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Doctoral Dissertation

Using Games to Study Psychological Aspects based on Variable Ratio Reinforcement Schedule

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Abstract

The Japanese proverb "好きこそ物の上手なれ" means "What one likes, one will do well." Arnold J. Toynbee referred to a related issue when he said: "The supreme accomplishment is to blur the line between work and play". Gamification is the strategic attempt to enhance systems, services, organizations, and activities by creating similar experiences to those experienced when playing games. Reward mechanisms are the most important part of this, with studies in animals showing that reward is associated with the activation of multiple dopamine systems and the orbitofrontal cortex. Unlike animals, humans are adept at predicting how reward signals will occur, so the uncertainty associated with reward mechanisms is even more difficult for humans to control. Uncertainty about not getting a reward causes people to produce more dopamine and thus more pleasure, which leads to a more robust reinforcement of the player feedback mechanism. This effect of reward uncertainty has been suggested to explain why humans are attracted to gambling and games of chance. However, it is difficult to quantify this pleasure and feeling based on this uncertainty, making it difficult to apply it precisely to reward mechanisms in various fields such as gaming, education and business.

An important question that needs to be answered is how to effectively increase the comfort and motivation of players in a way that can be maintained over time. In order to accomplish this objective, it is necessary to investigate the player's psychology and quantify the motions in mind. In the past, researchers have been able to successfully develop a model of motion in mind that is based on the motor actions that take place during play. However, additional research is required to find generalizable patterns for it.

This dissertation proposes a player satisfaction model that has been validated based primarily on variable ratio schedules with the definition of velocity in motion in mind model. It proposes to view gaming as a learning process, where players master the rules of the game by learning and adapting. The reward frequency variable is proposed in terms of the unpredictability of rewards in terms of acceleration or 'gravity' in the mind, analogous to the acceleration of gravity on the earth. The model establishes a relationship between the effort a player must make and the level of challenge of the game and calculates the gravity associated with various games as they evolve throughout history. The difference between intuitive and real likelihood, expressed by the positive energy differential, was discovered to be the source of player incentive. This dissertation examines how game refinement theory and the motion-in-mind model can be used to analyze energy changes and energy flows between games and players. Additionally, it proposes a new approach to unlock the harmonious relationship that exists between the game and the player by balancing the weights of player satisfaction and pleasure. The primary focus of the analysis is on applications not only in games but also in non-gaming domains such as autopilot and addiction, both of which are highly driven by the subjectivity of the player.

Keyword: *game uncertainty, player psychology, game refinement theory, schedules of reinforcement, motion in mind*

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Chapter 1

Introduction

1.1 Chapter Introduction

There is a well-known Japanese proverb, “好きこそ物の上手なれ” , which means What one likes, one will do well. In a similar vein, the British historian Arnold J. Toynbee referred to a related issue when he said: “The supreme accomplishment is to blur the line between work and play”. How can the line between work and play be blurred? Game is a good way to go about solving this problem and always be applied for enjoyment, educational method, business marketing etc domain. The way which uses game to drive the player/user attractiveness is called gamification. Gamification is the strategic attempt to enhance systems, services, organizations, and activities by creating similar experiences to those experienced when playing games in order to motivate and engage users [50]. This is generally accomplished through the application of game-design elements and game principles (dynamics and mechanics) in non-game contexts [37] [107].

But why such mechanics are so enjoyable and appealing to humans requires a deeper understanding of the game’s mechanics. Reward mechanisms are undoubtedly the most important part of this, with studies in animals showing that reward is associated with activation of multiple dopamine systems and the orbitofrontal cortex, and in humans, functional magnetic resonance studies have produced type of results based on reward-related activity causing activation of the striatum and orbitofrontal cortex. Unlike animals, however, humans are adept at predicting how reward signals will occur, so the uncertainty associated with reward mechanisms is even more difficult for humans to control. Even though the objective rewards are actually food, survival conditions, etc., the subjective rewards in humans are all pleasurable, and people have evolved over time a mechanism for obtaining pleasure, where different behaviours stimulate the secretion of dopamine in the part of the brain responsible for providing the reward, thus making people feel happy subjectively. This mechanism makes people's behaviour associated with pleasure, prompting more of such behaviour to be performed. At the same time, uncertainty thus establishes a corresponding incentive relationship with dopamine. Uncertainty about not getting a reward means that people's predictions of rewards accumulate as their behaviour increases, and uncertainty causes people to produce more dopamine and thus more pleasure, which leads to a more robust reinforcement of the player feedback mechanism. People's anticipation of the unknown promotes dopamine secretion that allows pleasure to arise.

Unfortunately, the effects of this uncertainty on humans cannot be fully quantified and clearly understood. Neuroscientists found that reward uncertainty appears to increase the types of dopaminergic responses associated with motivation [17]. This effect of reward uncertainty has been suggested to explain why humans are attracted to gambling and games of chance [115] This uncertainty reward has been seen as an important and enjoyable aspect of the challenge. However, it is rarely defined how to adequately quantify this pleasure and feeling based on this uncertainty. It is therefore difficult to apply it precisely to reward mechanisms in various fields such as gaming, education and business.

In this chapter, we will first discuss the history of the game as a testing ground for game mechanisms, as well as how it affects playful performance. As the primary focus of this thesis is on analyzing the psychological impact of the uncertainty reward on players and analyzing the results to see how it affects the measure of entertainment, we provide an overview of the reward reinforcing the psychological impact and measurement of players. Finally, we summarize our contributions and outline the contents of this thesis.

1.2 Historical Overview of Game and Game Psychology

Game is playing an important role in our daily life. It is human nature to seek pleasure. Actually, before the emergence of human civilisation, there are already many games that existed in secular life long, they have occupied an irreplaceable place in the long history of human civilisation. Common features of games include uncertainty of outcome, agreed-upon rules, competition, separate place and time, elements of fiction, elements of chance, prescribed goals and personal enjoyment[1].

The history of games goes back to ancient times of mankind. Play is an integral part of all cultures and is one of the oldest forms of human social interaction. Games are formal expressions of play that allow people to move beyond direct imagination and direct physical activity. Common features of play include uncertainty of outcome, agreed rules, competition, independent place and time, an element of fiction, an element of chance, prescribed goals and personal enjoyment. The Dutch cultural historian Johan Huizinga, in his 1938 book Homo Ludens, argued that play was a major condition for the emergence of human culture [57]. Huizinga saw playing games as "something older than culture, because culture, however inadequately defined, always presupposes human society. and animals did not wait for humans to teach them to play." [57]. Huizinga sees games as the starting point for complex human activities such as language, law, warfare, philosophy and art.

The renowned zoologist Jane Goodall has documented many ways in which chimpanzees played [45] [46]. Based on the pre-existing play behaviour of animals, as well as a range of archaeological findings and documentation, there is a well-known consensus in the academic community that play was born in human infancy - as long as there were humans, there was play [46]. In ancient times, because writing did not yet exist, human activity could not be recorded, but works would become objects and be preserved in various forms. For example, the earliest example of instant games - pottery gyro is found in the second half of the last century at major Neolithic sites in northern China, which date from 6,300–6,800 years before [73]. The pottery gyroscopes excavated from the Hanpo site in Xi'an and the Zijing site in Shang County, have a characteristic spiral groove, which facilitated the use of a special tool, the gyro whip, as when the player was pumping the gyro. It is evident that our ancestors were skilled in the game of pottery gyro back in the Neolithic era, before Chinese characters were invented, and mastered the principles of pottery gyro design and manufacture, as well as having a deep understanding of the relationship between the two.

The game could well be examined more closely as a medium of cultural memory, a living digital heritage.

1.2.1 Game Psychology

Where there are humans, there are games, and where there are humans, there is psychology. To see the first step in studying games is to understand what makes us feel happy. In this context, targeted cross-sectional research on the psychology of play is particularly important. Jesse Schell suggests that playing games is simply a problem-solving activity with a recreational attitude [111]. In the same way that life is, understanding the psychology of games can lead to a better understanding of the underlying logic of problem solving and competition, which can lead to better games and better human lives. Berni Good believes that the psychology of games studies not only the player experience but also ethics and responsibility [9]. The application of psychological theories to games allows for a better grasp of player psychology and increases player loyalty and immersion. Scientists have done a lot of research in this area and for example, some scientists have looked at the impact of game outcomes on players, Niklas Ravaj used the game Super Monkey Ball 2 as a source to study the impact of player success and failure in the game on engagement [110]. McGonigal studied the impact of game success and failure on player psychology from their findings. Some scientists have looked at the presentation of games to enhance the perception of psychological pleasure [19]. For example, Erika Johnson et al. studied the effect of eye-tracking on enjoyment with games [19], T. manninen T. Kujanpaa et al. studied the effect of communication strategies on enjoyment with games [81], S. Griffin et al. studied the effect of game interaction on player psychology through other gestures and somatic controllers [49], and K. Hew and G. Cassidy et al. studied the effect of game interaction on player psychology through the study of the effects of game voice systems, game music, etc. on player psychology [25].

These findings provide a multidimensional way of thinking about the psychology of play, from which the primary goal of this research is to understand why people play games and what factors influence their behavior and enjoyment of the games.

Game psychology research draws on theories and methods from psychology, sociology, and design to provide a comprehensive understanding of the player experience. Researchers use a variety of methods, such as surveys, interviews, experiments, and behavioral observations, to gather data and generate insights into player behavior and motivations.

The findings from game psychology research are used to inform game design, development, and marketing. By understanding what players want and what makes them enjoy games, game developers can create games that are more engaging, entertaining, and appealing to a wide range of players.

In addition to informing game design, game psychology research has broader implications for our understanding of human behavior and motivation. By examining the factors that influence player behavior and enjoyment, game psychology research can shed light on the psychological processes that drive behavior in other domains as well.

Overall, game psychology research plays a crucial role in advancing our understanding of player behavior and experience, and in creating better, more engaging games for players of all ages and backgrounds.

1.3 Operant Conditioning Chamber and the Principle of Reinforcement

Play behaviour is in fact a form of learned behaviour. In the process of playing a game, we work our way through a difficult level, defeat a boss or pass a level because we have gradually acquired the rules and techniques of the game through trial and error, and have learned how to solve problems in a game situation. In terms of applied psychology, we see the act of playing as a trial-and-error exercise in failure. This kind of learning does not emphasise the subjective will of the player, but places the learning process in the process of continuous trial and error, making the learning process more systematic and covert. This is the scenario in which what we call behaviourist psychology is applied.

Behavioural psychology is an idea introduced by Watson in 1913 in Psychology as the Behaviorist views it [134]. Since the birth of scientific psychology, consciousness has been the object of study. And as the psychology of consciousness did not solve the social problems of the time, behaviourist psychology was born. Watson argues that, *"Psychology, as the behaviorist views it, is a purely objective, experimental branch of* *natural science which needs introspection as little as do the sciences of chemistry and physics. It is granted that the behavior of animals can be investigated without appeal to consciousness. Heretofore the viewpoint has been that such data have value only in so far as they can be interpreted by analogy in terms of consciousness. The position is taken here that the behavior of man and the behavior of animals must be considered on the same plane; as being equally essential to a general understanding of behavior. It can dispense with consciousness in a psychological sense. The separate observation of 'states of consciousness', is, on this assumption, no more a part of the task of the psychologist than of the physicist. We might call this the return to a non-reflective and nave use of consciousness. In this sense consciousness may be said to be the instrument or tool with which all scientists work. Whether or not the tool is properly used at present by scientists is a problem for philosophy and not for psychology"* [135].

It shows how an organism, stimulated by rewards or punishments given by the environment, gradually develops expectations of the stimulus, producing habitual behaviour that yields the greatest benefit.

Behavioural psychology starts from the S-R (stimulus-response) research [128] [90], studying only that which can be seen heard and touched, and rejecting the unobservable and unverifiable mentalism of 'consciousness' and 'psyche' concepts such as 'consciousness' and 'psyche', which were then unobservable and unproven.

One of the earliest theories of S-R relationships was proposed by German psychologist Wilhelm Wundt [105], who argued that conscious experience is the result of an interaction between stimuli and response. This view was further developed by other early psychologists such as Edward Thorndike [90], who conducted experiments on animal learning and developed the laws of effect and of exercise, which describe the relationship between reinforcement and behaviour.

This line of thought in behavioural psychology can be said to have been inspired by the philosophy of mechanistic materialism, which holds that the world is a material world and that its true unity lies in its materiality.

Along with the S-R (stimulus-response) research, behaviourist psychologists discovered that biological learning problems have a reinforcing property, whereby organisms implement strategies that are beneficial to them more frequently in order to avoid harm.

The psychologist Ivan Pavlov [47] used the term " reinforcement" (reinforcement) in his monograph published in 1927 to describe the phenomenon whereby specific stimuli make organisms more inclined to adopt certain strategies [94]. A stimulus that reinforces behaviour can be called a reinforcer. The change in strategy that results from a reinforcer is called 'reinforcement learning' [120].

In particular, Skinner, a representative of neo-behaviourism, proposed a theory of reinforcement based on extensive research into the problem of learning, placing great emphasis on the importance of reinforcement in learning. Behaviourism got the idea that learning is a behaviour that increases the rate of response when the subject learns and decreases when it does not [121] [119] [118].

Psychologist Jack Michael's 1975 article 'Positive and negative reinforcement, a distinction that is no longer necessary' explains that reinforcement consists of positive reinforcement, positive reinforcement makes organisms tend to gain more benefits, and negative reinforcement makes organisms tend to avoid damage [85].

This type of reinforcement is used in various aspects of our lives, and rewards are widely used in games as a form of positive reinforcement. A game can contain a variety of rewards in the form of complimentary words, scores, extended play time, prop rewards, etc. Appropriately applied rewards can keep players focused, pace the game and allow players to reap the joy without realising it [99].

Artificial intelligence borrows this concept from behavioural psychology and refers to the learning process of interacting with the environment in a way that avoids harm as reinforcement learning [127]. In this paper, we focus on reward schedules to examine the psychological effects of positive reinforcement on gamers. In the next chapter, we will provide an overview of the types of rewards and the forms they take.

1.4 Game Refinement Theory and Motion in Mind Model

Game theory provides tools for analysing situations in which parties (called players) make interdependent decisions. This interdependence causes each player to consider the possible decisions, or strategies, of the other players when formulating strategies. Game theory considers the predicted and actual behaviour of individuals in a game and examines their optimisation strategies. Biologists use game theory to understand and predict certain outcomes of evolutionary theory [43].

However, game theory can only solve how to win the game which focuses on the player's side. To include the game side in the consideration, Iida et al. [62] presented game refinement theory in 2003. Game refinement theory focuses on the game entertainment and game design balance if there is a good balance between skill and challenge.

Moreover, game refinement theory gives a new point of view to understanding game and game development history. And it gives an idea of the extent that can apply to many areas such as business, education, sports et al. Through game refinement theory, engagement could be measured. And this would help in many areas mentioned above and also improve engagement as a standard of the effectiveness of the entertainment.

As a further development, motion-in-mind works through the analogous relationship between motion in physics and motion in mind, based on the assumption of a zero-sum game i.e. denoting that the sum of the benefits of all parties to the game is zero or a constant, i.e. if one party has income, the other parties must lose something. Establishing the rate (or speed) of victory v and the hardness of victory m links the physics model analogously to the game progression model. This correspondence represents the dynamic flow of player challenge and ability from a win-rate perspective. The calculation of the corresponding physical quantities allows for a greater and more comprehensive measure of the player's mental state [60]. We will describe this in more detail in the next chapter.2, how the various mental states of the player (parameters of motion-in-mind) are measured.

1.5 Problem Statement

Games have played a pivotal role in the long history of the world. While games satisfy the human instinct to seek pleasure, they also serve as a cultural vehicle in the sense that the history of games goes hand in hand with the history of mankind. Games are more than just games, and their influence is gradually extending beyond the games themselves. The importance of games is beginning to be recognised and grasped as a feedback mechanism, an effective motivator, a potential stimulant and a user stickler, and is used in education, entertainment, business and cultural preservation.

How to understand games scientifically and maximise their usefulness has become an important issue for us to consider. Moreover, games reflect cultural change, but how this change is measured in the world of games is a question worth examining.

Iida [61] proposed game refinement theory to concentrate on the attractiveness and the sophistication of games which considers properties that are essential to games, including outcoming uncertainty, game velocity, game length, etc. Recently, Iida advanced the theory further into motion in mind model more player motions could be measured, such as force in mind, energy in mind, momentum in mind, etc. However, either game refinement theory or motion in mind model is a fairly new method and hasn't been applied to the following area and be deeper theoretically segmented in the following research questions.

Problem Statement: Game refinement theory has been studied to derive a measurement of game sophistication. Recently, it has been developed as physics in mind, which may relate to the state of the player's feelings such as satisfaction and comfort in mind.

Research Question 1: The origin of games and play can be traced back to prehistoric times and has since undergone various transformations in terms of rulesets and forms of play. Different historical periods have witnessed a gamut of games enjoyed by diverse individuals, each with its unique features that potentially reflect cultural preferences. Despite the variability in game attributes, their enduring appeal has been attributed to the underlying human psychology, which presents a challenge for achieving objective validation. In this regard, the question arises as to how games relate to cultural identity and whether it is possible to identify universal characteristics of games that could be subjected to rigorous mathematical analysis. To address this issue, Chapter 3 offers an in-depth exploration of potential solutions.

Research Question 2: Game design is a multidisciplinary field that often employs psychological principles to foster player loyalty and immersion. The interactive and experiential nature of video games provides a unique platform for examining human emotions and understanding player psychology. Despite the prevalence of psychological concepts in games, a lack of empirical research exists in quantifying the complex interplay between player behavior, emotions, and game mechanics. Therefore, it is imperative to investigate how game methodology can be utilized to evaluate and measure player psychology, as it may inform game design practices and contribute to a deeper understanding of human behavior in digital contexts. Chapter 4,5 will be given for discussion about this.

1.6 Structure of The Thesis

The question of how to effectively increase the comfort and motivation of players in a sustainable manner is an important one that cannot be ignored. The research conducted so far has not previously attempted to quantify the world of ideas. Nor has research been conducted in the direction of better meeting the needs of players by breaking down the categories of players from their quantification. In order to achieve this goal, it is necessary to delve into the relationship between players and games and find the connections between them.

We focused on the relationship between players and games in our master's thesis research and analysed the psychology of players from their gaze using an eye camera, and then as a continuation of this, focused on the reinforcement schedule due to the relationship between players and games in our Ph.D. project and proposed a player satisfaction model. Previous research has successfully developed a model of movement in the brain that is based on motor actions during play. In order to find correlations between players and games, the validity of this model has not yet been proven in real-world situations and further research is needed to find generalisable patterns for it. In addition, the details of the model need further research, such as the need to further confirm the transformational relationship between game satisfaction and entertainment value.

To extend individual player-centred game satisfaction, we aim to apply the player satisfaction model practically proposed in the previous research. The project proposes a player satisfaction model that has been validated based primarily on reward mechanisms. Based on this idea, we propose a new approach to unlock the harmonious relationship between game and player by balancing the weights of player satisfaction and pleasure and constructing a method to increase motivation based on the new model. The main analysis focuses on applications not only in games but also in non-gaming domains such as autopilot and gambling, which are strongly motivated by player subjectivity.

Thus, this thesis comprises six main chapters, given as follows:

- **Chapter 1: Introduction**

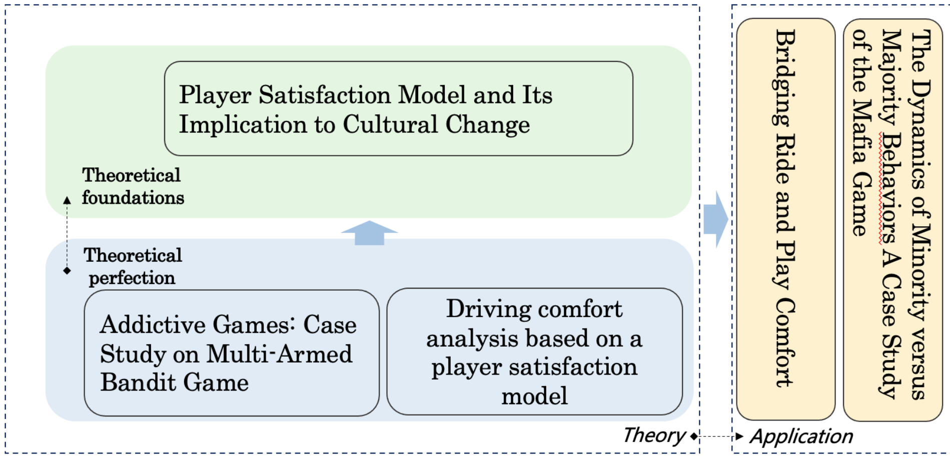


Figure 1.6.1: Overview of research content

The purpose of this chapter is to present the full picture of the study, such as its definition, the interrelationship of each keyword in the study, and a brief historical overview of the area under consideration. It serves to explain the main questions that the study aims to address. The introductory chapter also includes a statement of the research problem, as well as the study's objectives and significance. At the end of the chapter, the structure of the thesis is explained.

- **Chapter 2: Literature Review** This chapter is a review of the theoretical background relevant to this study and also presents state-of-the-art research in the field. The first part of this chapter is a review of research in the psychology of play, in which we review the historical development of the psychology of play. The second part contains a historical review of traditional behaviourist psychology, such as Thorndike's cat, Pavlov's dog, Skinner's box, etc. The third part of the literature review covers game refinement theory and the introduction of motion-in-mind, an uncertainty-based measure of gaming entertainment. At the end of this chapter, a conclusion will be presented leading to the justification of the research conducted in the thesis.

- **Chapter 3: Player Satisfaction Model and its Implication to Cultural Change**

  This chapter introduces and describes one of the results of this study, Player Satisfaction Model, which proposes a model for the satisfaction level of a player with a high satisfaction level in relation to the reinforcement of schedules and a comparable intelligence acceleration in terms of reward rates and equivalence. The experimental data was tested for this hypothesis. Secondly, the gravity of the world of thought (gravity of travel) was interpreted from the point of view of the gravity of the thinking world (gravity of travel) as an indicator of the information acceleration obtained from the model of the program's satisfaction, and the appropriateness of the rule was checked by comparing it with the data of the actual game. The need for modelling data related to online learning for further applications is mentioned later, and will be discussed in Chapter 4.

- **Chapter 4: The Correlation between Player and Game**

  The previous chapter presented a player satisfaction model. To further clarify the interaction between player and game to better improve the game experience, this chapter builds on this by proposing energy and momentum differences to represent the player psychological fallout. In this chapter, through the application of multi-armed slot machines, we find that the point when p_d is equal to E_d is defined as the player's motivation point. At this point, the player is very satisfied. Such an approach could also help developers and educators to improve the efficiency of edutainment games and make them comfortable zone.

- **Chapter 5: Analysis of Driving comfort through steering wheel information with a focus on Motion in Mind**

  This chapter has been chosen to apply to a non-game scenario, namely the driving experience, in order to better refine the model described earlier. We explore its application in terms of personalised driver comfort. Self-driving vehicles are complex systems that integrate environmental awareness, intelligent planning and decision-making, tracking and control. As vehicles become more intelligent, personalisation is an inevitable trend. Designs that match the driver's personality can lead to a better driving experience for the driver. The classification of driving types, therefore, plays an important role in constructing trajectory planning algorithms that take the driver's personality into account. The construction of trajectory planning algorithms that take into account the personal comfort of the occupant has an important role to play.

- **Chapter 6: Conclusion** Chapter 6 summarizes the dissertation contents, distils theories and fundamentals used to develop the research, highlights outcomes and achievements, points out limitations, and recommends future research and development.

Chapter 2

Literature Review

2.1 Chapter Introduction

This chapter provides an overview of the essential theoretical background and summarizes the most recent research in the topic. The first section of this chapter is a review of research in the psychology of play, in which the evolution of the psychology of play is discussed. The second section provides a historical overview of conventional behaviorist psychology, including Thorndike's cat [128], Pavlv's dog [93][94], Skinner's box [120][121], etc. The final section of the literature review discusses game refinement theory and the introduction of motion-in-mind, an uncertainty-based measure of gaming enjoyment. A conclusion will be offered at the end of this chapter that justifies the research undertaken for the thesis.

2.2 Game and Game Entertainment

As society continues to evolve, games have become not only a significant form of entertainment but also a form of culture that encompasses a variety of consciousnesses. This chapter will begin with an introduction to the concept of games, then cover the history and evolution of games, and conclude with a discussion of the evolution of game entertainment and player research.

2.2.1 The concept of game play

Numerous researchers in the realm of games have investigated the idea of play, and Johan Huizinga's [56] in-depth examination of the elements of play has formalized the study of play as a distinct field. He contends that the element of play has been highly active throughout the cultural evolution and has given rise to a variety of fundamental forms of social life. The first stage of civilisation originated in play, and play did not originate from civilisation; rather, civilisation originated in play as play and could not be separated from it.

Following this, numerous scholars have given a variety of definitions of play, which will be presented here. [67][59].

Our observation of the above definition of Table 2.1 shows that there is a consensus on the above definition of a game that restricts the flow of players through rules. However, if the game is only rules + objectives, the core elements of the game are lost. Because entertainment itself is so subjective there is very little research on games that involve entertainment. In the next section, we will look in more detail at the study of entertainment in games.

2.2.2 Game entertainment

Bernard Suits' research points out that laying a game is a voluntary attempt to overcome unnecessary obstacles [123]. As shown in Fig.2.2.1 If a line is drawn dividing the four elements of rules, obstacles, fun and challenge into two quadrants, games are a game of exploitation and consumption, with the developer playing by the rules of the game world and the player actively challenging these obstacles for fun. A good game must bring the various elements into balance [123].

A similar theory has been proposed by Iida [62], which called 'Three masters' model 2.2.2, which differs from his theory in that the Three masters model focuses on Master of Winning, Master of Playing, Master of Understanding [62]. The attractiveness of a game is proportional to the harmony of fairness, judgment, and thrill in games [59]. Master of winning focus on solving a game, facilitates the transition of a game with numerous options into a stochastic game with fewer possibilities [59]. Iida proposed game refinement theory to evaluate games from Master of Winning to Master of Playing [59].

Table 2.1: A brief overview of the definition of play

Author	**Definition**
Johan Huizinga [57] [67]	Play is a free activity standing quite consciously outside 'ordinary' life as being 'not serious,' but at the same time absorbing the player intensely and utterly. It is an activity connected with no material interest, and no profit can be gained by it. It proceeds within its own proper boundaries of time and space according to fixed rules and in an orderly manner
Rogar Caillois [22] [23] [67]	An activity which is essentially: Free (voluntary), separate [in time and space], uncertain, unproductive, governed by rules, make-believe.
Bernard Suits [124] [67]	To play a game is to engage in activity directed towards bringing about a specific state of affairs, using only means permitted by rules, where the rules prohibit more efficient in favor of less efficient means, and where such rules are accepted just because they make possible such activity.
Avedon, Sutton Smith [8] [67]	At its most elementary level then we can define game as an exercise of voluntary control systems in which there is an opposition between forces, confined by a procedure and rules in order to produce a disequilibrial outcome.
Chris Crawford [67] [28]	I perceive four common factors: representation [”a closed formal system that subjectively represents a subset of reality”], interaction, conflict, and safety [”the results of a game are always less harsh than the situations the game models”].
David Kelley [70] [67]	A game is a form of recreation constituted by a set of rules that specify an object to be attained and the permissible means of attaining it.
Katie Salen, Eric Zimmerman [123] [67]	A game is a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome.
Hiroyuki Iida [59]	Games, which epitomize uncertainty, evolved in their long history to refine uncertainty. This process employed a harmony between skill and chance in games, leading to evolutionary changes in noble uncertainty.

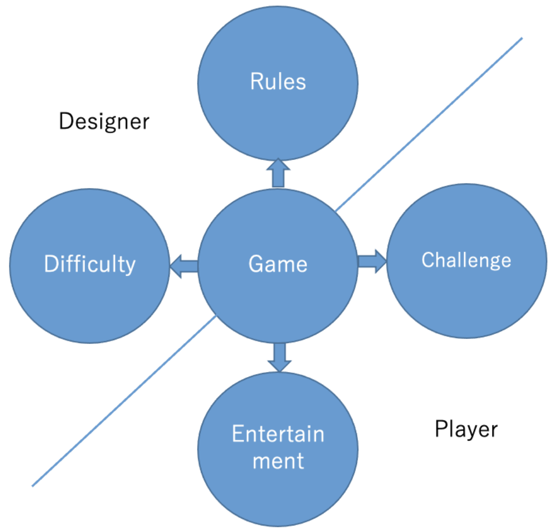


Figure 2.2.1: The basic elements of a game from Bernard Suits [123]

Concerning Master of playing, Iida et al. suggested a logistic model with uncertain results based on seesaw games or late chance [62]. An illustration of the model of game-outcome uncertainty [59] When assuming that the solved information x(t) is twice derivable at $T \in [0, t]$, T stands for the average length of a game, which means the average number of moves. Here, the second derivative represents the accelerating velocity of the resolved uncertainty as the game progresses. A high value of the second derivative at $t = T$ refers to a good dynamic seesaw game in which the outcome is unexpected in the very last movements of the endgame. This suggests that a game with a greater value is more thrilling, fascinating, and enjoyable [59]. While the master of understanding was discovered through game-solving, a proper understanding of a game necessitates the selection of the optimal beginning state from among several reasonable choices. The quality of the initial state would depend heavily on the intelligence or artistic sensibility of the game designers [59].

The enjoyment of the game is dependent on the balance of these feelings, which are very difficult to measure and have been studied by the psychological community through various experiments on behavioural and mechanistic settings, which will be described in detail in the following section of this dissertation. The mechanism of the game brings a variety of feelings, and the entertainment of the game depends on the balance of these feelings.

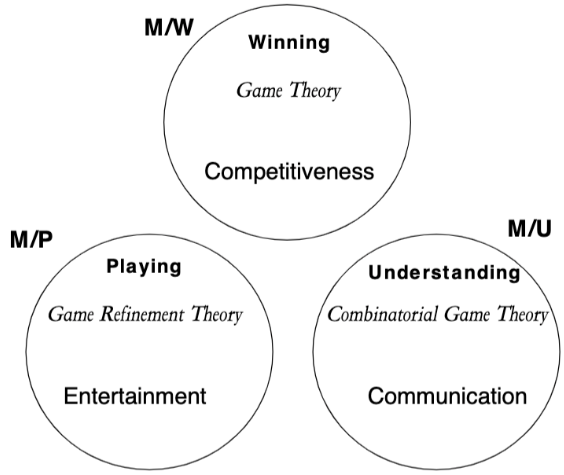


Figure 2.2.2: A model of three masters [59]

2.3 Player Psychology and its Basis Behaviourist Psychology

In any industry, the user's emotions and experience are of fundamental importance, and the gaming industry is no exception. To improve, games must be created with an understanding of player psychology and behaviour. How do players understand games and what motivates them to play? This chapter examines the psychology and behaviour of game players for player research, behaviourist design, and incentive reinforcement schemes.

2.3.1 Player Psychology Research

Understanding what players are playing for is one of the most essential aspects of player study [141] [131], psychology says that human behaviour is always influenced by a variety of circumstances [6]. Traditionally, early academics distinguished between intrinsic and extrinsic impulses [108]. Intrinsic drives, such as hormonal urges to sustain internal dynamics, are typically unconscious [11], whereas extrinsic drives are usually triggered by external circumstances that are rewarding in nature [108]. A person seeking food because they are hungry is an example of an intrinsic drive, whereas wanting to eat something because it tastes good is an example of an extrinsic desire [34].

However, it is difficult to define extrinsic and intrinsic drives in games; therefore, scholars have attempted to interpret players' game drives from a variety of perspectives; From Bartle, he categorizes players' game drives into eight types using four elements: interactivity and dominance of player behaviour, implicit and explicit [14], while Kellar et al. analyse them through educational purposes, classifying players' drives into four categories: mastery, environment, competence and participation [69]. And Sherry uses interviews to classify game motivations into six categories: arousal, challenge, competition, distraction, fantasy, and socialization [114]. However, Richard M Ryan identifies game behavioural drives as driven by basic human psychological appeals, namely autonomy, competence and relationship [109]. While Yee uses questionnaires to classify player drives into three categories: social, immersion and achievement [141]. And also there are also some scientists who put their attention to detailed work. As Tychsen focuses on the game drives of role-playing game (RPG) players; nevertheless, reasons for play are not simple constructs but rather comprise several motivational drivers that are intricately interconnected and function in concert [129], while Lee et al. divided the gameplay motivations of social network game players into six categories: social, self-expression, fantasy-inducing, time-wasting, amusement, and competition [76]. Bostan, on the other hand, classifies player drivers according to 27 fundamental psychological demands into five categories: emotion, competence, achievement, self-preservation, and curiosity [21].

From the above research, it is evident that there are various game drivers, however how to relate the game side to the player side behavioural drivers mentioned in the previous section. In games, players are simply concerned with getting longer play time, getting higher scores and ratings, higher satisfaction. How are these to be obtained from the game mechanics again. This requires some understanding of behaviourism.

2.3.2 The basis of behaviourism

Therefore, beginning with this section, we shall introduce the fundamentals of behaviourism. Imagine that we are watching a movie and that the soundtrack suddenly changes to a frightening sound; at that moment, we become instinctively aware of the oncoming danger and panic, and we may experience involuntary physical symptoms such as a racing heartbeat, shortness of breath, and so on. This physiological response is something that we have picked up from our past experiences of going to the movies, where our bodies have learned to learn to anticipate the formation of another stimulus. The term for this approach is behaviourism.

Behaviourism goes back to the study by Ivan Pavlov [93] in the early nineteenth century, When he realized that dogs could be trained to salivate and created the famous Pavlov's dog experiment, he formulated the standard theory of conditioned reflexes. He discovered that each time the dog was fed before the red light was activated and the bell was rung, the dog's performance improved. Over time, the dog began to salivate whenever the bell rang or the red light illuminated. In order to demonstrate the universality of this effect, it is sufficient to show that a neutral stimulus (bell, red light) that does not elicit an instinctive reflex is always accompanied by a stimulus that elicits the instinctive reflex, and that after a sufficient number of repetitions, the neutral stimulus also elicits the instinctive reflex [93].

Meanwhile, Thorndike [128], a behaviourist who conducted experiments with cats in maze cages, claimed that learning is the establishment of a link between the situation's stimuli and the animal's learned responses. Therefore, the cat responds appropriately to these stimuli, resulting in the anticipated outcome, such as tugging a rope and pressing a button. His stimulus-response association learning was achieved as the animal experienced common sense errors due to blindness, and he discovered that behaviours with a satisfactory outcome were more likely to occur in the future, whereas behaviours with an unsatisfactory outcome were less likely to occur in the future, and that associations became stronger when used and weakened when not used for a long time. By analogy, the player likewise plays the game by trial and error, and the act of playing itself is a process of making mistakes and then learning from them [128].

It is precisely this difficult learning process that enables players to find and implement the appropriate moves to extend the game and increase their score. It is more entertaining to play a game in which the player must repeatedly lose in order to win than to play a game in which they can win effortlessly. This risk-taking creates a genuine sense of suspense for the player, and the experience of attempting to survive on the edge of extinction is frequently highly compelling to gamers. However, this difficulty must be matched with a sense of control; otherwise, it might frustrate the user and diminish the game experience.

Skinner [120] expanded on Pavlov and Thorndike's research by arguing that behaviourism should focus on behaviour and its consequences, focusing more on what is external to the organism. Skinner [117] invented the theory of "operant conditioning" to explain the concept of study behaviours [84], which holds that humans and animals will do the corresponding actions to act on their environment in order to achieve their goals. In Skinner's experiments, the experimenter first establishes a proper behaviour, such as pressing a lever, and then releases the food when this occurs; with this apparatus, the animal is guided to learn the behaviour. If the outcomes of the behaviour are favourable, that behaviour will be repeated. Otherwise, they will be diminished or vanish. People can employ positive or negative reinforcement to impact the behaviour's consequences or to remedy inappropriate behaviour.

When Skinner and his colleagues investigated the best conditions for reinforcement's effectiveness [118], the reinforcement was separated into continuous reinforcement and interval reinforcement based on the interval between the occurrence of the behaviour and its appearance. Continuous reinforcement is intended to reinforce each proper response; in other words, as soon as the individual provides the correct response, reinforcement will arrive or cease. However, once a behaviour is developed and maintained by the use of continuous reinforcement, it will eventually diminish if reinforcement is withdrawn.

Figure 2.3.1 defines the forms of basic reinforcement schedules in relation to the book Learning and Behavior by Paul Chance [26].

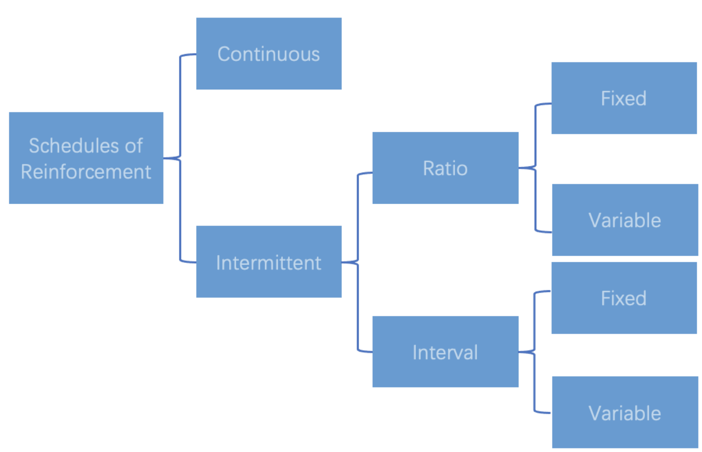


Figure 2.3.1: Types of simple reinforcement schedules

With the advent of the operant conditioning theory, behaviorists realized that reinforcement is not a simple process, numerous variables might influence the procedure. The typical two of them (timing and frequency of reinforcement) affected the ability to acquire new behaviors and the duration of behavior modification. Therefore, they found various reinforcement schedules that influence the process of operant conditioning [3][146]. Therefore, intermittent reinforcement refers to the occurrence or removal of reinforcement at a particular time period or rate. There are two types of intermittent strength training: interval and ratio. Fixed Interval Reinforcement and Variable Interval Reinforcement are the two types of interval reinforcement. Fixed Ratio Reinforcement and Variable Ratio Reinforcement are the two ratio types. Ferster and Skinner (1957) [40] developed many methods of reinforcement delivery and discovered that different reinforcement schedules have distinct effects on learning behaviours.

We show, in Figure 2.3.2, a chart recording of response rates of the four reinforcement schedules [55]. On a device designed by Skinner known as the "cumulative recorder," reaction rates are recorded.

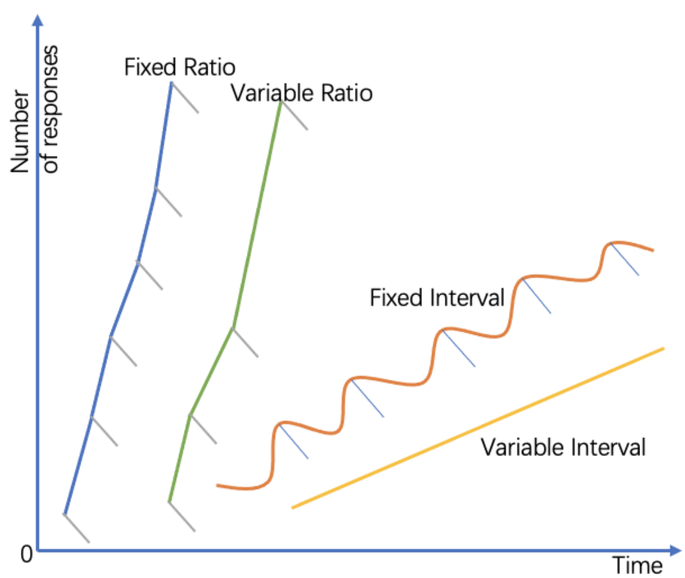
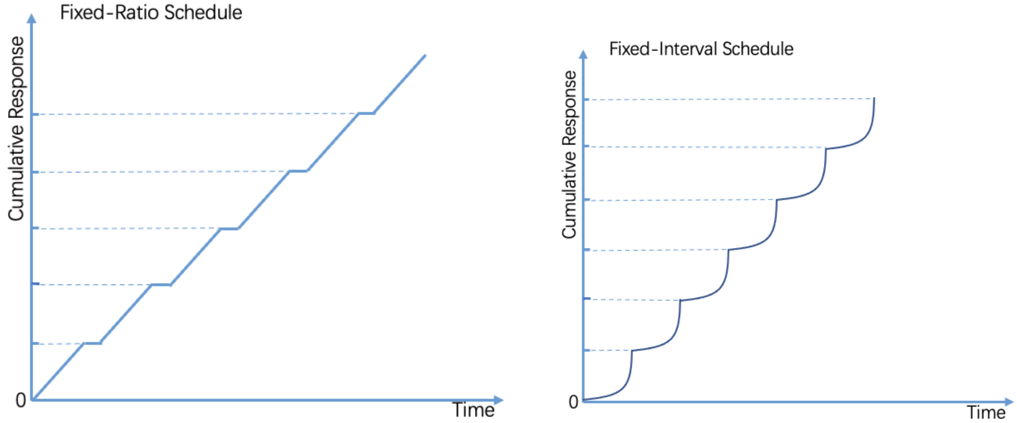


Figure 2.3.2: A chart demonstrating the different response rates of the simple schedules of reinforcement, each hatch mark designates a reinforcer being given [55].

Fixed Ratio Schedule (FR)

Skinner conducted his experiment by using mouse [117] and pigeons [120] which he placed in a ‘Skinner’s Box’. There is a lever on one side of the box’s wall for the mouse to press.



V

(a) Fixed-ratio schedule (FR)[40]

(b) Fixed Interval (FI)[40]

Figure 2.3.3: Fixed schedules [40]

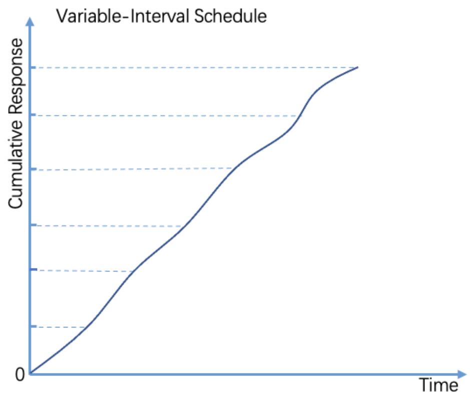
Near the lever, there is a small box for receiving food closing to the small hole of the box. Outside of the small hole is a food release device with granular food. The mouse presses the lever in the box, and a piece of food will fall into the small box from the small hole. A white rat was placed in the box after fasting for 24 hours. It began to explore inside the box and occasionally pressed the lever to get food.

Fixed Ratio Schedule was first mentioned in Roberts and his colleague's paper [106]. The reinforcement respond is reinforced after a set of frequency of responses. In Skinner's experiment [117], the Skinner's box drops food from the beginning, and after reducing it to every 1-minute step by step, pressing the button can drop the food by time probability. We found that the mouse could not stop pressing at the beginning. After a while, the mouse learned to press the button every 1 minute.

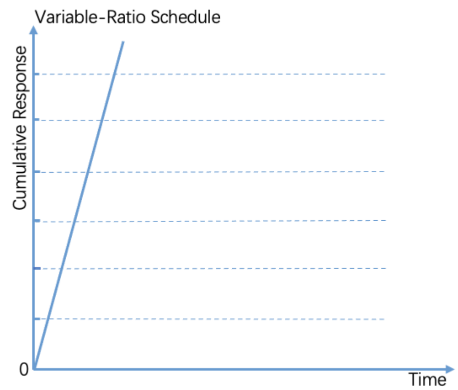
As shown in Figure 2.3.3(a), the fixed ratio schedule is systematic, it produces a high, steady rate of response. [52]. There is a pause after being reinforced every time. Accompanied by the increase in the ratio, the pause time turns longer.

Fixed Interval Schedule (FI)

Every period reinforces Fixed Interval Schedule, which is determined by the amount of reinforcement. The greater the number, the greater the likelihood of a reaction. Therefore, the people understands that the reinforcements cannot return in the near future given their recent appearance. But when individuals believe reinforcements are imminent, their response will intensify. In Skinner's experiment, the Skinner's box is programmed to drop



(a) Variable Interval Schedule(VI)



(b) Variable Ratio Schedule(VR)

Figure 2.3.4: Variable Schedules [40]

food at a predetermined ratio when the lever is depressed. We can predict that the rat will press the lever continuously. And when food is no longer dropped, the mouse's learning behavior decreases very gradually.

Figure 2.3.2 demonstrates that the FR schedule can provide a high response rate. Because under this type of stimulation, when people's reaction rate equals the preset ratio, their behaviours will be reinforced, and the outcome will increase the response rate again, we can expect that this program will maximize the excitation behaviours if no other things interfere. According to this timetable, the response rate is fan-shaped.

Variable Interval Schedule (VI)

Reinforced using a Variable Interval Schedule in which the intervals between reinforcements change at random [40]. Unlike the Fixed Interval Schedule, the Variable Interval schedule results in a steady rate of irregular authorization of the pigeon's behaviour. One of the trials of Skinner's experiment is as follows: Under the VI schedule, the pigeons pressed the button more than 18,000 times over the course of four hours before the reinforcement was removed. In addition, the behaviour didn't eliminate until 168 hours [117]. As is shown in Figure 2.3.4(a) the weakening of response is progressive, far lower than under the Fixed Interbal schedule.

Variable Ratio Schedule (VR)

Random ratios strengthen the Variable Ratio Schedule. When started training the pigeons with a low VR-5 ratio and gradually raised it. After the testing, the VR-110 pigeon had a response rate of over 12,000 times per hour. This makes them addicted. Awarding is not automatic. The response rate is steeper than other schedules because rewards are unpredictable [101]. Thus, reinforcer-followed reactions are more likely to occur again. Therefore, reinforcement plans may be employed to maintain the intended response. As seen in Figure 2.3.2, The fixed ratios have a high rate of responding with a small pause after reinforcement, whereas the variable ratio has a very high steady rate without pauses. Both ratios are resistant to extinction, but the variable ratio is more resistant than the fixed ratio. In addition, FI has our scalloping effect and is less resistant to extinction, whereas VI has a lower constant rate of responding and greater resistance to extinction than the VR schedule.

In reality, slot machines of a gambling type are regulated by variable ratio schedules, and the act of throwing coins into a slot machine sustains the gambler's behavior due to the uncertainty of when rewards would occur. In games, players are frequently required to perform a certain number of actions in order to receive a reward; however, the number of actions performed varies and the player does not know the exact number of actions required to receive the reward; instead, the player can only make educated guesses based on past experience. This average number is denoted as N in later chapters. This will be explained in the next section.

2.3.3 Summary

How can players maintain high levels of activity? From the aforementioned research, we can conclude that a variable rate schedule is a possible solution, with the ability to reward players for every action they perform. The more participants believe that a reward will occur next time, the more effort they will devote. A flexible timetable encourages participants to always move on to the next activity. Using variable ratio schedules as a foundation for the research of reward mechanisms, this chapter continues the investigation of the uncertainty mechanism of game refinement theory. This part explains the pertinent psychological foundations of this chapter by reviewing player experience research and its underlying behaviourist psychology.

2.4 Uncertainty in Entertainment: Game Refinement Theory

Based on the concepts of game progress and game information progress, a general model of game improvement is proposed [61]. It fills the gap between board games and sports [125, 139, 65] to the measure of its entertainment value. Game information progress presents the degree of certainty of a game's results in time or in steps. Let G be the winning player's score and T the total score of the game. Game progress $x(t)$ will be given as a linear function of time t with $0 \leq t \leq T$ and $0 \leq x(t) \leq G$, as shown in (2.1)[61].

$$x(t) = \frac{G}{T}\, t \tag{2.1}$$

However, the game information progress given by (2.1) is usually unknown during the in-game period. Hence, the game information progress is reasonably assumed to be exponential. This is because the game outcome is uncertain until the very end of the game in many games. Hence, a realistic model of game information progress is given by (2.2)[61].

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

Here n stands for a constant parameter which is given based on the perspective of an observer in the game considered. Then acceleration of game information progress is obtained by deriving (2.2) twice. Solving it at $t = T$, the equation becomes (2.3)[61].

$$x^{''}(T) = \frac{Gn(n-1)}{T^n} t^{n-2} = \frac{G}{T^2} n(n-1) \tag{2.3}$$

Hence, it is reasonably expected that the larger the value of (2.3) is, the more the game becomes exciting due to the uncertainty of the game outcome. Thus, we use its root square, given by (2.4) as a game refinement measure for the game considered. Here, in board games, B stands for the average number of possible moves and D stands for the average game length. In sports games, G stands for time or steps to achieve the goal, while T stands for a total score, accordingly(Table.2.2).

$$GR_{\text{board}} \approx \frac{\sqrt{B}}{D} \quad \text{or} \quad GR_{\text{scoring}} \approx \frac{\sqrt{G}}{T} \tag{2.4}$$

Table 2.2: Measures of game refinement for various games

	B/G	D/T	GR
Chess[61]	35	80	0.074
Shogi[61]	80	115	0.078
Go[61]	250	208	0.076
Table tennis [65]	54.86	96.47	0.077
Basketball [91]	36.38	82.01	0.073
Soccer [91]	2.64	22	0.073
Badminton [91]	46.34	79.34	0.086
DoTA v6.8 [138]	68.6	106.20	0.078

2.4.1 Motion in Mind

The game refinement theory is an important component in determining how sophisticated a game is. This is accomplished by calculating the rate of solved uncertainty along the length of the game, which is the point at which fairness, excitement, and thrills were identified [62, 61]. When a player has the impression that they are being treated fairly by the game they are playing, it is regarded to be entertaining for the player. This idea is investigated further through the use of the "motion in mind" theory, which defines the mind's subjective law of motions analogously to the natural law of physics [60]. In Table 2.3, an analogous relationship between motion in the mind and motion under natural physics is offered.

The definition for each analogy is as follows[60]:

- **Mass:** In the context of gameplay, mass refers to the level of difficulty experienced by the player. It is closely related to the frequency of risks encountered in the game.

- **Velocity:** Velocity is defined as the rate at which uncertainty is resolved by the player. It has an inverse relationship with a parameter denoted by m, where $m = 1 - v$.

Table 2.3: 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

- **Acceleration:** Acceleration is referred to as the "gravitational acceleration in mind" and serves as an indicator of the level of gamification experienced by the player. If the acceleration, denoted by GR, is within the range of 0.07 to 0.08, the player is likely to feel gamified.

- **Momentum:** Momentum is the product of the mass of an object and its velocity. In the context of gameplay, it represents the balance between the player's effort and ability.

- **Potential Energy:** Potential energy in gaming is defined as the amount of information required by the player to progress through the game. This definition draws an analogy to the concept of gravitational potential energy[60].

These concepts have been applied to both the calculation of players' engagements in board games and the scoring of sports contests. A comparison of the Motion in Minds units of the board games Go, Chess, and Shogi has revealed that the variance in these units is closely tied to the cultural origins of the games. In contrast, by comparing the motion in mind values of Table Tennis, Basketball, and Soccer, it is possible to quantify the engagements of these games and their influence on their popularity [60]. The definitions were also utilized to determine the association between game playing and rewarding experience based on the reward frequency variable[136].

Bearing the different definitions of motion in mind, the primary premises were built on the uncertainties and the difficulty of the game, both of which contributed to the entertainment value of the game.

2.5 An Overview of the Featured Games

This section would provide readers with an introduction to the games discussed in the dissertation. It would briefly summarize each game, giving readers a general view of the games.

2.6 Chapter Summary

In this chapter, antecedent works to the current thesis are presented. Reviewing the literature pertaining to the crucial terms game psychology, player psychology, and game refinement theory that sought to leverage reward information from uncertainty. In connection to entertainment, the Game Refinement theory introduces a measure of the entertainment part of the game that is heavily dependent on the uncertainty in the game. These studies are important because they serve as the foundation for the study conducted in this thesis about the influence of uncertainty based on variable ratio schedules to quantify the player psychology with a focus motion in mind and the relationship between psychology and the measurement of entertainment.

Table 2.4: An Overview of the Featured Games

Games	**Brief Introduction**
Go [?]	Go is an ancient Chinese board game in which two players position black and white stones on a grid board and compete to control the greatest territory. The rules govern stone placement, capture, and scoring. Around two millennia ago, ancient China invented Go. The mythical Emperor Yao devised the game to teach his son Danzhu discipline and attentiveness. In Korea and Japan, Go (Weiqi) became popular.
Chess [32]	Chess is a two-person strategic board game in which each player begins with 16 pieces and attempts to checkmate their opponent's king by making plays in accordance with strict rules governing the movement and capture of each piece.
Mah Jong [10]	Mahjong is a classic Chinese tile-based game that has evolved over the years, with the objective being to gather sets of tiles in accordance with rules that have varied over time, and it has garnered worldwide appeal.
Shogi [54]	Shogi is an ancient Japanese board game like chess that has been played for centuries, growing and getting more complicated over time. The purpose of the game is to capture the opponent's king, and each piece moves distinctly according to an evolving set of rules.
Basketball [89]	Basketball is a team sport that developed in the United States during the late 19th century. The purpose of the game is to earn points by tossing a ball through a hoop, while players move the ball by dribbling or passing it to one another. In basketball, a team receives two or three points for each successful shot into the hoop, depending on where the shot was taken, and the team with the most points at the conclusion of the game is considered the victor. Changes in the sport's regulations, equipment, and techniques adopted by players and teams have occurred over time.
Soccer [122]	Two teams of eleven players seek to score goals by kicking a ball into the other team's goal while adhering to a set of regulations governing gameplay and player conduct. There is evidence that comparable ball games were played in China and Greece in the second and third centuries BCE, respectively. Modern football, however, as we know it today, originated in England at the middle of the 19th century, with the adoption of codified rules and the formation of the Football Association.
Table Tennis [38]	Table tennis is a fast-paced indoor activity that needs good hand-eye coordination and reflexes. Two or four players use small paddles to strike a light ball across a table, following a set of rules. Table tennis has a brief but intriguing history, beginning in England in the late 19th century as an after-dinner parlour game. The sport became famous in Asia and an Olympic event in 1988.
Badminton [96]	Hit the shuttlecock into the opponent's court while following the rules. Since 1992, this Indian sports have become Olympic events. Badminton players hit a shuttlecock across a net. Without returning the shuttlecock, score points. 21 points decide best-of-three or five matches. The first player or team to score two points after

Chapter 3

Player Satisfaction Model and Its Implication to Cultural Change

This chapter is an updated and bridged version of the following publication:

- K. Xiaohan, M. N. A. Khalid and H. Iida, "Player Satisfaction Model and its Implication to Cultural Change," in IEEE Access, vol. 8, pp. 184375-184382, 2020, doi: 10.1109/ACCESS.2020.3029817.

3.1 Chapter Introduction

The study of game refinement theory has led to the development of measurement for game sophistication. It has recently been developed as physics in mind, which may relate to the player's emotional state, such as satisfaction and comfort. This chapter investigates the connection between game refinement theory and variable ratio schedules. We propose a method for quantifying the enjoyment of an activity relative to the variable rate of reinforcement schedule (N) reinforcement, through physically mindful measures. Players' satisfaction and complexity with the game are subsequently investigated by applying the new measure to a variety of gaming activities. On the basis of numerous well-known games, indicators for cultural changes and their implications for gaming landscapes and experiences were established. The link we clarified between game refinement theory and reinforcement schedules may imply that classifying games according to our mind's psychological activities is crucial for design decisions that significantly impact the quality of life of people.

3.2 Background

Games had been used in many areas (such as learning [66] and business [16]) to promote entertainment. Among the mechanisms used to increase enjoyment involves usage of game elements [16], competition [66], and psycho-physiology [126]. Since rewards played an integral part in gamified interventions [78], the underlying mechanisms of in-game rewards are relatively limited and understudied. Rewards have various forms, where popular examples are high score, experience points, feedback messages, and game-playing mechanic [78].

The concept of reward is linked with a reinforcement learning theory, advocated by [117], which is a doctrine of understanding and correcting human behavior [87]. In its most basic form, the reinforcement learning theory refers to the positive or negative consequences (remuneration or punishment) of an action [121][119]. The goal is to determine a behavior recurrence which constituted from an agent's probability response to stimuli. Based on many experiments conducted by Skinner on behavioral stimulation [119], variable-ratio (VR) schedules (rewards are given after a random number of correct responses) was found to have the highest response rate, which shows repetitive and straightforward rewards for doing one thing is not the best way to elicit the expected behavior. The effectiveness of such a schedule can be improved if the reward is randomly changed after several actions.

Game designers use this principle to create the illusions of implicit motivation for players to extend the playtime. Such a reward schedule model will encourage players to obtain rewards and continuously strengthen their attractiveness stimuli towards the games. Measuring the attractiveness of the game by identifying the underlying mechanisms of motion in mind concept had been proposed [60], which is derived from the game refinement (GR) theory [62]. It is a crucial evaluation standard which showed to be effective in many different game fields. The main point of game refinement is not winning games and beating opponents but concerned with the game sophistication and entertainment of the target game perceived by the players. The notion of motion in mind involves identifying the players' enjoyment and engagement, where the underlying characteristic of games are analyzed to improve its affinity [60].

In this chapter, a reinforcement paradigm based on the variable ratio (VR) schedule is adopted to establish the link between the reinforcement schedule and game refinement theory. The GR theory is also utilized as the methodology for assessing games, where a new game progress model and physics in mind measures based on the VR schedule were proposed. Then, the link between the underlying game mechanisms relative to various human culture was established.

3.3 Player Satisfaction Model in Games

3.3.1 Game Refinement Theory

Game refinement theory by [61] involves modeling the amount of solved uncertainty of the game as a function of $x(t)$ based on an increasing function of time t. A realistic formulation of game progress with the known outcome is given as (3.1).

$$x(t) = \left(\frac{t}{T}\right)^n \tag{3.1}$$

The GR measure has been adopted and verified in various types of games, as demonstrated by previous studies [102, 92, 137]. For the board and scoring games, the GR measure is determined by (3.2) using the model of move candidate selection and scoring rate [60]. Here, B and G stands for average branching factor and average goals, respectively. Meanwhile, D is the game length (total number of plies), and T is the total points or goals. These respective variables were collected from the average of the total number of play-testing experiments. The sophistication of games converges to almost similar sense of thrill (or noble uncertainty [142]) of $GR \in [0.07, 0.08]$ (Table 2.2).

$$GR_{\text{board}} \approx \frac{\sqrt{B}}{D} \text{ or } GR_{\text{scoring}} \approx \frac{\sqrt{G}}{T} \tag{3.2}$$

3.3.2 Variable ratio schedule (N) and winning hardness (m) in games

In VR schedules, the parameter N shows the average reward frequency, where $1 < N \in \mathbb{R}$. In this study, winning a game corresponds to obtaining a reward, then it implies the game length, which is D in board games (total number of plies) and T in scoring games (total points or goals). Hence, $N = D$ or $N = T$, implying a general form of reward frequency of the game's winning rate. Based on such a notion, the winning rate v and winning hardness m is defined by (3.3).

$$m = 1 - v \quad \text{with} \quad v = \frac{1}{N} \quad \text{or} \quad v = \frac{1}{T} \tag{3.3}$$

3.3.3 Motions in Mind

Analogical links between motions in physics and motions in mind had been previously established based on the notions of winning rate (or velocity) v and winning hardness m [60]. The correspondence between the physics model and the game progress models is established as in Chapter 2.4.1. Such correspondence enables the measures of physics in mind in various games, specifically on three quantities: potential energy, momentum, and force.

Table 3.1: Analogical link between game and physics [60]

Notation	Game context	Notation	Physics context
y	solved uncertainty	x	displacement
t	progress or length	t	time
v	win rate	v	velocity
m	win hardness	M	mass
a	acceleration	g	gravitational acceleration
E_p	potential energy	U	potential energy

The potential energy (E_p) in the game is defined as the game playing potential or the expected game information required to finish a game [60], given by (5.4). Meanwhile, momentum ($\vec{p}$) in the game refers to the competitive balance of a game, which involves the degree of challenge needed (m) and effort given (v) to drive the game progression [60], given by (3.5).

$$E_p = 2mv^2 = \frac{2(N-1)}{N^3} \tag{3.4}$$

$$\vec{p} = mv = \frac{(N-1)}{N^2} \tag{3.5}$$

Since $v = 1 - m$ and $\vec{p} = mv = m \cdot (1 - m)$, it can be observed that $\vec{p} \leq \frac{1}{4}$. This implies that momentum is maximized when $m = \frac{1}{2}$.

3.3.4 Force in Mind and player satisfaction

Arnold Toynbee, a British historian, had asserted that "the supreme accomplishment is to blur the line between work and play." Such assertion can be found when $F = \vec{p}$ demonstrated when having $a = \frac{1}{N}$. In such a situation, F corresponds to the player's effort to move in the game (work) while $\vec{p}$ corresponds to fascinating or seesaw in the game (play). Hence, sophisticated games had accomplished such a notion ($F = \vec{p}$), which blurred the boundary of work and play.

Previous work by [60] had defined the F as the player's strength to move a game or ability in general, where a is the growth rate of "flow" experience of the player in the game (since $a = \frac{F}{m}$, then F is the ability and m is challenge [29]). In this study, $a = \frac{1}{N}$ can be regarded as the sense of gravity in people's minds, where it is the source of cultural tendencies of people's minds in game-playing reflected at a specific time/era. Hence, the measure of F is given by (3.6).

$$F = ma = \frac{(N-1)}{N}\ a \tag{3.6}$$

Sophisticated board games such as Mah Jong, Chess, Shogi, and Go have distinctive origins and represent various developments of cultures, as given in Table 3.2 and depicted in Figure 3.3.2.

Based on the historical establishment of various board games, the Go game is the oldest (established in the 5^{th} century), followed by Shogi, Chess, and Mah Jong. At the time of Go game was established, the gravity of people's mind favors conservative play and long-term gain (frequency of reward is low; $N \simeq 200$). Meanwhile, Chess and Shogi both closely established during people's minds that gravitate towards more aggressive play

Table 3.2: Data of some major board games and Mah Jong

Games	B	$D = N$	a	GR	Century (AD)
Go (19×19)	250.00	208.00	0.00481	0.076	4th[116][39]
Shogi	80.00	115.00	0.00870	0.078	15th [77]
Chess	35.00	80.00	0.01250	0.074	16th [88][100]
Mah Jong	10.36	49.36	0.02026	0.065	20th [86][36]

B: branching factor; D: game length; $a = \frac{1}{N}$; $GR = \frac{\sqrt{B}}{D}$

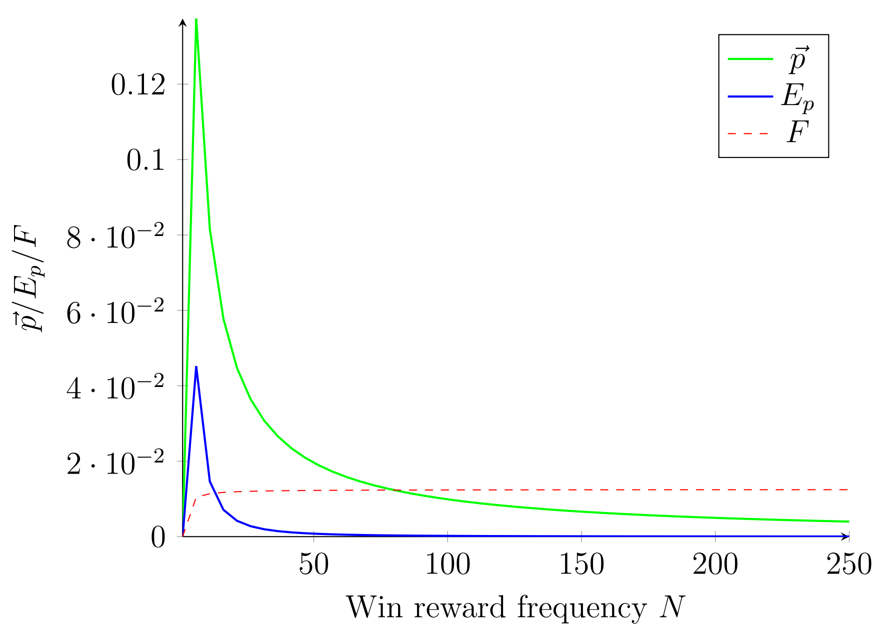


Figure 3.3.1: The F measures with other physics in mind measure

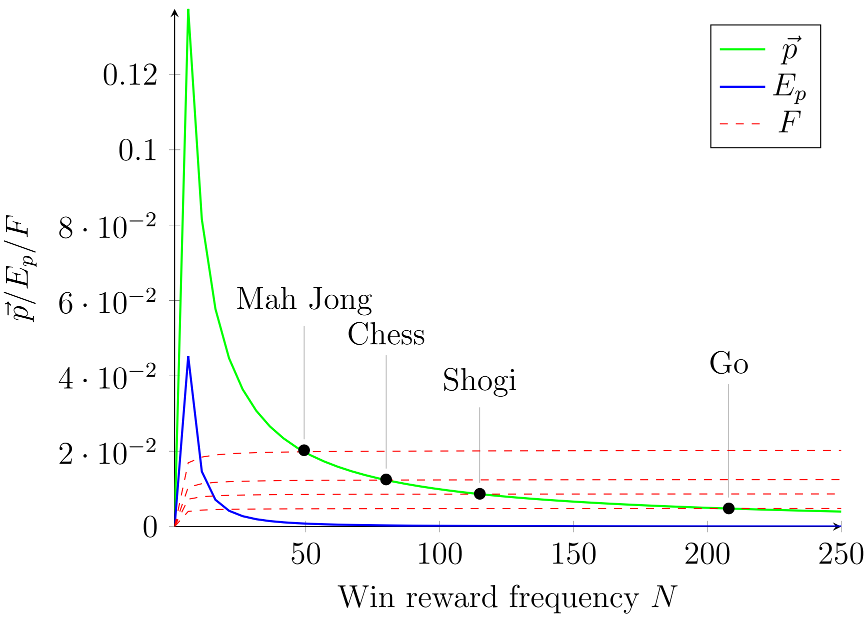


Figure 3.3.2: The F measures of various board games and its cross points ($F = \vec{p}$) relative to other physics in mind measure

and medium-term gain (medium reward frequency; $N \simeq 100$). Meanwhile, Mah Jong established relatively recent (20^{th} century), where the gravity of people's mind favors high reward frequency ($N \simeq 50$) and increasingly fast-paced (higher $\vec{p}$).

Concerning the GR measure, the convergence of the approximately similar values (or GR zone), can be explained by the sense of excitement and thrills given by the games at the respective time/era of their establishments.

Conjecture (Player satisfaction model). People would feel a sense of satisfaction, sophistication, and fairness in a game if $\vec{p} = F$. This situation also implies $N = \frac{1}{a}$, where 'a' changes in history and symbolizes the cultural drive at the time, which is equivalent to the magnitude of gravity in people's minds.

3.4 Physics in Mind and Cultural Change

The definition of play, as given by [56], is the essential activity for striving societies and provided the necessary conditions for the cultivation of culture. Like the development of a civilization, a play requires structure and participants willing to create within specific limits. Starting with Plato, [56] traces such notion, in the contribution of "Homo Ludens," (or "Man the player") through Medieval Times, the Renaissance, and into the modern civilization. The concept of culture and play evolves side-by-side as a civilizing function that ultimately influences people's value of life. To demonstrate such values, games are analyzed from the perspective of reward frequency N using the notion of gravity in mind (a) to identify relevant phases of cultural changes.

3.4.1 First phase from Go evolution

Observing from the oldest board game, the Go board has the longest history [116], which originated more than 4000 years ago and a history of the development of around 2500 years B.C. (Table 3.3). Its development had been observed to change from $N \simeq 60$ to $N \simeq 200$, with $a = 0.01$ to $a = 0.004$, respectively (Figure 3.4.1). It can be inferred that people strive towards conservative activities where the culture changes from short-term to long-term reward frequency. Such an environment fosters increasingly stable conditions (low $\vec{p}$ and E_p) and knowledge-driven (based on its increasing B; more options per move).

Table 3.3: Data of the Go variants [143]

Games	B	$D = N$	a	Century
9×9	52.1	62.06	0.01611	BC 24th
13×13	107.4	105.73	0.00946	BC 2nd
15×15	152.3	145.31	0.00688	BC 2nd
17×17	203.4	175.51	0.00570	AD 1st
19×19	255.5	210.90	0.00474	AD 4th

B: branching factor; D: game length; $a = \frac{1}{N}$

3.4.2 Second phase from Chess evolution

Based on the Chess historical development (Table 3.4), it can be observed that Chess has a history of about 1200 years of development from its first descendant (Chaturanga) to the modern western Chess, approximately 1600 years ago [88][100]. Its development is observed to change from $N \simeq 200$ to $N \simeq 100$[1], with $a = 0.05$ and $a = 0.01$, respectively (Figure 3.4.2). During this time, the evolutionary directions of Chess are in contrast to

[1] $N = 100$ indicates that computer self-play experiments have a longer game length compared to human data (Table 3.2) due to the lack of resignation.

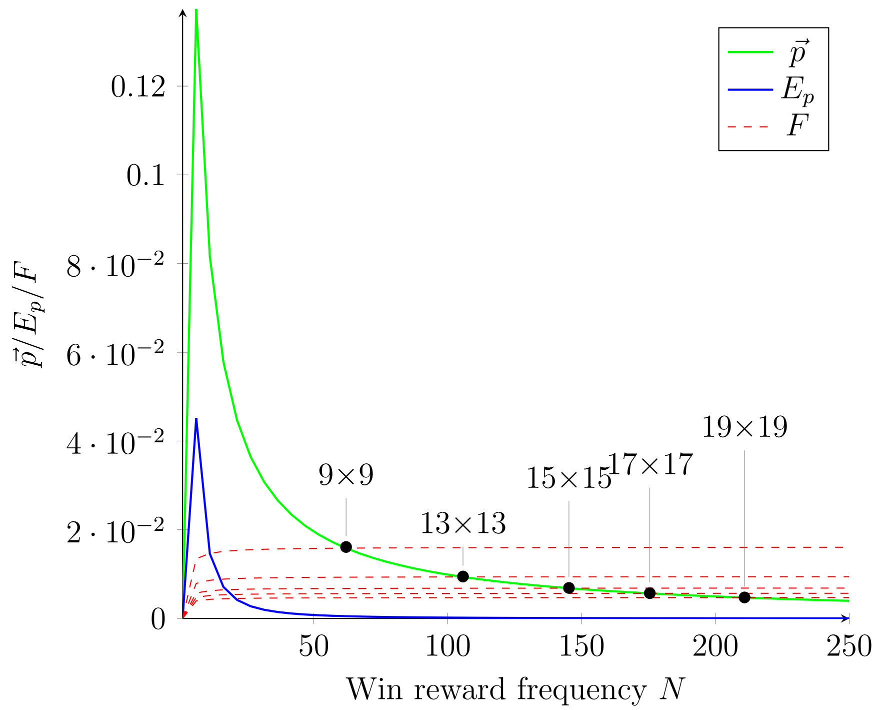


Figure 3.4.1: The Go developmental history based on various physics in mind measures

the Go, where the culture promotes medium-term reward frequency (moderate $\vec{p}$ and E_p), albeit knowledge is valued (small increase in B; more options per move).

Table 3.4: Data of the Chess variants [62, 27]

Games	B	D	a	Century
Chaturanga	19.00	176.00	0.00568	AD 4$^{\text{th}}$
Shatranj	19.20	222.30	0.00450	AD 6$^{\text{th}}$
Medieval I	20.20	230.60	0.00434	AD 8$^{\text{th}}$
Medieval II	21.00	217.50	0.00460	AD 12$^{\text{th}}$
Medieval III	20.80	185.30	0.00540	AD 15$^{\text{th}}$
New Chess	26.70	100.90	0.00991	AD 16$^{\text{th}}$
Chess	27.00	100.10	0.00999	AD 16$^{\text{th}}$

B: branching factor; D: game length; $a = \frac{1}{N}$

3.4.3 Third phase from Mah Jong evolution

Mah Jong had originated about 600 years ago, with around 50 years of development (Table 3.5), which is demonstrated by $N \in [30, 50]$ and the $a \in [0.02, 0.05]$ that roughly stays within a relatively similar value (Figure 3.4.3). This situation showed that people's

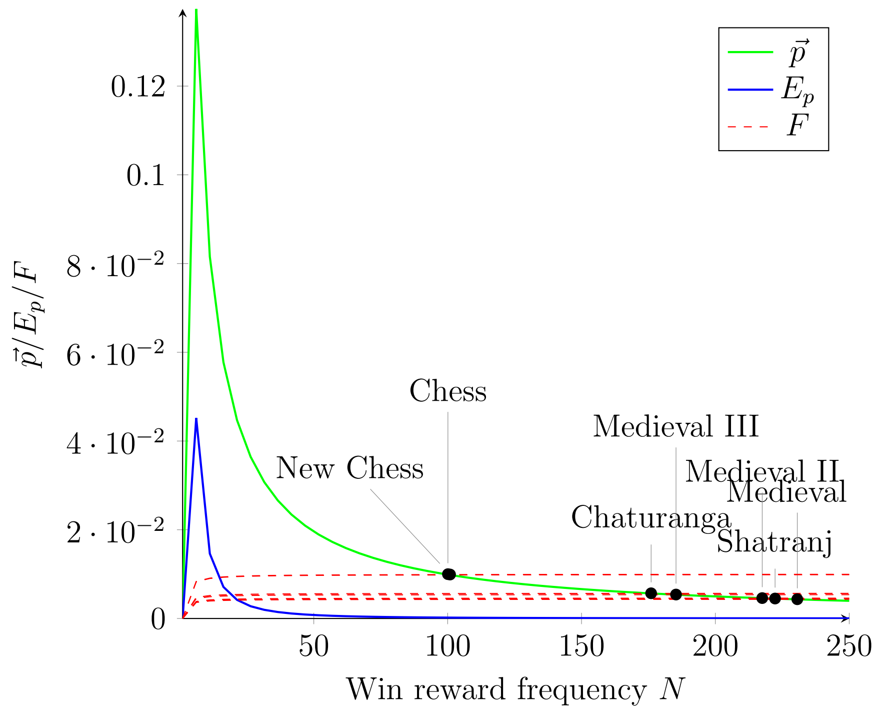


Figure 3.4.2: The Chess developmental history based on various physics in mind measures [142, 27, 62]

culture favors high reward frequency ($N < 50$), where fast-paced activities (high $\vec{p}$ and E_p) were found more attractive, and they are more engaged when the game is less complicated and leave rooms for uncertainty (small B; fewer options per move).

Table 3.5: Data of the Mah Jong variants [61, 142]

Games	B	$D = N$	a	Century
Madiao	4.50	32.00	0.03125	AD 15$^{\text{th}}$
Mohu	11.00	18.67	0.05356	AD 17$^{\text{th}}$
Penghu	7.79	24.65	0.04057	AD 18$^{\text{th}}$
Mahjong	10.36	49.36	0.02026	AD 20$^{\text{th}}$

B: branching factor; D: game length; $a = \frac{1}{N}$

3.4.4 Evolution of sports games

Meanwhile, popular sports games such as Basketball and Soccer were also analyzed to observe the evolution of a, where minor incremental changes were observed in both games. The data from the world's league games of Basketball and Soccer games were collected

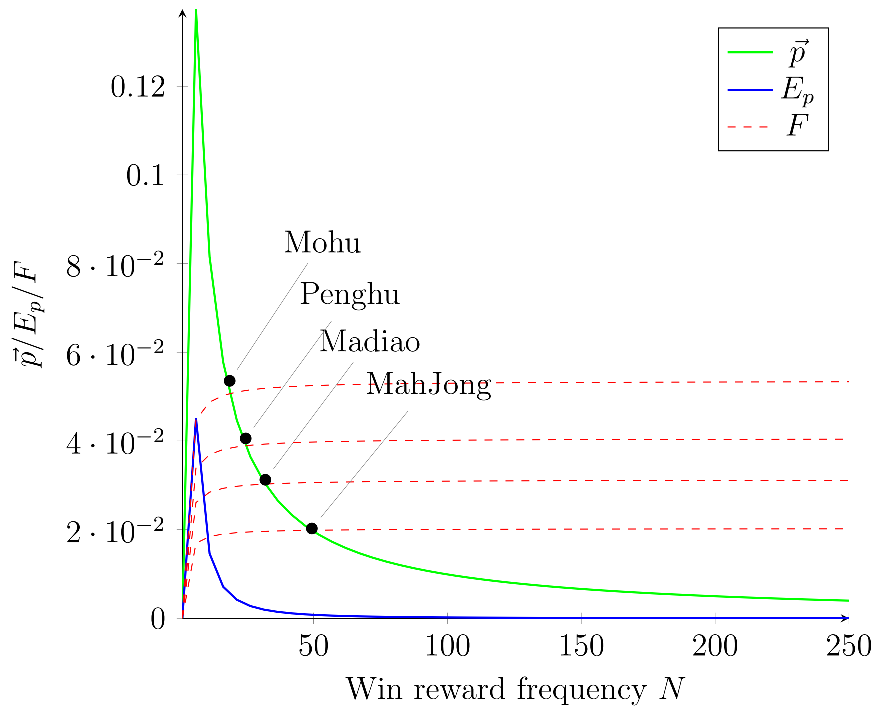


Figure 3.4.3: The Mah Jong developmental history based on various physics in mind measures [142]

(NBA[2] and FIFA[3]), where G is the average shots (or scores), and T is the average total shots attempts (or tries) (exception for the blocked shots per game in Basketball).

The data of Basketball and Soccer are given in Table 3.6. It can be observed that sports games took different directions compared to board games (Figure 3.4.4). Both games showed contradicting trends, where Basketball becomes very difficult to gain a reward (high N and m) and demands skillful play (resembling mind sports, i.e., board games). Meanwhile, Soccer is becoming more stochastic (high $\vec{p}$) and fast-paced (low N), matching the gravity felt by people's minds in modern times. This condition is interesting since Soccer had a relatively long history (2000 years of history[4]), albeit widely accepted as a contemporary sport worldwide.

Another example of contemporary sports such as Table Tennis, was also observed to change a when its rule changes from 21-point system ($N \simeq 200$) to 11-point system ($N \simeq 100$) [65]. Such evolution of gravity (a) may still be on-going in many modern games (such as video games), where a increases closer to the addiction zones ($E_p = F$),

[2]National basketball association team statistics (2015-2020 seasons): `https://www.basketball-reference.com/`

[3]FIFA team statistics (2010-2018 seasons): `https://www.fifa.com/`

[4]`https://www.footballhistory.org/`

Table 3.6: Results on basketball games

NBA (Season)	G	$T = N$	v	m	a
2015-2016	55.90	206.00	0.0049	0.9951	0.00485
2016-2017	56.90	207.60	0.0048	0.9952	0.00482
2017-2018	56.20	205.80	0.0049	0.9951	0.00486
2018-2019	58.80	214.60	0.0047	0.9953	0.00466
2019-2020	58.00	213.40	0.0047	0.9953	0.00469
Average	57.20	209.40	0.0048	0.9952	0.00478
FIFA (Year)	G	$T = N$	v	m	a
2010	2.27	21.40	0.0467	0.9533	0.04673
2014	2.67	31.60	0.0316	0.9684	0.03165
2018	2.64	15.80	0.0633	0.9367	0.06329
Average	2.52	22.80	0.0439	0.9561	0.04386

N: reward frequency; T: attempted goals; G: average goals; v: winning rate; m: winning hardness; $a = \frac{G}{T^2}$: informational acceleration;

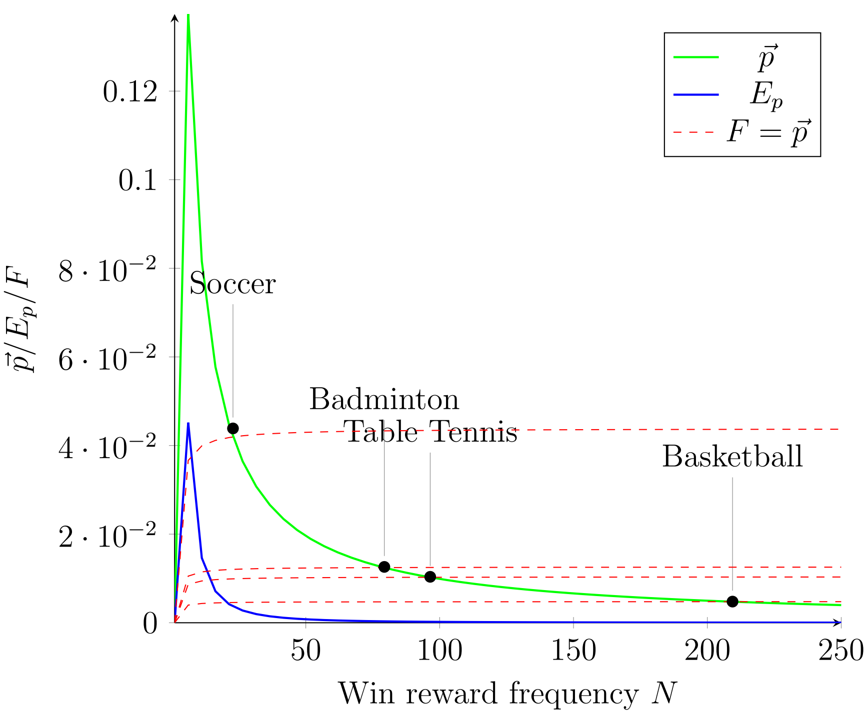


Figure 3.4.4: The developmental history of Basketball and Soccer games based on various physics in mind measures

which logically sound with the increasingly aggressive game markets.

3.4.5 Evolution of action video games

Since the 1980s, video gaming has become a popular form of entertainment and a part of modern popular culture in most parts of the world. In video games, players' experiences and feelings will be sought out by immediate stimulation to their eyes and ears [138]. One of the sub-genres of video games called action games is a video game that emphasizes physical challenges, including hand-eye coordination and reaction time. Video game includes a large variety of sub-genres, such as fighting games, shooter games, and platform games. Based on the previous study conducted on fighting video games [148][149], T and G is the average actual attacks and the effective attacks, respectively. The results are given in Table 3.7, which reflected the development of action games.

By observing and analyzing the fighting games released between 1985 to 2017 (see Table 3.7 and Figure 3.4.5), it can be deduced that modern people's minds gravitate towards increasingly fast-paced (increasing $\vec{p}$) and a more frequent reward gains. This situation justified that fighting games are focusing on increasing entertainment where the game consists of high tension or pace onto the players (e.g., high moving speed), rather than merely competing. Also, the decline of T and increasing G from 1985 to 2017 showed that fighting games are trying to let players feel playful longer within moderate game length [149].

3.5 Discussion and Implications

3.5.1 Development and current trends of game and history

Since the value of a can be regarded the measure of gravity in people's mind (a), it serves as an indicator to the core culture of people of a specific era or time, as suggested by [56]. Hence, analyzing the changes of a provides insights into people's cultural tendency, based on their game playing experience and comfort.

According to the Merriam-Webster definition of game[5], one of the tacit meaning of the term is used in hunting, referring to wild animals hunted for sport or food. Based on the

[5] `https://www.merriam-webster.com/dictionary/game`

Table 3.7: Results on action video games

Year‡	G	T	v	m	a
1985	11.60	104.60	0.0096	0.9904	0.00956
1991	14.10	105.60	0.0095	0.9905	0.00947
1993	13.10	77.60	0.0129	0.9871	0.01289
1995	41.20	146.60	0.0068	0.9932	0.00682
1997	21.30	97.80	0.0102	0.9898	0.01022
2002	23.50	92.20	0.0108	0.9892	0.01085
2006	21.10	82.60	0.0121	0.9879	0.01211
2012	31.20	89.40	0.0112	0.9888	0.01119
2016	49.20	126.20	0.0079	0.9921	0.00792
2017	26.30	80.20	0.0125	0.9875	0.01247

‡: Title release by their given year are Yie Ar Kung Fu (1985), Street Fighter II: The World Warriors (1991), Samurai Spirits (1993), Mortal Kombat 3 (1995), The King of Fighters '97 (1997), The King of Fighters 2002 (2002), Virtua Fighter 5 (2006), Dead or Alive 5 (2012), The King of Fighters XIV (2016), Tekken 7(2017).
T: attempted goals; G: average goals; v: winning rate; m: winning hardness; a: informational acceleration;

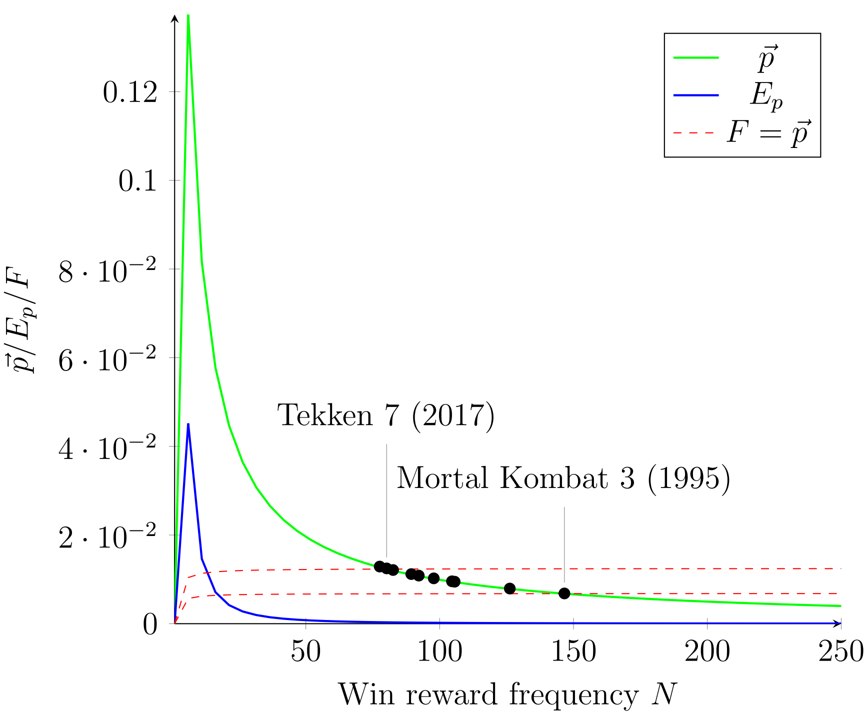


Figure 3.4.5: The evolution of different versions (1985–2017) of action video games relative to various physics in mind measures

historical development of Go game (B.C. 23^{rd} to A.D. 5^{th}), the reduction of a demonstrates the transition of people from nomadic culture (hunter-gatherer) into sedentary culture (agriculture), where people search for a more stable lifestyle (first phase; Section 3.4.1). Suppose that the N is approximated as the day with the reward a year, then the hunting processes is equivalent with the reward requiring short-term work ($N \in [50, 100]$), while agriculture (e.g., crops like wheat and rice) requires long-term work ($N \in [150, 200]$).

Another direction of history is the transition from agriculture to a more exciting lifestyle (leading to the industrial revolution and free capitalism), where a increases and N decreases (second phase; Section 3.4.2). Such historical development is related to the Chess game (A.D. 4^{th} to A.D. 16^{th}), where war, conquest, strategy, and tactics, played an essential role in the early people's lifestyles (only the elite played such board games). The people's culture then shifted towards capitalism (efficient transportation such as horse-powered transport and railroads, and voluntary goods trading) and industrialization (mass production and machinery usage), allowed more frequent reward gains with medium- to short-term work (from $N \simeq 200$ into $N \simeq 100$).

The third phase of the evolution of Mah Jong is the period of transition in history, where both the a increases further and decreases again (N decreases and increases). Such historical development implies changes in people's culture towards fast-paced and highly accessible goods via inventions (such as mechanization since 13^{th} century and computing devices in early 19^{th} century) and modernization (first and second industrial revolutions). With such changes, the reward frequency significantly improved ($N \simeq 30$) and stabilizes with an increase of urbanization ($N \simeq 50$).

Based on the historical development of a for the board games along the period of their development (Figure 3.5.1), a symmetry-like trend was observed, bordering at about 4^{th} to 5^{th} century. Such a trend overlaps between the Go and Chess game's development, where a showed opposing trends between Go and Chess. Such a symmetrical border implies the turning point of the game's development, which is demonstrated by the first phase (Section 3.4.1) and the second phase (Section 3.4.2) of the game's evolution. It would also represent the border between competitive and mastery activities.

Conjecture (Border of Competitive and Mastery). The historical development trend of popular board games showed that $N \simeq 200$ is the border between competitive and mas-

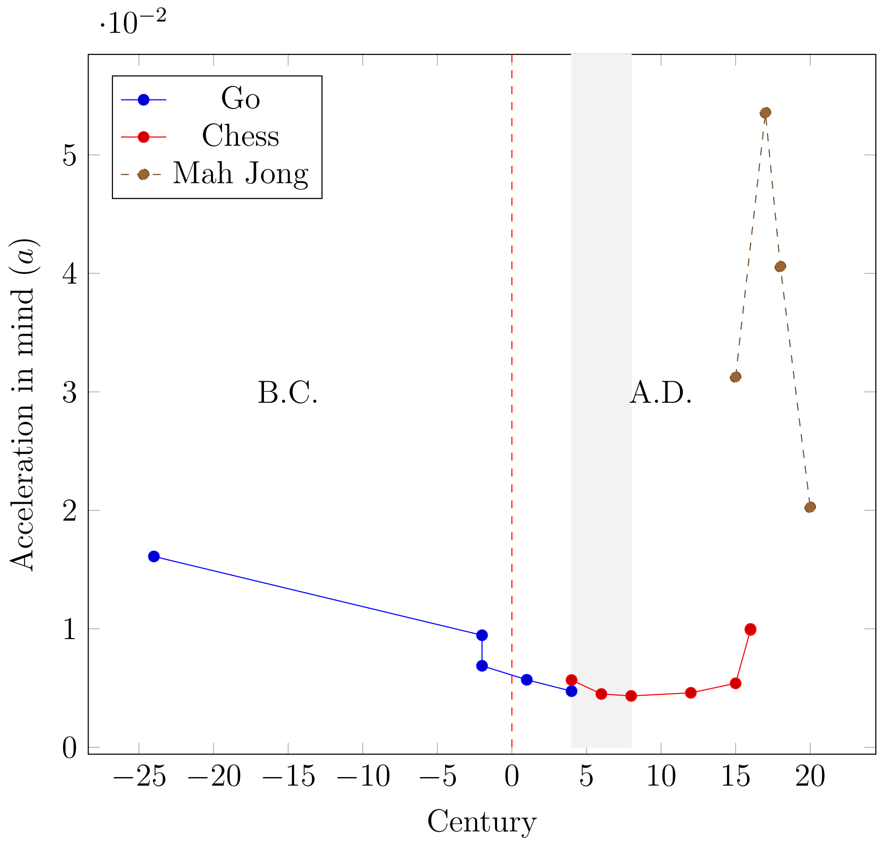


Figure 3.5.1: The historical development trends of Go, Chess, and Mah Jong variants. The gray-shaded region is where the occurrence of the symmetry-like trends between Go and Chess games.

tery, where it possessed a low ‘a’ (leisurely play) and extremely low E_p (knowledge-driven or skill-based). Beyond such a border gives $F > \vec{p}$, implying that players’ ability to overcome the competitiveness of a game and experience rarely becomes rewarding. Such a situation also is equivalent to a turning point of gravity in people’s minds, at about $a \simeq 0.005$.

3.5.2 Game - playing landscapes

Various games considered in this study constitute three distinct sports landscapes: mind (or m-sports; e.g., board games or abstract games such as Go, Shogi, and Chess), physical (or p-sports; e.g., Basketball, Soccer, Table Tennis, and Badminton), and electronic (or e-sports; e.g., DoTA and action games). A rough approximation of the ranges of the respective three landscapes of sports was depicted in Figure 3.5.2. It can be observed that those sports developed within an overlapping range of about $N \in [20, 200]$. However, their distinction was based on their individual development.

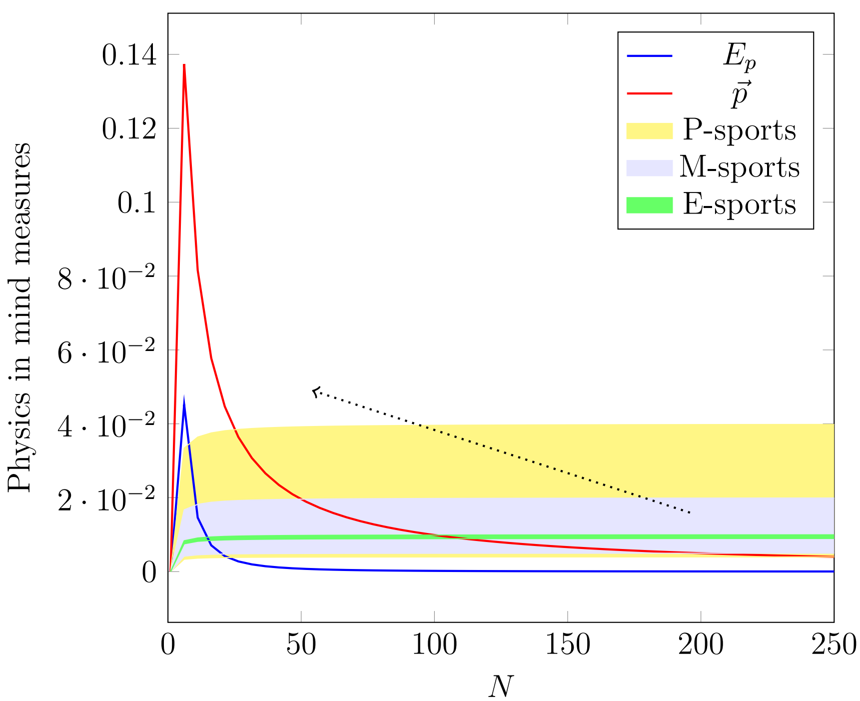


Figure 3.5.2: The convergence of p-sports, m-sports, and e-sports based on the a indicators, relative to the physics in mind measures

P-sports have been observed covering most of the ranges of the N, although sampled from a very specific game. However, this showed that physical-based activities had undergone a stable development since it is one of the oldest forms of play in existence alongside human civilization. As such, p-sports have been observed to provide a multitude of different game playing experiences, from luck-based play (e.g., Soccer), fair play (e.g., Table tennis and Badminton), to a skill-based play (e.g., Basketball). However, the implications of p-sports development remain too broad to be adequately determined and classified.

Meanwhile, m-sports have been observed to overlap with half the ranges of N of the p-sports. However, m-sports converge at about $N \in [60, 200]$, where the game provides more specific game playing experiences where little to very knowledge-driven games are valued. Also, e-sports have been observed to change rules within a short time (less than ten years or less) while maintaining a range of values that are situated as the middle ground between those observed in the m-sports and p-sports. The game playing experiences of the e-sports also specialized in balancing skill and chance elements in the game. Interestingly, the direction of the three sports landscapes seems to be closing the gap between the $E_p = F$ and $\vec{p} = F$, where the order of the gap size reduces from the e-sports, followed by the m-sports, and then the p-sports.

With reference to Figure 3.5.2, a summary of the possible landscape of known games, is given in Table 3.8. For the region of $N \leq 20$, the reward's frequency is very high and requires low ability, motivation, and effort, which drives the player's curiosity. Such a region implies an activity that exhibits reinforcement effects that closely resemble the *continuous reinforcement schedule* that posses high reinforcement extinction effect [33], which could potentially lead to addiction. Meanwhile, a region of $20 < N \leq 200$ involves a rapid change of E_p and $\vec{p}$, which relates to competitive activities where it is often rewarding and sometimes motivating, which is dependent on the player's ability (or skill). The region beyond $N > 220$ is where both the ability and effort are high (mastery) where the activity becomes habitual and challenging to be motivating.

Table 3.8: Classification of activities according to the interplay of physics in mind measures ($\vec{p}$, E_p, and F) and reward frequencies (N)

Range	**Reward frequency**	**Implication**	**Activity type**
$\vec{p} \geq E_p \geq F$	$N \leq 20$ (frequent)	Low ability, motivation drives effort (curious)	Addictive
$\vec{p} \geq F > E_p$	$20 < N \leq 200$ (often–sometimes)	Ability drives effort (challenge), some motivation	Competitive
$F > \vec{p} > E_p$	$N > 200$ (rare)	High ability & effort, little to no motivation	Mastery, Art

F: force in mind; E_p: potential energy in mind; $\vec{p}$: momentum in mind; N: reward frequency

3.6 Chapter Summary

Game is a learning process where players learn and adapt to grasp the rules of the game. Similarly, reinforcement schedules, which were explored by Skinner [40], had been widely used in the learning environment. Based on such circumstances, game settings become essential factors that affect the player's experience[60]. Game refinement theory and its application in various games have recently shown significant effects for evaluating games' entertainment—-a successful bridge between learning and the player's engagement.

The variable-ratio of the reinforcement schedule, specifically the reward frequency variable (N), defines the unexpectedness of achieving a reward (or score), which allowed the establishment of such a link, where various physics in mind measures were formulated. Potential energy defined the expected game information required to finish a game, implying that high energy would require less effort to play. Meanwhile, momentum defines the competitive balance of a game between effort and challenge to drive game progress, where high momentum makes a game exciting and fair (or having more frequent seesaw turnover). Force in the game defines the player's strength to move a game or ability in general.

The player satisfaction model given by $a = \frac{1}{N}$ is identified as the magnitude of gravity in people's mind when $\vec{p} = F$. In addition, a was demonstrated to represent changes in history where it serves as an indicator for the cultural drives that is equivalent to the feeling of gravity in mind of people at different time. Game development trends also indicate the border between competitive and mastery in conducting tasks, which suggests a direction towards the higher value of $\vec{p}$ and E_p, while smaller N (such as $N \leq 20$). Such a condition would be inferred that high $\vec{p}$ and E_p with $N \leq 2$ would relate to a situation that induces high curiosity (motivated effort) to addiction.

The measures of physics in mind and player satisfaction model successfully established the relationship between game-playing and rewarding experiences, albeit in a minimal perspective. Potential future works may include exploring the dynamics of challenge and its relations to addiction. Such a measure can also be incorporated to improve game playing experience where a timely rewards schedule can be catered according to the psychological needs of specific players and their playing behavior (related to the field of player modeling).

Chapter 4

The Correlation between Player and Game

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

- Kang, X.; Ri, H.; Khalid, M.N.A.; Iida, H. Addictive Games: Case Study on Multi-Armed Bandit Game. Information 2021, 12, 521. https://doi.org/10.3390/info12120521

The interaction between a player and a game can be viewed as a mutually influential relationship. The player's abilities, tendencies, and game-play style significantly impact the overall gaming experience, while the game, in turn, provides various challenges and opportunities for player development and enjoyment. An effectively designed game has the potential to sustain player engagement and drive motivation for continued play, whereas a seasoned player can bring a unique set of strategies and perspectives to the game. The player-game relationship can be considered a symbiotic one, where the two entities are intricately connected and the outcome of the gaming experience is the result of their interplay. In this section, we will use gambling games as an example, to analyse the game-player energy flow to further observe the player-game relationship.

The attraction of games comes from the player being able to have fun in games. Gambling games that are based on the Variable-Ratio schedule in Skinner's experiment are the most typical addictive games. It is necessary to clarify the reason why typical gambling games are simple but addictive. Also, the Multi-armed Bandit game is a typical test for Skinner Box design and is most popular in the gambling house, which is a good example to analyze. This article mainly focuses on expanding on the idea of the motion in mind model in the scene of Multi-armed Bandit games, quantifying the player's psychological inclination by experimental simulation data. By relating with the quantification of player satisfaction and play comfort, the expectation's feeling is discussed from the energy perspective. Two different energies are proposed: player-side (E_r) and game-side energy (E_i), while player-side energy shows player confidence, game-side energy shows entry difficulty. This provides the difference of player-side (E_r) and game-side energy (E_i), denoted as E_d to show the player's psychological gap. Ten settings of mass bandit were simulated. It was found that the setting of E_r and E_i can balance player expectations. The simulation results show that when $m = 0.3, 0.7$, the player has the biggest psychological gap, which expresses that the player will be motivated by not being reconciled. Moreover, addiction is likely to occur when $m \in [0.5, 0.7]$. Such an approach can also help the developers and educators increase edutainment games' efficiency and make the game more attractive.

4.1 Introduction

In the development of games, player motivation is always the goal object for game designers. Reward motivation can stimulate the pursuit to achieve the goals that are often used for behavior guidance in many areas such as business, education, human resource management, to name a few. A representative work on behaviorism by Skinner believed that after a specific behavior is rewarded, the specific behavior will be strengthened and solidified after continuous reinforcement [117]. The rules, conditions, and intensity of reward will also affect the incentive mechanism's effectiveness and the driving force of behavior. In previous clinical studies conducted on the animal, the dopamine system in the brain is associated with Beta signal, which is related to the activation of the orbitofrontal cortex when confronted with rewarding activities such as getting food [97]. Interestingly, similar results were obtained in human experiments [35]. However, different from animals, humans are good at learning how to predict the recurrence of reward signals [12, 42].

Gambling games that typically have the highest uncertainty in games are typical reward-driven games. Usually, the result cannot be determined before placing a bet, and the game starts after stopping the betting. So the reward mechanism in gambling games expresses an immense appeal to players, and there is a definite possibility to cause addiction in the player. The mechanism of gambling games relies on the reward mechanism, and an instant reward feedback mechanism makes the player have a great curiosity to win the game.

Moreover, the reward setting of gambling based on reinforcement schedules makes the game more unpredictable and heavily reliant on information uncertainty. In terms of physiological mechanisms [130], rewards lead to the secretion of dopamine, which gives players a sense of pleasure. Also, the body's physiological mechanisms always seek for dopamine release repeatedly, at any cost, making it keen to explore and try new things, and this has an escalating effect on the player's motivation. The game has clear and specific goals, and each time a player completes a challenge, he or she is rewarded with a reward that disappears in the form of obstacles such as enemies, increases in experience and ability, an extension of the challenge time, or the opening of the next level. This situation is immediate, continuous and varied, and has an essential motivational impact on the player [48].

The first Multiarmed Bandit game is the mechanical slot machine called the Liberty Bell with three spinning reels, which was invented in 1895 by a car mechanic, Charles Fey [15] which then became one of the most popular slot machines in the gambling house. Such phenomenon acts as the motivation to adopt Multi-armed Bandit games for conducting analysis relative to the player's perceived psychology of the rewards obtained from such games. Game refinement (GR) theory, which was first introduced by Iida et al. [62], proposes the idea of analyzing and understanding game progress based on the uncertainty of the game result. It is a crucial evaluation standard and plays an essential role in every different game field. Based on variable ratio schedules, the player satisfaction model [136] provides a link between game refinement theory and reinforcement schedules. By connecting with the reward ratio (say N), the game's energy could be calculated, which shows how much the game satisfied the player based on the reward mechanism.

However, previous studies mainly focused on classifying players based on their motivations. For example, Malone initially believed that entertainment motivations are divided into three categories: challenge, fantasy, and curiosity [80]. The three types of motivations complement each other and are the deep reasons why humans like games. In Bartle's player model, motivations are analyzed to classify players, but the model does not explain the motivations of multiplayer games itself [13].

Meanwhile, the theory of motivation in game-playing makes up for the shortcomings of the MUD player model and analyzes multiplayer through five motives as the classification factors [140]. However, these models are based on classification, and there is no motivation analysis based on quantification. The quantitative psychological gap proposed in this chapter analyzes the difference between players' expectations and reality by computational methods. Thus, the classification of players' intrinsic motivation comes from their confidence or unwillingness towards a reward.

The objective of this chapter is two-fold: firstly, the reward mechanism of the gambling machine, the Multiarmed Bandit games, is presented for the first time to clarify it via the player satisfaction model. Secondly, such a model attempts to quantify the player's psychology during the game and analyze the underlying reasons for addiction. The main research questions for the paper is why gambling game are addictive and whether is it able to estimate players' psychological inclination.

Therefore, to the best of our knowledge, the player's psychological gap changes are defined for the first time based on the motion-in-mind model. Furthermore, analysis via simulation data of the two Multi-armed Bandit games under different settings was conducted to determine the player's psychological tendencies. The experiment verifies the computational method of the player's psychological tendency where its potential applications were outlined.

4.2 Theoretical framework

4.2.1 Multi armed Bandit

A Multi-armed Bandit [82] is an example of a classical game for the gambler's psychology. Balancing the benefits of exploration and exploitation demonstrates the impact of uncertainty on future decisions. A gambler is presented with several slot machines without knowing to advance each slot machine's actual profit. Each device provides a random reward from a probability distribution specific to that machine. The gambler aims to maximize the sum of rewards earned through a sequence of lever pulls[82, 18]. In this situation, based on the actual representation of the prior and posterior probabilities, the gambler will have an expected reward before each choice act is performed and will receive feedback, i.e., a real bonus, after completing the action. There will be a difference between the two rewards causing uncertainty in this game, which affects the judgment of performing the next choice and continuing the action. An appropriate psychological difference will stimulate the player's behavior, while too little or too much will reduce the player's interest in the game and affect the player's game life.

During the game process of the Multi-armed Bandit game, the crucial trade-off the gambler faces at each trial is between "exploitation" of the machine with the highest expected payoff and "exploration" to get more information about the anticipated profits of the other devices. The expectation and variance of winning money in each slot machine are different. The player would need to choose the slot every time to maximize the revenue.

An example of reward distribution for the 10-arm bandit , where reward each time was obtained from the sampling results of the Gaussian distributions [127]. Each of the violin plots corresponds to a different Gaussian distribution, with their respective mean and variance values. The actual probability would be the winning probability of such a mechanism. The action values $q_\star(a)$, $a = 1, \ldots, 10$ were chosen according to a normal (Gaussian) distribution with mean 0 and variance 1 of the normal (Gaussian) distribution to be chosen.

4.2.2 Reward Mechanism in Games

Reinforcers are stimuli that could select appropriate behaviors and teach the player what to do [117]. The reward is one of the positive reinforcers [120]. As an essential feature of games, rewards exist in all types of games. Rewards come in many shapes and sizes, and if done right, can significantly increase the enjoyment and longevity of the game. Skinner's experiments on operand conditioning revealed reward on behavior reproduction, known as reinforcement theory. The reward schedule leads to the enjoyment of the game itself[121]. [83] quoted: "The reward mechanism can help us to improve through random obstacles linked to our performance and better feedback mechanisms to make us work harder." It was used in many areas such as business [132], managements [71], educational areas [48], and so on. Specifically, psychological needs such as satisfaction may be associated with various feedback mechanisms provided by a game to the player. However, most of them focus on the reward mechanism itself, while few studies focus on the reward acquisition's uncertainty. As reward causes encouragement, uncertainty of a reward makes a situation thrilling, sense of crisis or urgency, and stimulate motivation [63].

Fiorillo [41] examined the influence of reward probability and uncertainty on the activity of primate dopamine neurons. They found that the effect was greatest when reward uncertainty was 50 percent. Human studies on fMRI also reported evidence for a similar relationship between reward and uncertainty [115]. In addition, studies showed that large amounts of dopamine are released in uncertain situations of long-term uncertainty and significant rewards. This increase in dopamine output may contribute to the rewarding properties of gambling, with increased dopamine release during gaming and gambling-like tasks [115]. These studies suggested that reward uncertainty is indeed the key to player interest by controlling the uncertainty of reward and observing the dopamine levels and other neural signals.

On this basis, this chapter intends to study further how the uncertainty of reward affects players' interest and leads to addiction at the psychological level of players. The Multiarmed Bandit game is based on a variable ratio schedule. Based on previous work [60, 136], the game speed of the Multiarmed Bandit game is $1/N$ (N is the average ratio of the reward), which means that the average of N times attempts in the game would reinforce the player. The risk frequency ratio m, which is the risk frequency over the whole game length is defined as $m = 1 - 1/N = (N-1)/N$. As such, this section explores the players' entertainment effect by analyzing the reward frequency (which will be discussed in detail in the next section).

4.2.3 Motions in Mind and Internal Energy Change in Games

Games are earning processes where players learn and adapt to grasp the rules of the game. Similarly, reinforcement schedules, which were explored by Skinner [40], were widely used in the learning environment. Based on such circumstances, game settings become essential factors that affect the player's experience [60]. Analogical links between motions in physics and motions in mind had been previously established based on the notions of winning rate (or velocity) v and winning hardness m, where the correspondence between the physics model and the game progress models is established based on the assumption of zero-sum game setting (Table 4.1).

Table 4.1: Analogical link between game and physics [60]

Notation	Game Context	Notation	Physics Context
y	solved uncertainty	x	displacement
t	progress or length	t	time
p	win rate	v	velocity
m	win hardness	M	mass
a	acceleration	g	gravitational acceleration

According to the game progress model, the slope (v) of $y(t) = vt$ of a game progress model has a contradictory relationship to m. In the current context, v is generally implying the rate of solving uncertainty, whereas m implies the difficulty of solving such uncertainty ($m = 1 - v$) [60]. Such correspondence enables indication of "physics in mind" in various games, specifically on three quantities: potential energy, momentum, and force. The potential energy (E_p) in the game is defined as the game playing potential or the expected game information required to finish a play [60], given by (4.1). At the same time, m is the game 'mass' (associated with the difficulty of solving the uncertainty), and v is the 'velocity' (associated with the rate of solving the uncertainty). According to the potential energy, player satisfaction could be expressed by employing reward mechanisms, and the "gravity" implied on such mechanism to the player [136], while $v = 1/N$.

$$E_p = 2mv^2 \tag{4.1}$$

Definition 1. Internal Energy Change (ΔU) in real-world physics can be defined as [24]: "For a closed system, with matter transfer excluded, the changes in internal energy are due to heat transfer (Q) and due to thermodynamic work (W) done by the system on its surroundings.' Accordingly, the internal energy change (ΔU) for a process is written as (4.2).

$$\Delta U = Q - W \text{ (closed system, no transfer of matter)} \tag{4.2}$$

Internal Energy Change definition provides the basis for this chapter, which explores the formulation of internal energy change concerning the games. To define the change in Internal Energy Change of a game, we first need to clarify the concept of internal energy in relation to games. In this chapter, we assume that the play process is metaphorically a closed system composed of the game and the player, where the heat transfer (Q) is the player-side energy associated with the expectation from the player. In contrast, the thermodynamic work (W) is associated with the game's feedback (or game-side energy). Relative to the motion in mind model, the internal energy related to the changes in energy difference will be discussed further in the subsequent section.

4.3 Methodology

4.3.1 Energy Difference in Games

Two distinct energies were considered with a focus on player-side actual probability and game-side intuitive probability. The player-side energy E_i focused on the mass and velocity with a value of intuitive probability, whereas the game-side energy E_r based on the mass and velocity with a value of return rate. E_i and E_r are given in (4.3) and (4.4), where v_i and v_r stands for the intuitive probability and return rate respectively, hence $m_i + v_i = 1$ and $m_r + v_r = 1$ hold.

$$E_i = 2m_i v_i^2 \tag{4.3}$$

$$E_r = 2m_r v_r^2 \tag{4.4}$$

Table 4.2 provides the comparison of the two potential energies. The energy difference E_d is given by (4.5), which shows the player psychological discrepancy caused by the velocity difference between player and game.

Table 4.2: Two potential energies compared.

Notation	**Game-Side**	**Player-Side**
E_i	intuitive probability based game velocity	entry difficulty
E_r	return rate based game velocity	engagement(confident)

$$E_d = E_i - E_r \tag{4.5}$$

Remark. When $E_d > 0$, player confidence influences more profoundly than the game side, reflecting player confidence in gambling games. When $E_d < 0$, the game side influences more profoundly than the player side, reflecting high entry difficulty and causing player frustration similar to the one experiencing in chess-like games.

This section assumes that player-side energy (E_i) is based on the intuitive probability, which is the prior probability before every choice. Correspondingly, game-side energy (E_r) is based on the return rate, associated with the actual probability after a choice was made.

4.3.2 Upper Confidence Bound Method

4.3.3 Methodology Introduction

The focus of our research paper is to analyze the energy flow involved in human decision-making, which is influenced by a gap between psychological perceptions and real-world outcomes. However, due to the lack of adequate data in this field, we faced challenges in accessing human player data sets to investigate the matter. Thus, we experimented to gather data on the intuitive energy of human players and the payoffs they receive before playing gambling games. To emulate a human player, we employed the UCB algorithm, given that a trade-off exists between information gathering and reward collection in human learning and decision-making. In a game featuring multiple options with uncertain payoffs, a human player tends to try various options initially to gauge potential payoffs before focusing on the most promising option[44]. Similarly, the UCB algorithm explores all available options and gradually selects the option with the highest expected payoff based on prior performance. Furthermore, the UCB algorithm employs Bayesian inference to update its estimate of the expected payoff for each option, akin to how humans modify their beliefs about the world based on new information and experiences[112].

Methodology in Multi-armed bandit game

UCB (Upper Confidence Bound) is a method first proposed by Lai and Robbins [74] that utilizes upper confidence values for dealing with the exploration-exploitation dilemma in the Multiarmed Bandit problem. The gambler's goal is to win more money and get the greatest return.

The algorithm steps: first try it for each arm, then at any moment calculate the score for each arm according to the following formula (4.7), and select the arm with the largest score as the choice. Next, observe the selection results and update t and $n_{i,t}$, where $\hat{\mu}_{i,t}$ denotes the average reward obtained from the slot machine i with $i_t \in [1, 2...N]$, followed by $\sqrt{\frac{lnt}{n_{i,t}}}$ being called the bonus, which is essentially the standard deviation of the mean, is the number of trials so far, and t is the number of times i was played.

Upper confidence bound (UCB) algorithms provide a simple but efficient heuristic approach to bandit problems [75]. In this section, UCB method was employed to simulate the player selection process. The predicted reward and actual reward of every step are counted during 10,000 times training in the experiments. At each round, the UCB algorithm would select the arm with the highest empirical reward estimate up to that point plus some term that is inversely proportional to the number of times the arm was played.

More formally, define $n_{i,t}$ as the number of times arm i was played up to time t. Then, $r_t \in [0, 1]$ denotes the reward observed at time t, while $i_t \in [1, 2...N]$ is the choice of the arm at time t. Then, the empirical reward estimate of arms i at time t is shown in (4.6). UCB assigns the following value to each arm i at each time t as shown in (4.7).

$$\hat{\mu}_{i,t} \in \frac{\sum_{s=1:I_s=i}^{t} r_s}{n_{i,t}} \tag{4.6}$$

$$UCB_{i,t} := \hat{\mu}_{i,t} + \sqrt{\frac{lnt}{n_{i,t}}} \tag{4.7}$$

To briefly describe the UCB algorithm, the following were the steps involved:

- Initialize the number of round, random generator, and arm choices (line 12–17). Then, try it for each arm (line 18).

- Calculate the score for each arm randomly (line 13–15) and according to formula (4.7) (line 20–21), of which the arm with the largest score is then selected.

- Then, based on the observed selection results, update t (line 16) and n_i, t (line 22).

4.3.4 Experiment Setup

The player energy changing over various masses were compared to clarify how a player feels engaged in the game process. Because of the data particularity, there is no such accurate

Algorithm 1: UCB Algorithm (Modified from original source [144] to the source code given at `https://github.com/KANG-XIAOHAN/Multi-Armed` accessed on 3th Dec 2021)

t:= arm number;
N:= total number of arms, number of rounds;
T:= total time of playing arm, where $T \geq N$;
$tround$:= the round of player test;
$reward$:= the reward obtained when plays;
$chosen$:= the number of chosen arm;
sc:= simplify for $chosen$;
$ucbVal$:= the UCB values estimate for each arm;
μ:= mean of distribution for each arm;
$PL \leftarrow$ `play(`$tround$`)`;
$R \leftarrow$ `random()`;
$INIT \leftarrow$ `init()`;
if t **to** *10* **then for** $chosen$ **to** *10* **do**
    $chosen \leftarrow$ `random()`;
    if *reward is max* **then** $chosen \leftarrow$ `play(`$chosen$, $tround$`)` ;
    $tround \leftarrow +\ 1$;
$INIT \leftarrow$ `init()` ;
for t **to** T **do** `// play arm t one by one,`$t \in N_+$
    $chosen \leftarrow$ `play(`$chosen$, $tround$`)`;
    if $chosen > 0$ **then** $ucbVal = \hat{\mu}_{t,sc} + \sqrt{\frac{lnsc}{n_{tsc}}}$;
    $chosen \leftarrow$ `play(`$reward + ucbVal$`)`;
    $chosen \leftarrow$ `update(`t, $chosen$, $reward$`)` `// depends on the` $reward$ `and` $ucbVal$`, we update the arm we choose for getting the maximum reward`

open data for intuitive probability and actual probability for different mass values. In this section, 10 settings were simulated. The experiment took a random distribution conditional on m being selected from 0 to 1, where the details of the distribution for each m are given in Table 4.3 and Table 4.4 for the 3-armed bandit and 10-armed bandit, respectively. Such an experiment was designed to separate the effects of each Multiarmed Bandit in a different mass by controlling each arm's distribution sets.

The Multiarmed Bandit in this simulation follows Gaussian distribution, where every arm follows the Gaussian distribution. For Bayesian, the probability of spending money at each slot machine has a prior distribution assumption as long as we enter the same casino. After pushing the slot machines, the corresponding posterior distribution can be adjusted according to the related feedback. There are 10 sets of experiments in this section that correspond to different reward distributions. The simulated slot experiment aims to estimate the overall expectation of slot machines throwing money through the known sample distribution. It is a Bayesian process since each arm obeys the Gaussian distribution. Suppose that the component with a higher feedback rate among n arms can be found. In that case, the joint distribution of multiple Gaussian distributions needs to be analyzed, which is the binomial distribution process. Based on this, two sets of experiments with 3-armed and 10-armed were performed to analyze player psychology, and 11 groups of experiments were compared. Uncertainty of the game is controlled by setting up different reward distributions as shown in Table 4.4–4.3. There are 10,000 times training for each setting to simulate the selection process using the UCB method to maximize the next-choice reward. We collected data on predicted expectations before each choice and true rewards after each option, and then compared and analyzed them.

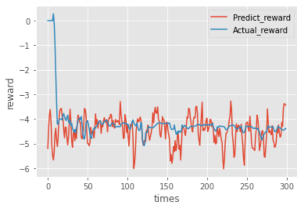
Table 4.3: Experiment setting for 3-armed bandit.

Arm Setting Distribution	m	**Arm Numbers**
(0,1)(0,1)(0,1)	0	3
(−1.03,1)(−1.22,1)(−1.75,1)	0.1	3
(−0.77,1)(−0.68,1)(−1.12,1)	0.2	3
(−0.14,1)(−0.51,1)(−0.99,1)	0.3	3
(−1.03,1)(−0.55,1)(0.71,1)	0.4	3
(0.30,1)(−0.56,1)(0.22,1)	0.5	3
(2.04,1)(0.20,1)(−0.71,1)	0.6	3
(0.61,1)(0.73,1)(0.25,1)	0.7	3
(4.13,1)(0.77,1)(0.31,1)	0.8	3
(4.16,1)(1.32,1)(0.80,1)	0.9	3
(4.27,1)(4.27,1)(4.27,1)	1.0	3

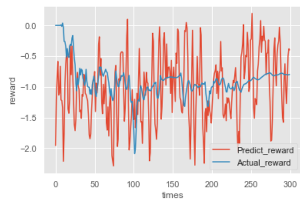
Table 4.4: Experiment setting for 10-armed bandit

Arm Setting Distribution	m	**Arm Numbers**
(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)(−4.5,1)	1.0	10
(−2.07,1)(−0.94,1) (−1.42,1) (−4.77,1) (−0.90,1) (−1.28,1) (−1.07,1) (−1.04,1) (−1.36,1) (−1.46,1)	0.9	10
(−0.43,1)(−0.78,1)(−3.46,1)(−1.01,1)(−0.75,1)(−0.65,1)(−1.21,1)(−1.22,1) (−0.47,1) (−0.59,1)	0.8	10
(−0.87,1)(0.20,1)(−0.80,1)(−0.86,1)(−1.07,1)(0.17,1)(−1.40,1)(−0.21,1)(0.19,1)(−1.62,1)	0.7	10
(−0.09,1)(0.75,1)(0.52,1)(1.36,1)(−0.83,1)(−1.53,1)(−2.22,1)(−0.58,1)(−1.18,1)(−0.09,1)	0.6	10
(−0.92,1)(1.13,1)(−0.80,1)(−0.82,1)(0.50,1)(0.19,1)(0.53,1)(0.78,1)(0.24,1)(−0.94,1)	0.5	10
(0.74,1)(0.82,1)(0.11,1)(0.17,1)(0.65,1)(0.06,1)(−0.55,1)(0.31,1)(−0.23,1)(0.62,1)	0.4	10
(−1.99,1)(−0.90,1)(−0.29,1)(−1.55,1)(−1.10,1)(−0.75,1)(−0.50,1)(−0.68,1)(−0.42,1) (−1.27,1)	0.3	10
(0.39, 1)(0.69,1)(0.39,1)(1.77,1)(0.89,1)(1.60,1)(0.92,1)(0.79,1)(1.03,1)(0.73,1)	0.2	10
(2.18,1)(1.11,1)(1.91,1)(1.25,1)(1.76,1)(1.22,1)(0.53,1)(1.01,1)(1.33,1) (2.50,1)	0.1	10
(0,1)(0,1)(0,1)(0,1)(0,1)(0,1)(0,1)(0,1)(0,1) (0,1)	0	10

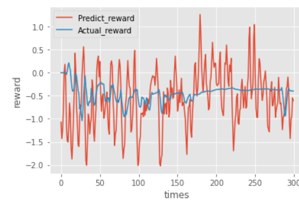
An example of the 3-armed bandit game was depicted in Figure 4.3.1, where it showed different game levels between the predicted reward and actual reward. The blue line shows the predicted reward, and the orange line shows the actual reward. The figure demonstrates the first 300 training results by using the Savizky-Golay filter to less noise.



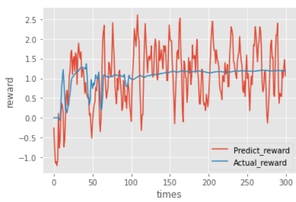
(a) $m = 1.0$



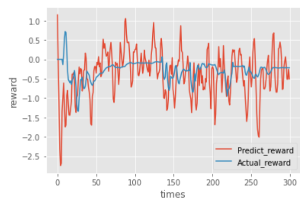
(b) $m = 0.9$



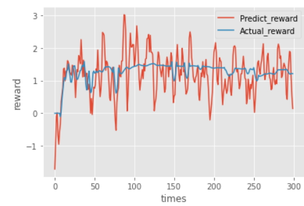
(c) $m = 0.8$



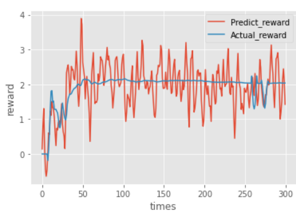
(d) $m = 0.7$



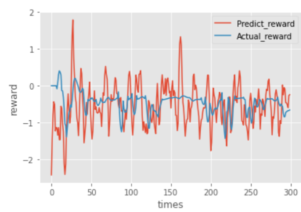
(e) $m = 0.6$



(f) $m = 0.5$

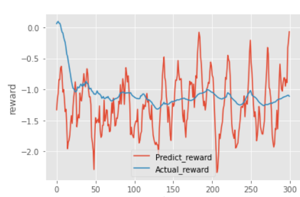


(g) $m = 0.4$

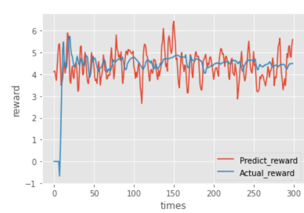


(h) $m = 0.3$

(i) $m = 0.2$



(j) $m = 0.1$



(k) $m = 0$

Figure 4.3.1: Comparison of predicted reward and actual reward with a game length of 300 steps with $m \in [0, 1]$ (m is mass in game).

4.3.5 Results and Analysis

In this chapter, two sets of experiments with 3-armed and 10-armed bandits were performed to analyze player psychology, and 11 groups of experiments were compared. Uncertainty of the game is controlled by setting up different reward distributions as shown in Tables 4.3 and 4.4. There are 10,000 times training for each setting to simulate the selection process using the UCB method to maximize the next-choice reward. We collected data on predicted expectations before each choice and true rewards after each option, and we then compared and analyzed them.

4.3.6 Psychological Gap Expressed by Energy Difference

Higgins [53] proposed the theory of ego-fall, where he argues that the ideal-self and the real-self are the standards that guide the authentic-self to reach. When the gap between the real-self and the ideal-self is created, the motivation to reduce this gap arises, and this motivation drives behavior and makes people strive.

As is shown in Figure 4.3.1, the range of the predicted reward is larger than the actual reward. Furthermore, in the game length for each level, the range of the predicted reward is always more extended than the actual reward range, which indicates that player prediction is unstable. Therefore, there is always a difference between actuality and prediction. In other words, the player's perception of uncertainty fluctuates much more than the actual reward; thus, creating a psychological gap between prediction and reality while playing.

To differentiate the difference of the psychological gap between prediction and reality in gaming, energy difference E_d is computed and reported in Tables 4.5 and 4.6. There are two peaks as m increases, where $m = 0.3 - 0.4$ and $m = 0.6 - 0.7$. The energy difference can be up to 0.29504 and 0.24365 for two settings (Figure 4.3.2). When $m = 0.3 - 0.4$ and $m = 0.6 - 0.7$, the player has the biggest psychological gap, which expresses that player will be motivated by not reconciled. The high psychological gap makes players think that they may win in the next pull which makes them continue to play. In this experiment, the energy difference is decreasing when m is decreasing since the uncertainty of the game is decreasing, which shows that the players gain more confident in their prediction. When $m = 0$ and $m = 1$, the energy difference is reaching to 0, which shows that the actual game results satisfied the player prediction.

It is an extreme case that no-lose or no-win would happen in the game, which is easy to predict. The compared energy difference between 10-armed bandit and 3-armed bandit shows that the energy difference is in a similar range. Moreover, there is always a sudden drop while $m = 0.5$, which shows when the game is relatively fair game-side energy is closer to player-side energy. A 3-armed bandit expressed more unstable than 10-armed

Table 4.5: Results of energy difference in 3-arm bandit.

m	**Actual Probability**	**Intuitive Probability**	**Energy Difference E_d**
1.0	0.00000	0.00000	0.00000
0.9	0.00001	0.08100	0.01206
0.8	0.00014	0.23491	0.08444
0.7	0.00150	0.34777	0.15776
0.6	0.33433	0.38396	0.03282
0.5	0.66537	0.50869	−0.04202
0.4	0.66776	0.59327	−0.00998
0.3	0.99994	0.69022	0.29504
0.2	0.99983	0.81218	0.24744
0.1	0.99995	0.89007	0.17408
0.0	0.99997	1.00000	−0.00001

Table 4.6: Results of energy difference in 10-arm bandit.

m	**Actual Probability**	**Intuitive Probability**	**Energy Difference E_d**
1.0	0.00000	0.00000	0.00000
0.9	0.00002	0.17683	0.05147
0.8	0.00013	0.30717	0.13074
0.7	0.99744	0.58729	0.27960
0.6	0.99973	0.88805	0.17603
0.5	0.99978	0.91979	0.13527
0.4	0.99962	0.81684	0.24365
0.3	0.00003	0.46733	0.23266
0.2	0.99989	0.96995	0.05632
0.1	0.99988	0.99971	−0.00033
0.0	0.99990	1.00000	−0.00019

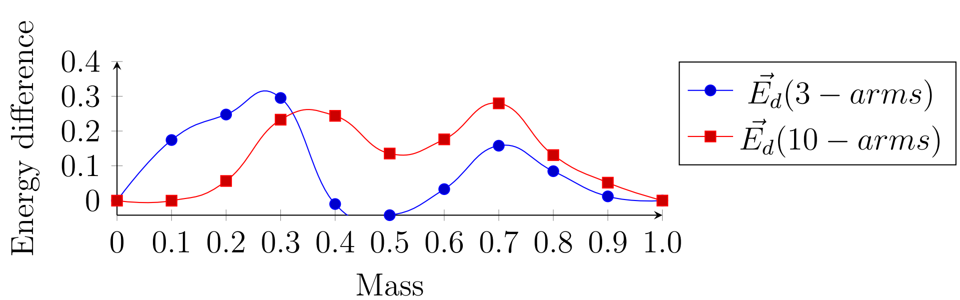


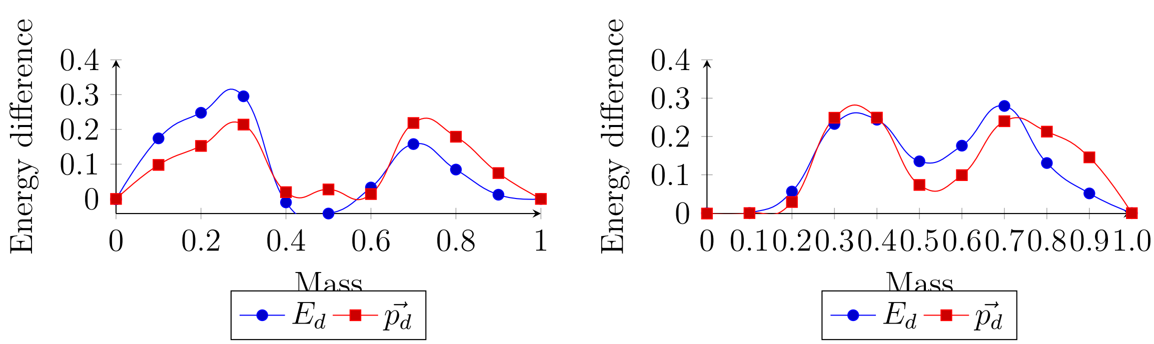
Figure 4.3.2: Changes of energy difference measures.

since it has fewer choices, while one judgment will reflect more than 10-armed bandit.

4.3.7 Link between Satisfaction and Competitive in Game Playing

Based on the previous study by [60], potential energy is 'skewed' towards a player with a sufficiently high (but not necessarily perfect) ability, while momentum is the greatest when the player possesses the ability similar to the majority of the players of such game. Momentum makes players more competitive to play [2], while energy determines whether or not players are satisfied with the game. In the moment where momentum equals energy ($\vec{p} = E_p$), player satisfaction and competitive feeling are well balanced (denoted as player motivated point). When $\vec{p} > E_p$, the player would be more competitive. Meanwhile, $\vec{p} < E_p$, the player would be more satisfied but less motivated.

Energy difference E_d provided the player psychology gap in-game process. As shown in Figure 4.3.3, in 3-armed bandit, when $\vec{p_d} = E_d$, $m \in [0.3, 0.4]$ and $m \in [0.6, 0.7]$. Meanwhile, for 10-armed bandit, $m \in [0.2, 0.3]$ and $m \in [0.7, 0.8]$ when $\vec{p_d} = E_d$. The range on both settings was closely similar, which can be associated with players who are well-motivated due to competition and satisfaction. Nevertheless, there were some limitations in light of this section's findings. With the change of exact arm setting, the mass value will make subtle differences. The section results highlight the need for future research to use a representative sample.



(a) Changes of E_d and $\vec{p_d}$ of 3-arm bandit

(b) Changes of E_d and $\vec{p_d}$ of 10-arm bandit

Figure 4.3.3: Changes of energy difference measures.

4.4 Discussion

4.4.1 Application with player fairness domain

In the motion in mind model [60], $m = 0.5$ is the absolute middle-ground between fair and unfair. However, when $m > 0.5$, the play condition will favor the game side and become more competitive. In contrast, the play condition will favor the opposite (player side) when $m < 0.5$, which is associated with being more satisfied. As mentioned before, the player motivated point is around $m \in [0.3, 0.7]$, as shown in Figure 4.4.1. It can be conjectured that when $0.3 < m < 0.5$, the player would be more satisfied but less competitive; naturally, in the educational context, which needs more encouragement and less uncertainty. When $0.5 < m < 0.7$, the player would be more competitive but less satisfied, which appears in sports and competitive games.

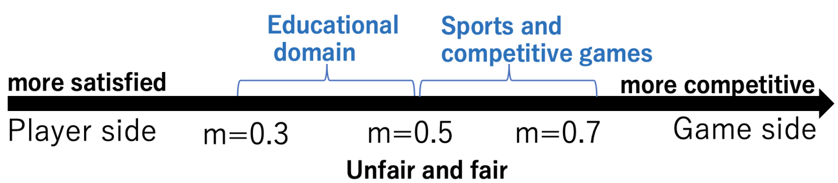


Figure 4.4.1: Application with player fairness domain.

4.4.2 Why is the Multi-armed Bandit Addictive?

The physical excitement of gambling, the great joy, and the sadness caused by the substantial psychological gap between winning and losing bring pleasure to the body. Like roller coasters and skydiving, it is difficult for other recreational activities to provide. The pursuit of this kind of exciting fun is the most direct, simple, and initial reason. The energy difference E_d provides the difference between prediction and actual reward to show the player psychology gap.

Secondly, the motivation which pushes a player to continue the game is to balance the psychology gap. When E_i is more extensive, the player side has more influence. On the contrary, the game side will influence more. To encourage the player to play the game, energy difference E_d will be positive for strengthening player confidence and reinforcing the reward effect. Furthermore, when $\vec{p_d}$ equals E_d (player satisfaction and competitive feeling are well balanced), m lands up to around 0.3, 0.7 in the two settings of this section. Additionally, gambling needs to be considered to guarantee a profit while encouraging the game continuation, so m lands up to around 0.3, which can be evaluated in real gambling games.

Thirdly, energy difference E_d can be applied to many areas to analyze whether player confidence was motivated, such as educational areas and business models. It is suggested that the mass of such a game could be controlled in the range of $m \in [0.3, 0.5]$. The games that focus on competitive and thrilling feelings should be at the stage of $\in [0.5, 0.7]$. In essence, the mass value should always be $\in [0.3, 0.7]$ to fill the psychology balance.

Finally, the game is a process in which the player constantly tries to balance their psyche and make behavioral judgments through empirical evaluation. In this learning process, expectations and disparities shape the player's psychology. Expectations can be understood in the abstract related to challenges, and differences are formed mainly by the gap between reality and ability or between the opponent/game's side and the player's side. Therefore, a good game can help the player achieve a balance between psychological competition and satisfaction while encouraging and guiding the player to continue the game process and achieve psychological comfort. In the education sector, such gamification can be designed to facilitate learning planning and goal attainment.

4.4.3 Limitation

This chapter selects one of gambling's multi armed slot machines for study and analysis. The single nature of the game's reward mechanism makes it the best object of study to examine the psychology of players based on a reward system. The findings may be limited to application for the quantification of player psychology in the context of any randomized reward system. In addition, on an individual basis, this chapter's methodology can also be limited to player segmentation. For example, players who maintain a solid willingness to continue playing when the energy difference is negative and consistently pessimistic can be called unbeatable players. Players who continue to play only when their energy is positive can be referred to as encouraging players.

4.5 Chapter Summary

In this section, we identified the reward mechanism of Multi-armed Bandit games using the analogy of energy difference in games. Thus, the player's interactivity and games can express the psychological gap to understand motivation and possibly addiction better. This situation addresses our first objective to better clarify the psychological gap of players by mapping the reward of the Multiarmed Bandit games relative to the player satisfaction model [136]. Furthermore, it was found that the difference between intuitive and actual probability is where player motivation comes from, as denoted by the positive energy difference. Thus, high reward expectations, in spite of low actual returns, motivate players, while some negative energy difference causes the experience to be surprised and encouraged.

This section demonstrated that the game process could be a motivational tool for learning and entertainment, where players react differently regarding rewards and uncertainty. In addition, the measures of energy difference provide a quantification tool to better analyze the player psychology of the Multi-armed Bandit game by providing a controlled environment of uncertainty (based on the m value). Finally, based on the simulation results, a balanced setting provided a fair and potentially motivating point (in contrast to addictive) that could be useful for learning and entertainment perspectives. These points highlighted the underlying mechanisms behind players' psychological inclinations and possible reasons why gambling games are addictive; thus, achieving our second objective of the study.

Based on the energy difference (E_d) in Multiarmed Bandit games, it was found that a player's psychological gap can be computationally estimated to identify player confidence ($E_d > 0$) which encourages the player to continue gaming. In contrast, player frustration ($E_d < 0$) can also be identified, discouraging players due to entrance difficulty. Furthermore, considering the relations of the energy measures to the momentum ($\vec{p}$), the intersections between momentum difference and energy difference ($E_d = \vec{p_d}$) potentially describe the player's motivation point, which fulfills player satisfaction and the sense of competitiveness.

In essence, a game is a process where players constantly try to balance their psyche and judge their behavior through empirical evaluation, shaped by the expectation and disparities of their learning process. Thus, the challenge faced by the players is abstracted by their expectations. Meanwhile, the disparities were demonstrated based on the gap between the game element and the player's psyche. As such, a well-designed game help players psychologically achieve a balance between competitiveness and satisfaction while encouraging and guiding the player to continue the gaming experience. Such a case would be beneficial in modeling educational and business processes concerning the concept of gamification [78], where learning in both contexts can be optimized while providing an enjoyable experience.

Chapter 5

Analysis of Driving Comfort through Steering Wheel Information with a Focus on Motion-in-mind

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

- Kang Xiaohan, Muhammad Nazhif Rizani, Mohd Nor Akmal Khalid, Hiroyuki Iida, Analysis of Driving comfort through steering wheel information with a focus on *motion−in−mind*, ASEAN Workshop on Information Science and Technology 2022, Nomi, Ishikawa, Japan.`https://drive.google.com/file/d/1pGzOPoUBKIUDA9ZL44P7m2$_$Y64l2KXDQ/view`

- Xiaohan Kang, Muhammad Nazhif Rizani, Mohd Nor Akmal Khalid and Hiroyuki Iida. "Analysis Of Driving Comfort Through Steering Wheel Information With A Focus On Motion-In-Mind," In the proceedings of the Asean workshop on information science and technology, 14-15 december 2022, pp. 234–244.

In Chapter 4, we examined the feasibility of motion-in-mind theory in the study of psychological fallout, using gambling games as an example, highlighting the importance of player feedback in the iterative process of gameplay. In this chapter, to further refine psychological fallout and explore its real-life application, we investigate its application to driving comfort. Driving comfort is defined and analysed through the study of information about the driver's turning manoeuvres during driving, through energy conversion.

Overall, we found that motion in mind can be applied to the analysis of driving comfort by providing a framework for quantifying the driving experience and could help the comfort designers for iterative improvement based on driver instant energy conversion feedback.

5.1 Introduction

With the development of Self-driving technology, vehicles are becoming more and more intelligent and the goal of fully Self-driving will eventually be achieved. Human drivers will not need to spend efforts to maintain safe and smooth driving, but they will also face the loss of driving pleasure, so how to achieve the appropriate inclusion of driving pleasure while ensuring safety is the future challenge that vehicle designers will eventually face. Therefore, it is essential to research the principle of driving comfort.

In recent years, a great deal of research has focused on ride comfort. The main way in which current research has been able to control the comfort of the algorithm is by setting thresholds for various parameters, such as acceleration, deceleration, lateral acceleration and other ride comfort indicators, and by setting appropriate thresholds to ensure ride comfort. However, driving comfort and ride comfort are different.

Even with the same comfort metrics, the driver and the rider feel very differently. We consider this in terms of a game concept, where we consider the driving process to be the operator of the game and the driving process to be an interactive manipulation of the operational process. The driver applies forces to the steering wheel, brake and other manipulative elements through the upper and lower limbs to achieve the driving intention. The player (the driver) participates in the game (the driving process) from a first-person perspective, and any actions or decisions made by the player (the driver) will receive feedback from the game itself (e.g. speed, acceleration and other kinematic parameters), which will influence the player's next actions. The sense of handling is considered to be the main source of driving pleasure.

In contrast, the ride is a one-way experience, where the rider unilaterally feels and experiences the movement of the vehicle. In analogous games, the player (rider) participates in the game process from a third-person perspective; the player's (rider's) own activities do not have an impact on the game process (the ride) and therefore do not receive feedback from the game and do not feel involved. The pleasure of the ride is thought to come more from the player's own feedback which is the player's perception of the uncertainty of the unknown, e.g. people like to ride roller coasters because through them the rider feels the thrill of the unknown which is not under the player's own control and this uncertainty constitutes the pleasure of the comfort of the ride.

Therefore, most existing studies focus on the effects of various motion indicators on the perceived comfort of the rider and do not distinguish well between driving and riding comfort. This section will define and analyse driving comfort from this problematic point of view using a gamification analysis approach, Game Refinement theory [61], focusing on the attractiveness and sophistication of games. In game refinement theory, the uncertainty of the game outcome is described with classical physics (Theory of Kinematics) based models. Game Refinement (GR) measure reflects the attractiveness of a game from the viewpoint of the players. This theory has been applied to almost all board games [62] [125]. Later, it has been used not only in board games [58] but also in video games, educational games [5], business [147], and riding comfort [145] as well. In this chapter, game refinement theory has been adopted assuming that the action of driving or the experience of a driver when assisted through a smart system is the most comfortable when it is the most enjoyable. Developed from Game Refinement theory, there are Motion-in-mind model [60] and Player Satisfaction model [136]. The Motion-in-mind model [60] defines a player's feelings during a game by finding the relationship between game-play indicators and the movement of information in the player's mind indicators. Each of these indicators represents a game-play feeling of the player, such as sense of control, motivation, curiosity, etc. A balanced perception of the player's experience in each dimension of the game can bring satisfaction to the player. Player satisfaction model [136] which focuses on the reward system using a reward ratio [40] has been developed which provided a new method to balance the Motion-in-mind values which could help in driving cases.

In this chapter, linking driving with the game, refers to the use of game-based methods in non-game environments that engage people and motivate action. Our previous work has been based on game refinement theory to measure the entertainment, and user experience, of gamification processes. In this section, we argue that the comfortable experience of driving is also a process that can be gamified and analysed, and that finding a link between the two will allow for a better analysis of user satisfaction in autonomous driving situations.

5.2 Literature Review and Methodology

5.2.1 Driving comfort

With the boom in Self- driving in recent years, the comfort of the car has become an issue of great concern. In the existing research, the comfort of the car is divided into ride comfort and driving comfort. As the name suggests, ride comfort is concerned with the comfort of the occupants, while driving comfort is concerned with the driver.

We consider this in terms of a game concept, where the driving process is the operator of the game and the driving process is an interactive manipulation of the operational process. The driver applies forces to the steering wheel, brake and other manipulative elements through the upper and lower limbs to achieve the driving intention. The player (the driver) participates in the game (the driving process) from a first-person perspective, and any actions or decisions made by the player (the driver) will receive feedback from the game itself (e.g. speed, acceleration and other kinematic parameters), which will influence the player's next actions. The sense of handling is considered to be the main source of driving pleasure.

In contrast, the ride is a one-way experience, where the rider unilaterally feels and experiences the movement of the vehicle. In analogous games, the player (rider) participates in the game process from a third-person perspective; the player's (rider's) own activities do not have an impact on the game process (the ride) and therefore do not receive feedback from the game and do not feel involved. The pleasure of the ride is thought to come more from the player's own feedback which is the player's perception of the uncertainty of the unknown, e.g. people like to ride roller coasters because through them the rider feels the thrill of the unknown which is not under the player's own control and this uncertainty constitutes the pleasure of the comfort of the ride. The study of ride comfort is usually divided into three categories: the physical evaluation method [30], which measures vibration, noise, temperature and other indicators of driving and determines the range of comfort according to the pattern and correlation of their influence on ride comfort. However, this type of comfort indicator can only be judged by natural indicators and does not fully reflect the entertainment.

Peng et al. compared the main types of ride comfort are summarized first according to the sources of discomfort, including static comfort, vibration comfort, noise comfort, aural pressure comfort, thermal comfort and visual comfort [95]. And the researchers also studied by physiological evaluation method [64], confirmed through bio-measurement that a reduction in vibration acceleration does not always result in optimal ride comfort for the passenger. Real-time measurements can therefore quantify the heart rate variability of the pressure and propose a control method that feeds back into the active suspension and confirms its effectiveness through fundamental validation. From physical to psychological, scientists did relatively comprehensive studies about ride comfort. However, driving comfort is totally different thing from ride comfort.

Thus, for the driver, the driving process is a dynamic manoeuvring process, in which the driver's upper and lower limbs are directed towards the steering wheel, pedals and other manipulators to realise the driving intentions and the feedback from the vehicle's own motion parameters. Based on the characteristics of the driving process, researchers have proposed various methods to measure driving comfort Rebiffe [104] [103]has proposed comfort indicators based on the analysis of driving tasks and the study of joint angles in static driving positions. Later, Seidl [113], Poter and Gyi [98], Kyung and others [72], refined the study of static driving posture comfort through rigorous simulation techniques to obtain a more accurate range of joint angles.

With the research development, scholars have attempted to define driving comfort through a number of dynamic driving postures. Dynamic driving posture comfort is mainly defined by the driver's comfort during steering, acceleration and deceleration. For example, Liu Y H et al. [79] measured the surface electromyographic signals of shoulder muscles through steering manoeuvres experiments and showed that muscle activation can be used to predict driver-specific manoeuvre comfort. Dairou, Priez et al. [31] measured driving comfort through the brake pedal stiffness, a comfort indicator of pedal operation, and Wang. X et al. [133] explored physiological parameters based on the evaluation of pedal manoeuvre comfort, Franziska Hartwich et al [51] investigated the effect of driving automation and driving style familiarity on driving comfort, enjoyment and system acceptance. Therefore, Hussin et al. evaluated comfort during driving by means of real-time driver limb change characteristics.

However, compared to studies on ride comfort, studies on driving comfort have rarely focused on the individual comfort perceptions of the driver's psychology and have not analysed his or her comfort from a psychological perspective. Different psychological states or emotions of the driver can largely influence his or her driving conditions in that situation. This immediate psychological condition can also have a great impact on the driving condition. In this section, in order to better analyse the driver's comfort experience, the analysis of the driver's condition is calculated for the improvement of the car performance and the early warning of the driver for the different states of the driver, which is also of great significance for the driving safety.

5.2.2 Game refinement theory

Game refinement theory is a mathematical method that judges the entertaining property of game by focusing on the solving uncertainty during game process [61]. In Game Refinement theory, it provides a point of view that, the decision space is the minimal search space without forecasting, the dynamics of decision options in the decision space has been investigated and it is observed that this dynamics is a key factor for game entertainment. Thus, it provides the common measures for almost all board games [62] [125]. Later, it has been used to not only board games [58] but also video games, educational games [58], sports and so on. Also, it helps on gamification area like education [5], business [147], and riding comfort [145] as well.

For the board and scoring games, the GR measure is determined by Equation(5.1) using the model of move candidate selection and scoring rate [60]. Here, B and G stand for average branching factor and average goals, respectively. Meanwhile, D is the game length (total number of plies), and T is the total points or goals.

These respective variables were collected from the average of the total number of play-testing experiments. The sophistication of games converges to almost similar sense of thrill (or noble uncertainty [142]) of $GR \in [0.07, 0.08]$.

$$GR_{\text{board}} \approx \frac{\sqrt{B}}{D} \quad \text{or} \quad GR_{\text{scoring}} \approx \frac{\sqrt{G}}{T} \tag{5.1}$$

5.2.3 Variable ratio schedule (N) and winning hardness (m) in Games

In VR schedules, the parameter N shows the average reward frequency, where $1 < N \in \mathbb{R}$. In this chapter, winning a game corresponds to obtaining a reward, then it implies the game length, which is D in board games (total number of plies) and T in scoring games (total points or goals). Hence, $N = D$ or $N = T$, implying a general form of reward frequency of the game's winning rate. Based on such a notion, the winning rate v and winning hardness m is defined by (5.2).

$$m = 1 - v \quad \text{with} \quad v = \frac{1}{N} \quad \text{or} \quad v = \frac{1}{T} \tag{5.2}$$

5.2.4 Motions in Mind

Analogical links between motions in physics and motions in mind had been previously established based on the notions of winning rate (or velocity) v and winning hardness m [60]. The correspondence between the physics model and the game progress models is established as in Chapter 2.4.1. Such correspondence enables the measures of physics in mind in various games, specifically on three quantities: potential energy, momentum, and force.

Previous work by [60] had defined the F as the player's strength to move a game or ability in general, where a is the growth rate of "flow" experience of the player in the game (since $a = \frac{F}{m}$, then F is the ability and m is challenge [29]). In this chapter, $a = \frac{1}{N}$ can be regarded as the sense of gravity in people's minds, where it is the source of cultural tendencies of people's minds in game-playing reflected at a specific time/era. Hence, the measure of F is given by (5.3).

$$F = ma = \frac{(N-1)}{N}\ a \tag{5.3}$$

The potential energy (E_p) in the game is defined as the game playing potential or the expected game information required to finish a game [60], given by (5.4). Meanwhile, momentum ($\vec{p}$) in the game refers to the competitive balance of a game, which involves the degree of challenge needed (m) and effort given (v) to drive the game progression [60], given by (5.5).

$$E_p = 2mv^2 = \frac{2(N-1)}{N^3} \tag{5.4}$$

$$\vec{p} = mv = \frac{(N-1)}{N^2} \tag{5.5}$$

Similar with the law of conservation of energy in classical physics, E_p is expected to be conserved, where the momentum of the game playing motions, while differing in level, contains both objective(in-game) and subjective (in-mind) recognition [60]. Potential Energy is transformed into the sum of the momentum from the game's motion ($\vec{p_1}$) and the momentum of the mind's motion ($\vec{p_2}$), i.e.,$E_p = \vec{p_1} + \vec{p_2}$. Hence, it is expected that $\vec{p_2}$ is a reliable measurement of engagement. Applying Equation(4.1) and Equation(5.6), Equation(5.7) is obtained. Then, the first derivative of Equation(5.7) is solved, where m= $\frac{3\pm\sqrt{3}}{6}$ is obtained and represents high excitement (m= $\frac{3+\sqrt{3}}{6}$) and high expectancy (m= $\frac{3-\sqrt{3}}{6}$). Hence, $\vec{p_2}$ has two peak that play engagement will be maximized. Respectively, objective winning rate v_1 and subjective winning rate v_2 are given by Equation(5.8) and Equation(5.9). Subjective acceleration a_2 is given by Equation(5.10), then the subjective force F_2 in mind can be considered as Equation(5.11). Be solving Equation(5.6) and Equation(5.7), then E_q is given by

$$\vec{p_1} = mv \tag{5.6}$$

$$\vec{p_2} = E_p - \vec{p_1} = 2m^3 - 3m^2 + m \tag{5.7}$$

$$v_1(m) = 1 - m \tag{5.8}$$

$$v_2(m) = 2m^2 - 3m + 1 \tag{5.9}$$

$$a_2(m) = 4m - 3 \tag{5.10}$$

$$F_2(m) = ma_2 = 4m^2 - 3m \tag{5.11}$$

$$\delta E = \vec{p_1} - \vec{p_2} = 2m^2 - 2m^3 = 2m^2 v \tag{5.12}$$

The analogous connections between the physics model and the game progress model were presented in Table 3.1. In this section, for the application aspect of Motion-in-mind in a driving environment, Table.5.1 shows an analogous connection between Motion-in-mind Model in game and driving environment.

Table 5.1: Analogical link between motion in game and driving

Notation	Game context	Motion in mind in Driving
y	solved uncertainty	displacement
t	progress or length	time
v	win rate	Frequency of operation
m	win hardness	Difficulty rate of operation
a_1	objective acceleration	objective acceleration
a_2	subjective acceleration	subjective acceleration
E_p	potential energy	Objective Potential Energy(Perfect normal Comfort)
E_q	Subjective Potential Energy	Subjective Potential Energy(Driver)
$p1$	Objective momentum	Objective momentum
$p2$	Player momentum	Subjective momentum
vk	Subjective outcome/reward of a player with ability k	Subjective outcome/reward of a driver with ability k
mk/mx	2-person and N-person game inequality mass	Driver and rider mass
$E0$	Objective reinforcement energy	Super standard driver energy
Ek	Subjective energy/Freedom with k parameter of skill	Subjective energy of driver based on k

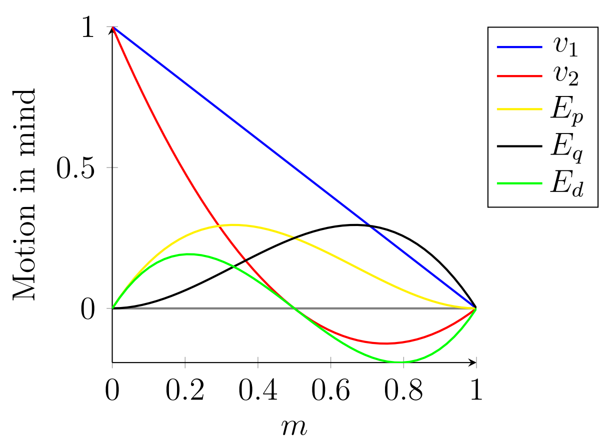


Figure 5.2.1: Motion in mind measures with $m \in [0, 1]$

$$E_d(m) = E_k - E_0 = 2km^2(1-m)^2(km-2) \tag{5.13}$$

In this section, the driving would be relative to the various analogies of motion and its conservation is considered by translating the driving process into two types of quantities: game refinement value and motion in mind. From an information science point of view, the driving activities are considered a linear amount of solved uncertainty. It is a continuous process of accepting uncertainty and adjusting to it, and here we also consider the difference between subjective and objective motion in mind value to be important, and the player/user's perception of uncertainty to be an important factor in determining the perception of comfort. This article will therefore start by comparing and analysing their comfort through subjective and objective differences.

In the previous work, the energy difference in gambling is defined as a difference between the energy from the return rate and win rate focusing on the reward function. Here, with a focus on the personality of the player, the energy difference(E_d) is defined as $E_p - E_q$ shown as Equation(5.13). Solving $E'(d)$=0, then m=$\frac{3\pm\sqrt{3}}{6}$ which has the two peaks of energy difference shows the maximum gap in the player psychology or between objective and subjective.

Conjecture (Driving comfort). With a focusing interest on driver psychology, driving comfort is considered as the distance of drop. When E_d is in the positive range, we consider the objective energy to be dominant and the driver to lose initiative, specifically in terms of the driver's inability to control the vehicle feedback. As a result, there is always a large psychological gap between what is unexpected and what happens. When E_d is in the negative range, we believe that the driver takes the initiative, which is reflected in the driver's strong control, and the larger the absolute value, the greater the range of the driver's ability to master the unexpected.

5.2.5 Motion-in-mind in driving

Following the player satisfaction model, we know that N represents the average number of rewards in the game activity and also the gravity unit in the mind, which is an important indicator and unit to measure user experience. The collection of N values as units of the motion-in-mind model is therefore particularly important in order to verify the appropriateness of the N value setting and thus the validity of N values for the classification of driving styles.

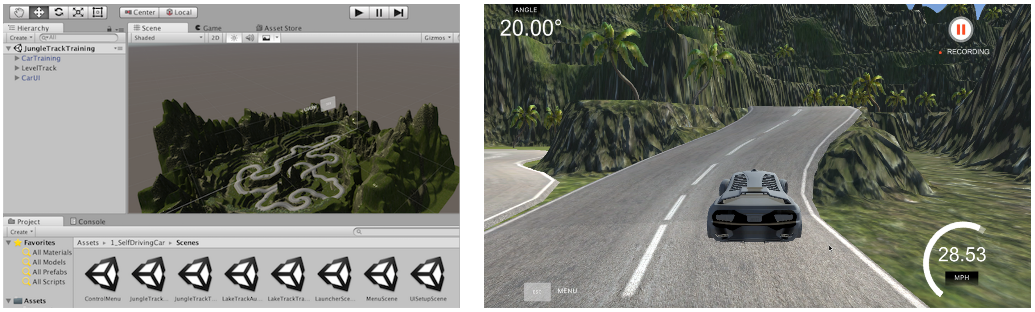


Figure 5.2.2: Simulator from Udacity's self-driving car nanodegree

5.2.6 Simulation based on End-to-End Deep Learning

Starting from the problem definition, current autonomous driving systems in industry are composed of numerous modules, e.g., detection (of traffic signs, lights, cars, pedestrians), segmentation (of lanes, facades), motion estimation, tracking etc. The results from these components are then typically combined in a planning module that feeds the control. However, this requires robust solutions to many open challenges in scene understanding in order to solve the problem of manipulating the car's direction and speed. Furthermore, auxiliary loss functions are required to train each module (e.g., object detection, semantic segmentation) independently, hence ignoring the actual goals of the driving task which include travel time, safety, and comfort.

As an alternative, several methods consider autonomous driving as an end-to-end learning problem. In these approaches, the tasks of perception, planning, and control are combined, and a single model is trained end-to-end using a deep neural network. Most end-to-end autonomous driving systems map from sensory inputs(front-facing camera images et al.) directly to driving actions such as steering angle, and so on.

In this chapter, all driving was recorded in Udacity's Self-Driving Car Nanodegree (Figure.5.2.2). The Nanodegree project is designed to teach students how to train self-driving cars and navigate road courses using deep learning. All the assets in this repository require the free game-making engine Unity. This section is based on an End-to-End autonomous driving deep learning algorithm from Bojarski et al. [20].

In this model, CNN has been used to map the raw pixels from a front-facing camera to the steering commands for a self-driving car. This powerful end-to-end approach means that with minimum training data from humans, the system learns to steer, with or without lane markings, on both local roads and highways. The system can also operate

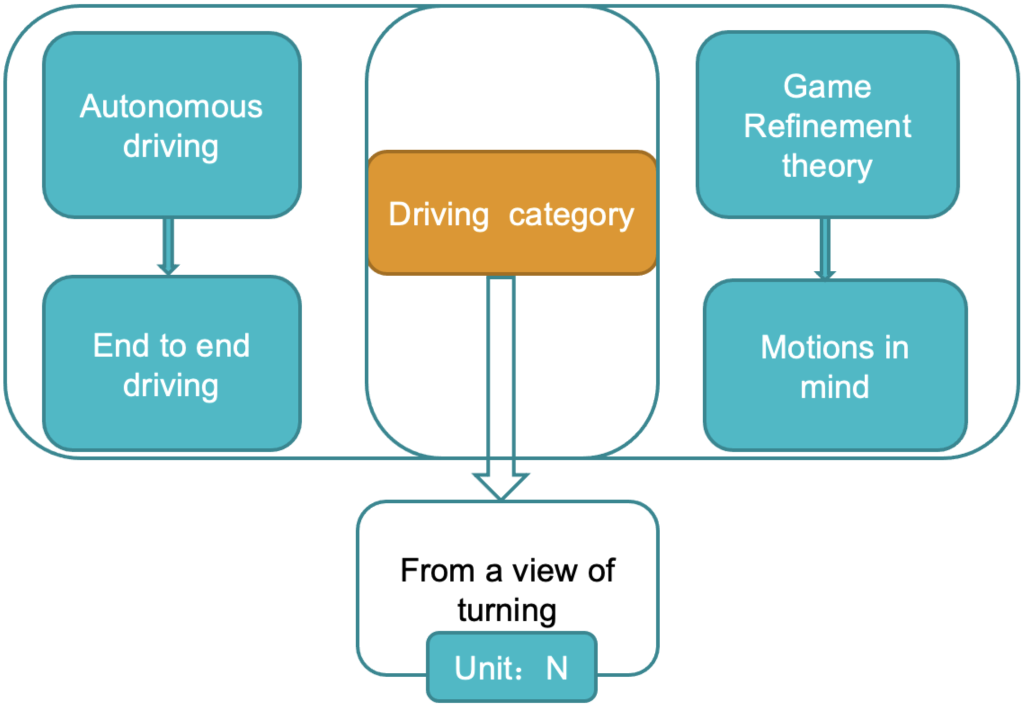


Figure 5.3.1: Flow chart

in areas with unclear visual guidance such as parking lots or unpaved roads. There are five convolutional layers and three fully coupled layers, and the network is very small compared to networks commonly used in image recognition.

5.3 Experiment Setting

The research methodology in this section is twofold. Firstly, experiments are conducted with human players, in which data is collected on the performance of human players during driving. Secondly, experiments are conducted using artificial intelligence (AI) players, where an end-to-end learning algorithm is used to train the AI average players and collect data on their performance in the same scenario. Based on these two experiments, adequate comparisons can be made and players can be further classified by using different motion-in-mind parameters.

5.3.1 Experiment with human players

In this experiment, we focus on the performance of the steering wheel at different times for different drivers, and there is few existing driving data set that focuses on this aspect,

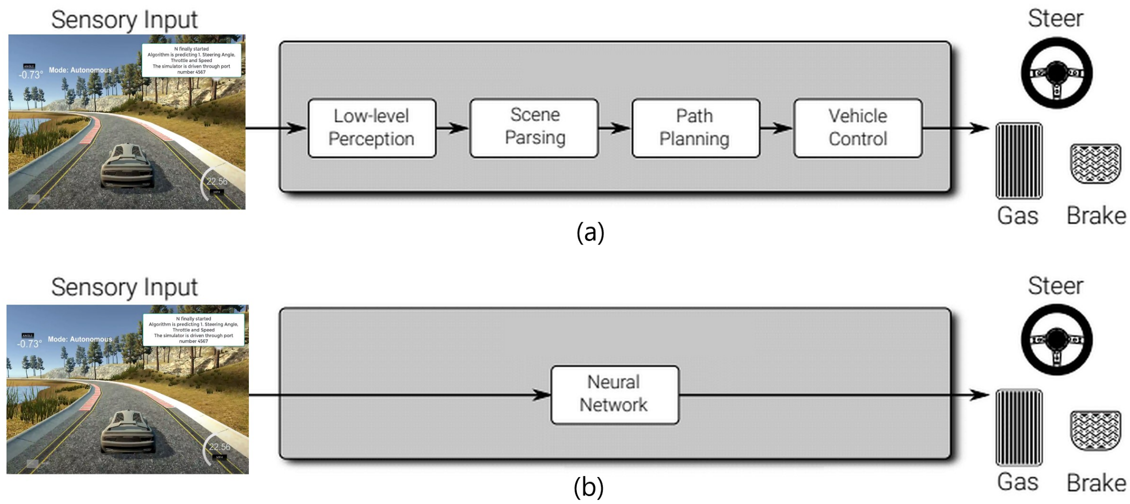


Figure 5.3.2: Learning approaches for self-driving; (A) traditional model; (B)End-to-End model

so in order to collect a simulation of the jungle track scenario, from Udacity's Self-Driving Car Nanodegree, to teach students how to train cars and how to navigate road courses using deep learning. All the assets in this repository require Unity. The image5.3.2 shows the details of the page for the simulation simulator.

Given the convenience of data collection, 12 students of varying ages and personalities who had never played the simulator before and who had real-life driving qualifications were sought as subjects. Previously an experiment was done where a person ran 85 times and the value of N was very stable by the time almost 20 laps were posted. Therefore, we chose a value of 20 laps. Due to the unreliability of the data, we chose data from 10 out of 12 people as typical. Also, to avoid ambiguity in the data, we used their first 5 innings and last 5 innings as a representation of their novice and veteran periods.

5.3.2 Experiment with AI players

Since it is not available to determine a standard type of racking through the data of 10 people, it is needed to get a relatively objective average standard of the model through training.

State-of-the-art autonomous driving systems currently used in the industry typically combine several modules (e.g. detection of motion estimation, tracking of traffic participants, reconstruction, etc.) into a single planning module for control, but due to the need to understand the scenario and manipulate the direction and speed of the car, in addition to auxiliary loss functions to train each module independently. As a result, the comfort of the driving task is neglected. In contrast, there are approaches that treat autonomous driving as an end-to-end learning problem, such that the tasks of perception, planning and control are combined into a single model using deep neural networks for end-to-end training. Many end-to-end autonomous driving systems map directly from sensory inputs (e.g. front camera images) to driving actions (e.g. steering angles). This approach then greatly facilitates the use of comfort in autonomous driving algorithms. Therefore, this approach is also taken in this section for the training of simulation players.

This section uses, a deeper end-to-end deep convolutional neural network proposed by Bojarski et al [20] for lane tracking. It is designed to derive steering control commands directly end-to-end from the input video from the camera. There are five convolutional layers and three fully coupled layers, and the network is very small compared to networks commonly used in image recognition.

The network learns based on actual human driving data in the vehicle, so it cannot learn when the vehicle is out of lane or facing the wrong way. This makes it impossible to get back into the lane, so images from the left and right cameras are used to simulate misalignment and rotation by translating the viewpoint of the images.

We used this method to train on all of the above data i.e. 200 laps of approximately 500 minutes of data and we used the unique model that we trained, as a standard-level AI player model, in order to see how it performed in the same scenario compared to different types of human models. Also, the first 5 and last 5 times of each person's data were selected and trained into a model separately. By training the model, it is possible to generate a large amount of data based on a fixed personality.

5.3.3 The validity of N

In the motion-in-mind model, the game speed v and uncertainty m conform to a zero-sum relationship. That is, $v_0 + m = 1$. And the game velocity is defined based on game as Variable Ratio of reinforcement schedule ($VR(N)$), which is $\frac{1}{N}$ which means the velocity of an expected reward or the rate of solving uncertainty, while N is the average frequency operations of getting reward once. Hence, N is an important unit for measuring player satisfaction.

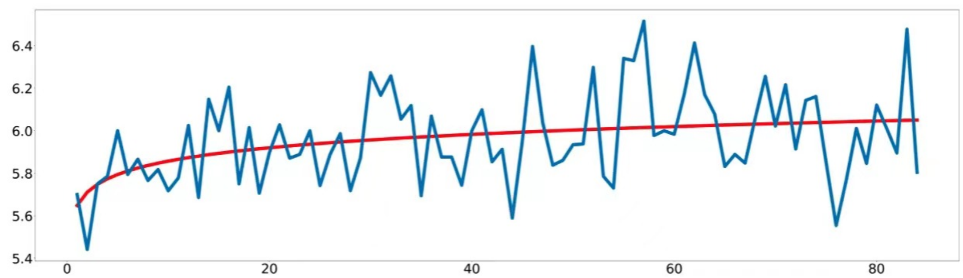
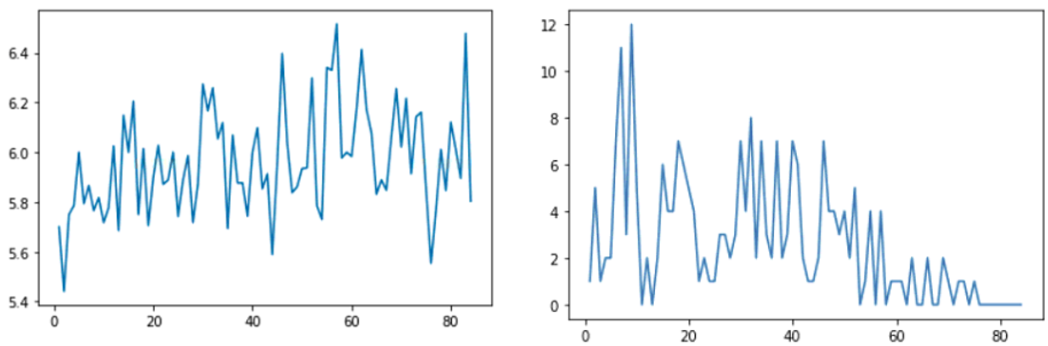


Figure 5.3.3: Fitting function of player growth



(a) N change during 85 turns (b) Shaking turns during one turn

Figure 5.3.4: N changes and shaking turns during 85 turns

In this section, since we focus on the steering wheel during a turning operation, we consider this operation as a game process, in which the driver completes a turning operation by steering wheel manipulation. In measuring the driver's manoeuvre, we consider N as the frequency of the steering wheel's oscillation. The driver will adjust the steering wheel once the vehicle feedback deviates from his or her expectations during a complete turning operation, and through N steering wheel adjustment operations, a turning operation is finally completed successfully. We consider a perfect driver operation to be no different from mental expectations, and therefore only 1 operation is required to complete the turning behaviour. That is $v_0 = 1$.

In order to investigate the reasonableness of the N setting, we have conducted an experiment. The experiment was set up as follows. Using the unity simulation environment, we asked the same subject to drive the same mountain road section (with many bends) 100 times in a row and observed the change in the subject's growth. In our prediction, the subject's N will slowly increase. We excluded the unavoidable factors such as 15 crashes, and as shown in Figure 5-4(a), we plotted the change in N over the 85 experiments. We found that N stabilised from around 4 at the beginning to 6 eventually.

This phenomenon indicates that N is relatively effective as a measure of driving. We then compared the number of jitters artificially generated by each hair in each of the 85 innings (the occurrence of left and right jitters every 350 milliseconds was counted as once), and as shown in Figure.5-4(b) we found that the number of jitters decreased as the number of innings increased, and the driving process gradually smoothed out and eventually converged to zero, indicating that the driver's proficiency over the the course of the 85 experiments was the process of increasing, consistent with the results of the N changes described above.

We thus conclude that the N changes discussed above are valid for the classification of driving styles, The diagram5.3.5 shows an example of the change in the steering wheel angle of a subject during travel(red part shows an example of one right turn process), with the vertical axis being 1/r to representing the directional control command, where r is the radius of the turn in metres. The purpose of using 1/r instead of r is to prevent singularities when travelling in a straight line (infinite turn radius for straight travel). The value of 1/r is negative for left turns and positive for right turns. Where in the diagram we have circled in red boxes a representation of N, the number of consecutive returns in the same direction during travel, which we assume is an N. In a turning manoeuvre, the magnitude of the turn and its fluctuations are determined by the number of turns completed. The more turns the steering wheel makes in the same turn, the less the bodywork changes with each turn and the smoother the turn. Conversely, the fewer the number of turns, the greater the change in magnitude and the more violent the turn feels. Here, we consider driver characteristics only from the point of view of cornering, so that subjects are asked to complete the entire course at a relatively constant speed range to highlight the effect of the turning manoeuvre. We have therefore taken N as the average number of steering wheel manoeuvres for a turn.

5.4 Discussion

The main idea of this section is that we determine the driver's driving comfort by the feedback from the vehicle and its expected psychological fallout during cornering. The comparison of subjective and objective energy is therefore the focus of the analysis. In the measurement of subjective energy [5], the relation between objective velocity v_0 and

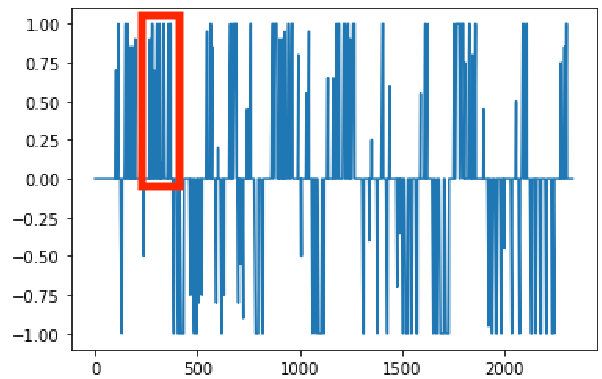


Figure 5.3.5: An example of the change in steering wheel angle(x-axis: times, y-axis: 1/r)

subjective velocity v_k is generalized as v_k using a parameter (say k where $0 \leqq k \in R$) that is the nature of the game under consideration, as shown in Equation(5.14).

$$v_k = (1 - km)v_0 \tag{5.14}$$

Thus, potential energy of play (E_k) is given by $E_k = 2mv_k^2$ which is subjective reinforcement. For the perfect player or game theoretical reward (k = 0), we call objective reinforcement E_0. Here, in this case, $E_d = E_k - E_0$.

Table 5.2: Motions in the experiment for human players

Player	N	v0	v_k	k	mx	my	E0	E_k	E_d
1	2.6122	0.383	-0.326	3.241	0.309	0.617	0.181	0.131	-0.050
2	1.8396	0.544	-0.201	4.382	0.228	0.456	0.270	0.037	-0.233
3	2.4504	0.408	-0.317	3.379	0.296	0.592	0.197	0.119	-0.079
4	2.3482	0.426	-0.308	3.483	0.287	0.574	0.208	0.109	-0.100
5	1.7946	0.557	-0.183	4.517	0.221	0.443	0.275	0.030	-0.245
6	1.7892	0.559	-0.181	4.534	0.221	0.441	0.276	0.029	-0.247
7	2.6	0.385	-0.325	3.250	0.308	0.615	0.182	0.130	-0.052
8	1.6667	0.600	-0.120	5.000	0.200	0.400	0.288	0.012	-0.276
9	1.7411	0.574	-0.159	4.699	0.213	0.426	0.281	0.022	-0.259
Average	2.094	0.493	-0.235	4.054	0.254	0.507	0.240	0.069	-0.171

Table 5.2 shows the Motions' values for the human players for about 600 samples total. In the table, we list the values of N, vo, v_k, m_x, m_y, E_0, E_k, $E_d$etc. Where Ek in the game motion-in-mind is subjective energy and represents the energy connection between the player and the game, when the Ek value is large the player has high subjective energy and a stronger subjective connection to the game. Through the data, we can see that the mean value of Ek is 0.069, while the E0 value is much larger than the Ek value, with a value of around 0.24. The objective game energy is greater compared to the player's

energy connection to the game, and the driving activity is an activity with low freedom, where the driving process is limited by road settings, safety considerations and other factors, and the objective settings of the activity itself place great restrictions on the driver's behaviour, thus the objective energy needs to be greater than subjective energy.

Unlike the direct sensation of riding, the comfort of the motor aspect of the driving activity comes mainly from the repeated validation of self-expectations, so that the relationship between subjective and objective energy is particularly necessary. Based on an average situation, k in this case is about 4.054. Here, in Figure 5.4.1 the motion in mind values have been drawn.

Starting from E_d, we take the derivative E_d=0, when m is approximately equal to 0.37108, the largest subjective-objective difference, and when m is approximately equal to 0.88786, the smallest subjective-objective energy difference.

When E_d is small, the difference between the subjective and objective energies is small and the expectation is small, which means that the driver is operating properly and the mental expectation is in line with the objective operation and the driving state is comfortable and safe from a motion-in-mind perspective. When E_d is large, the difference between subjective and objective energy is large, and the difference between expectations is large, which means that the driver's own level does not match the actual vehicle feedback, and the mental expectations do not match the objective operation. At this point the driving state is not comfortable at the motion-in-mind level, it represents a large psychological gap for the driver, which may be due to immature technology or to the driver dropping the ball, resulting in a balance between subjective and objective energy.

5.4.1 Discussion of E_d

In this section, we defined E_d and solving for $E'_d(m)$=0, we get $k = 0, k = \frac{4(2m-1)}{m(5m-3)}, m \neq 0, m \neq \frac{3}{5}, m \neq 1$. As described before, the core of our discussion in this section is reinforcement, and therefore when $E'_d(m)$=0, the reinforcement from the game process has the strongest reinforcement reflection. Table 5.3 shows how the E_d maximum point changes as k changes, firstly towards the previously discussed, E_d is the difference between the expected energy and the objective energy exchange, when E_d is negative, we consider the objective energy payoff to be greater than the expectation, and conversely, positive, it is less than the expectation.

As shown in the table, as k gradually increases, the E_d maximal minima points are all gradually closer to the origin. The larger k is the smaller the absolute value of the minima, corresponding to a smaller m, while the larger the maximal value, corresponding to a smaller m. when k is unlimited, the m peak for negative will close to 0.

Show that as k becomes larger, the difficulty required for a relatively comfortable point, i.e. $E_d = 0$, gradually decreases and is easier to satisfy (minimal values near the far point), and the m required for the highest energy difference gradually becomes smaller, making the player more easily manipulated by the difficulty of the game. k tends to infinity, E_d will always be greater than 0, and expectations will always be greater than reality and cannot be satisfied. k tends to 0, E_d will always be greater than 0 and expectations will always be met.

Table 5.3: Max reinforcement points when $k = 0, 1, 2, 3...(0 < m < 1)$

k	E_d	$m_{peak}(negative)$	$E_{d\_peak}(negative)$	$m_{peak}(positive)$	$E_{d\_peak}(positive)$
0	0	-	-	-	-
1	$2m^5 - 8m^4 + 10m^3 - 4m^2$	0.46	-0.19	-	-
2	$8m^5 - 24m^4 + 24m^3 - 8m^2$	0.4	0.28	-	-
3	$18m^5 - 48m^4 + 42m^3 - 12m^2$	0.33	0.30	0.8	0.06
4	$32m^5 - 80m^4 + 64m^3 - 16m^2$	0.28	0.27	0.72	0.29
5	$50m^5 - 120m^4 + 90m^3 - 20m^2$	0.23	-0.27	0.69	0.66
6	$72m^5 - 168m^4 + 120m^3 - 24m^2$	0.2	0.24	0.67	1.18

5.4.2 Discussion of Motion in mind measure in driving comfort

Based on motion in mind, Figure 5.4.2 is drawn. In the above image vo denotes objective process speed, v_k denotes subjective process speed, E_0 denotes objective energy, E_k denotes subjective energy, and E_d denotes the difference between subjective and objective energy. As shown, we assume $k = 3$, at which point $E_k = 0$, which is considered the highest objectivity and is the fairness point of the game[4][7]. Since v_k is 0 at m=1/k and E_k is 0 at m=2/k, the masters are expected to have a capacity of k=3.

The intersection points in the diagram are illustrated according to the above setting. Intersection 1, $E_d = E_k$, is to the left of the point where E_k has been increasing because the difficulty$m$ is relatively low and the player's self-confidence increases with difficulty, reaching a peak of confidence in the novice period at intersection 1, as the individual is

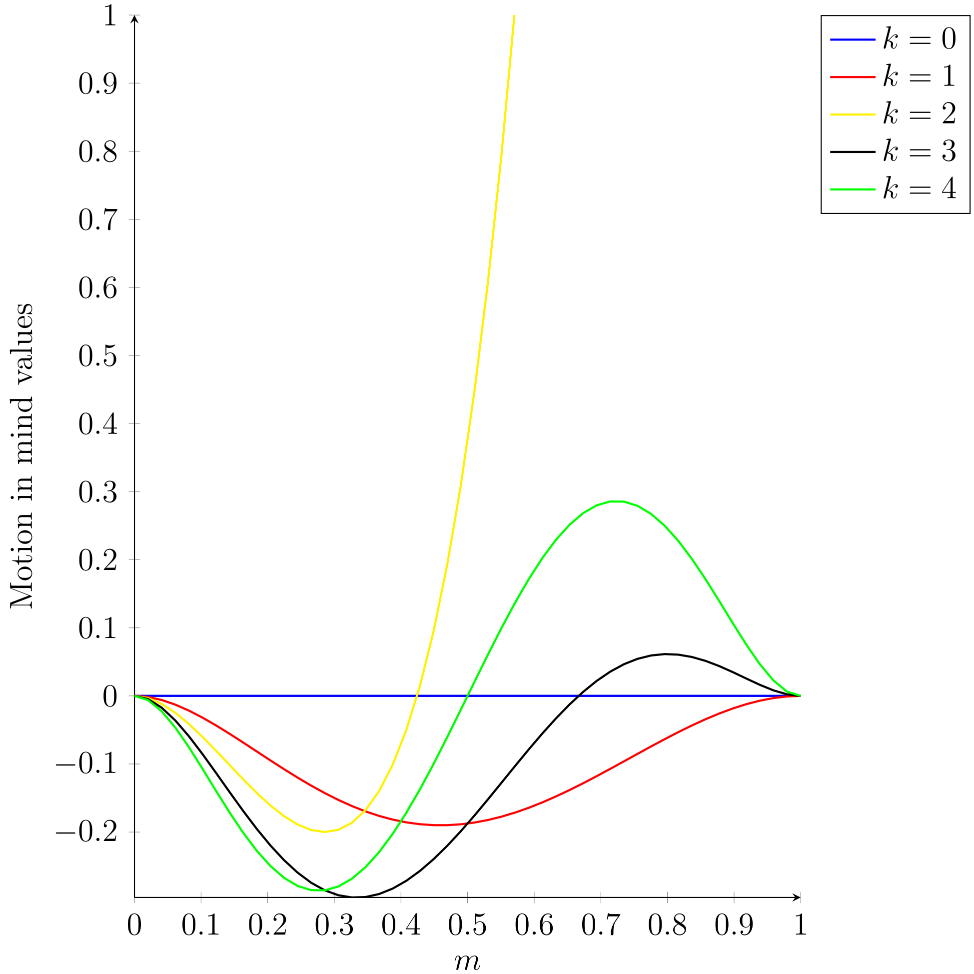


Figure 5.4.1: E_d curve with various k

able to make full use of his or her abilities in a highly certain environment, reaching a peak in perceived competence and confidence in themselves. Later, as difficulty increases, subjective energy E_k decreases and objective energy increases to intersection 2, where m $= \frac{1-\sqrt{\frac{1}{2}}}{k}$, at which intersection $E_k = E_d$, the subjective energy is found to be zero, at which point the player will be motivated to learn until intersection 3. energy, N is smaller and the driver is in a cautious learning state. At m=2/k, the intersection where E_0=E_k, i.e. the subjective and objective energy is constant (E_d=0), we believe that in this setting the objective and subjective can be perfectly balanced, so that in the driving scenario we believe that the driving behaviour is well balanced, i.e. the driver does not feel overly challenged or bored. The individual's perception of his or her own ability is balanced, neither underestimating nor overestimating his or her own ability. Combined with the fact that the subjective speed of vk is also at its lowest point, i.e. the driver is in a calm state

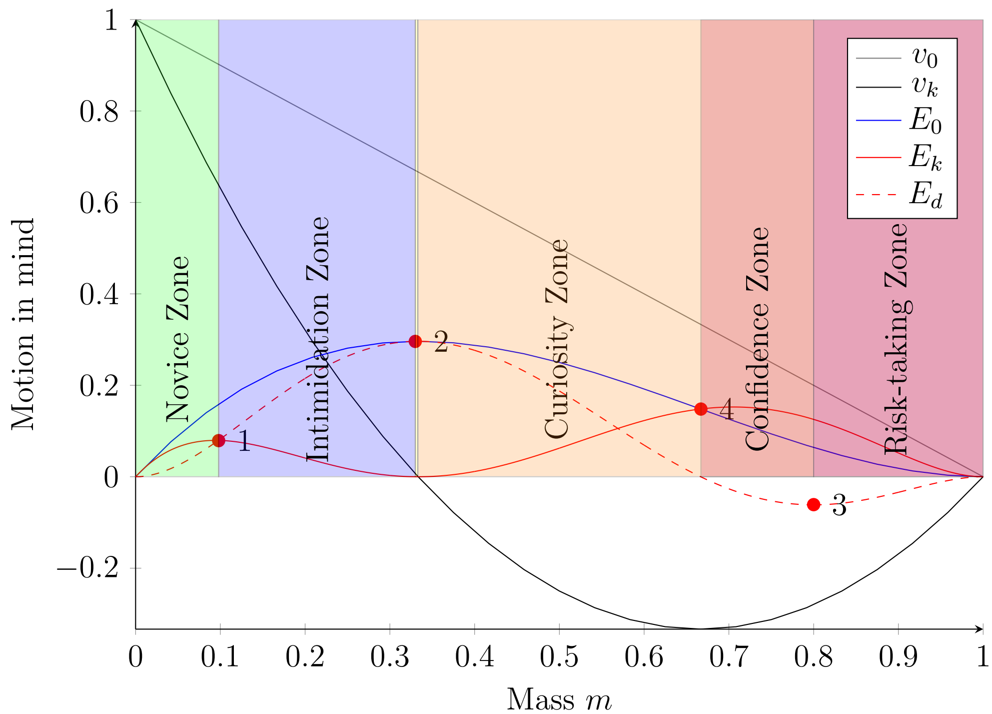


Figure 5.4.2: Objective and subjective reinforcement when $k = 3$

of mind, we consider this to be a zone of driving comfort. As m continues to increase, the subjective will continue to be greater than the objective energy and the individual may be overconfident and believe that their ability exceeds their actual level, which may lead to overly risky behaviour. and at m = 0.8, E_d is minimised, i.e. the individual's perceived subjective ability is at its maximum. In a highly uncertain environment, individuals may overestimate their own abilities, or they may prefer to remain optimistic about their abilities due to the uncertainty of the situation. After that, their subjective energy gradually decreases close to objective until m=1. In this experiment, m converging to 1 means that N increases, i.e. the number of corrective manoeuvres increases, and as the driver corrects multiple manoeuvres, again this indicates that the perception of their ability exceeds the actual level and may lead to over-risky behaviour.

5.4.3 Evaluation experiment

In order to verify the accuracy of the results, the data of these 10 drivers were trained into 20 models representing their personal styles using their novice period and experienced period data, respectively, through an end-to-end learning approach, as detailed in Chapter 2.5. These models were each used to go driving in the same mountain scenario and 20 driving videos with their personal style were recorded. 10 subjects were asked to complete watching each of the 20 anonymous videos, choose the one that matches themselves the most.

The cosine similarity is used to calculate and compare the differences between the subjective and objective data of these players. The results are shown in the table5.4. Compare with E_d shown in Figure.5.5.1, we can find that Ed and cosine similarity go in the opposite direction, with E_d being effective for discriminating between subjective and objective differences. However, although we find it valid, at the same time we also find that during the AI player training process, the model training pursues smoothness and therefore self−correction far more than human players, with a substantially higher number of N. Although, for subject−objective relative errors are small, the impact of AI strength will also be further explored in our future work.

Table 5.4: Comparison of the objective and subjective difference based on motion in mind

Player	Classification	N	v0	v_k	k	mx	my	E0	E_k	cosine similarity
1	Objective	6.8	0.147	-0.229	4.690	0.426	0.853	0.037	0.332	0.9997
	Subjective	7.1	0.141	-0.222	4.656	0.430	0.859	0.034	0.085	
2	Objective	13.09	0.076	-0.135	4.331	0.462	0.924	0.011	0.034	0.9782
	Subjective	7.89	0.127	-0.205	4.581	0.437	0.873	0.028	0.074	
3	Objective	10.705	0.093	-0.161	4.412	0.453	0.907	0.016	0.047	0.9999
	Subjective	10.38	0.096	-0.165	4.426	0.452	0.904	0.017	0.049	
4	Objective	9.775	0.102	-0.173	4.456	0.449	0.898	0.019	0.054	0.9957
	Subjective	8	0.125	-0.203	4.571	0.438	0.875	0.027	0.072	
5	Objective	10.865	0.092	-0.159	4.405	0.454	0.908	0.015	0.046	0.9778
	Subjective	6.92	0.145	-0.226	4.676	0.428	0.855	0.036	0.088	
6	Objective	7.605	0.131	-0.211	4.606	0.434	0.869	0.030	0.077	0.9984
	Subjective	8.53	0.117	-0.193	4.531	0.441	0.883	0.024	0.066	
7	Objective	7.05	0.142	-0.223	4.661	0.429	0.858	0.035	0.086	0.9526
	Subjective	7.34	0.136	-0.217	4.631	0.432	0.864	0.032	0.081	
8	Objective	6.37	0.157	-0.240	4.745	0.422	0.843	0.042	0.097	0.8397
	Subjective	12.53	0.080	-0.141	4.347	0.460	0.920	0.012	0.036	
9	Objective	7.14	0.140	-0.221	4.651	0.430	0.860	0.034	0.084	0.9998
	Subjective	7.34	0.136	-0.217	4.631	0.432	0.864	0.032	0.081	
10	Objective	9.42	0.106	-0.179	4.475	0.447	0.894	0.020	0.057	0.9989
	Subjective	8.53	0.117	-0.193	4.531	0.441	0.883	0.024	0.066	

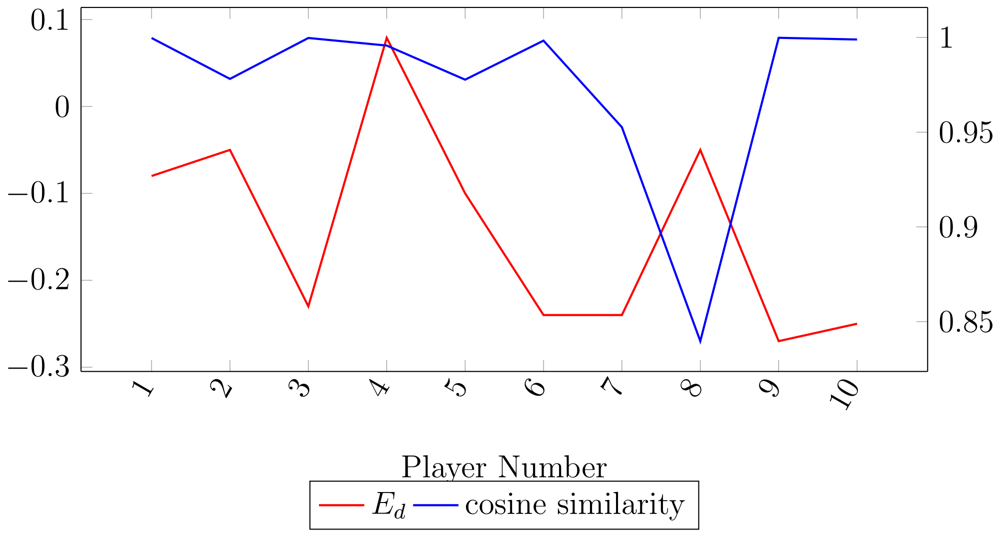


Figure 5.5.1: Comparison of E_d and cosine similarity

5.5 Chapter Summary

This section focuses on the definition of driving comfort at the psychological level of the game, through the definition of energy fluctuations, when energy fluctuations exist, driver expectations and vehicle feedback are not constant, the player is unable to properly control the driving process and needs to be reminded by the assistance system to focus on driving more carefully, as far as the specific breakdown needs to be verified deeper.

Chapter 6

Conclusion

In this chapter, we provide the dissertation's conclusion and respond to the research questions and problem descriptions. Next, future projects are addressed.

6.1 Concluding Remarks

The study of game refinement theory has led to the development of a measurement for game sophistication. It has recently been created as a physics of the mind, which may relate to the state of the player's emotions, such as curiosity, uncertainty, and engagement, across various fields.

However, there are several uncleared facets of the player experience that have not been researched, such as what exactly influences the user's desire to play. In order to better segment the player psychological experience and comprehend the nature of play, this paper combines motion-in-mind with psychology to develop a study that explores the definition of player gravity, player psychological gap, and then expands the concept of motion in mind in the context of historical and cultural evolution, the psychology of single player gambling addiction, the energy change of multiplayer werewolf killing, and motion in mind in the application of virtual reality.

This thesis focuses on two directions: the evolution of player satisfaction in cultural trends and the applications of player psychology assessment based on the motion in mind model.

The key components are summarized below:

1. Games and the act of playing existed before the beginning of human civilization. However, games have developed throughout history, with new rules and ways of play being abolished on a regular basis. In turn, this has resulted in people appreciating different parts of each sort of game at various eras, a vivid representation of the cultural inclinations that define each century. This study advocates seeing gaming as a learning process in which participants grasp the game's rules through learning and adaptation. The reward frequency variable is presented in terms of the unpredictability of rewards in terms of acceleration or 'gravity' in the mind, akin to the acceleration of gravity on Earth, based on a variable rate schedule in a reinforcement scheme. In an appropriately granular game. The model draws a correlation between the amount of effort a player must exert and the difficulty of the game. encompassing historical board games such as Chinese Go, Chess, and Xiangqi, popular sports such as football, tennis, and basketball, and electronic games such as combat games and strategic games, as they progress throughout history. Define thinking about gravity forces that have been found to signify historical change, which serve as markers of cultural factors corresponding to people's perceptions of gravity at various periods.

2. The abilities, interests, and play styles of players have a significant impact on the entire gaming experience, and games present a range of options for player growth and enjoyment. An properly designed game has the capacity to retain player interest and build momentum for extended play, whereas an experienced player can provide new strategies and views. Therefore, the relationship between player and game may be viewed as symbiotic, as the two entities are tightly interwoven and the gaming experience is determined by their interaction. The difference between intuitive and real likelihood, as expressed by the positive energy differential, was discovered to be the source of player incentive. Thus, high reward expectations, despite low actual returns, motivate players, but some negative energy difference allows the experience to be pleasantly surprising and encouraging, as evaluated by the Multi-armed bandit game.

3. By characterizing energy fluctuations, it is argued that psychologically speaking, driving is safe when the driver is in a constant condition, i.e. the flow state. When energy variations exist, i.e., when the driver's expectations and the vehicle's feedback are not constant, the driver must be cautioned against being reckless or overly daring.

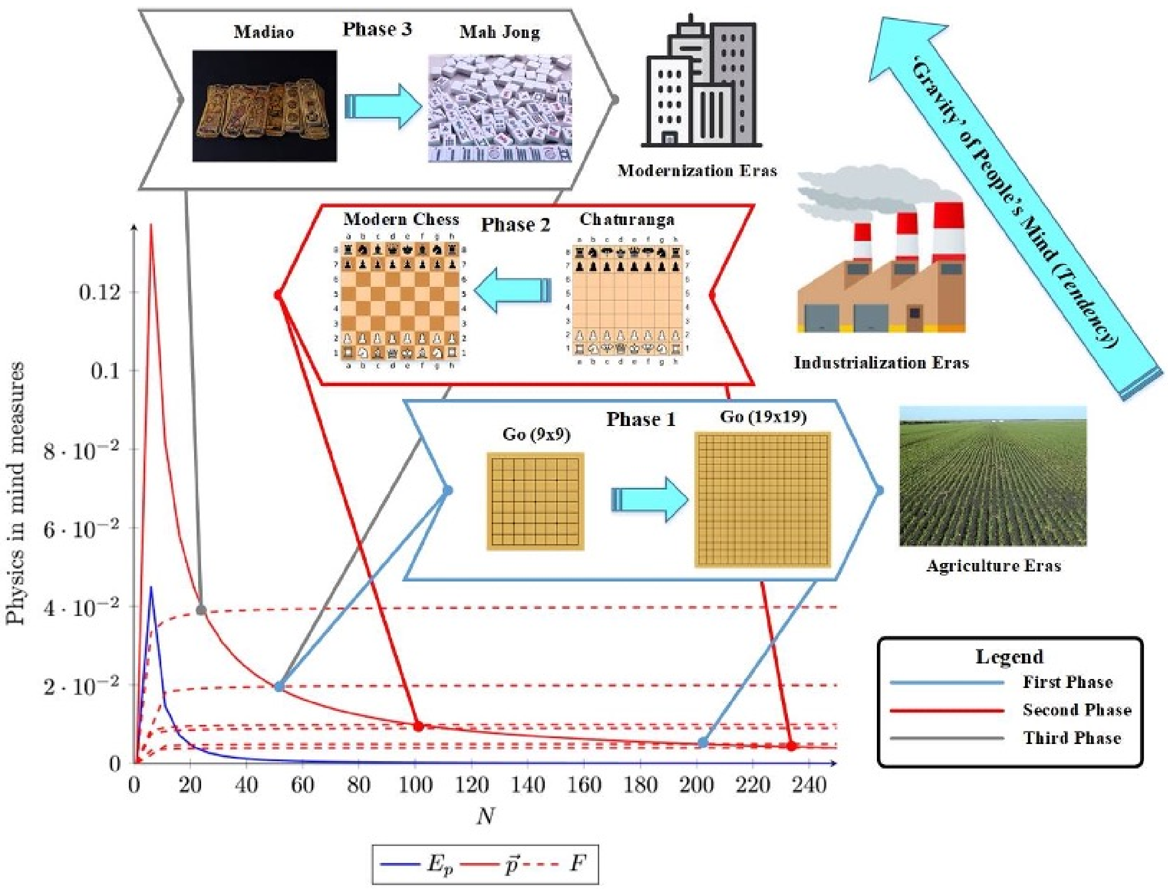


Figure 6.1.1: A historical perspective on the evolution of the rules

6.2 Answer to RQ1, RQ2

Above all of the contents in this dissertation, thus the research questions are answered as below:

Research Question 1:

The origin of games and play can be traced back to prehistoric times and has since undergone various transformations in terms of rulesets and forms of play. Different historical periods have witnessed a gamut of games enjoyed by diverse individuals, each with its unique features that potentially reflect cultural preferences. Despite the variability in game attributes, their enduring appeal has been attributed to the underlying human psychology, which presents a challenge for achieving objective validation. In this regard, the question arises as to how games relate to cultural identity and whether it is possible to identify universal characteristics of games that could be subjected to rigorous mathematical analysis.

Answer to RQ1

People living 4000 years ago valued slow-paced games like ancient Go with a long period between rewards, the medieval and industrial era favored more aggressive and mid-paced games like Chess and Shogi. Similar trends were also found for various sports and video games of the modern era. This implies that people at different times enjoyed different aspects of each game, which constitute a vivid reflection of the cultural tendencies of each era.

The value of gravity in the mind changed, for each type of game, in sync with historical and cultural trends.

Based on a combination of game refinement theory, reinforcement schedules and motion in mind, a reward in the psychological sense can be winning a game in a given match, the link between psychology and game based on VR schedules can be established. In addition, it identifies the weighty forces of thought that are demonstrated to symbolize historical development as cultural drivers.

Research Question 2: Game design is a multidisciplinary field that often employs psychological principles to foster player loyalty and immersion. The interactive and experiential nature of video games provides a unique platform for examining human emotions and understanding player psychology. Despite the prevalence of psychological concepts in games, a lack of empirical research exists in quantifying the complex interplay between player behavior, emotions, and game mechanics. Therefore, it is imperative to investigate how game methodology can be utilized to evaluate and measure player psychology, as it may inform game design practices and contribute to a deeper understanding of human behavior in digital contexts.

Answer to RQ2

Playing game is a learning process where players learn and adapt to grasp the rules of the game. From this point of view, reinforcement feedback like game settings become essential factors that affect the player's experience and psychology.

-From Game Classification

According to the interplay of physics in mind measures ($\vec{p}$, E_p, and F) and reward frequencies (N), games can be classified into Addictive($N \leq 20$(frequent)), Competitive($20 < N \leq 200$(often–sometimes)), and Mastery, Art($N > 200$(rare)). Game development trends also indicate the border between competition and mastery in conducting tasks, which suggests a direction towards the higher value of $\vec{p_1}$ and E_p, while smaller N (such as $N \leq 20$).

-From Play Comfort

In accordance with the Energy accumulation conversion between the game side and player side ($E_d > 0$, $playerside > gameside$), the energy difference between intuitive probability-based game velocity and return rate-based game velocity created a psychological gap between the game side and player side ($E_d > 0$, $playerside > gameside$). Energy differential that updated with player ability k based on the number of corrective operations N helped to explain player states ($E_d > 0$, the game is under control).

6.3 Future Works

Despite the fact that this article has integrated Motion in mind with player psychology and applied it in a number of areas, there is still a great deal of potential for improvement in terms of the current state of affairs. By merging previous research, the following areas might be studied in more depth in the near future:

The problem of refining complex reward mechanisms: The studies in this paper are all based on variable ratio studies, but in real life, rewards are not only variable ratio, but frequently the result of a combination of complex reward mechanisms. In such a case, the uncertainty introduced by the reward has an impact on player psychology and game engagement that calls for further study.

Dynamics of player psychology: A connection between games and satisfying experiences has been successfully established, albeit from a limited perspective, using measures of mental physics and player satisfaction models. The analysis of the game process in existing work has taken into account all of the information that is now available about it, but it has not taken into account the dynamics of player psychology. Future work may include dynamic ties to player psychology. Such metrics could also be used to enhance the gaming experience, allowing for timely reward arrangements that are dependent on the psychological requirements of individual players and their gaming style (in relation to the player modelling domain).

Exploring the Factors Influencing Driving Comfort: In this dissertation, driving comfort has been analyzed from the only steering wheel. However, it is strongly related to road condition such as for the straight way. Compared with the method we used now, the other index of velocity, acceleration and jerk should be focused more, at this time, the basis N value showed in this dissertation would be related to these values, such as the accelerated numbers and so on.

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