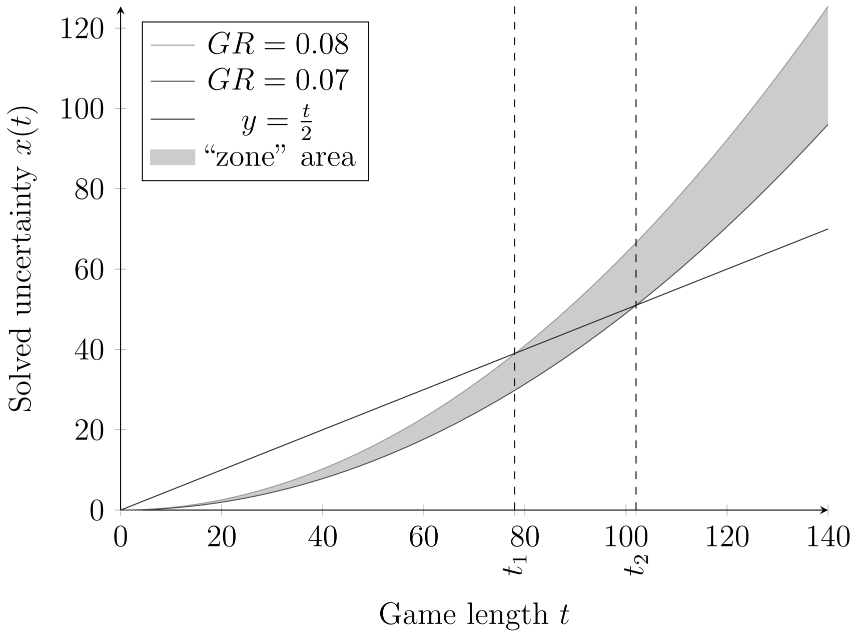


Figure 2-4: Game refinement values of the most comfortable game points for table tennis is situated within the sophisticated "zone" of $GR \in [0.07, 0.08]$. $GR = 0.07$ and $GR = 0.08$ is the lower bound and upper bound of the game sophistication "zone", respectively.

Table 2.1: Analogical Link Between Motion in Mind and Motion in Physics.

Notation	Game	Notation	Physics
y	solved uncertainty	x	displacement
t	total score or game length	t	time
v	winning rate	v	velocity
m	winning hardness	M	Mass
a	acceleration in mind	g	gravitational acceleration
$\vec{p}$	momentum of game	$\vec{p}$	momentum
E_p	potential energy of game	U	potential energy

- **Mass:** In the concept of motion in mind, mass is defined as the level of challenge experienced by the player during the gameplay. It is related heavily to the frequency of risk in the game.

- **Velocity:** Defined to be the rate of solving uncertainty. It has an opposing relationship to m ($m = 1 - v$).

- **Acceleration:** Defined as the "gravitational acceleration in mind". It is an indicator of the gamified feeling occurring in the player's mind. It is determined that if the acceleration, GR, is located between 0.07 and 0.08, the player will feel gamified.

- **Momentum:** Defined as the mass of the object times the velocity. In the game context, refers to the balance between effort and ability given by the player.

- **Potential Energy:** Defined as the required amount of information needed by the player while progressing in the game, following the analogy definition of gravitational potential energy [58].

These definitions have been applied to calculate players' engagements in board games as well as scoring sports games. Comparison between three board games, Go, Chess, and Shogi has shown that the difference in the games' motion in mind units is closely related to the cultural aspects of the game's origin. On the other hand, comparing motion in mind values of Table Tennis, Basketball, and Soccer results in the ability to measure the said sports' engagements and their effect on the sports' popularity [58]. The definitions have also been used to establish the relationship between game-playing and rewarding experience based on its reward frequency variable [121].

As observed from the variable definitions of motion in mind, the central premises were made based on the uncertainties and the game's hardness, both related to the sense of entertainment in the game. The notion of energy conservation had been proposed as a potential measure of engagement, where the formulation of momentum in the game ($\vec{p_1}$) and potential energy in the mind (E_p) are given by (2.6) and (2.7), respectively [70]. Then, based on the conservation of energy in mind, given by (2.8), the momentum in mind ($\vec{p_2}$) can be derived, which is associated with the measure of player's engagement, given by (2.9).

$$\vec{p_1} = mv \tag{2.6}$$

$$E_p = ma\left(\frac{1}{2}at^2\right) = \frac{1}{2}ma^2t^2 = 2mv^2 \tag{2.7}$$

$$E_p = \vec{p_1} + \vec{p_2} \tag{2.8}$$

$$\vec{p_2} = E_p - \vec{p_1} = 2m^3 - 3m^2 + m \tag{2.9}$$

The analogy of gravitational potential energy in the game, denoted as E_p, defines the amount of information required to finish the game or the magnitude of information perceived by the player based on the amount of possibility and magnitude of expectation; thus, associated with motivation [58, 70]. A game that may be perceived to be simple and easy to play may encourage more people to play, but a game that is perceived to be difficult may discourage them from playing. Such a situation is associated with the magnitude of difference between the momentum of the game's motion ($\vec{p_1}$) and the momentum of mind's motion ($\vec{p_2}$), defining the subjective measures of the motivation in mind (E_q).An illustration of the various motion in mind measures, relative to the original concept of the motion in mind [58] and energy conservation [70], is given in Figure 2-5.

2.6 Chapter Summary

In this chapter, related works prior to the current thesis were introduced. Works related to the important keywords, namely the advantage of initiative issue, komi systems, and inequality indicators in economics. In relation to the entertainment aspects, a measure of the fairness aspect of the game that highly depends on the competitiveness in the game, the motion in model, is introduced. These studies are significant as it serves as the base for the research carried out in this thesis regarding the impact of fairness as well as the link between games and culture in society.

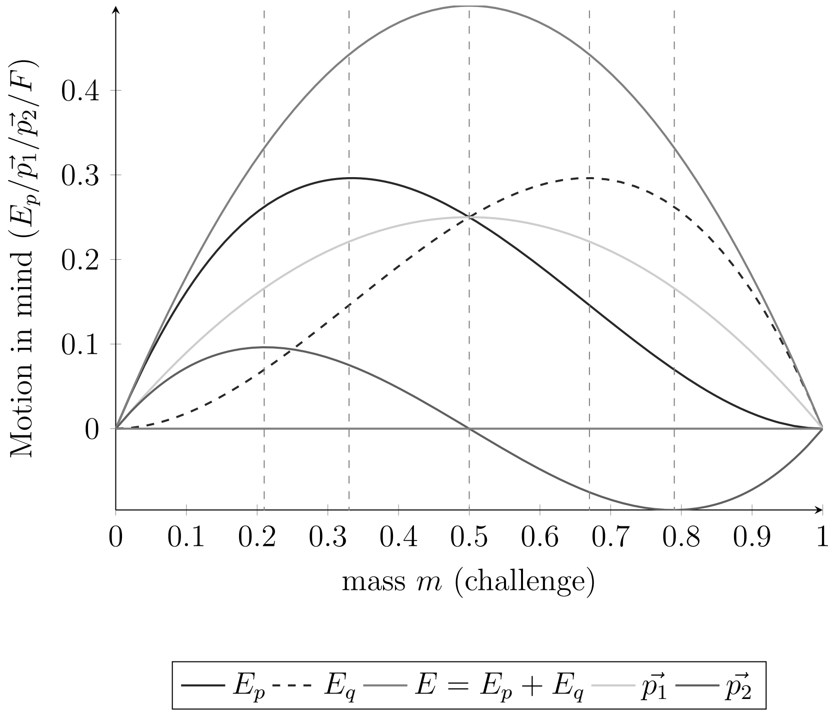


Figure 2-5: Illustrations of the physic analogy that outlined based on the zero-sum assumption where the motion in mind and energy conservation concepts were defined. The notion of motivational potential (E_p and E_q), in-game freedom (E), and player-game motions ($\vec{p_1}$ and $\vec{p_2}$) were introduced. Adopted from [58] and [70]

Chapter 3

Characterizing the Advantage of Initiative (AoI) and Notion of Fairness

This chapter is an updated and abridged version of the following publications:

- Htun Pa Pa Aung, Hiroyuki Iida. Advantage of Initiative Revisited: A case study using Scrabble AI. Proceedings of International Conference on Advanced Information Technologies (ICAIT 2018), 1-5, 2018.
- Htun Pa Pa Aung, Mohd Nor Akmal Khalid, Hiroyuki Iida. Can we save near-dying games? An approach using advantage of initiative and game refinement measures. International Conference on Informatics, Engineering, Science and Technology (INCITEST 2019), EAI, 2019.
- Htun Pa Pa Aung, Mohd Nor Akmal Khalid, Hiroyuki Iida. Towards a fairness solution of Scrabble with Komi system. 2019 IEEE International Conference on Advanced Information Technologies (ICAIT 2019) , 66-71, 2019.

3.1 Chapter Introduction

In this chapter, we include the result of experiments that leads to the advantage of initiative using Scrabble as a test bed. Recently, the list of solved two-person zero-sum games with perfect information has increased. Among them, most of the games are a win for the first player (i.e., the advantage of initiative), some are draws, and only a few games are a win for the second player. Self-play experiments using Scrabble AIs were performed in this study. The results show that the player who established an advantage in the early opening took a higher win expectancy. This implies that the advantage of initiative should be reconsidered to apply to all levels including nearly perfect players. Thus, we meet a new challenge to improve the rules of a game to maintain fairness. The game of Scrabble gives an interesting example while giving a randomized initial position. This chapter will start with the basic overview of Scrabble and the early work of Scrabble, followed by the advantage of initiative from AI's perspective. Following that, the methodology of the research will be presented as well as the result and discussion. Experimental evidence on playing Scrabble by AI will be presented and the traits of advantage of initiative will be included in its conclusion, which also leads to the following chapter.

3.2 Related Works and Motivation

In 1956, Arthur Samuel of IBM introduced a self-learning, adaptive checkers program [5]. Just like any excellent checker player, the computer not only sees several moves ahead but is also able to learn from the checker's manuals. The IBM704 was the first computer that can play against humans, with a speed of 200 moves per second around 1958. The Deep Thought computer defeated Bent Larsen, the Danish master player, with an average speed of 2 million moves per second in 1988 [4]. In 1997, IBM's Deep Blue, a chess-playing computer, shocked the world with two wins, three draws, and one defeat in matches against the reigning world chess champion Garry Kasparov, using a heuristic search technique. In 2001, the German Deep Fritz chess-playing computer defeated nine of the ten top chess players in the world, with a record-breaking speed of 6 million moves per second.

In October 2015, AlphaGo, an AI computer program developed by Google DeepMind, defeated 2-dan professional player Fan Hui, the European Go champion, by five games to nil [3]. This was the first time a computer player had defeated a human professional Go player, an unprecedented step in the development of artificial intelligence. The program uses a new method to computer Go that combines Monte Carlo simulation with two deep neural networks: value networks, to determine board positions; and policy networks, to choose moves, which significantly reduces the effective search space. Since the previous world Go champion Li Sedol was defeated in a one-to-four series in March 2016, AlphaGo has increased its rank to number two in the world. In the face of these successive computer victories, the inevitable question [5] became whether, now that the world's chess and Go champions have been defeated, who can say that the computer is not intelligent?

The latest development of the super-human performance of AI (level of performance that goes beyond that of the professional human players) had been revealed by the AlphaZero program [105]. Table 3.1 shows the results of the games played by Alpha Zero. While game engagement had been due to the attempt and skills required from the player to complete them (or, in the case of puzzles, solve them), this super-human performance raised concerns about whether it would provide engagement or even be fair to its opponent. As compared to the results of human players collected from various Chess tournament databases (Table 3.2), the winning rate as a first player or second player had been roughly balanced ($\approx 50\%$) which gave the sense of engagement in the game. As such, if the performance of the AI program continues in this direction, the Chess game and Chess-like games may not be interesting or engaging anymore to the player, or even lose their attractiveness to the observer or the participants of the gameplay.

Table 3.1: The results of Alpha Zero in Chess and Shogi [105]

			Win Games		Win Rate (%)	
	vs AI	Draw	White	Black	White	Black
Chess†	Stockfish 8	958	286	56	0.84*	0.16*
Shogi*	Elmo	0	55	45	0.55	0.45

*excluding the draw games.
†total games is 1300; *total games is 100.

3.3 Test Bed for Fairness: Scrabble

Scrabble is a popular worldwide word anagram game with numerous national and international Scrabble associations and a biennial world championship. There are 2 or 4 players that competitively score points by placing tiles that must be accepted by the dictionary onto a 15×15 board. The competitive tournament of the Scrabble game is very popu-

Table 3.2: The statistical data of human players in Chess and Shogi [6]

	Total	Draw	Win Games		Win Rate (%)	
			White	Black	White	Black
Chess†	898,173	252893	339149	306108	0.53⋆	0.47⋆
Shogi*	533,413	0	391,970	141,443	0.57	0.43

⋆excluding the draw games.
†the game covered for the years of 1475 to 2019 (545 years).
*the game covered only on public matches.

lar and continues to attract more players each year like chess and bridge. Besides, the Scrabble game has also reached an advanced community of players in the digital age with digital versions of the game from Hasbro licensee, Electronic Arts [2].

Although one of the fundamental goals of developing AI games is to understand and develop intelligent systems that have all the capabilities of humans, computer AI players have already outperformed human opponents in competitive Scrabble. They also have achieved a level of performance that exceeds that of the strongest human players. MAVEN was created by Brian Sheppard and became the first program to demonstrate this against human opposition. Table 3.3 shows that Maven has maintained at least a slight superiority over human experts since its debut in 1986 according to Maven's tournament statistics where the total matches and tournament record is 3500 wins and 1500 losses against an average rating of 1975. Currently, Maven and Quackle are the leading Scrabble AI's, where both have defeated the best human champions in tournaments [97].

Table 3.3: MAVEN and human experts compared [97]

	MAVEN	Human expert
Average Bingo per game	1.9	1.5
Average tiles played per game	4.762	4.348
Average turns per game	10.5	11.5
Chance to play Bingo if exists	100%	85%

Between the time when simulation became available as an analytic tool in 1990 and simulations were first used in competitive play in 1996, human players have improved their positional skills by studying simulation results [97]. However, this may be the earliest time at which a computer program achieved world-class status over human masters in a non-trivial game of skill. Quackle, is the second strongest Scrabble AI, an alternative to

Maven. Our previous work also showed that there is an issue such as the *advantage of initiative* (AoI) in Scrabble AI [14]. The prospect of advancement in Scrabble AI raises important research questions:

- How could Scrabble be analyzed with two aspects, the entertainment aspect, and the fairness aspect?
- What can ensure a fair game environment for all levels of Scrabble AI players?

Early work shows that the game is unfair when the players become stronger than the grandmaster level. The higher the level of the player is, the greater the winning percentage he/she takes [14]. In this study, the initiative was redefined as an action of both players in the first stage "to take the advantage" (i.e., to be the first winner in the earlier stages of the game). Based on this definition, an experiment in Scrabble game with the varying performance level of AI players is conducted and the appropriate solution to maintain fairness until the end of the game is determined. A statistical score-based Komi method is proposed as an innovative way to make the game stay fair.

3.3.1 Entertaining Aspect

This section presents the entertaining aspect of Scrabble. The game refinement (GR) theory is applied to quantify the sophistication of the games [59]. The property of the game and player were considered by defining two models: the game model and the player model.

Game Model

The GR theory is an approach to quantifying the attractiveness of a domain based on the uncertainty of outcome [79]. Two types of models were considered, known as the game progress model[110] and the board game model [59].

Game progress model (see Eq. 3.1) is considered by calculating the G (the average number of successful attempt) and T (the average number of attempt) in order to assess the typical scoring games [110][112][122][92]. Meanwhile, the board game model (see Eq. 3.1) is considered by computing the B (the average branching factor) and D (the average game length) in order to assess a typical board game [59]. The B and D are observed by developing an artificial intelligence (AI) player.

$$GR_{progress} = \frac{\sqrt{G}}{T} \tag{3.1}$$

$$GR_{board} = \frac{\sqrt{B}}{D} \tag{3.2}$$

Swing model (GR_{swing}), derived from the $GR_{progress}$, is defined for Scrabble by considering the number of attempts to turn the table over the game length [69]. Let S be the average number of successful turnover, then the GR_{swing} (see Eq. (3.3)) can be considered as the approximation of the $GR_{progress}$. Swing is a state transition during the game progress among some possible states.

$$GR_{swing} = \frac{\sqrt{S}}{D} \approx \frac{\sqrt{G}}{T} \tag{3.3}$$

The GR theory has been used to quantify the engagement of the game. As shown in Figure 3-1, Scrabble is analyzed by using both models [68]. In previous works, GR value had been calculated in various games (see Table 3.4) and two spectra of GR interpretation are speculated [59, 110]. A high GR value expresses the aspect of chance-related and unpredictability, entertaining experience, or frustrating feeling of the player. On the other hand, a low GR value expresses the aspect of skill-related and predictability, serious experience, or competitive feeling of the player. Early works show that the comfortable setting is when $GR \in [0.07, 0.08]$, which is called the "sophisticated zone" [59]. Figure 3-1 shows the calculated GR value of Scrabble with two models (0.092 and 0.531 for the swing model and the board game model, respectively). It also figures out an inconsistency between two different models.

According to the history of the application of game refinement theory, popular games tend to have an appropriate game refinement measurement. Although the realistic interpretation of the game refinement GR is still an immense question, the practical use of game refinement in real-world applications has become more tangible. The subsequential research work has proved the compatibility in an application of game refinement theory to other domains, e.g., video games [36], educations [52], and businesses [126]. In Scrabble, the tendency between GR measure and player performance level noticeably depends on the dictionary size, as shown in Figure 3-1.

Table 3.4: Correlative measures of legacy game refinement

Subject	G	T	B	D	GR
Chinese chess			38	95	0.065
Soccer	2.64	22			0.073
Basketball	36.38	82.01			0.073
Western chess			35	80	0.074
Go			250	208	0.076
Table tennis	54.863	96.465			0.077
UNO®	0.976	12.684			0.078
DotA®	68.6	106.2			0.078
Shogi			80	115	0.078
Badminton	46.336	79.344			0.086
SCRABBLE (swing)	10.78	35.85			0.092
SCRABBLE (board game)			361.8	35.85	0.531

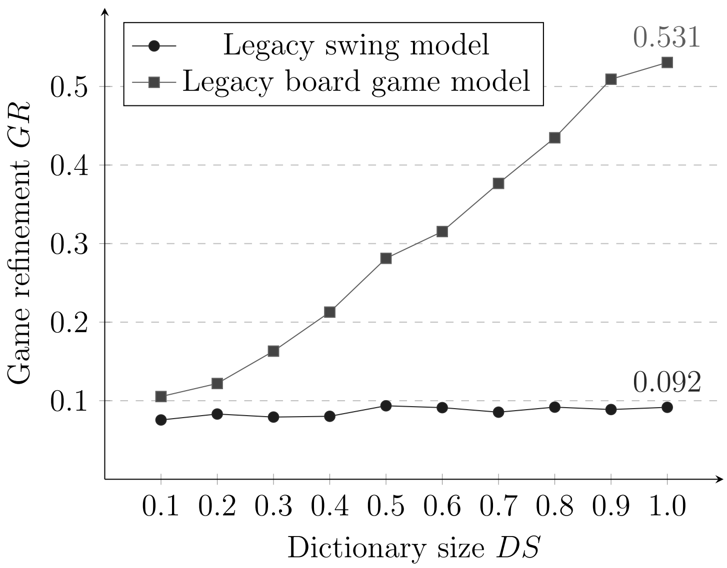


Figure 3-1: Comparison of two GR measures using perfect player level

3.3.2 Player Model

Among the solved games, many games are advantageous to the first player of taking such initiative. Therefore it is worth investigating what happens if that initiative fails and the game allowed the second player to win. The importance of fairness, AoI had been previously investigated and proved through a conclusive and elegant theorem on first-player wins over the second-player win [108]. The concept of the initiative seems to be a predominant notion under the requirement that the first player has sufficient space to fulfill the goals [117]. Another recent work also takes into account the AoI issue in the context of the player's strength, which revisited the concept of AoI and redefined the initiative as the first "to take the advantage" among the players in the early stage (i.e., to be the first winner in the earlier stages of the game) [14].

Previous work that addresses the AoI aspect had been investigated to determine the impact of the initiative on the game-theoretic value through a large number of k-in-a-row games and 200 Domineering games as a function of the board size [115]. Another study adopted self-play experiments using AI in Scrabble games where a player that established an early opening advantage took a higher winning expectancy [14]. Besides, an interesting illustration with a randomized initial position was figured out using Quackle AI in Scrabble. In fact, since AI in Scrabble showed that the level of performance beats the professional human players, maintaining fairness is becoming a difficult feat since the gap between machine and man performance is increasing. As such, this study is pushed towards addressing the challenge of keeping fairness, specifically, in the game of Scrabble.

The AoI aspect in Scrabble is assumed by assessing different performance levels among the players of the respective game (see Figure 3-2). With respect to the previous results of tournament data (see Table 3.1 and Table 3.2), it is reasonable to assume that human professional players would be pinpointed somewhere between the performance level of $\{h_l, h_u\}$, where h_l and h_u corresponds to lower bound and upper bound of human experts, respectively. As shown in Figure 3-2, the AoI measure is expected to be roughly balanced for human players. However, that of super-performance level players like Alpha Zero is a whole other issue. Our previous work studied that there is a linear relation between AoI measure and the skill level of the players [14]. The results indicate that having the initiative in the early stages of the games is a clear advantage under the special condition that the player is much stronger than grandmaster level (estimated at $LV = 0.7$) and the board size is standard 15×15 [14].

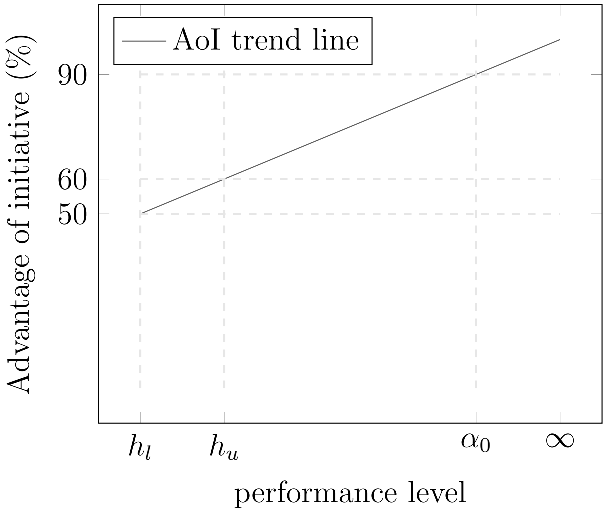


Figure 3-2: Illustration of assumed advantage of initiative (AoI) over different performance levels of the players

3.4 Defining Near-Dying Games

In this section, two illustrations are presented considering two models: the player model and the game model to understand the attractiveness of the games.

3.4.1 From the Perspective of AI

To illustrates the AoI, different performance levels of the player have to be considered (see Figure 3-2). Based on the previous tournament data, it is reasonable to assume that human experts would be located somewhere between $\{h_l, h_u\}$ in the performance level, where h_l and h_u corresponds to lower bound and upper bound of human experts, respectively.

Meanwhile, AI such as AlphaZero (denoted as α_0) has a performance level around 90% or more, and the perfect performance level corresponds to ∞. Suppose that the performance level of the player increases (as seen by the current trend of AI development), it can be conjectured that the AoI would also become greater. As such, any game under consideration would lose its attractiveness due to unfairness being far beyond the acceptable AoI margin. In essence, that game would approach the "near-death" stage since it would not be attractive to play competitively or even for fun.

3.4.2 From the Perspective of the Game Attractiveness

The general model of game refinement (GR) was proposed based on the concept of game information progress, where the gap between board games and sports games was bridged [55, 110]. Assuming the average length of games D and the average branching factor or the number of possible moves B played by human experts [60, 56] and Alpha Zero [106], the GR value can be calculated which is given in Table 3.5 and illustrated in Figure 3-3.

Table 3.5: The game length and the GR value of Chess and Shogi games played by human experts and AlphaZero

	Human	GR	Alpha Zero	GR
Chess	80	0.074	130	0.04
Shogi	115	0.073	204	0.04

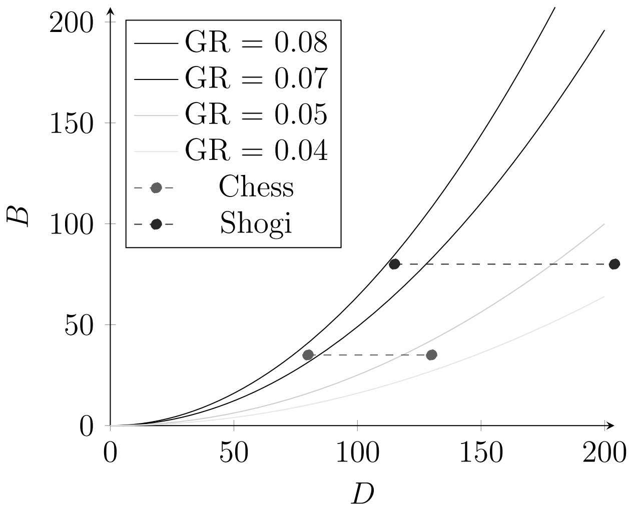


Figure 3-3: The average number of possible moves B and game length D in chess and shogi: human experts and Alpha Zero compared

The tendency of GR value typically converges towards a comfortable zone ($GR \in [0.07, 0.08]$), which is associated with the measures of game entertainment and sophistication, involving a balance between the level of skills and chance of the game [123, 57]. Based on this fact, an entertaining experience had been demonstrated by the human experts based on the GR value that was in the comfortable zone. However, AlphaZero AI demonstrates serious experience due to its low GR value. This contrasting situation implies that gameplay with super-human performance would not be enjoyable and less entertaining, thus losing its attractiveness (hence, "dying" in the sense that the game becomes predictable and causes frustrations instead of fun).

3.5 Experimental Setup

Scrabble AI program was built to simulate multiple Scrabble matches. 10,000 distinct games are simulated with 100 iterations each. To calculate the win ratio with respect to the AoI, the individual and total scores, the number of wins, and the number of losses, were collected. The performance of the AI player can be explored from several points of view.

In this study, different strength levels of AI players were adopted based on various dictionary sizes (DS) and different performance levels of the AI player (LV). The participants of the Scrabble matches were AI players who played Scrabble games with systematically varied levels of strength. It was found that the probability measure has a linear relation with LV when the player is much stronger than grandmaster LV (estimated at $LV = 0.7$) and the board size is standard 15×15 [14].

3.6 Computational Results and Discussion

In this section, we illustrate three experimental results over different levels of AI players from the advantage of initiative (AoI) perspective.

3.6.1 Experimental Result on keeping Advantage of Initiative over Different Performance Levels

Table 3.6 and Figure 3-4 presents the win ratio of keeping the advantage of initiative for different dictionary size (0.5, 0.7 and 1.0) and its depiction in graph form. This reveals that the original setting of Scrabble has the advantage of initiative for the very strong players ($LV \geq 0.5$).

An increase in the dictionary size (DS) corresponds to the strength of the player. As such, higher DS is more likely to increase the winning ratio when reaching a value greater than 0.5 (stronger than the grandmaster level). Resetting of dictionary size (DS)

Table 3.6: Winning ratio of keeping advantage of initiative over different performance levels

Performance	**Dictionary Size**					
Level	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
0.1	0.5	0.5	0.5	0.5	0.5	0.5
0.2	0.5	0.5	0.5	0.5	0.5	0.5
0.3	0.5	0.5	0.5	0.5	0.5	0.5
0.4	0.5	0.5	0.5	0.5	0.5	0.5
0.5	0.5	0.5	0.5	0.5	0.5	0.5
0.6	0.54	0.6	0.6	0.65	0.67	0.69
0.7	0.55	0.68	0.71	0.73	0.76	0.78
0.8	0.56	0.7	0.76	0.8	0.82	0.84
0.9	0.58	0.73	0.8	0.82	0.85	0.7

on standard board size in Scrabble cannot maintain the fairness of the game outcome (in this context, win ratio) until the end of the game.

One possible enhancement is to reduce the board size (Figure 3-5). This results in keeping the outcome of the game to be unclear, as shown in Figure 3-6. A question now arises: how large is the board size needed for the Scrabble for the player to earn the winning advantage (AoI) in the early stage? With the focus on different levels of players (0 to 1), the 15×15 Scrabble board turned out to be a winning criterion for the player who gets the advantage in the first stage under the condition that both players are much stronger than the grandmaster level. However, fairness can be maintained by resetting the board size of Scrabble to 13×13 which keeps the probability of AoI of both players in each stage of the game.

3.6.2 Experimental Result on AoI Measure and Changes in the Search Space

With the focus on different performance levels of the players (normalized levels $\in [0, 1]$) and the winning ratio (see Figure 3-7), it turned out that the original Scrabble board size (15×15) or larger are advantageous to the player who gets the advantage in the first stage, under the condition if both players are much stronger than grandmaster level (assumed to be $\approx$0.5). From the experiments performed, the corresponding AoI for larger two board sizes (15×15 and 17×17) showed that higher skill leads to unfair gameplay. This reveals

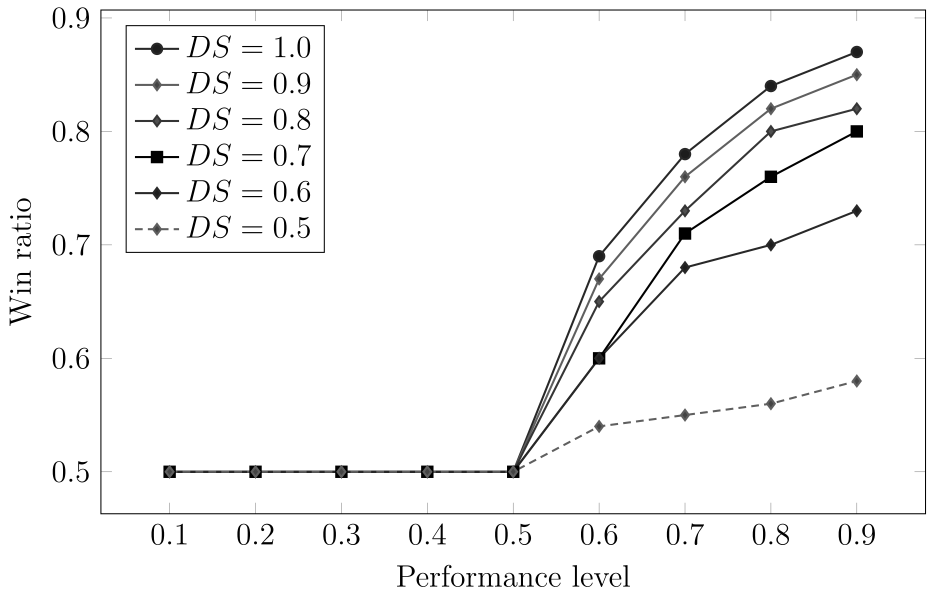


Figure 3-4: Win ratio for keeping the advantage of initiative over different performance levels for different sizes of dictionary.

$2W$				$3L$				$3L$				$2W$
	$2W$				$2L$		$2L$				$2W$	
		$2W$				$2L$				$2W$		
			$2W$						$2W$			
$3L$				$3L$				$3L$				$3L$
	$2L$				$2L$		$2L$				$2L$	
		$2L$				$2W$				$2L$		
	$2L$				$2L$		$2L$				$2L$	
$3L$				$3L$				$3L$				$3L$
			$2W$						$2W$			
		$2W$				$2L$				$2W$		
	$2W$				$2L$		$2L$				$2W$	
$2W$				$3L$				$3L$				$2W$

Figure 3-5: 13x13 variant of Scrabble board

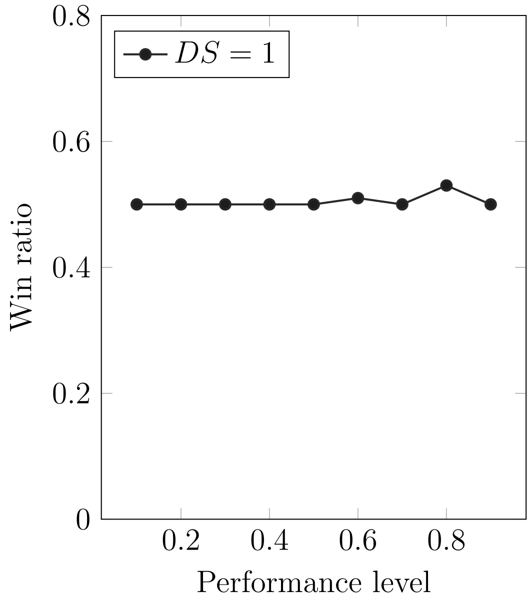


Figure 3-6: Win ratio keeping the advantage of initiative over various performance levels on 13x13 board size

that the original setting of Scrabble needs to be reevaluated.

One possible enhancement is reducing the board size to 13×13. Interestingly, this can significantly provide fair gameplay for both players until the end of the gameplay. However, the 15×15 and 17×17 board sizes of Scrabble do not solve the AoI issue. One reason for this is that no matter how strong the player (in this context, the ability to look ahead of the game board states), the possible winning position is limited due to the limited positions of the board itself. However, this solution may be limited to smaller board games; thus, quite limited in terms of applicability in a larger and more complex board game.

3.6.3 Experimental Result on AoI Measure and Incorporation of The Komi System

In the game of Go, Black has the advantage of the first move. To compensate for this, White can be given an agreed number of points before starting the game. These points are called komi [85]. The statistical analysis has been used to judge whether a given value of Komi makes the gameplay fair or not. Since the 1930s, the compensation (Komi) system was introduced into the game of professional Go in Japan as a gradual process

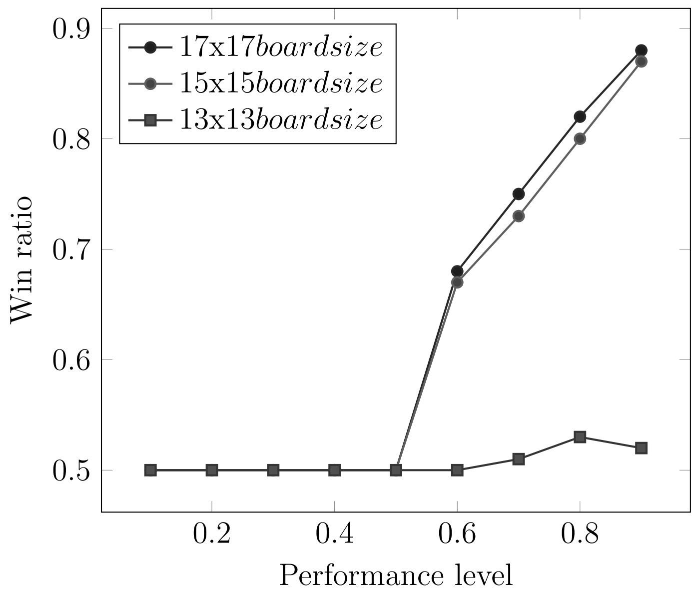


Figure 3-7: Win ratio keeping the advantage of initiative over different performance levels for three different board sizes.

of innovation. Since the professional opening strategy has evolved, the correct value of Komi has been reevaluated over many years [119].

In this paper, different performance levels of AI players were adopted by proposing appropriate Komi values for each level of players via a score-based statistical method, that adapts the Komi value calculated from E[score], the expected scores over AI Scrabble simulations. Scrabble AI program was built to simulate multiple Scrabble matches. To calculate E[score] concerning the AoI, the individual score, the total score, the number of wins, and the number of losses were collected. The performance of the AI player considered for this experiment is relative to the grandmaster level and beyond (levels $\in [0.6, 1]$). It was found that our proposed Komi values can achieve a fair game result that approximately balanced the winning percentage for both participants (Table 3.7 and Figure 3-8).

Table 3.7: Win ratio keeping advantage of initiative over different performance levels

Performance Level	**Komi Values**
0.6	57.3
0.7	92
0.8	68.9
0.9	64.7
1	52.6

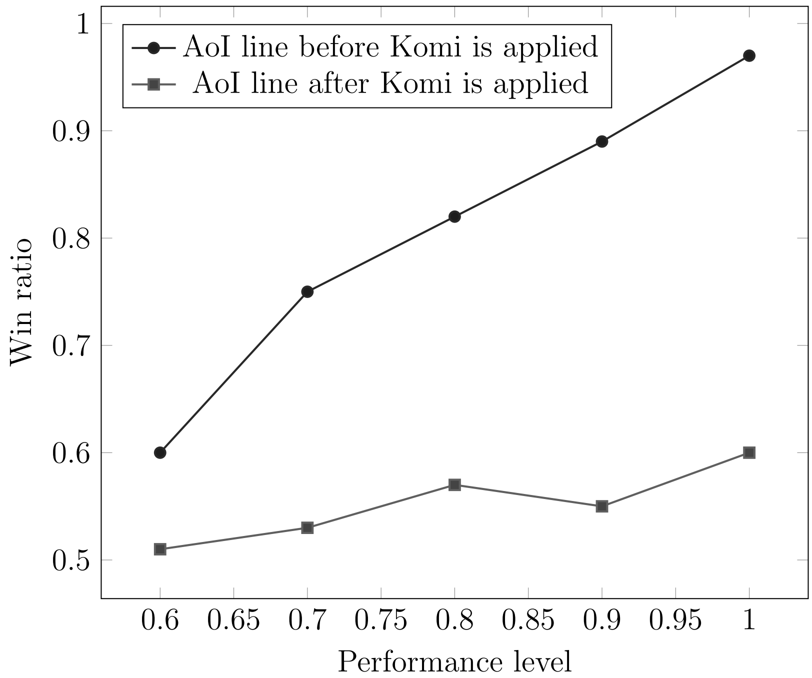


Figure 3-8: Illustration of AoI Measure over different performance levels before and after Komi is proposed

3.7 Chapter Summary

While Artificial Intelligence is getting more powerful and about to beat human experts not only in some games but also in other areas, this fact demonstrates fairness to be an important aspect of competitiveness.

Thus, the advantage of initiative (AoI) has been revisited using Scrabble as a test bed for different levels of AI players. This study focuses only on two aspects: the size of the search space (board size) and the quality of AI players (strength of players based on AI levels and dictionary size) of Scrabble from the viewpoint of the advantage of initiative.

First, the link between the search space and the quality of players was investigated. 13×13 board size is suitable enough to keep the balance of the information about the game outcome that is not clear at the very end of the game. But for 15×15 board size, one player can maintain his advantage until the end of the game if he can establish an advantage in the first stage of the game. The experiments show that the winning percentage of the player who is established in the first stage is higher than the opponent when the level of the player is between 0.6 and 1.

Self-play experiments in our previous work using Quackle AI players show that Scrabble is a game with a large AoI for a high-level AI environment. However, this study only considers dictionary size and the performance level of the players. Besides, considering the search space reduction of the game by reducing the board size to 13×13 as the possible enhancement that maintains fairness in Scrabble may be short-lived. Addressing such an issue had been proposed through the compensation (Komi) system in Scrabble AI. This ensures a fair game environment for all levels of players by introducing appropriate Komi values that correspond to the level of the players.

Chapter 4

Finding the Critical Aspect of Fairness in Games

This chapter is an updated and abridged version of the following publications:

- Htun Pa Pa Aung, Mohd Nor Akmal Khalid, and Hiroyuki Iida. What Constitutes Fairness in Games? A Case Study with Scrabble.Information 2021, 12(9), 352.

4.1 Chapter Introduction

The fourth chapter of the dissertation covers research carried out related to the notion of fairness and proposes the concept of *dynamic* komi Scrabble. The compensation system called komi has been used in scoring games such as Go. In Go, White (the second player) is at a disadvantage because Black gets to move first, giving that player an advantage; indeed, the winning percentage for Black is higher. The perceived value of komi has been re-evaluated over the years to maintain fairness. However, this implies that this *static* komi is not a sufficiently sophisticated solution. We leveraged existing komi methods in Go to study the evolution of fairness in board games and to generalize the concept of fairness in other contexts. This work revisits the notion of fairness and proposes the concept of *dynamic* komi Scrabble. We introduce two approaches, *static* and *dynamic* komi, in Scrabble to mitigate the advantage of initiative (AoI) issue and to improve fairness. We found that implementing the *dynamic* komi made the game attractive and provided direct real-time feedback, which is useful for the training of novice players and maintaining fairness for skilled players. A possible interpretation of physics-in-mind is also discussed for enhancing game refinement theory concerning fairness in games. This chapter mainly describes the proposed *dynamic* komi idea and how it can efficiently be used to give a fair game environment for different performance levels.

4.2 Literature Review and Related Work

In the past, the Go board game was listed as one of the grand challenges of AI [42]. By 2006, the strengths of computer Go programs were generally below 6-*kyu* [84, 27], which is far from the strength of amateur *dan* players. With the adoption of Monte Carlo tree search (MCTS) in 2006, computer Go programs started to make significant progress up to 6-*dan* in 2015 [71, 113, 43, 21, 32, 17, 42]. In 2016, this grand challenge was achieved by the AlphaGo program [104] when it defeated (4:1) against Lee Sedol, a 9-*dan* grandmaster who had won most of the world Go champion titles in the past decade. Many thought at the time that the technology was a decade or more away from surpassing this AI milestone. A new approach was introduced to computer Go which uses deep neural networks trained by a novel combination of supervised learning from human expert games. In addition, games of self-play were conducted to evaluate board positions and select moves, and a new search algorithm was introduced that combines Monte Carlo simulation with value and policy networks [104].

In the traditional computer Go program with MCTS, *dynamic* komi is a technique widely used to make the program play more aggressively, especially for handicap games [17]. With the growing availability and use of machine learning techniques and faster computer hardware, superior computer programs against human beings in the most popular perfect information games have emerged, including checkers, chess, shogi, and Go [107]. It is challenging to keep fairness when designing a game. Games have survived for a long time by changing the rules to seek fairness and become more attractive and engaging. Several board games maintain fairness; this includes chess, which was studied in [55]. In the history of Chinese and Western chess, the rules have been changed many times. As a result, a draw outcome became prominent in competitive tournaments. In Gomoku or Connect5, Allis [10] proved that the first player always wins when playing perfectly on a 15×15 board. As such, some of the game rules were changed to ensure fairness. In the game of Renju (a professional variant of Gomoku), the first player is debarred from playing some moves while the second player gets to swap color pieces after the second move of the first player [1]. However, there is still some advantage for one side under this rule. Hence, Connect6 was developed, which is much fairer than Gomoku in some ways. Scrabble is a unique game that is considered a scoring game (Go-like game) and a board game (checkers-like game) while being imperfect information (a card-based game). In Scrabble, the current player is unaware of the opponent player's rack, making it difficult to guess the opponent's next move until the end of the game. There is also inherent randomness present in Scrabble, as random letters are drawn from the bag to the current player's rack. The state space in Scrabble is also quite complicated because the tiles are marked with specific letters instead of Black and White. Currently, Maven and Quackle are the leading Scrabble AI programs. Maven was created in 2002 by Brian Sheppard [93], whereas Quackle is an open-source Scrabble AI developed by Jason Katz-Brown and John O'Laughlin [20].

4.3 The Proposed Assessment Method

In this section, we shortly sketch game refinement theory, the basic concept of gamified experience, and the notion of fairness to define different levels of fairness in games.

4.3.1 Game Refinement Theory

Game refinement theory has been investigated based on the uncertainty of game outcome [79, 59, 61]. It has been studied not only in fun-game domains such as video games [126, 122], board games [59], and sports [112, 111], but also in non-game domains such as education and business [127, 52]. The tendency of game refinement value typically converges towards a comfortable zone ($GR \in [0.07, 0.08]$), which is associated with the measures of game entertainment and sophistication involving a balance between the level of skill and chance in the game [57, 123].

The information on the game's result is an increasing function of time (i.e., the number of moves in board games) t, which corresponds to the amount of solved uncertainty (or information obtained) $x(t)$, as given by (4.1). The parameter n (where $1 \leq n \in N$) is the number of possible options and $x(0) = 0$ and $x(T) = 1$.

$$x'(t) = \frac{n}{t}\, x(t) \tag{4.1}$$

$x(T)$ stands for the normalized amount of solved uncertainty. Note that $0 \leq t \leq T$, $0 \leq x(t) \leq 1$. The rate of increase in the solved information $x'(t)$ is proportional to $x(t)$ and inversely proportional to t, which is given as (4.1). By solving (4.1), (4.2) is obtained. It is assumed that the solved information $x(t)$ is twice derivable at $t \in [0, T]$. The accelerated velocity of the solved uncertainty along the game progress is given by the second derivative of (4.2), which is given by (4.3). The acceleration of velocity implies the difference in the rate of acquired information during game progress. Then, a measure of game refinement (GR) is obtained as the square root of the second derivative (Equation (4.4)).

$$x(t) = \left(\frac{t}{T}\right)^{n} \tag{4.2}$$

$$x''(t) = \frac{n\,(n-1)}{T^{n}}\, t^{n-2}\, |_{t=T} \quad = \frac{n\,(n-1)}{T^{2}} \tag{4.3}$$

$$GR = \frac{\sqrt{n\,(n-1)}}{T} \tag{4.4}$$

A skillful player would consider a set of fewer plausible candidates (b) among all possible moves (B) to find a move to play. The core part of a stochastic game assumes that each among b candidates may be equally selected. Knowing that the parameter n in (4.4) stands for the number of plausible moves b, $n \simeq \sqrt{B}$ is obtained. Thus, for a game with branching factor B and length D, the GR can be approximated as in (4.5).

$$GR \approx \frac{\sqrt{B}}{D} \tag{4.5}$$

4.3.2 Gamified Experience and the Notion of Fairness

Fairness perception is critical in any domain, including the workplace and society at large, because it influences emotions, attitudes, judgments, decisions, and behaviors. Equality and equity are two processes where we can achieve fairness that provides different entertainment settings.

Let p be the probability of selecting the best move among n options, which implies $p = (\frac{1}{n})$. As such, a gamified experience can be defined based on the notion of the risk frequency ratio. The risk frequency ratio m (risk frequency over the whole game length) is defined as $m = 1 - p = \frac{n-1}{n}$. Then, a gamified experience is gained if and only if the risk of failure occurs half the time ($m \geq \frac{1}{2}$), which implies $n \geq 2$.

Definition of Outcome Fairness

Based on the gamified experience, one notion of fairness can be defined as an *outcome* fairness or equality. The winning ratio p (focus on game outcome over the whole game) is defined as $p = \frac{1}{2}$. Then, outcome fairness or equality is gained if and only if the winning ratio occurs with $p = \frac{1}{2}$ for White and Black players.

Let t and $y(t)$ be the time or length of a given game and the uncertainty solved at time t, respectively. Hence, a player who needs to solve uncertainty by the average ratio v is given by (4.6). Information acceleration felt by the player is given by (4.7). By considering the cross point between (4.6) and (4.7) found at $t = D$, the relation (4.8) is obtained.

$$y(t) = vt \tag{4.6}$$

$$y(t) = \frac{1}{2}at^2 \quad \text{where } a = GR^2 \tag{4.7}$$

$$a = \frac{2v}{D} \tag{4.8}$$

The cross point D indicates the correct balance between skill and chance concerning the gamified experience as well as comfortable thrill by the informational acceleration in the game under consideration. In other words, a sophisticated game postulates an appropriate game length to solve uncertainty while gaining the necessary information to identify the winner. Moreover, if the game length is too long (or too short) or the total score is too large (or small), the game would be boring (or unfair).

Definition of Process Fairness

In score-based games, game length is not a reliable measure, since it can vary between multiple game sets. Thus, a different measure p is utilized in this context. Focusing on outcome fairness or equality could lead to a situation where the game is not attractive and interesting from an entertainment perspective. Assume that $P1$ is the player that gets the advantage first in the early stages of the game, and that $P2$ is the player who fails to get the advantage. Let W be the number of advantages by $P1$ and L be the number of advantages by $P2$ (the number of disadvantages by $P1$); then, another notion of fairness can be defined, namely, process fairness.

Process fairness or equity is achieved when a game is competitive and fair if $m = \frac{1}{2}$, based on (4.9) and (4.10) . This notion leads to the interpretation of mass m in game playing, which is determined based on the target domain: (1) board games, and (2) scoring board games.

(1) Board games:

Let B and D be the average number of possible moves and game length, respectively. The score rate p is approximated as (4.9), by which the approximation of p is derived originally from the approximation in (4.5).

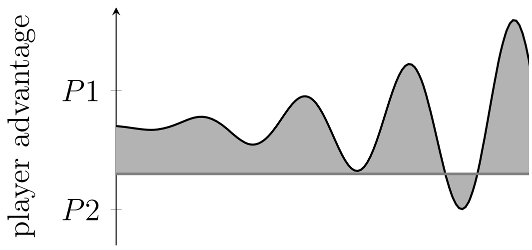
$$p \approx \frac{1}{2}\frac{B}{D} \quad \text{and} \quad m = 1 - p \tag{4.9}$$

(2) Scoring games:

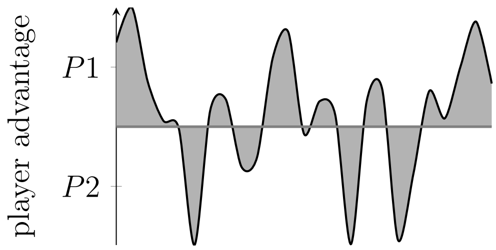
Let W and L be the number of advantages and the number of disadvantages in the games that have a game pattern with an observable score. The score rate p is given by (4.10), which implies that the number of advantages W and the number of disadvantages L are almost equal when a game meets fairness.

$$p = \frac{W}{W+L} \quad \text{and} \quad m = 1 - p = \frac{L}{W+L} \tag{4.10}$$

Figure 4-1 describes two types of game progression curves. A game is considered fair if each of an evenly matched group of players has a prior equal chance of winning for any given starting position. Each player in a regular fair game between two players should win about 50% of the time when both players are playing at the same proficiency level. Figure 4-1a shows the progression curve for games with a first-player advantage, where many games are won by the first player. A seesaw game with a good dynamic is one where the result is unpredictable to the very last moves of the endgame stage. This implies that the game is more exciting, fascinating, and entertaining. As such, it is expected that this ideal game progression is the most important to achieve *process* fairness for a well-refined game. It indicates that both players have a good chance of winning the game through the equity process, as shown in Figure 4-1b.



(a) Game with AoI: One-sided game pattern



(b) Ideal game: Seesaw game pattern

Figure 4-1: A rough illustration of the game progression curves for a game with the advantage of initiative and for an ideal game.

Momentum, Force, and Potential Energy in Games

Various physical formulations have been established around the motions of an object in physics. The most fundamental formulations are the measure of force, momentum, and potential energy. We adopt these measures in the context of games, where $m = 1 - p$ is the mass, $v = p$ is the velocity, and $a = \frac{2m}{D} = GR^2$ is the acceleration. Then, the force, momentum, and potential energy (based on gravitational potential energy) are obtained as (4.11)–(5.2), respectively.

$$F = ma \tag{4.11}$$

$$\vec{p} = mv \tag{4.12}$$

$$E_p = ma\left(\frac{1}{2}at^2\right) = \frac{1}{2}ma^2t^2 = 2mv^2 \tag{4.13}$$

4.3.3 Evolution of Fair Komi in Go

Komi (or compensation) is a Japanese Go term that has been adopted in English. In a game of Go, Black has the advantage of the first move. In order to compensate for this, White can be given an agreed-upon set number of points before starting the game (the typical value is from 5 to 8 points). These points are called komi [48]. Before 1937, komi was rarely used in professional tournaments, and its gradual introduction into professional play was not without controversy. Now, almost all Go tournaments (amateur and professional) use komi.

Although there were some games played with compensation in the 19th century, more substantial experiments came in the first half of the 20th century. Several values were experimented with until a value of 4.5 became the standard from the 1940s onward. Game results from the next two decades showed that 4.5 komi still favored Black, so a change was made to 5.5 komi, which was mostly used for the rest of the 20th century in both Japan and China [48]. At the start of the 21st century, the komi was increased yet again to 6.5 (Korea and Japan) and 7.5 (China) as shown in Figure 4-2.

In theory, the perfect komi for a given ruleset is a clear concept: it is the number of points by which Black would win provided optimal play by both sides. Unless the ruleset allows fractional winning margins (which none of the common ones do), this is necessarily a whole number. Due to the absence of perfect players in Go, this number cannot be determined with certainty. However, it is possible to make a reasonable guess at it, at least for some rulesets. For this study, the current komi system is called *static* komi because it is determined based on the statistical scores of previously played games.

Black wins		White wins	
B+R	557	W+R	557
B+T	2	W+T	2
B+0.5	70	W+0.5	70
B+1.5	68	W+1.5	63
B+2.5	65	W+2.5	43
B+3.5	47	W+3.5	58
B+4.5	37	W+4.5	41
B+5.5	29	W+5.5	26
B+6.5	21	W+6.5	25
B+7.5	18	W+7.5	19
B+8.5	21	W+8.5	14
B+9.5	14	W+9.5	8
B+10.5	5	W+10.5	3
B+11.5	4	W+11.5	5
		W+12.5	1
B+13.5	2	W+13.5	2
B+14.5	2	W+14.5	2
B+15.5	1		
B+16.5	1	W+16.5	3
		W+17.5	2
		W+19.5	1
B+20.5	1		
B+24.5	1		
B+29.5	1		
Total	967		945
	50.58%		49.42%

(a) Komi 6.5

Black wins		White wins	
B+R	124	W+R	140
B+T	1	W+T	2
B+0.5	1	W+0.5	13
B+1.0	13	W+1.0	2
B+1.5	16	W+1.5	2
B+2.5	1	W+2.5	10
B+3.0	11	W+3.0	9
B+3.5	6	W+3.5	4
B+4.5	1	W+4.5	4
B+5.0	6	W+5.0	6
B+5.5	4	W+6.0	1
		W+6.5	1
B+7.0	6	W+7.0	4
B+7.5	4		
		W+8.0	1
B+8.5	1	W+8.5	1
B+9.0	3	W+9.0	4
B+9.5	2	W+9.5	2
		W+10.5	1
B+11.5	1		
B+15.5	2		
Total	203		207
	49.51%		50.49%

(b) Komi 7.5

Figure 4-2: Comparison of Komi 6.5 and Komi 7.5

4.4 Research Methodology

In this section, we present the idea of *dynamic* and *static* komi in Go. Then, we illustrate the experimental setup to demonstrate and analyze the effect of the *dynamic* komi approach.

4.4.1 *Dynamic* versus *Static* Komi

Since perfect play is not yet possible in Go, statistical analysis was used to judge the fairness of a given komi value. To illustrate how komi is determined, the statistics of professional games played on a 19 × 19 board with a komi of 5.5 are given in Table 4.1. The data show that a komi of 5.5 slightly favors the Black. Therefore, the compensation is not sufficient for the White to overcome the first-move advantage of the Black player.

Table 4.1: Example Go game statistics with a komi of 5.5 (adopted from [107]).

	No. of Games	Winning Probability
Black	6701	53.15%
White	5906	46.85%
Total	12,607	

Although it is tempting to use this as evidence to grant a komi of one point higher, the greater proportion of games would then be won by White, which is not entirely fair. The problem is that professional Go players play to win since winning by a little or winning by a lot is still winning (the same is true for losing). Thus, a change of strategy only happens when a player loses or gains the advantage. A player who is behind will try to get ahead by introducing complexities, even losing points in the process. The leading player may be willing to play sub-optimally in order to reduce complexities and give up a few points to maintain the lead.

The advent of AlphaGo and other AI bots induces the need for performance benchmarking through an explicit probabilistic evaluation. With the standard komi value of 7.5, the bots believe their opponent is ahead by 55–45%. Similarly, KataGo increases the performance evaluation of its opponent scores by half a point, making the fair komi value 7 instead. Thus, substantial evidence of the perfect komi (or upper bound) is needed. A much more reliable statistic can be obtained from games won by gaining the advantage of W (or disadvantage L) for a given komi value.

In the context of Scrabble games, previous work adopted a similar concept of komi by proposing a *static* komi method that corresponds to the players' level to ensure a fair game environment for all levels of players [16]. However, the approach is dependent on the board situation, where the program adjusts the komi value internally either giving the program a "virtual advantage" where the AI player is losing or burdening it with a virtual disadvantage when it is winning too much in the actual game. This approach may be limited since constant komi values are statistically computed based on the expected score difference of the player's level over a specific number of simulations. It may also lead to a second-player advantage, meaning that the player could hide their best move (by making the highest-score word) before receiving the komi in the earlier stages. This study proposes a new approach called *dynamic komi*, allowing adjustment of the score based on each particular game match. Since the correct *static* komi only depends on the board size and the player's ability, the proposed *dynamic* komi method significantly enhances the fairness level over the original AI programs, and over the *static* komi method. Implementing *dynamic* komi in Scrabble could help to achieve process fairness through an equity process by recognizing each player's different circumstances and skills.

4.4.2 Experimental Setup

This section discusses the experiments conducted and the results obtained in this study. The Scrabble AI program was implemented in C#, and one hundred distinct match settings were simulated with five hundred iterations each. These experiments were executed on an ASUS PC machine with 16 GB RAM and a quad-core processor with Intel Core i7-10700 on the Windows 10 operating system. We collected the average results of the conducted self-play games to analyze the likely winning rate of each game for each setting. Our program took 120,000–320,000 s to finish 10,000 simulations.

Following a previous work [15], several experiments were performed to demonstrate and analyze the effect of the *dynamic* komi approach based on ten different performance levels in the game (ranging from 1 to 10). The first experiment focused on analyzing the impact of *dynamic* komi on the winning probability in the game of Go. The second experiment focused on analyzing the impact of *dynamic* komi on the winning probability in four different game phases of Scrabble. Subsequently, game refinement theory was applied to determine the optimal play strategy over various performance levels.

4.5 Computational Results and Discussion

In this section, we present the analysis of *dynamic* komi in the game of Go and Scrabble. Then, we discuss optimal play strategy in Scrabble and identify the link between play strategy and fairness from the entertainment perspective.

4.5.1 Analysis of *Dynamic* Komi in the Game of Go

The motivation for applying *dynamic* komi to the game of Go is because the use of komi originates from this game. The results of the winning probability for each komi value using both *static* and *dynamic* komi in the Go game are given in Table 4.2 and Figure 4-3. The results were collected from an analysis of 2650 games of Go, where the winning probability was computed based on different komi values.

Table 4.2 presents the experimental results of *dynamic* and *static* komi incorporated in Go. The compensation (komi) system was introduced into professional Go in Japan as a gradual process of innovation, beginning in the 1930s. As a professional opening strategy has evolved, the correct value of komi has been re-evaluated over the years. Initially, *static* komi (compensation) is given to balance the initiative of playing first. Although 6.5 points was a common komi as of 2007, each country, association, and the tournament may set its own specific komi. By far, the most common type of komi is a fixed compensation point system. A fixed number of points, determined by the Go organization or the tournament director, is given to the second player (White) in an even game (without handicaps) to make up for the first-player (Black) advantage.

In another work, *dynamic* komi was proposed based on the observation of different values (win rates), and was simultaneously trained for different komi settings to improve the game-playing strength [120]. However, that study found no significant difference when adopting *dynamic* komi compared to the *static*komi in the Go game. This implies that the evolution of fairness might be dependent on the initial game condition. *Static* komi is suitable for games having a fixed initial position, such as Go. Meanwhile, a random initial

Table 4.2: Winning rate analysis of Black Player based on *static* komi versus *dynamic* komi in the game of Go.

Komi	**Static Komi**	**Dynamic Komi**
3.5	53.30%	53.10%
4.5	55.00%	52.90%
5.5	53.15%	52.50%
6.5	50.58%	51.40%
7.5	49.51%	50.15%

position in Scrabble should incorporate the *dynamic* komi approach to ensure expected fairness.

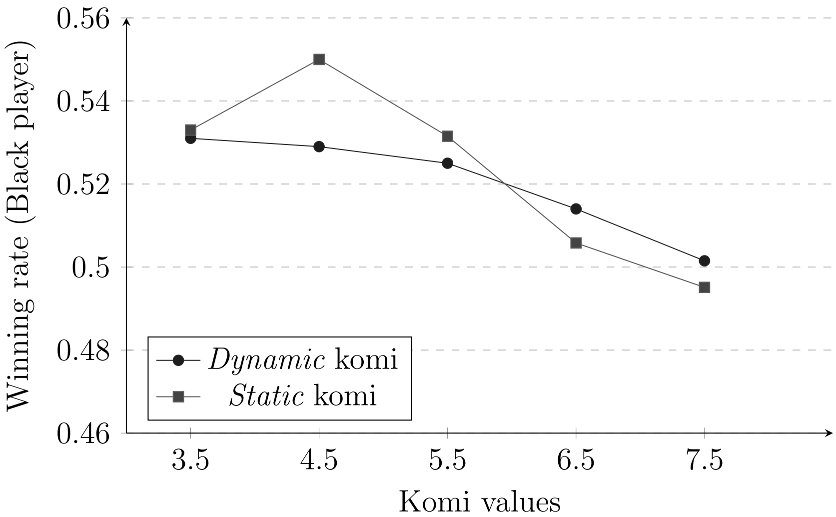


Figure 4-3: Komi variation versus winning probability in Go.

Monte Carlo tree search (MCTS) tends to produce varying results when faced with extreme advantages (or disadvantages) due to poor move selection in computer versions of Go. This variation is caused by the fact that MCTS maximizes the expected win probability, not the score margin. This situation can be found in handicap games of players with different performance levels. The handicap consists of the weaker player (always taking the Black color) placing a given number of stones on the board before the stronger player (White) gets their first move (handicap amount of between one to nine stones). Thus, when playing against a beginner, the program can find itself choosing a move to play on board with nine Black stones already placed on strategic points.

In practice, if a strong human player is faced with an extreme disadvantage (handi-

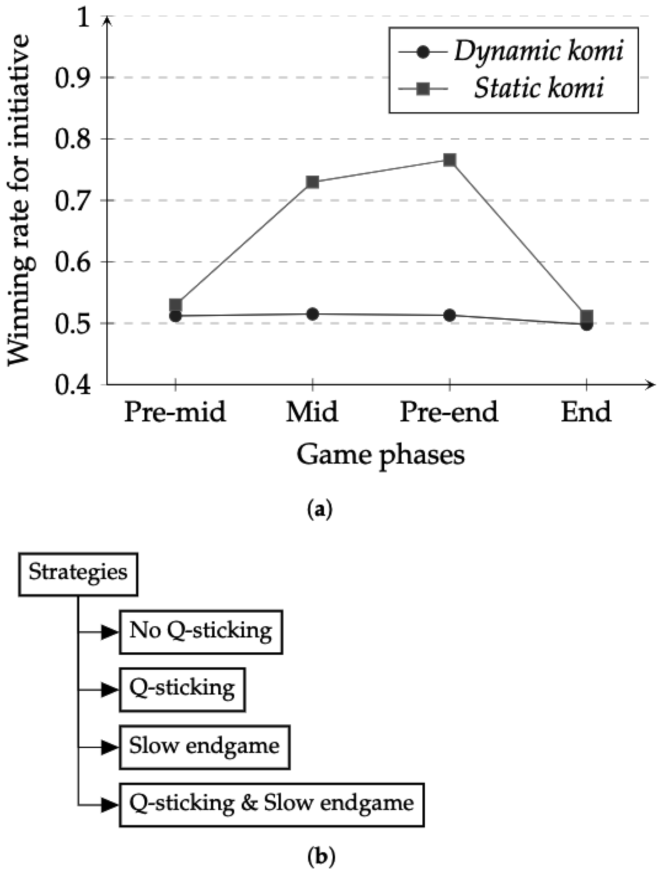


Figure 4-4: The application of *dynamic* komi to different game phases, and the adopted endgame strategies. (**a**) Komi variation versus winning probability over different game phases in Scrabble. (**b**) Four variants of Scrabble AI's endgame strategies.

cap game), they tend to play until the opponent makes mistakes to catch up patiently. Similarly, a strong human in an advantageous position will seek to solidify their position, defend the last remaining openings for an attack, and avoid complex sequences with unclear results to enlarge their score margin. The *dynamic* komi technique was used as one possible way to tackle the above extreme problem in Go. It has long been suggested, notably by non-programmer players in the computer Go community, that the *dynamic* komi approach should be used to balance the pure win rate orientation of MCTS.

4.5.2 Analysis of *Dynamic* Komi in the Game of Scrabble

Figure 4-4a presents the komi variation over different game phases in Scrabble. While the expected winning rate remained within the limits of what is considered fair (≈50%), the primary concern is the application of the komi. Specifically, in what game phases should the komi be applied to provide the optimal impact on the winning rate or outcome of the game?

Hence, the attention of this study is shifted toward the endgame phases. Scrabble endgames are crucial real-world scenarios that determine the success or failure of Scrabble tournaments. Having the right approach may turn a losing player into a winner. A basic greedy-based strategy for gaining maximum points is insufficient [81]. As such, three variants of endgame strategies were implemented in the Scrabble AI (Figure 4-4b), where a general winning percentage probability approach was applied ("Q-sticking" is a strategy where one player is stuck with the "Q" and cannot play it, creating the possibility of the opponent gaining 20 points from an unplayed "Q" while making no open spot to dump it. Another strategy called "slow endgame" was utilized when the player was behind on their score and wished to maximize their point spread by slowly playing off available tiles while preventing the opponent from playing out.). Based on the experimental results, *dynamic* komi overcame the AoI issue flexibly while maintaining fairness in each phase of the Scrabble game.

4.5.3 Optimal Play Strategy in Scrabble

Strategies for simpler games like tic-tac-toe are simple enough to determine simply by playing and analyzing a couple of games. For more complicated games such as chess, the optimal strategy is too difficult even for modern computers to calculate. As such, it is interesting to determine the optimal strategy for Scrabble.

An analysis of the GR value and the strategy changes of different player levels was conducted to determine the optimal strategy for the Scrabble game. According to earlier studies on board games and time-limited games [59, 112], a sophisticated game should be situated in the ideal value of $GR \in [0.07, 0.08]$ (Table 4.3).

The results in Figure 4-5 indicate that the change in the endgame strategies affected the progress of the game match. Relative to the ideal GR value ($GR \in [0.07, 0.08]$), all strategies trended proportionately to increase the player's performance level. However, only two endgame strategies (Q-sticking and a combination of Q-sticking and slow endgame) provided the appropriate sophistication level to the Scrabble game when the

Table 4.3: Correlative measures of legacy game refinement (GR) measures (ordered by game refinement value).

Game	$\boldsymbol{G}$	$\boldsymbol{T}$	$\boldsymbol{B}$	$\boldsymbol{D}$	$\boldsymbol{GR}$
Xiangqi			38.00	95	0.065
Soccer	2.64	22.00			0.073
Basketball	36.38	82.01			0.073
Chess			35.00	80.00	0.074
Go			250.00	208.00	0.076
Table tennis	54.86	96.47			0.077
UNO®	0.98	12.68			0.078
DotA®	68.6	106.20			0.078
Shogi			80.00	115	0.078
Badminton	46.34	79.34			0.086
Scrabble*	2.79	31.54			0.053
Scrabble **	10.25	39.56			0.080

$*$ With advantage of initiative; $**$ with *dynamic* komi; G/B: scoring options/branching factors; T/D: total scores/game length; GR: game refinement value, where the comfortable zone $\in [0.07, 0.08]$.

player's performance level was $LV \geq 0.6$.

From another perspective, all of the considered strategies were less beneficial for an inexperienced player. In a way, the player must have a better skill-based play (e.g., better knowledge of vocabulary). Additionally, an inexperienced player may find strategies (i.e., without Q-sticking and slow endgame) to be challenging to master since it involves the slightest uncertainty; this may be the reason for the GR value greater than 0.08. On the other hand, Q-sticking and the combination of Q-sticking and slow endgame strategies were beneficial for experienced players. Nevertheless, regardless of the player's performance levels, the strategies did not result in a GR value of less than 0.07. This situation indicates that Scrabble shares similar features to board games where skill is an essential element of play.

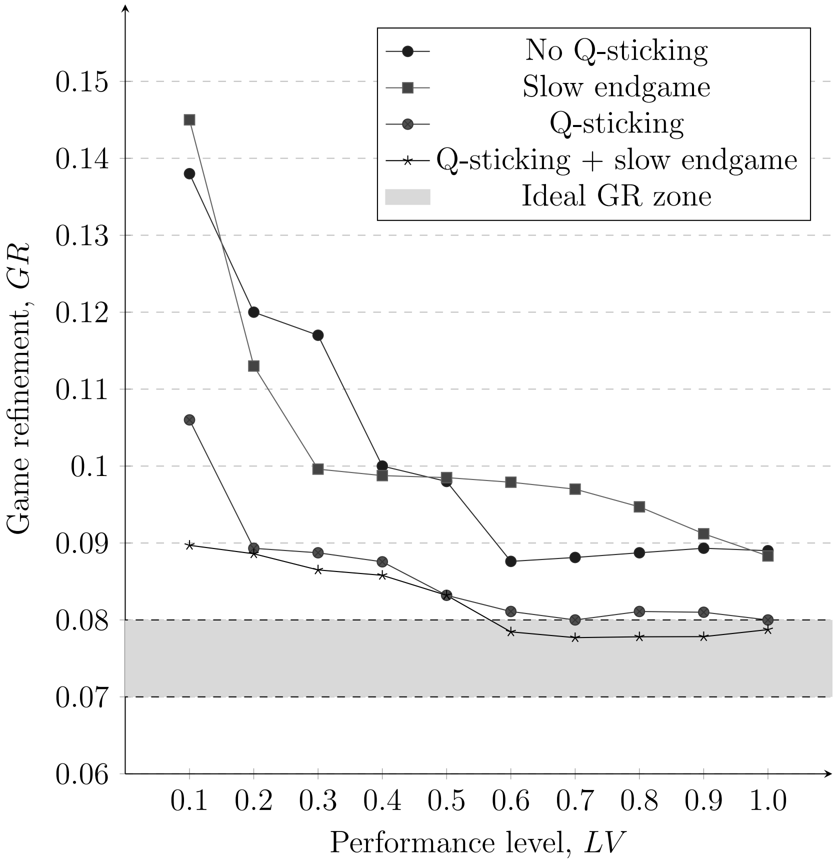
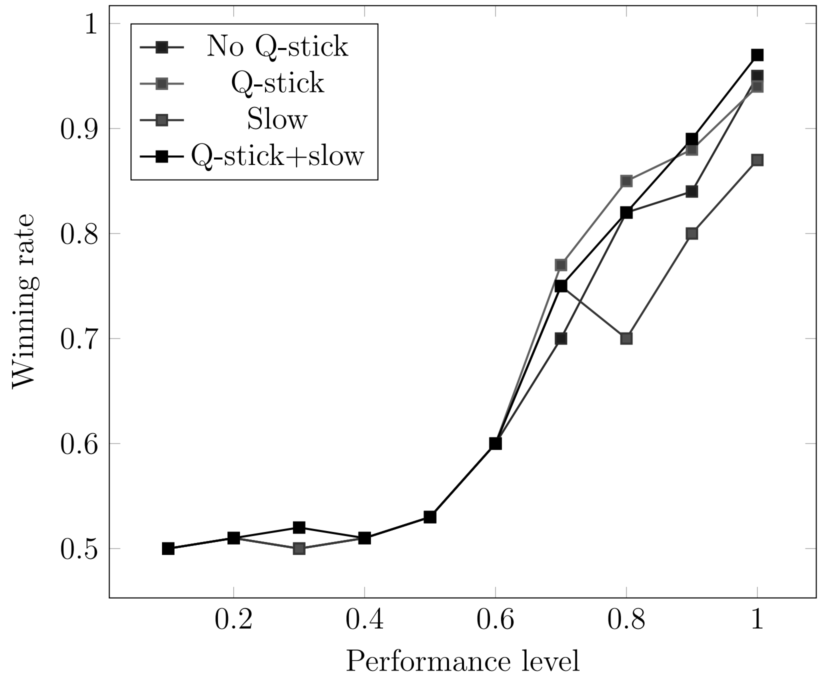


Figure 4-5: Relationship between end-game strategies and refinement measure.

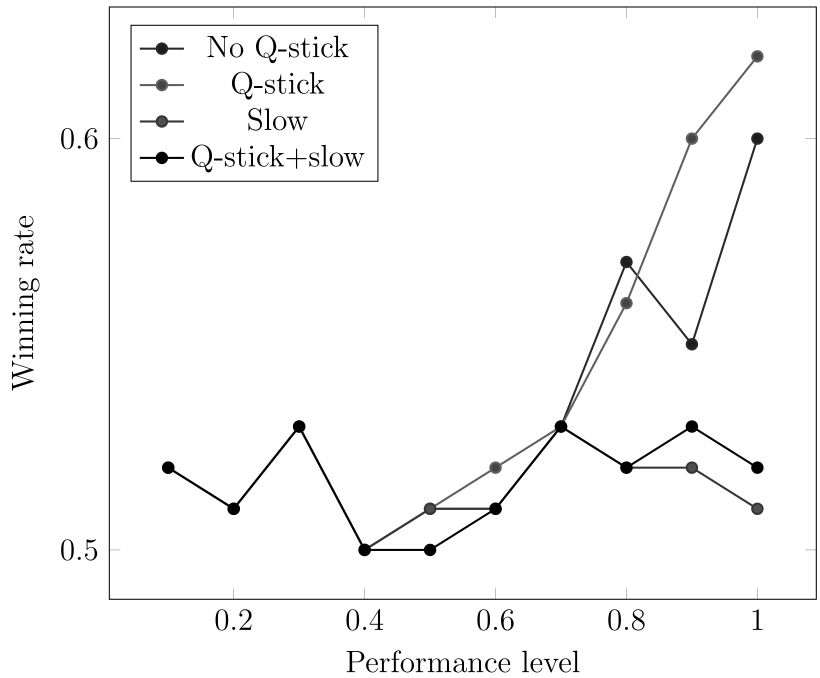
4.5.4 Link between Play Strategy and Fairness

From the entertainment perspective described in the previous section, the combined Q-sticking with a slow endgame strategy was the most sophisticated setting across all Scrabble player performance levels. While this strategy may be sophisticated, investigating its expected fairness and justifying its optimality are the main interests of this study.

Figure 4-6a,b shows the relationship between different endgame strategies and the proposed *dynamic* komi before and after its application. It can be observed that the winning rate of a player at performance level $LV \leq 0.5$ did not differ much before or after the application of the *dynamic* komi. However, the application of *dynamic* komi substantially affected the winning rate of the player with performance level $LV > 0.5$, within the range $\in [0.5, 0.6]$.



(a) Before *dynamic* komi



(b) After *dynamic* komi

Figure 4-6: Illustration of winning rate obtained using different strategies before and after *dynamic* komi was applied.

The application of *dynamic* komi showed that the slow endgame and the combined Q-sticking/slow endgame strategies provided the best fairness (≈50% winning rate).

Aligning with the previous experimental results, the combination of Q-sticking and slow endgame is the most optimal endgame strategy for Scrabble, leading to gameplay that is both entertaining and fair (Figure 4-5).

4.6 Chapter Summary

In this chapter, a new mechanism is proposed for improving the fairness of the Scrabble game, referred to as *dynamic* komi, focusing on three factors: winning rate over different player performance levels, application of komi in different game phases, and optimal end-game strategies. These three factors are equally essential to maintain the expected fairness of a game. As a result, *dynamic* komi provided a much more fair game environment (such as a random initial position like Scrabble), and the experimental results demonstrated that it could be a possible solution for all performance levels of each variant. We also evaluated the effectiveness of *static* komi and found that it has limitations for second player advantage; however, an evaluation in Go proved that *static* komi worked well for games with the fixed initial position.

We also evaluated the effect of play strategy on the sophistication of Scrabble. Our results demonstrated that the mixed end-game strategy called Q-sticking with a slow-end game was sophisticated enough to make the game more interesting and attractive. Furthermore, it was found that the proposed *dynamic* komi provided a feedback mechanism to maintain the perceived fairness of the game in real-time. This mechanism could be a valuable tool for training players and potentially improving engagement in skill learning or acquisition (This mechanism can be observed to provide timely feedback to players in games.). For instance, Pokemon Unite (`https://unite.pokemon.com`, accessed on 25 July 2020), a new multiplayer online battle arena, shows the performance gap of one team against another at a specific time. Nevertheless, this mechanism would affect the psychological aspects of the game for human players, which could be further explored in a future study.

Chapter 5

Huizinga's Homo Ludens Revisited: A New Perspective from Motion in Mind Approach

5.1 Chapter Introduction

This chapter covers research concerning fundamental quantities of fairness in two different contexts: two-person games and n-person games, where the two aspects of fairness framework in a game context for both objective and subjective sense are formalized. The notion of fairness related to the motion-in-mind model and a new measurement of fairness in the domain of two-person competitive games will be included. Following that, the notion of fairness in the domains of n-person games related to economic inequality will be presented. Then, an overview of Huizinga's Homo Ludens Revisited and the current related findings for the link between play, society, and culture and the evolutionary changes from a fairness perspective will be discussed.

5.2 Early Works on Fairness

In this section, we present an overview of early works on fairness in the domain of classical two-person board games such as Chess and Go.

5.2.1 Fairness in Two-Person Games

In the two-person game context, the concept of fairness was discussed where the concept of initiative (which implies the "right" to move first) is a prevailing notion for various two-person zero-sum games to analyze the fairness issues in the game context [115]. For games with three outcomes, possible draws can be easily included in this line of reasoning, stating that first-player wins should abound over the draws and second-player wins, but such reasoning is constrained when the search space is small. From an investigation of solved games, the concept of the initiative seems to be a prevailing notion under the requirement that the first player has sufficient space to fulfill the goals [117], coining the term "advantage of initiatives" [115, 14, 15].

Fairness had been previously discussed where a game is fair if its game-theoretic value is a draw and both players have roughly an equal probability of making a mistake [117]. Another definition of fairness is observed in terms of the evolution of games [55]. Prior work had investigated the definition of fairness, the nature of Scrabble and its underlying fairness mechanism, and its evolution in gameplay via game refinement theory to discover the underlying process of fairness [14, 15, 16]. The reasonable initial position plays a vital role from the artistic perspective to maintain fairness and maximize the formal beauty of the games[54]. When a game is often perceived as a metaphor for various things such as economy and life, an important issue is that all matters must feel fair during the game process. Accordingly, the game development and its refinement process in its long evolution show how fairness can be realized in games, aside from keeping some degree of competitiveness and thrills [55]. Several issues had been raised based on different dimensions of fairness (input, output, experience, knowledge, compute, psychological, and common sense) when a human playing versus a computer agent [24]. Currently, agent ability has featured the propensity of the wealth of information (e.g., look-up tables for opening and endgame) and massive state space simulations (e.g., usage of a forward model), associated with *knowledge* fairness and *compute* fairness, respectively. Inferring human-level intelligence implies an entirely fair competition achievable with an artificial system that is essentially equivalent to a flesh and blood human. With the pervasive of machine learning models and approaches, discrimination against sensitive attributes becomes a critical agenda, where biases need to be detected and guarantee fairness instead of those attributes' importance for prediction [30].

Designing and evaluating fairness in human versus AI in a competition setting was discussed where the claim of superiority of AIs over humans is unfounded until AIs compete with and beat humans in a structurally the same as common human versus human competitions [67]. The notions of game *extrinsic* factors (i.e., competition format and rules) and game *intrinsic* factors (i.e., different mechanical systems and configurations within a game) were introduced. Meanwhile, the effects of framing and perceived vulnerability were examined on dishonest behavior in constant-sum, competitive games where the role of social preferences such as fairness, reciprocity, and altruism in economic decisions was explored [13]. It was found that minor variations of the process (i.e., the harm inflicted on others) can lead to a decreased endorsement of dishonesty and provide a justification to act against their self-endorsed beliefs about fairness; thus, deviating from the fairness norms that they endorse.

To this end, it can be inferred that inequality and fairness are primarily influenced by the perception and context of the subjects in question, and the former may not affect the latter and vice versa. To the best of our knowledge, however, there is no existing study that mechanistically investigates the relations between inequality and fairness in the context of games or gamified activities. As such, in this study, inequality and fairness are considered two different yet interrelated dimensions.

5.3 Research Methodology

In this section, we shortly sketch game refinement theory, the basic concept of motion in mind model, and the Gini coefficient to propose a new measurement of equality and comfort.

5.3.1 Game Refinement Theory

A sophisticated game postulates an appropriate game length to solve uncertainty while gaining the necessary information to identify the winner [59]. The cross-point area between $y(t) = vt$ and $y(t) = \frac{1}{2}at^2$ where $a = \frac{B}{D^2}$ is indicated with noble uncertainty zone of $GR(= \sqrt{a}) \in [0.07, 0.08]$ [58]. It meets fairness, gamified experience, and the sense of comfortable thrill, as depicted in Figure 2-4.

When the game length is too short, it would be unfair to decide the winner. When the game length is too long, it would be boring or non-competitive. It is likely that the GR zone includes a border between fair and unfair, or competitiveness and non-competitiveness. This implies a link between fairness and competitiveness in games.

5.3.2 Motion in Mind Model

The concept of motion in mind revolves around the velocity (v) and mass (m), which can be determined by analogically identifying the winning (or success) rate and winning hardness (or difficulty) [58]. Table 5.1 describes the analogy of the motion in mind in the physics and games context. The basic assumption here is that $v + m = 1$ which is based on the zero-sum assumption [70]. Such an assumption describes the dynamics of challenge and ability experienced by the player.

Table 5.1: Analogical link between physics and game [58]

	Physics context	**Game context**
y	displacement	solved uncertainty
t	time	progress or length
v	velocity	win/scoring rate
m	mass, M	win/scoring hardness
a	acceleration, g (gravity)	acceleration (thrills)
F	Newtonian Force	force in mind
$\vec{p}$	Momentum	Game momentum
E_p	potential energy, U	Game energy

It is important to note that there is a distinctive computation of the v for the board and scoring games [58]. In scoring games, the success rate is defined as $v = \frac{G}{T}$, where G and T are the average successful score and the total scores. Meanwhile, in board games, the success rate is defined as $v = \frac{B}{2D}$ where B is the average branching factor, and D is the average game length.

The notion of energy conservation had been proposed as a potential measure of engagement, where the formulation of momentum in the game ($\vec{p_1}$) and potential energy in the mind (E_p) are given by (5.1) and (5.2), respectively [70]. Then, based on the conservation of energy in mind, given by (5.3), the momentum in mind ($\vec{p_2}$) can be derived, which is associated with the measure of player's engagement, given by (5.4).

$$\vec{p_1} = mv \tag{5.1}$$

$$E_p = ma\left(\frac{1}{2}at^2\right) = \frac{1}{2}ma^2t^2 = 2mv^2 \tag{5.2}$$

$$E_p = \vec{p_1} + \vec{p_2} \tag{5.3}$$

$$\vec{p_2} = E_p - \vec{p_1} = 2m^3 - 3m^2 + m \tag{5.4}$$

Applying (5.4) while assuming $\vec{p_2} = mv_2$, the subjective reward v_2 is given by (5.5).

$$v_2 = 2m^2 - 3m + 1 \tag{5.5}$$

Knowing $2m^2 - 3m + 1 = (1 - 2m)(1 - m)$, we find a relation between objective velocity v and subjective velocity v_2, as shown in (5.6). This relation is generalized as v_k using a parameter (say k where $0 \leq k \in \mathbb{R}$) that is the nature of the game under consideration, as shown in (5.7).

$$v_2 = (1 - 2m)v \tag{5.6}$$

$$v_k = (1 - km)v \tag{5.7}$$

The analogy of gravitational potential energy in the game, denoted as E_p, defines the amount of information required to finish the game or the magnitude of information perceived by the player based on the amount of possibility and magnitude of expectation; thus, associated with motivation [58, 121, 70]. A game that may be perceived to be simple and easy to play may encourage more people to play, but a game that is perceived to be difficult may discourage them from playing. Such a situation is associated with the magnitude of difference between the momentum of the game's motion ($\vec{p_1}$) and the momentum of the mind's motion ($\vec{p_2}$), defining the subjective measures of the motivation in mind (E_q).

An illustration of the various motion in mind measures, relative to the original concept of the motion in mind [58] and energy conservation [70], is given in Figure 5-1.

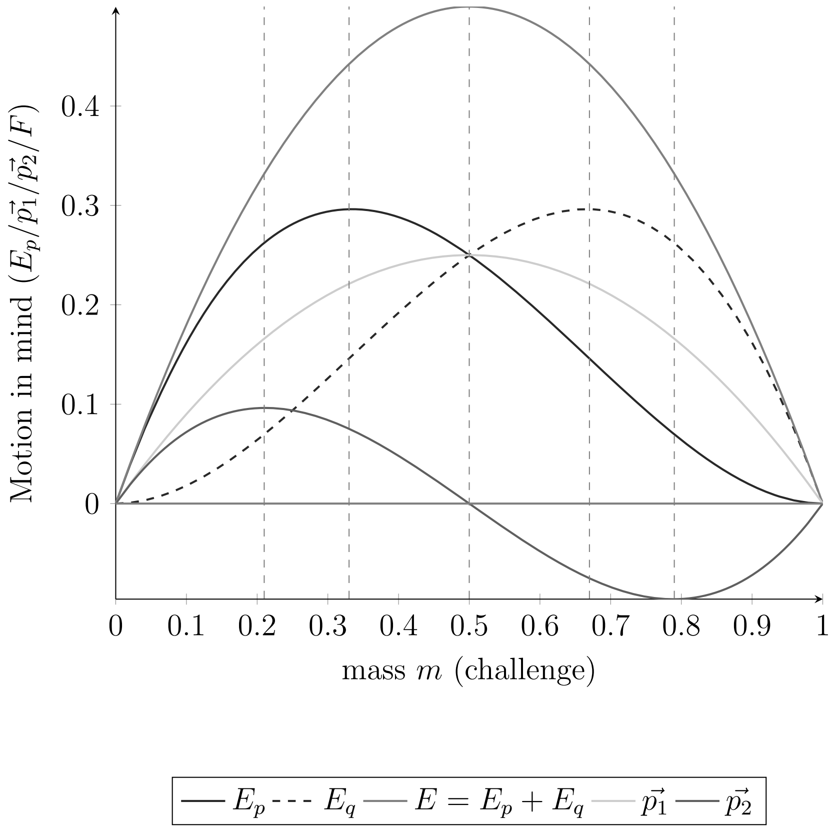


Figure 5-1: Illustrations of the physic analogy that outlined based on the zero-sum assumption where the motion in mind and energy conservation concepts were defined. The notion of motivational potential (E_p and E_q), in-game freedom (E), and player-game motions ($\vec{p_1}$ and $\vec{p_2}$) were introduced. Adopted from [58] and [70]

5.3.3 Gini Coefficient and Economic Inequality

In welfare economics, the Pigou–Dalton principle (PDP) is a principle related to the condition of social welfare functions, which defines that when all other things are equal, a social welfare function should prefer allocations that are more equitable [91, 35]. This is related to an inequality measure to rise (or at least not fall) in response to a mean-preserving spread [64]. In other words, a transfer of some defined variable (for example, utility or income) from the rich to the poor is desirable, as long as it does not bring the rich to a more impoverished situation than the poor. Most measures in the literature, including the Generalized Entropy class (GE), the Atkinson class, and the Gini coefficient, satisfy this principle with the main exception of the logarithmic variance (LV) [33].

The Gini coefficient's closely related economic indicators were the decomposition analysis such as the mean logarithmic deviation (MLD) and the squared coefficient of variation (SCV). A decomposition analysis involves calculating income source based on the proportion of total inequality associated with different income sources (i.e., earnings, property income, public, and private transfers, and taxes), where the proportion is a function of its inequality index, of its share of disposable income and its correlation with disposable income. The MLD and SCV are the decomposition indicators by population groups and by income sources, respectively [64]. Those decomposition formulae of the MLD and SCV were first developed and a ranking consistent is yielded with the Gini coefficients [83, 100, 101].

Gini coefficient (G), also known as the Gini index or Gini ratio, was proposed by Corrado Gini, a famous Italian economist, statistician, and sociologist, as a comprehensive investigation of statistical dispersion intended to represent the income inequality or wealth inequality, [44], in which since then has been an essential international analysis indicator [118]. The Gini coefficient (G) is a popular inequality index mostly associated with the descriptive approach to inequality measurement. The G coefficient is usually defined mathematically based on the Lorenz curve, which plots the proportion of the population's total income cumulatively earned by the population (Figure 5-2). Thus, the line at 45 degrees represents the perfect equality of incomes.

Issues of economic inequality are at the center of politics, and recent studies of attitudes toward economic inequality suggest that people worldwide prefer low levels of inequality,

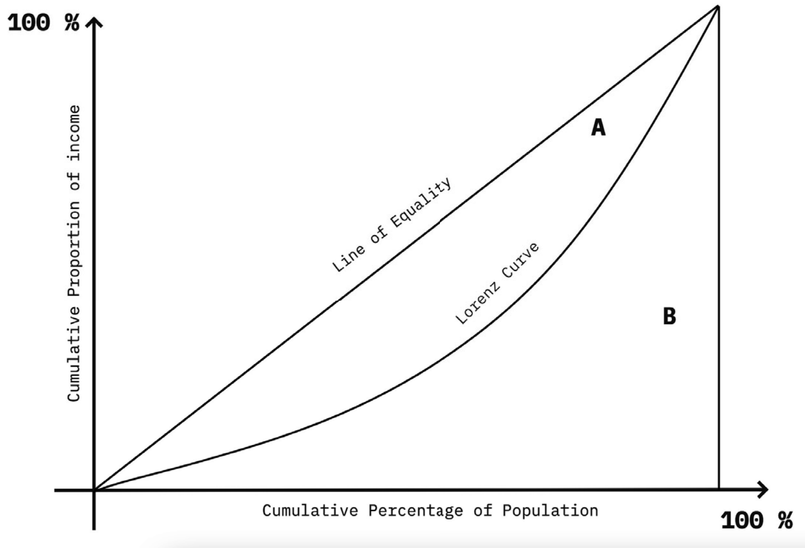
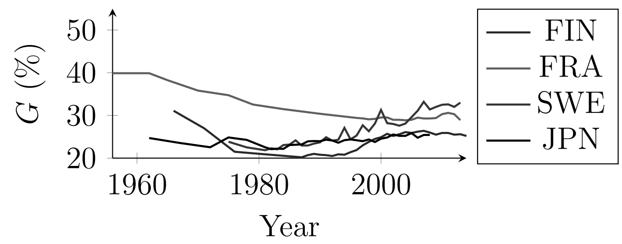


Figure 5-2: Graphical representation of the Gini coefficient (G): G coefficient is equal to the area marked A divided by the sum of the areas marked A and B, that is, $G = \frac{A}{A+B}$. It is also equal to 2A and to $1-2B$ due to the fact that $A+B = 0.5$ (since the axes scale from 0 to 1).

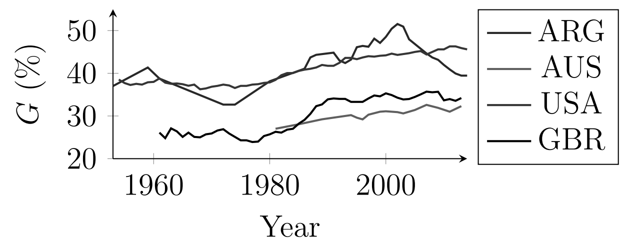
despite well-known trends toward greater inequality within many countries [89]. Income inequality has constantly been increasing since the early 19$^{\text{th}}$ century when considering the income distribution of all people worldwide (Figure 5-3). The global income inequality was observed based on the G score exhibited a steady increase between 1853 to 2002 and a significant increase between 1980 and 2002. The trend appears to have peaked and begun a reversal with rapid economic growth in emerging economies, particularly in the large populations of the BRIC[1] countries [82].

Agreement on the ideal level of economic inequality, regardless of the measures, is typically influenced by the underlying effects of "anchoring" and "bias," ultimately changing and steering the people's perception and judgment [89]. In the perspective of the ideal level of economic inequality, the potential anchor is the perceived level of the current economic indicator (i.e., G score). In contrast, the potential bias is the resulting ratio between two numbers that induce meaningful attitudes towards inequality (i.e., monetary versus multiplier comparison). Meanwhile, societal characteristics can be better understood in which economic inequality critically interacts with the way institutions function and adapt to changes, while the capacity to implement effective coping mechanisms and

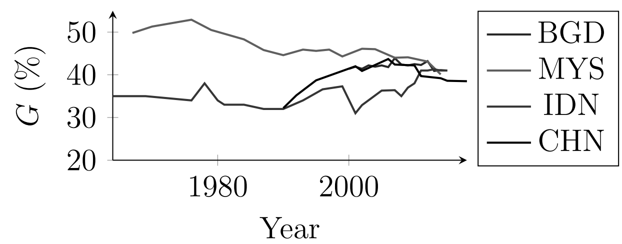
[1]An acronym for the economic bloc of countries consisting of Brazil, Russia, India, China, and South Africa



(a) Gini coefficient for Finland, France, Sweden, and Japan



(b) Gini coefficient for Argentina, Australia, United States, and United Kingdom



(c) Gini coefficient for Bangladesh, Malaysia, Indonesia, and China

Figure 5-3: The world since 19th Century as described by Gini coefficient for (a) level 1: European countries and Japan, (b) level 2: Developed countries, and (c) level 2: Asian countries adaptive strategies is strictly dependent on community resilience [116].

Although the Gini coefficient is a popular index in economics, it can theoretically be applied in any science field that considers a distribution. It has also been used to quantify biodiversity in ecology, where the cumulative proportion of species is plotted against the cumulative proportion of individuals [90] and monitoring the emission of potent greenhouse gas [94]. It has also been adopted to evaluate the inequality of health-related quality of life in a population [12, 40, 7], and measure the inequality of universities [47], and regional development [103]. Gini coefficient has been used in chemistry to express protein kinase inhibitors' selectivity against kinases [46], in engineering to evaluate the fairness achieved by an internet router in scheduling packet transmissions from different traffic flows [98], and in decision-making for task allocation of multi-robot systems with limited energy [118]. It has also been used to measure the discriminatory power of rating systems in credit risk management [29].

A study suggests that inequality increases risk-taking because individuals selectively make upward social comparisons, independent of their resources and relative standing [88]. It has been shown that inequality reflects structural economic forces and behavioral responses to unequal economic contexts where inequality in outcomes becomes self-perpetuating due to preference over high-risk options (i.e., significant gains for a few individuals but losses for most). The effect of one's income also determines the level of happiness because of their comparison to others in the same gender-ethnic group, highlighting the importance of social comparison [77]. It was previously established that social comparison effects are consequential when one's referents are those close in social, structural, and physical distance, especially when inequality is greater. Another empirical study had shown that people tolerate more income inequality in countries with more actual inequality, where high-inequality countries accept almost four times more income inequality than otherwise similar low-inequality countries [96].

Income inequality was also associated with increased mistrust and increased anxiety about social status, which explains some of the resulting adverse outcomes such as lower happiness, lower social cohesion, weaker morality, higher mortality, worse health, and weaker governance [23]. However, it was scrutinized that fairness and equality differ where most findings were consistent with both a preference for equality and a preference for fairness since the studies are designed so that the equal outcome is also the fair one [109]. Fairness and equality typically arise from normative evolutionary traits, the propensity of rewards and punishments, and acts of selfishness; thus, implying the importance of fairness rather than equality.

5.4 The Proposed Assessment Method

In this section, we propose the measures of equality and comfort with a focus on the difference between objective and subjective ones, in order to identify the link between play, culture, and society.

5.4.1 New Measure of Equality and Comfort

Game is defined as *Variable Ratio* of the reinforcement schedule $VR(N)$ where N stands for the reward frequency [121]. Following the motion in mind model [58], $v = \frac{1}{N}$ is defined as the velocity of an expected reward or the rate of solving uncertainty. Mass is the winning hardness, defined as $m = 1 - \frac{1}{N}$. Hence, (5.8) is obtained to describe the relations of v and m.

$$v_0 + m = 1 \tag{5.8}$$

Given parameter k with $0 \leq k \in \mathbb{R}$, reward function v_k is given by (5.9), it satisfy v_0 as given by (5.8). v_0 and v_k corresponds to the objective reward (i.e., game-theoretical value) and subjective reward, respectively [70].

$$v_k = (1 - km)v_0 \tag{5.9}$$

Let δ_k be the difference between objective reward v_0 and subjective reward v_k, which defines the momentum of play, as given by (5.10).

$$\delta_k = v_0 - v_k = kmv_0 = k\vec{p} \tag{5.10}$$

δ_k in (5.10) represents the intensity of the game's motion or swing frequency of the score during a game, which is an important aspect of the game's nature, denoted as the momentum of play. δ_k would be higher (lower) in a stochastic (deterministic) game. It also corresponds to a non-competitive (competitive) game. This implies that the player would seek a good balance between deterministic and non-deterministic nature, or between skill and chance.

In addition, the game could produce a potential energy of play by which the player would feel engagement or reinforcement. Potential energy of v_0 (objectivity) and v_k (subjectivity) in the motion in mind is given by $E_0 = 2mv_0^2$ and $E_k = 2mv_k^2$, respectively. In this study, E_0 and E_k are denoted as objective reinforcement and subjective reinforcement, respectively.

Classical board games such as Go, Chess, and Shogi were thought to be sophisticated since they have been continuously developed and survived over more than a thousand years of history [60, 31]. Such sophisticated and competitive games are played worldwide by various level players, from novices as mass entertainment, to grandmasters as professional mind-sports athletes. This implies in the motion in mind context that such a game (having its mass m_y) postulates a fundamental characteristic that the objective reinforcement meets the subjective reinforcement, i.e., $E_k(m_y) = E_0(m_y)$.

Table 5.2: Social comfort and play comfort

N	k	m_k	m_y	Games/Sport
5	2.5	$\frac{2}{5}$	$\frac{4}{5}$	Western chess
3	3.0	$\frac{1}{3}$	$\frac{2}{3}$	Japanese chess (Shogi)
2	4.0	$\frac{1}{4}$	$\frac{1}{2}$	Modern sport (i.e. Table tennis)
$\frac{5}{3}$	5.0	$\frac{1}{5}$	$\frac{2}{5}$	Go

Conjecture 1 ***Gaming comfort*** *is given by a harmonic balance between competitiveness and entertainment, which is determined as the cross point m_y between the objective and subjective reinforcement where $E_0(m_y) = E_k(m_y)$ holds.* ***Gaming culture*** *is characterized by its gaming comfort.*

Table 5.2 describes the connection between social comfort and play comfort based on the N, E, and m, together with example games/sports. Focusing on the subjective reinforcement, $E_k = 0$ holds at m_x. This situation reflects that social comfort is highest due to its equality since the majority of the people in the society would behave altruistically to

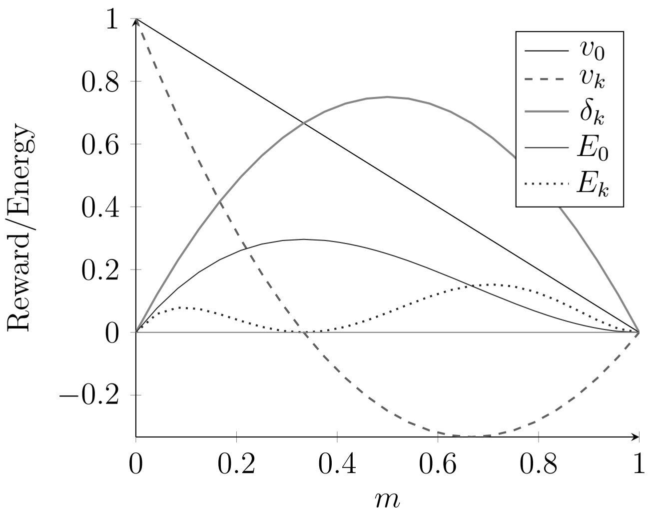


Figure 5-4: Measures of motion in mind for $k = 3$

maintain equality. In contrast, $E_k = 1$ at $m_x = 0$ which implies people would follow egoism or liberal economy to maximize their own benefit. In such a case, the society would be most competitive, and serious disparity problems would occur. Hence, society needs to consider a good balance between equality and competitiveness. Meanwhile, seeking $E_k = E_0$ at m_y would lead to a game that is purely objective from the competitive context where playing the best move is strongly expected or enforced. Figure 5-4 illustrates the motion in mind measures for the case $k = 3$, in which $E_k = 0$ at $m = \frac{1}{3}$ designated the highest social comfort while maintaining the equality as n-person cooperative game.

The notion of game comfort enables the determination of the parameter k of reward function v_k which corresponds to the player's model. Then, it is expected that such a player's model reflects the gaming culture. Considering the link between gaming culture and society, Huizinga Johan pointed out in his book "Homo Ludens" the importance and reality of the play element in culture and society while suggesting that play is primary to and a necessary (although not sufficient) condition of the generation of culture [51]. Following Huizinga's hypothesis, gaming comfort must be related to the cultural issues in a society with respect to the perspective of competitiveness (equality/disparity) and entertainment. The notion of gaming comfort is given in the competitive context ($v_k < 0$), whereas the notion of social comfort is given in the non-competitive context ($v_k \geq 0$).

Conjecture 2 ***Social comfort*** *is influenced by the corresponding gaming culture (m_y), which is determined as the game where $v_k(m_x) = 0$ (fully equal reward when n approaches* *to the infinity) and $E_k(m_x) = 0$ (altruism) hold. Society, as a n-person cooperative game, is characterized by social comfort (m_x).*

Fairness in an n-person cooperative game is realized when the individual reward v_k is given by $v_k = \frac{v_0}{n}$ which obtained $m = \frac{n-1}{kn}$. For the case of a huge number n, the limit of m_x is approximated as (5.11). It is reasonably expected that people in a society would feel comfortable at m_x due to its full equality in the n-person cooperative games. In case, altruism can be observed which is given by no subjective reinforcements ($E_k = 0$) at m_x.

$$m_x = \lim_{n\to\infty} m_F = \frac{1}{k} \tag{5.11}$$

However, people in society might not always be so altruistic, but might be egoistic while following the liberal economy or so. As such, this leads to a definition given by g which is denoted as an equality ratio, given by (5.12).In such a condition, people would feel social comfort when $g = 0$, but discomfort when g becomes larger. This condition implies there is a cultural transition occurred, and it will affect the original gaming culture as well. It shows a possible interaction between gaming comfort (i.e., gaming culture) and social comfort in history. One possible way is to have the same competitiveness level in both society and competitive games.

$$g = \frac{v_k}{v_0} \text{ where } 0 \leq g \leq 1 \tag{5.12}$$

Conjecture 3 *People in society would feel comfort depending on the inequality ratio g. A smaller (larger) ratio gives higher (lower) comfort. This implies that social comfort is given by a harmonic balance between the cooperative mind (altruism) and the competitive mind (egoism).*

Solving (5.9) and (5.12), (5.13) was obtained.Consider when $\Delta_k(m_c) \leq \Delta_k(m)$, in which m_c is a (negative) peak of Δ_k. Then, it was found that it was approximate to the $m_c = 0.8$ when $k = 3$, which is the mass of Chess. This condition implies that society must be less competitive than in highly competitive games such as Chess, where $g \leq 0.4$ when $k = 3$. As such, g is likely to share similarity to the measure of the Gini coefficient, G.

$$m = \frac{(1-g)}{k} \tag{5.13}$$

5.5 Computational Results and Discussion

In this section, we present the analysis of the evolutionary changes of various games using the proposed measures. Then, we identify the link between play, culture, and society, as claimed by Huizinga's Homo Ludens concerning the interaction between play comfort in gaming culture and social comfort.

5.5.1 Huizinga's Homo Ludens Revisited

Revisiting the term, "Homo Ludens," as it translates as "Man the player," involves focusing on the element of play as a significant recipe of a cultural phenomenon [51]. Based on the mechanistic framework of motion in mind model in the perspective of equality (or disparity), such conditions were true in the game-playing context, where entertainment and competitiveness were found to shape society's culture according to the board game design that evolved throughout time. In such respect, several measures were introduced, derived from the motion in mind model, reflecting cultural transitions within society from disparity (or cooperative) to comfort (or competitive), or vice versa.

As Table 5.3 and Table 5.4 show the trends of evolutionary changes from classical board games with a focus on the gravity of play where the measure of fairness using the proposed inequality indicators, δ_k, and g were adopted. It can be observed that the trend δ_k is decreasing (towards more equality) in Chess history. However, the opposite was observed (increasing) in the domain of Go. Go is the oldest board game with more than 4000 years of history [102], which was developed around 2500 years [124]. Its development had been observed to change from $\delta_k \approx 1.217$ to $\delta_k \approx 1.194$, with $g \approx -1.92$ to $g \approx -0.97$, respectively (Table 5.3). This condition suggests that players seek conservative activities with a good balance between deterministic and non-deterministic activities in nature. Such an environment promotes increasingly stable conditions (reducing δ_k) and knowledge-driven choices (based on its increasing B; more options per move).

Based on the Chess historical development in Table 5.4, It can be observed that chess has an evolutionary history of about 1200 years from its first descendant (Chaturanga) to modern western chess about 1600 years ago[86]. Its development is observed to change from $\delta_k \approx 0.127$ to $\delta_k \approx 0.284$, with $g \approx -1.36$ to $g \approx -1.16$, respectively as shown in Table5.4.During this time, the evolutionary directions of Chess are in contrast to the Go, where the culture promotes stochastic nature (high δ_k), albeit knowledge is valued (small increase in B; more options per move).

Table 5.3: Measures of fairness for Go evolutionary changes (original data adopted with permission from [124])

Board size	**B**	**D**	v_0	v_k	δ_k	g	E_0	E_k	Δ_k	m
9×9	52.1	62.06	0.419	-0.798	1.217	-1.92	0.204	0.739	0.534	0.58
13×13	107.4	105.73	0.507	-0.741	1.249	-1.46	0.253	0.541	0.287	0.492
15×15	152.3	145.31	0.524	-0.723	1.247	-1.37	0.261	0.497	0.236	0.475
17×17	203.4	175.51	0.579	-0.638	1.21	-1.1	0.282	0.343	0.061	0.42
19×19	255.5	210.90	0.605	-0.588	1.194	-0.97	0.289	0.272	0.016	0.394

*B = branching factor; D = game length

Meanwhile, in the historical development of Chess in Table 5.4, it can be observed that Chess has an evolutionary history of about 1200 years from its first descendant (Chaturanga) to modern western Chess about 1600 years ago [86]. Its development is observed to change from $\delta_k \approx 0.127$ to $\delta_k \approx 0.284$, with $g \approx -1.36$ to $g \approx -1.16$, respectively (Table 5.4). During this time, the evolutionary directions of Chess were in contrast to Go, where the play culture promotes stochastic nature (increasing δ_k), albeit knowledge is valued (small increase in B; more options per move). Interestingly, g

Table 5.4: Measures of fairness for Chess evolutionary changes (original data adopted with permission from [31])

	B	**D**	v_0	v_k	δ_k	g	E_0	E_k	Δ_k	m
Chaturanga	19.00	176.00	0.054	-0.073	0.127	-1.36	0.005	0.01	0.004	0.946
Shatranj	19.20	222.30	0.043	-0.06	0.261	-1.39	0.003	0.006	0.003	0.956
Medieval I	20.20	230.60	0.044	-0.06	0.261	-1.39	0.003	0.007	0.003	0.956
Medieval II	21.00	217.50	0.048	-0.066	0.262	-1.37	0.004	0.008	0.004	0.951
Medieval III	20.80	185.30	0.056	-0.076	0.264	-1.35	0.005	0.011	0.005	0.943
New Chess	26.70	100.90	0.132	-0.154	0.283	-1.16	0.03	0.04	0.011	0.867
Chess	27.00	100.10	0.135	-0.156	0.284	-1.16	0.031	0.042	0.011	0.865

*B = branching factor; D = game length

was increasing for both Go and Chess evolutionary changes. This situation reflects that society, albeit taking different routes in optimizing play experience and activities, slowly transitions towards having better equality, albeit being competitive (or conservative). Based on these two board games, their evolutionary changes showed a harmonic balance between E_0 and E_k ($\Delta_k \to 0$), where the gaming comfort is reached, forming its gaming culture. Regardless, increasing Δ_k for Chess evolution implies the gaming culture of Chess that optimizes the subjective reinforcement dominates over the objective one in the competitive game context (high motivation to play competitively). Meanwhile, the gaming culture of Go involves maximizing the fairness in the play interactions due to the massive gaps between the objective and subjective information (highest δ_k) while optimizing the play engagement (i.e., reducing the Δ_k trend).

Meanwhile, a popular sports game, such as Soccer, was also analyzed to observe the evolution of δ_k. The data from the world's league Soccer games were collected (FIFA [80]), where G is the average shots (or scores), and T is the average total shots attempts (or tries) given in Table 5.5. Minor incremental changes of δ_k were observed, implying that Soccer is becoming more stochastic (highest $\delta_k \approx 0.55$), where people would feel more comfortable due to its fairness (or somewhat unpredictable) game mechanism than other classical board games. Such property would also typically be found in other team-based, two-sided, fast-paced sports, where the game outcomes are unpredictable and highly competitive (e.g., Table tennis [65]).

Table 5.5: Measures of fairness for Soccer games development variants

FIFA (Year)	**G**	**T**	v_0	v_k	δ_k	g	E_0	E_k	Δ_k	m
2010	2.27	21.4	0.106	-0.273	0.379	-2.57	0.02	0.133	0.113	0.893
2014	2.67	31.6	0.08	-0.22	0.309	-2.66	0.013	0.092	0.079	0.915
2018	2.64	15.8	0.16	-0.389	0.55	-2.33	0.046	0.252	0.206	0.832

*G = average goals; T = attempted goals

In the n-person cooperative games with large n (like society or nation), it is observed that people in a society such as the countries with small g (e.g., SVN, NOR, FRA, JPN) would feel the highest equality where their δ_k value is maximized (Table 5.6). On the other hand, with its smallest g value, Slovakia shows that society is characterized by social comfort where the lowest v_k and E_k values hold. Moreover, the dynamic of objective reinforcement/motivation (E_0) was shown to be high when g is low, implying the resulting Δ_k balances people's competitiveness (towards economic growth) and reinforcement/motivation in living or enjoying various activities in the society (or stay playing in the game).

Table 5.6: Interpretation of Gini Coefficient g with its relative to various physics in mind measures for various countries

Countries	Gini Coefficient g	v_0	v_k	δ_k	E_0	E_k	Δ_k	m
SVK	0.22	0.74	0.1628	0.577	0.285	0.013	0.27	0.26
NOR	0.262	0.754	0.197	0.556	0.279	0.019	0.26	0.246
FRA	0.292	0.764	0.223	0.54	0.275	0.023	0.252	0.236
JPN	0.33	0.779	0.264	0.51	0.267	0.307	0.237	0.22
CHN	0.385	0.795	0.306	0.488	0.259	0.038	0.22	0.205
IND	0.39	0.797	0.311	0.485	0.258	0.039	0.218	0.203
MYS	0.41	0.803	0.329	0.473	0.253	0.043	0.211	0.193

*g = Gini Coeficcient

In essence, it can be observed that a strong link between play, culture, and society existed, as claimed by Huizinga's Homo Ludens by observing that fairness/equality is cultivated while incorporating the cultural interactions between comfort (of play) in gaming and comfort (in social) in society. As such, the generalized measures of motion in mind model were identified and summarized in Table 5.7.

5.5.2 Identifying a link between Play, Culture, and Society

It can be observed that fairness is essential in a competitive setting (such as two-person games like chess). In contrast, it is observed that equality is fundamental in the domain of n-person games while keeping freedom, such as the economics of society. Such a condition suggested that there is a possibility to derive a standard measure of fairness/equality that can fit various n-person games. The design of a sophisticated game postulates the maintenance of fairness/equality in a good way. This concept has been changed in history according to people's playing ability and environmental influences. In competitive board games, several enhancements have been observed throughout their evolutionary changes that incorporate engagement while maintaining fairness [15, 16]. For instance, the draw rate has been increased in Chess competition to reduce the advantage of initiative, whereas *komi* (compensation) was introduced and repeatedly updated in the history of Go [124, 125].

However, such concepts were more complicated in n-person games like economics in society. The comparison between play (e.g., two-person competitive games) and society (economic game as the n-person game) using fairness/equality measures was found to share similar increasing trends (or decreasing of unfairness/inequality), albeit differ based on specific external needs. Moreover, several forms of ideas were proposed throughout history to maintain fairness in competitive games and social equality (i.e., the development of Go rules was influenced by the historical progression of the region and societal conditions [125]). Therefore, it is reasonable to consider the shared artifacts (such as the Go board game associated with Chinese, Korean, and Japanese) that directly interact with society and people of a certain period and environment as the tool to determine the development of fairness. The issue of fairness is not foreign, especially considering equality within the context of a functional society. People need to enjoy their freedom or chances to sufficiently show their strength [88]; otherwise, they will be less motivated or less engaged in societal activities (e.g., social acceptance and comparison [77]). This situation implies that disparity will appear due to the variety of skill differences, which in a real-world context, could lead to various psychological feedback [23], such as dishonesty [13] and selfishness [109]. Thus, it is crucial to have a good balance between skill and chance, or competitiveness and equality, in which the essential ingredients involves maintaining the fairness that reinforces the sense of engagement in such activities (both in games or society).

Table 5.7: Generalized interpretation of play comfort and social comfort

Range	$m^\star$	Implication	Context	Example
$E_k = 0$	$\frac{1}{3}$	Social Comfort	n-person cooperative game	Society (perfect equality)
$\max \Delta_k$	$\frac{1}{2}$	Fairness Comfort	2-sided stochastic game	Soccer
$E_0 = E_k$	$\frac{2}{3}$	Play Comfort	2-sided harmonic game	Shogi
$\max E_k$	$\frac{4}{5}$	Competitive Zone	2-sided competitive game	Chess

*: Approximated value;

Moreover, considering the development of games and society, playing is a good practice or informative way to learn the mechanism involved in maintaining fairness or equality involving diverse and complicated situations concerning societal culture and diverse economic preferences. A different perspective of fairness was cultivated in the playing context [115, 55, 13, 24, 14, 67, 30], which were translatable to the social context in which the society is inciting the game-playing culture towards a fair play. Thus, there is a link

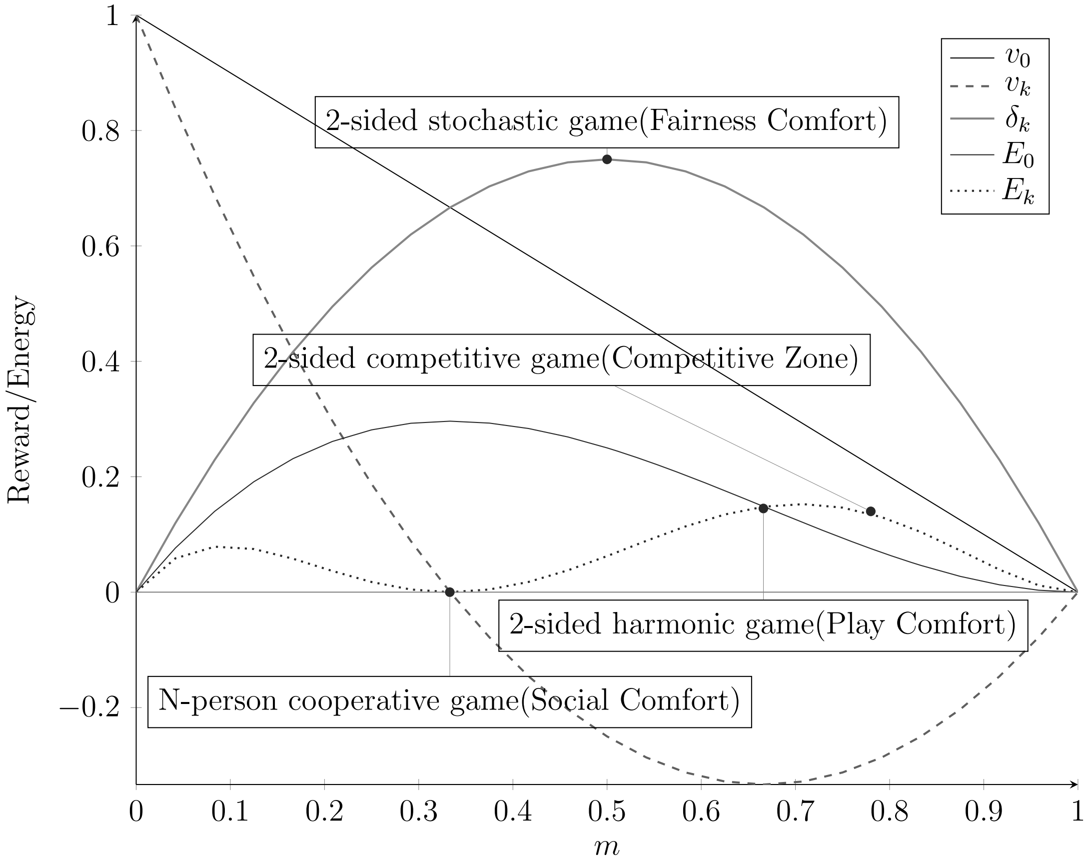


Figure 5-5: Interpretation of play, social and fairness comfort

between play, culture, and society, as Huizinga's Homo Ludens claimed several decades prior.

5.6 Chapter Summary

Our proposed measurement indicates the competitiveness of a game state getting to a balanced state with focusing on fairness. Understanding essential components in games enables people to develop the sophisticated game mechanisms in the play context and expand such ideas leading to other domains such as entertainment, economics, and education. Furthermore, observing gaming comfort and social comfort highlights another aspect where the balance between competition and entertainment affects the game's culture and society, respectively. This condition shows that regardless of the number of players and context, our proposed measurement can be an indicator for analyzing the balance between competitiveness(equality/disparity) and entertainment while seeking fairness in the corresponding context (games/society).

Chapter 6

Conclusion

Understanding essential components in games enables people to develop the sophisticated game mechanisms in the play context and expand such ideas leading to other domains such as entertainment, economics, and education. In this thesis, we are initially focusing on the advantage of initiative from two aspects: the size of the search space (board size) and the performance level of AI players using Scrabble as a test bed. Employing the search space reduction of the game by reducing the board size to 13×13 leads to the possible enhancement that maintains fairness in Scrabble. A new mechanism is proposed for improving the fairness of the Scrabble game, referred to as *dynamic* komi, focusing on three factors: score rate over different player performance levels, application of komi in different game phases, and optimal end-game strategies. Experiment with *dynamic* komi shows that these three factors are equally essential to maintain the expected fairness of a game. As a result, *dynamic* komi provided a much more fair game environment (such as a random initial position like Scrabble), and the experimental results demonstrated that it could be a possible solution for all performance levels of each variant. The mixed end-game strategy called Q-sticking with slow-end game was sophisticated enough to make the game more interesting and attractive.

To generalize fairness measurement, we analyzed the evolutionary changes from two-person classical board games by demonstrating the competitiveness of a game state getting to a balanced state with focusing on fairness. Observing the objective reinforcement Δ_k trend highlights another aspect where the balance between competition and mass entertainment affects the game's result. We expanded into society context which is an n-person cooperative game by establishing the link between play, culture, and society. This condition shows that regardless of the number of players and context, our proposed measurement can be an indicator for analyzing the harmonic balance between competitiveness and entertainment while seeking fairness in the corresponding context (games/society). This indicates that fairness plays a crucial role in the game that gives a balance between competitiveness and entertainment.

Research carried out in the scope of this thesis is guided by the following objectives: (1) To find the impact of advantage of initiative over different performance levels and changes in the search space, (2) To define the gamified experience and notion of fairness, and (3) To identify the link between play, culture, and society by proposing the new measurement of equality and comfort.

The answer to the first question was obtained by using games as test beds to characterize the advantage of initiative and the notion of fairness. The link between the search space and the quality of players was investigated where 13×13 board size is suitable enough to keep the balance of the information about the game outcome is not clear at the very end of the game. The experiments show that the winning percentage of the player who is established in the first stage is higher than the opponent when the level of the player is between 0.6 and 1. Besides, considering the search space reduction of the game by reducing the board size to 13×13 as the possible enhancement that maintains fairness in Scrabble may be short-lived. Interestingly, reducing the board size can significantly provide fair gameplay for both players until the end of the gameplay. However, the 15×15 and 17×17 board sizes of Scrabble do not solve the AoI issue. One reason for this is that no matter how strong the player (in this context, the ability to look ahead of the game board states), the possible winning position is limited due to the limited positions of the board itself.

The second and third objectives are closely related to one another. The link between play, culture, and society is observed as Huizinga's Homo Ludens claimed from the experimental results of our research. In the domain of the two-player game, the draw rate has been increased in chess to reduce the advantage of the initiative, whereas komi was introduced and repeatedly updated in the history of Go. It is more complicated to do so in n-person games like economics. On the other hand, people need to enjoy their freedom or chances to sufficiently show their strength. Playing is good practice or informative to learn how to maintain fairness/equality in such complicated situations affecting their play culture and society. The comparison between play (e.g., two-person competitive games) and society (economic game as the n-person game) using fairness/equality measurement shows some similarity. The fairness perspective is cultivated in the game context, which translates to the social context, i.e. society is influenced by such a fair play perspective by observing the gaming comfort and social comfort which indicates the balance between competition and entertainment. In the end, we can conclude that fairness plays an important part in game playing as well as society, even more, it has been fundamental in both competition and entertainment measures, as it impacts both the quality of games as well as the quality of people's lives.

Future works in this research direction are: (1) exploring the application of the proposed motion in mind model in measuring the fairness/equality in organizational settings (i.e., business or government institutions) with a small to a medium number of people cooperating (group-driven) for a given task yet competing against the rival organization. (2) further investigation of the proposed measurement which includes comparing other economic and non-economic indicators and adopting the measure for other historical development of games (puzzle games, video games, sports, etc.) to determine the underlying influences on their cultural and societal counterparts.

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