Okinawa Institute of Science and Technology
Graduate University

Thesis submitted for the degree

Doctor of Philosophy

Intrinsic Motivation in Creative Activity

by

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April, 2021

Declaration of Original and Sole Authorship

I, Shoko Ota, declare that this thesis entitled Intrinsic Motivation in Creative Activity and the data presented in it are original and my own work.

I confirm that:

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Abstract

Intrinsic Motivation in Creative Activity

Intrinsic motivation is a fundamental basis for creativity. However, little is known about which factors are essential in a behavioral environment for creative activity. I propose a hypothesis that intrinsic motivation in creative activity is facilitated by a higher variety of expressions using simpler rules. To examine the hypothesis, I conducted a novel human behavioral experiment with 42 participants using the original game designed based on the Game of Life cellular automata. The simplicity of a rule is controlled by the parameters of state transition function and quantified by the complexity measures formulated in the theory of cellular automata. The variety of expression is quantified by the features of the cell states, such as entropy of local patterns and empowerment. The degree of intrinsic motivation is measured by subjective enjoyment, playing time, and frequency of touch interaction. The results of two-way ANOVA of the scores of enjoyment for the four rules showed that participants were more intrinsically motivated with a higher variety of expression and a simpler rule, which supports the hypothesis. Regression analyses revealed that the variety of local patterns was a major factor for subjective enjoyment and also suggested two types of subjects. Subgroup analyses showed that participants had opposite preferences for simple and complex rules. The present results are generally consistent with the hypothesis but point to the necessity of considering individual differences.

Acknowledgment

I would first like to thank my supervisor, Professor Kenji Doya, for the great advice, guidance, and support. I would also like to thank the other committee members, including my former committee, Professor Jeff Wickens, Professor Greg Stephens, and Prof. Izumi Fukunaga, and Professor Kenji Matsumoto of Tamagawa University very supportive and encouraged me with crucial advice. I would also like to thank the former supervisor for my master thesis, Prof. Koichi Hori of The University of Tokyo, for his books which inspired me to start this research. Thank you to the OIST members who participated in this experiment, Eri Kanemoto, who helped me attain ethical approval of the human behavioral experiment, and the RUAs, Emi-san, Kikuko-san, and Misuzu-san of the Doya Unit who helped me to experiment. I would also like to thank the former group leader Dr. Eiji Uchibe for teaching me all the basics of Ph.D. studies. Thank you also to former members of the Doya Unit, Makoto Ito-san and Prof. Junichiro Yoshimoto, for your advice. I would especially like to thank Hiromichi Tsukada-san, who supported and helped me mainly with my personal issues. Thank you, Kazumi Kasahara, Yuzhe Li, Qiong Huang, Jessica Verena Schulze, and Farzana Rahman, for all your advice and fun times, especially when we have lunch or a couple of coffee or tea together. I would also like to thank Tadashi Kozuno, who was my teacher of coding and machine learning. Thank you also to the graduate school members, especially Kozue Higashionna, Midori Morinaga, Rie Ishikawa, and Harry Wilson. I really thank Dr. Darren George at Ganjuu Wellbeing Service at OIST, who always supported me with his life wisdom. I could not have finished this study without your support. My path into research would not have been possible without the support of my mother, who first encouraged and supported my efforts to pursue a career at OIST. I would also like to thank my family and my friends for all their support. Finally, I would like to thank my lovely daughter Mone who inspires me every day with her creativity which keeps me creative.

Abbreviations

AIC	Akaike's Information Criterion
CA	Cellular Automata
CCA	Canonical Correlation Analysis
GOL	Game of Life Cellular Automata
IM	Intrinsic Motivation
RL	Reinforcement Learning
VIF	Variance Inflation Factgor

To my sweet and lovely daughter Mone
who inspires and encourages me with her creativity every day

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Chapter 1

Introduction

1.1 Toward a theory of creativity

Creativity is a fundamental ability to solve problems with relevance and novelty that includes any technical, theoretical, social, and practical problems in our daily lives. Creativity is an essential condition to survive this dynamic world by designing and developing new and useful strategies and tools. Not only educators but also parents have been seeking an optimal environment for nurturing the creativity of children. However, there is still no systematic approach for educating in tandem with children's creativity. The fact is that educators and parents have to be highly creative to teach creativity. How can we be more creative? What is the theory of creativity to explain what humans have achieved? There is a compelling need for a unified theory of creativity that can be practically implemented with an educational method.

Schmidhuber (2010) defined "a theory of creativity, fun and intrinsic motivation" as:

> The simple but general formal theory of fun and intrinsic motivation and creativity is based on the concept of maximizing intrinsic reward for the active creation or discovery of novel, surprising patterns allowing for improved prediction or data compression.

Children are intuitively keeping the curiosity doors open and they are actively interacting with the environment to learn how to discover something new and surprising. Interestingly, as observed by Jean (1962), children sometimes play as if everything is alive. They interact with every new item they encounter and explore until an exciting event happens. Through playing in this way, children learn how to discover and invent new things.

Creativity depends on contexts such as the environment, time, culture, and personal background (Sternberg, 2006). Among many approaches to understand creativity, the creative cognition (Ward, Smith, and Finke, 1999) is one of the most practical approaches to understand the cognitive process and structures that underlie human creativity. Finke (2014) combined the experimental method and creative exploration by investigating the conditions that promote creative insights. Finke, Ward, and Smith (1992) and Finke (2014) noted that human participants performed more creatively when 1) they have more limitation of the component, 2) they are given a functional or categorical constraint (e.g., an object to sit on) for what they create rather than given a particular product (e.g., a chair), 3) they provide an interpretation to what they create than to what other people create, and 4) they first create a form and then consider the form's function (function follows form) rather than if they first think of a function and then create the form (form follows function).

In these previous studies, researchers have assessed creativity based on the factors such as the behavior of the subjects, the quality of their products, and the cognition expected behind them. Despite the large body of research done on creativity, however, the assessment of creativity remains an essential challenge (Kaufman and Sternberg, 2010; Amabile, 1996).

On the measure of creativity

How is creativity measured in scientific behavioral experiments? The concept of creativity contains vast and complex factors such as small-c (everyday creativity that is the personal creative activity of a personal nature or problem solving for hobbies and work) vs. big-c (eminent creativity that can impact culture or society) and P-creativity (psychological creativity that is novel and meaningful just to the person or agent) vs. H-creativity (historical creativity that is creativity recognized as a novel by society) (Boden, 1996).

In this study, I focus on personal or psychological creativity. Personal or psychological creativity includes several aspects of creativity ,from cognitive processes to environmental factors. These factors of creativity are fundamentally difficult to capture quantitatively. Another point of consideration is the lack of standardized laboratory tasks that manipulate the factors for "creativity" in the experiment (Kidd and Hayden, 2015). Some tasks require preliminary skills, which are modulated by prior knowledge and experiences. I designed the task as a creative activity without requiring preliminary skill or knowledge. The task outcomes are creative outwork consisted by grid cells so that the target factors can be quantitatively measured.

Psychologists have been developing test theories for measuring creativity. Amabile (1996) proposed the componential theory of individual creativity, which has three individual components, including domain-relevant skills or expertise, creativity-relevant processes or creative thinking, and task motivation. Task motivation is intrinsic motivation to engage in the activity out of curiosity, enjoyment, or a personal sense of challenge. Amabile (2012) added another component outside the individual, which is the surrounding environment, such as the social environment. The theory specifies that creativity requires a confluence of these components. Creativity should be higher when a person is intrinsically motivated with high domain expertise and higher skills in creative thinking, which are helpful in an environment.

Sternberg and Lubart (1991) developed the investment theory of creativity that asserts creative people are those who are willing and able to metaphorically "buy low" and "sell high" in the realm of ideas. The theory claims six sources: abilities, knowledge, thinking style, personality attributes, motivation (especially intrinsic motivation), and environment. Creative people see the potential of specific ideas and how to develop said ideas by combining the sources(Sternberg, 2006).

Regardless of the validity of these theories, measuring creativity remains difficult because creativity is something more than the sum of these components or sources. Moreover, there are also biases in evaluating creativity if the creative products of experimental tasks are assessed by humans, even if they are experts.

There are also measuring theories for statistical consistency, standardization, and minimizing bias (e.g., Classical Test Theory (Crocker and Algina, 1986)). These theories work for measuring creativity as a part of intellectual ability or for measuring creative personality, requiring large sample sizes in the thousands or more.

In contrast to these classical creative measurements, what I focus on in this study is the learning environment in which people can be more creative. Here, the learning environment does not include a social environment. In addition, I do not try to measure creativity itself but rather intrinsic motivation and influencing factors as a dominant condition of creativity when engaging in creation.

1.2 Intrinsic reward and intrinsic motivation

Children learn and develop as they play. They play in a playground and learn how to enjoy the power of gravity. At home, some children play with building blocks and learn how to build their ideas. Others play with dolls and learn how to communicate or how to make up a story. Children inherently become creative through doing what they like to do. What motivates them in such cases is called intrinsic motivation. With intrinsic motivation, the learning activity itself is rewarding for learners while learning "for its own sake"(Berlyne, 1966). Decades of investigations by psychologists identified that intrinsic motivation is crucial for children's autonomous development(Ryan and Deci, 2000a). Intrinsically motivated learning is a fundamental condition for intelligence and creativity(Deci and Flaste, 1996; Boden, 1998).

Recently, investigations of intrinsic motivation are a subject of active research in adaptive robotics and machine learning. Learning algorithms using the concept of intrinsic reward have been successfully applied to an artificial agent for improving learning progress (Oudeyer, Kaplan, and Hafner, 2007). However, both the cognitive mechanisms and the environmental conditions for intrinsic motivation are not well understood, which may be because of the variable nature of intrinsic motivation, especially with the presence of extrinsic motivation.

Even though intrinsic motivation is essential for learning, children begin to consider extrinsic motivation more as they grow increasingly. In many educational environments, children are exposed to extrinsic rewards such as treats, high grades, and prizes rather than intrinsic rewards such as interest, curiosity, and surprise. Providing an environment with the careful use of extrinsic rewards is effective, but its effectiveness is partial and temporary. Despite their convenience, extrinsic rewards are found to be less sustainable or practical, especially in promoting creative activities (Deci and Flaste, 1996; Schmidhuber, 2010). An environment for intrinsically motivated learning is required by understanding how humans are intrinsically motivated.

1.2.1 Intrinsic reward

What is a reward for a human? Adults get a salary for hard work. Children get a good grade for studying. One cannot live without eating and drinking. Some fall in love and desire to have children. A baby's smile generally provokes joy. These things can be rewarding for humans. They are instinctive and common rewards for welfare, survival, and reproduction. Moreover, humans engage in hobbies such as reading books, watching movies, and playing sports without any manifest reward in return. Some prefer a beautiful view of the ocean and others prefer that of mountains. Some like both. Children start playing whenever they are free. Some simply like running around. Others like reading picture books or making up a story with a doll through their imagination. These activities also seem to be rewarding. They have acquired behavior, and each child has a preference and talent for doing them. They are good at finding rewards in playing so that they can learn an ability they seem to lose as they grow up. Reward plays a key role in motivation and learning, whereas; Only conventional elements like water, food, and money have been used as rewards in most experiments.

Types of reward

There are many different ways of characterizing rewards. One way of characterization is primary and secondary rewards. Primary reward is an inherent reward directly related to survival and reproduction, such as food and mating. Secondary reward is an artificial reward such as money. Another categorization is the distinction between extrinsic reward (e.g., money, score, status) and intrinsic reward (e.g., curiosity, fun, novelty), which are important in learning (Ryan and Deci, 2000a). Reward and reward signals are differentiated when we evaluate an organism receiving a reward given from the external environment, and evaluates it. In this case, a reward is an object or event in the environment and the reward signal is the critic's signal, which decided whether things are better or worse than the prediction after an action, generated internally by the organism (Mirolli and Baldassarre, 2013). In terms of evaluation with an organism, "liking" (pleasure/ palatability) and "wanting" (appetite/ incentive motivation) are also different types of reward (Berridge, 1996). Most of us want money. However, we do not know whether we like money. Also, the same amount of money is not literally the same value for each person.

Individual differences in reward processing

We have our own preferences for reward, which is not static even on an individual level (Durik and Harackiewicz, 2007; Hidi, 2015). When we are full, food is not a reward anymore. The amount of perceived reward depends on a set of the process of rewarding objects and events that an individual experienced. It also depends on situations and contexts (Nakahara, Itoh, Kawagoe, Takikawa, and Hikosaka, 2004). Furthermore, when it comes to intrinsic reward, our experiences influence what we perceive as reward signals in the course of learning. Two types of learners, holistics who are global learners and serialists who are step-by-step learners, presumably do not use the same intrinsic reward in their learning processes because their learning strategies are different (Pask and Scott, 1972). Children who have a developmental disorder may have different sensitivities to a reward stimulus. For example, children with ADHD prefer immediate reward over delayed reward (Tripp and Alsop, 2001) and children with autism have lower sensitivity, especially to social reward in learning (Zeeland, Ashley, Dapretto, Ghahremani, Poldrack, and Bookheimer, 2010).

Reward in learning and motivation

A reward is used as a reinforcer in learning and motivation. A reinforcer is a stimulus that can strengthen specific behaviors. Operant conditioning is learning by reinforcement (Skinner, 1938). In contrast to the Pavlovian conditioned response that is associative learning of stimulus and a reward, operant conditioned response operates in an environment that produces a certain reward to learn associations between instrumental manipulation and a reward. Reinforcement is a powerful way for associative learning by associating an action and an extrinsic reward. However, associative learning does not consider the internal state of individuals, such as internal feelings, drives, and desires, which are directly related to motivation.

1.2.2 Intrinsic motivation

Intrinsic motivation has been studied mainly in psychology over many decades. In the last several years, intrinsically motivated learning algorithms have received more attention in the fields of reinforcement learning and developmental robotics. Furthermore, a biological substrate of intrinsic motivation has just started to be elucidated in neuroscience.

Intrinsic motivation in psychology

Intrinsic motivation is defined as the action humans take for its own sake out of fun or satisfaction through cognition such as curiosity, surprise, or novelty. In an expanded sense, autonomy, competence ,and relatedness can motivate people intrinsically (Ryan and Deci, 2000a). Not only human beings but other animals are also spontaneously willing to explore without an extrinsic reward. For example, mice would keep a manipulating instrument (Kish, 1955) and rhesus monkeys would keep manipulating a puzzle to solve(Harlow, Harlow, and Meyer, 1950) without food or other special incentives as a reward. A recent study showed monkeys sacrificing the reward of water in order to get more information about the outcomes of a gamble (Blanchard, Hayden, and Bromberg-Martin, 2015). These activities are called "drives to manipulate" based on classical theories of drives (Skinner, 1938; Hull, 1943). "Drives to explore" is another account of intrinsic, such as spontaneous exploratory behaviors (Montgomery, 1954). Rhesus monkeys were trained through visual-exploration incentives (Butler, 1953).

There are some theories that explain intrinsic motivation. Reduction of cognitive dissonance theory asserts that motivation is more substantial when organisms can reduce the discrepancy between structures of internal cognition and perception of external situations. In the theory of optimal incongruity, Hunt (1963, 1965) postulated that a discrepancy between perception and stimulus induced interest.

Challenges to the optimal incongruity theory bring up the concepts of motivation for effectance (White, 1959), competence, and self-determination (Ryan and Deci, 2000b). Organisms engage in exploratory, playful, and curiosity-driven behaviors autonomously

(White, 1959). Animals and humans tend to seek more robust sensory simulations for sensation ,such as reading detective stories or driving cars at high speeds (Hebb, 1949). Berlyne (1966) compiled these drives as "collative variables." In his experiment, he observed that it is the most rewarding case when the difference between familiar and new situations is at a middle level of novelty. Lepper and Hodell (1989) considered four factors, challenge, curiosity, control, and fantasy, as sources of intrinsic motivations.

Throughout this long history, the inherent nature of active exploration by organisms that is independent of drives to survive is seemingly a key for intrinsic motivation. The feature does not only be the nature of animals and humans, whose mental states could be highly cognitive or disordered; it seems more like evolutionary, social problems. In conclusion, there are diverse factors related to intrinsic motivation, and it has no standard definition of it.

Computational models of intrinsic motivation

Investigations in computational modeling, robotics, and machine learning (e.g.,reinforcement learning) have proposed various mechanisms that capture certain aspects of intrinsic motivations (Schmidhuber, 1991; Thrun, 1995; Saunders and Gero, 2004; Oudeyer et al., 2007; Uchibe and Doya, 2008; Merrick and Maher, 2009; Santucci, Baldassarre, and Mirolli, 2013; Barto, Mirolli, and Baldassarre, 2013). However, there is no integrated definition of intrinsic motivation; Neither is there a concrete framework nor formal computational model, although intrinsic motivation has been focused upon more in the fields such as developmental robotics and reinforcement learning (Barto, Singh, and Chentanez, 2004; Oudeyer et al., 2007). Oudeyer et al. (2007) implemented an intrinsically motivated learning system called IAC (Intelligent Adaptive Curiosity) to the Sony AIBO robot, and AIBO successfully exhibited a developmental progression in learning about its environment from simpler to more complex understanding.

The computational models that I reviewed use collative variables (Berlyne, 1966) as intrinsic motivation measures. Reinforcement learning architecture could be applied these measures for cognitive modeling of intrinsically motivated reinforcement learning, in which these measures are intrinsically generated by action selection systems in a reinforcement learning framework such as Q-learning or Sarsa. Basically, in these measures, temporal difference error is regarded as a reward. The three categories of measures of intrinsic motivation on the concept of Berlyne's collative variables by referencing Oudeyer and Kaplan's paper (Oudeyer et al., 2007) is introduced.

Knowledge-based models of intrinsic motivation

Prediction error and novelty are the factors in these models that motivate an agent to gain new knowledge about an environment. Information theory and distributional models are one approach. The probability distribution of particular events occurred e^k for discretized spaces are represented by using the entropy definition:

$$H(E) = -\sum_{e^k \in E} P(e^k) \ln P(e^k) \tag{1.1}$$

A temporal reduction of entropy after event e^k happened is defined as Information gain motivation:

$$r(e^k, t) = C \cdot (H(E, t) - H(E, t + 1)) \tag{1.2}$$

C is a constant number. It defines the decrease of uncertainty in an agent's knowledge as rewarding. Another example of reward measurement is empowerment (Capdepuy, Polani, and Nehaniv, 2007), which encourages an agent to maximize the environment's information with sensory perception. It uses the concept of a channel capacity thorough the series of actions $A_t, A_{t+1}, \cdots, A_{t+n-1}$ to the perceptions S_{t+n}:

$$r(A_t, A_{t+1}, \cdots, A_{t+n-1} \rightarrow S_{t+n}) = \max_{p(\vec{a})} I(A_t, A_{t+1}, \cdots, A_{t+n-1}, S_{t+n}) \tag{1.3}$$

where $p(\vec{a})$ represents the function of probability distribution in the series of actions, and I represents mutual information.

Predictive models that use neural networks or support vector machines to predict future events as predictive models are another approach. Prediction novelty motivation regards the maximum prediction error as rewarding (Barto et al., 2004). Schmidhuber (1991) proposed a computational formalization of learning progress motivation. Oudeyer and Kaplan (2007) used a mechanism that allows a robot to classify similar situations in specific regions within which comparison is meaningful and monitoring the evolution of prediction errors in each region for learning progress. Mohamed and Rezende (2015) have proposed a new approach applying the concept of empowerment for mutual information maximization.

Competence-based models of intrinsic motivation

This model is derived from psychological theories of effectance (White, 1959), competence, and self-determination (Deci and Flaste, 1996) or flow (Csikszentmihalyi, 2014). The basic concept of this motivation is a challenge by setting a higher goal. Hierarchical deep reinforcement learning is successfully applied to the environment with sparse and delayed rewards by setting sub-goals for intrinsic motivation (Kulkarni, Narasimhan, Saeedi, and Tenenbaum, 2016).

Morphological models of intrinsic motivation

The previous two models essentially use measures of comparison between past and present information. By contrast, morphological models are based on measures comparing information by simultaneous perception from different stimuli. Synchronicity motivation uses measures of synchronicity based on an information theoretic measure of correlation. A typical example is a situation in which synchronicity is rewarding in the learning of causation and contingency. Recently, it is noted that intrinsic motivation/reward plays a more critical role in reinforcement learning, especially in the presence of extrinsic sparse rewards. With the intrinsic reward, agents can explore the environment to discover novel states (Bellemare, Srinivasan, Ostrovski, Schaul, Saxton, and Munos, 2016), maximize their ability to influence the environment (Houthooft, Chen, Duan, Schulman, De Turck, and Abbeel, 2016; Mohamed and Rezende, 2015), or do both, such as in the case of curiosity-driven learning (Pathak, Agrawal, Efros, and Darrell, 2017; Forestier and Oudeyer, 2016).

1.3 Intrinsic motivation for creativity

It is important to note that every child is born to be creative. As the painter Pablo Picasso said, "Every child is an artist. The problem is how to remain an artist once they grow up." This may have two reasons.

First, we lose the variable nature of intrinsic motivation when we are exposed to extrinsic motivation (Deci and Flaste, 1996). Adults are sometimes confused whether they are doing something for its own sake out of fun or cognitive satisfaction such as curiosity or wonder or extrinsic rewards such as a compliment, compensation or prize. Realistically, adults almost inevitably utilize these extrinsic motivations to make constant signs of progress.

Second, adults have obtained many more tools than children, which the former can more easily apply for expression and creation than children. Without these tools, children put a lot of creativity into their expression. The prime example is the use of metaphors. Children create their word expressions to express something they do not know the name or verb; for example, "soy sauce for strawberry" to represent condensed milk, "wear an umbrella" to represent holding an umbrella. Children try to find the analogy between a new element to elements that are already learned and stored in their internal linguistic systems, which are constantly under construction alongside the development of the children's lexicon. Once a new word element is learned, the system is also updated and modified. This is how children (ages 3-5) learn languages (Imai, Gentner, and Uchida, 1994), and this ability to find and utilize analogy to represent something new with the limitation of the elements essentially corresponds to the claim both by (Schmidhuber, 2010) and Finke (2014). This ability enables us to invent new expressions and products against the restriction of the world, which is one of the essences of creativity. In this sense, interaction with the environment is essential to update the internal systems. Children also seem to prioritize understanding the system itself over memorizing elements.

From another perspective, the so-called "Goldilocks Effect" states that children (even infants) prefer intermediate complexity for absorbing new information efficiently by avoiding events that are too simple or too complex (Kidd, Piantadosi, and Aslin, 2012). This optimization is guided by the desire to maximize the learning opportunity by interacting with the environment through taking into account what is available to the learner's internal state (Twomey and Westermann, 2018).

I generally support the idea that the desire to maximize learning opportunity leads to the preference for more variety of expression without too much complexity in creations, such as artistic activity. Here, the desire to maximize learning opportunity can be restated as intrinsic motivation. This study claims that the motivation to express something in a richly varied manner by the combinations of simple elements constitutes the intrinsic motivation when people are engaging in creative activity. The more elements are learned and available, the more variety of expression can be created. However, there are costs for learning to effectively select methods for various expressions. This trade-off makes the cycle of creativity (Figure 1.1). Given intrinsic motivation, a learner performs a creative activity with restrict elements. When a variety of expression, such as surprising patterns, is achieved, it produces an intrinsic reward. As more intrinsic reward is obtained and the learner becomes capable of predicting the effects

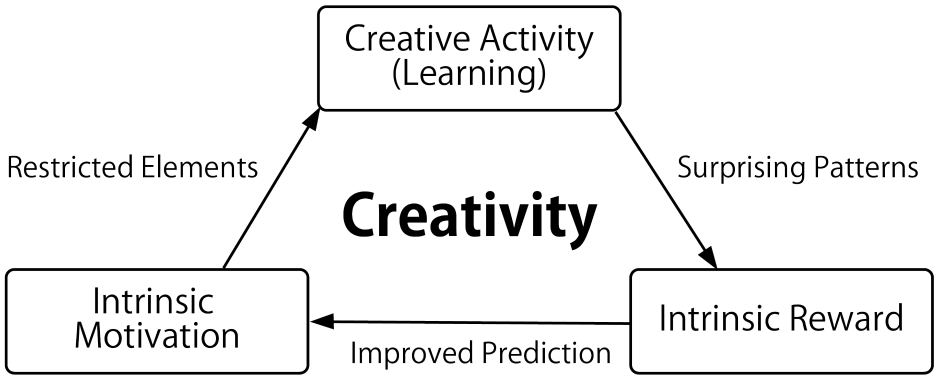

Figure 1.1: Interaction among Creativity, Intrinsic Motivation, and Intrinsic Reward for creativity

the elements, intrinsic motivation is enhanced for further creative activities.

In sum, I propose the hypothesis that intrinsic motivation is facilitated when higher variety of expressions using simpler rules can be obtained in creative activity. The learner generates the information themselves and observes it. To make the expression varied, choosing a simple learning environment to learn and utilize elements is a wise decision.

The goal of this study is to investigate the hypothesis by conducting a human behavioral experiment. To this end, the learning environment will be designed to manipulate both the simplicity/complexity of the learning environment and the variety of expression. The environment will be practically developed as an original computer game based on the framework of the game of life cellular automata. Using this framework, the two factors, the simplicity/complexity of the environment as rules and the variety of expression, are manipulated by parameters of state transition function and quantified by the complexity measures formulated in the theory of cellular automata. The experimental task is designed as an original interactive game with a touch screen. The task is to draw dynamic patterns on a grid by learning and utilizing the cellular automata system's rule by interacting with the environment.

The hypothesis is examined with the game by collecting and analyzing behavioral data while participants are engaging in the drawing task of the experiment. In my approach to understand creativity, I avoid measuring the score of "creativity" in any specific context. Instead, I try to focus on the role of intrinsic motivation in the engagement of creative activity, specifically the activity resemblant to drawing in this study. More importantly, the experimental task design can eliminate the potentials of extrinsic motivation related to the task. The task has neither a clear goal (e.g., what to draw) nor scores. The task absolutely does not have a treat.

Everyone has a moment in which they become aware of their creativity. A key question in this study is what is the fundamental intrinsic reward for the creativity? Although the principles governing intrinsic motivation in creative activity are too complicated to integrate into a single model, optimizing learning opportunities and maximizing the variety of expression are important drives as intrinsic motivations in learning and creation. The hypothesis embraces both drives and makes claims regarding the two hypothesized factors of the simplicity/complexity of the learning environment and the variety of expression. The hypothesis encourages the consideration of both factors together. Rather than examining each factor independently corresponding with the concept of the intermediate complexity theory, the trade-off between these factors may be crucial to maximizing intrinsic reward. It also elucidates learner's, participants' in the experiment, "pure" intrinsic rewards by refining extrinsic rewards, which sheds light on understanding mechanisms of intrinsic motivation. The findings of this study can help to design classroom assignments that are intrinsically motivating for children. Moreover, the results make specific suggestions beyond understanding the mechanisms of intrinsic motivation to the processes that establish conditions that would spark more creativity in general and the values in artworks that tend to impress people. All of this can serve as the basis for modeling creativity with influential factors.

Chapter 2

Experiment: How can we measure the factors of intrinsic motivation in creative activity?

2.1 Objectives

Humans will spontaneously make an effort to create something new and meaningful even without obtaining extrinsic rewards, which implies that we are intrinsically motivated to be creative by nature. Intrinsic motivation is a desire to learn for its own sake (Berlyne, 1966) and a fundamental condition for intelligence and creativity (Csikszentmihalyi and Csikzentmihaly, 1991; Ryan and Deci, 2000a; Boden, 1998). A large body of literature and practices have already been accumulated regarding the mechanism of intrinsic motivation. Novelty, variety, and prediction errors are hypothesized as critical factors to explain the mechanisms of intrinsic motivation in learning and these factors have been implemented and achieved incredible results by the models using a concept of intrinsic motivation. (Barto et al., 2019; (Oudeyer et al., 2007; Schmidhuber, 1991). However, few experiments are investigating intrinsic motivation regarding creativity especially when the task, such as drawing, has no clear goals and most of the output from creative tasks do not clear, readily defined goals. Regarding such tasks, what environmental conditions influence intrinsic motivation is still a controversial topic. It is because measuring creativity is so multifaceted that the assessment of creativity in the experiments tends to be too general and veering into intelligence measurement, biased by judges, or too specific in terms of weight of preliminary skills for task completion. Hence, I set our research question not on creativity itself but the most crucial element of creativity, intrinsic motivation. I designed an experiment for measuring intrinsic motivation in which human subjects engage in a creative activity. I implemented a design of a behavioral experiment to measure intrinsic motivation and its predictive variables with a task resembling a drawing that does not require a prerequisite of specific skills or knowledge. Moreover, I carefully designed the task to be devoid of extrinsic motivations such as points or assessments. Simultaneously, I manipulated a level of predictive variables in our hypothesis to compare different conditions.

The objectives of the study are:

1. To investigate what environmental conditions influence intrinsic motivation in creative activity.

2. To understand how the factors fostering intrinsic motivation are different individually

As I propose in more detail in the next section, I focus on two factors influencing intrinsic motivation in creative activity, which are a variety of expression and simplicity/complexity of environmental rules. Intrinsic motivation is not a single set phenomenon that can be measured by simply asking one general open-ended question. Instead, intrinsic motivation, especially when engaging in creative activity, is not easy to evaluate uniformly. Psychologists have developed numerous differing methods, such as learning a skill for creation, harnessing a constraint for creation, and creating artwork. The goal of this study is to elucidate a fundamental condition of the learning environment which affects intrinsic motivation.

2.2 Hypothesis: More variety with simpler rules makes people more intrinsically motivated.

To reach the objectives, I focused on two factors of the learning environment: the simplicity/complexity of a rule and the variety of expressions produced by the rule. With these two factors as variables, a hypothesis has been presented that intrinsic motivation is facilitated when humans can observe a higher variety of expressions using simpler rules. The hypothesis is verified in the human behavioral experiment. The experimental environment was developed as an original computer "creative activity" game based on a framework of CA (Cellular Automata), particularly the GOL (Game of Life), was introduced in the introduction section.

In the GOL framework, a variety of expressions are manipulated by the state transition function parameters, which are represented as x and y in By/Sx, where By stands for a set of the numbers for birth and Sx stands for a set of the numbers for survival. The complexity of a rule is controlled by a number of cell states, a number of interacting neighbors, and a number of elements in set x and y of By/Sx. More details about the rule settings will be described in Subsection 2.3.3. The hypothesized mechanism of intrinsic motivation was examined by collecting behavioral data during play and answers to the questionnaire after playing. The data were analyzed to evaluate how the degree of intrinsic motivation depends on each unique condition. In this study, the degree of intrinsic motivation is evaluated in terms of enjoyment, measured by a subjective score in the questionnaire, the length of playing time consumed by participants, and the frequency of interaction during play.

If the hypothesized mechanism of intrinsic motivation is varied, it can help with understanding the fundamental mechanism of intrinsic motivation, and in designing an environment for fostering intrinsic motivation by adjusting the variables.

2.3 Materials and Methods

2.3.1 Ethics

All methods were approved by the institutional review board of humans subject research of Okinawa Institute of Science and Technology. All participants gave written consent to take part in the experiment.

2.3.2 Task

The task is simple: Draw patterns on eight by eight grids as you like. The significance of the task is that the task does not have either a clear goal as an extrinsic reward or a need for specific preliminary skills. Furthermore, the pattern as an artifact of the task can be interpreted as quantitative data due to its low quality of just 64-bit data per image.

I carefully designed the task so that learning is not done through memorizing numbers or names and just for solving a specific assignment. I used rules of CA for game settings which manipulate environmental conditions of the environment for the task. The rule of CA is very simple, and it only requires three parameters to be set, but it is too difficult to figure out the by a three by three grids, can produce 2^9 i.e., 512 patterns as determined by a rule. Moreover, if a participant find out the parameters during the task or even if the experimenter reveals the parameters, it is still too difficult to control the pattern from 512 possible patterns of intertwining three by three grids on an eight by eight grids and so prevents the participants from simply selecting an arbitrary pattern out of all possible patterns rather than control the dynamics of the world of a cellular automaton.

Figure 2.1 shows the interface of the task. Participants were asked to draw on the grid. To draw the patterns, participants set the initial states of the cells (5 cells at maximum) by touching the cells, and run the cellular automata by touching the start button, then continue to interact by touching cells to understand how it works in order to control and try to make what they want to create.

2.3.3 Parameter design of task

Parameters of the state transition function

To be examined the hypothesis, the framework of GOL cellular automata was applied for rule implementation. Variation of the GOL rules was chosen to manipulate variables in the hypothesis by parameterizing the required number of neighbors to be alive or dead in the next generation as Sx and By, respectively. With these parameters, the rule is stated as follows.

1. Any live cell remains alive with Sx live neighbors; otherwise, it dies.

2. Any dead cell with By live neighbors becomes alive.

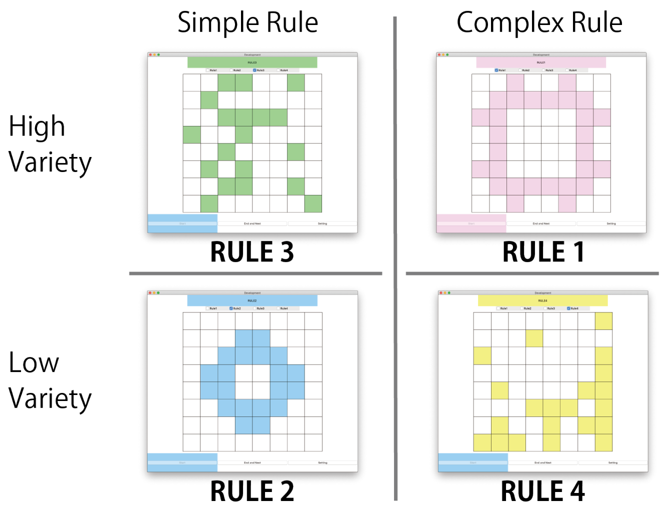

Figure 2.1: Task Interface
The four rules are implemented parameters of a cellular automaton with Moore neighborhood, which has nine neighbors, including the center cell. Rule 1 is stated as $B2/S234$, Rule 2 as $B3/S234$, Rule 3 as $B2/S23$, and Rule 4 as $B3/S34$.(Sx stands for a set of the numbers for survival. By stands for a set of the numbers for birth.) The lambda parameters of each rule is RULE1:0.35, RULE2: 0.41, RULE3:0.22, RULE4:0.35. RULE1 and RULE4 are more complex rules than RULE 2 and RULE3.The details are described in Appendix A.

Sx stands for a set of numbers for survival. By stands for a set of the numbers for birth. For example, the standard GOL is denoted $B3/S23$ in the form By/Sx. Both x and y can be set as multiple variables as long as the number is not over the number of neighbors. The actual parameters of rules which were implemented in the experimental task are described in Table 2.1. Four rules were chosen. Rule 1 is stated as $B2/S234$, Rule 2 as $B3/S234$, Rule 3 as $B2/S23$, and Rule 4 as $B3/S34$. All rules have a Moore neighborhood that has eight cells as neighbors, excluding a center cell itself.

In the pilot study, I tried to manipulate the simplicity/complexity of rules by changing the number of neighborhoods and the number of states (more than two) in addition to By/Sx. However, participants never clearly saw which neighborhood or how many states each rule has, which caused unnecessary confusion rather than giving participants an impression of the different levels of rule simplicity/complexity. During the interviews after playing a task in the pilot experiments, participants showed that they did not comprehend the exact numbers of neighborhoods or states but did notice through their interactions how the dynamics of the pattern in each rule worked. Therefore, I applied the same number of neighborhood and two states (colored or not colored) to all rules.

Lambda as the complexity measures of cellular automaton

Defining simplicity/complexity is controversial and context-driven, but the definition of complexity is generally based on the predictability of behaviors on a system (Johnson,

Table 2.1: Rule settings with parameters of cellular automata

Rule No.	States	neighborhood(cells)	B/S	λ	Complexity	Variety
Rule 1	2	Moore (9)	B2/S234	0.35	complex	high
Rule 2	2	Moore (9)	B3/S234	0.41	simple	low
Rule 3	2	Moore (9)	B2/S23	0.22	simple	high
Rule 4	2	Moore (9)	B3/S34	0.35	complex	low

2009) and compression efficiency in terms of computational resources (Kolmogorov, 1965).

The behavior of cellular automata is generally too complex to predict accurately, and there is no common quantitative measurement to define the complexity of its behavior. Langtons' λ (Langton, 1986) statistically organizes behaviors of rules into four groups of Wolfram classes. According to the λ parameter, Rule 1 and Rule 4 of our game are classified into Class IV, which is the most unpredictable because the behavior shows both cyclic and chaotic patterns. Rule 2 is categorized as Class II, which tends to show cyclic patterns that are more predictable than Class IV patterns. Rule 3 is categorized as Class III, which shows chaotic patterns. Class II and Class III behaviors are supposed to be less complex than those in Class IV in terms of predictability and 2.

In summary, I classify Rule 1 and Rule 4 as complex rules and Rule 2 and Rule 3 as simple rules by the Wolfram classes.

2.3.4 Procedure

The experiment was conducted individually. A participant was seated at a table where the touch panel screen is set. Before the beginning of the sessions, the participant reads an explanatory instruction on how the game works and how to play it. At the outset of the experiment, the participant was also told that the entire experiment would end within one hour, regardless of their performance. Subsequently, a demo session started, and the initial screen was shown as an eight by eight square of grid cells in a quiescent state. The participant then instructed an experimenter that the experiment consisted of three sessions and one questionnaire (Figure2.2). The first session was for showing demos on how to play with all the given rules. In the subsequent two sessions, the participant played timed games with a rule selection (Session 1 and Session 2). After all sessions were completed, the participant filled out a questionnaire form. Participants were not told the explicit purpose of the study before they had completed all sessions to avoid biases in their performances. After all sessions and the questionnaire were completed, an experimenter briefly shared the purpose of the study with the participants.

Demo session and questionnaire

For the first session, the experimenter showed the participant demos with each rule, starting with the four different initial cell states. The order of the rules to be demonstrated was randomized for each subject. Each rule was assigned a particular color so that the participant could distinguish which rule is being applied. Watching the demos enabled the participant a general idea of how the game works and how to play it. The participant also filled out a questionnaire about how they evaluated the dynamic patterns in terms of complexity, variety, and enjoyment and were informed that they would answer the same questions after they finished the subsequent two sessions. The data and the questionnaire from the demo session were not used for the analysis. This session aimed to familiarize the participants with the Game of Life and let them understand what activities they were going to play.

Play Session 1

For the first play session, the order of rules to be played was randomly selected and played five times per rule. Each game lasted for one-minute maximum. The participant could end the game before one minute by pressing the end button on a screen and start the next new game by pressing the start button. The procedure in this session was as follows.

1. One rule is randomly selected as the first rule to be applied, and an initial page of the game appears.
2. The participant sets initial cell states by touching cells to change the colors (5 cells at maximum).
3. The participant touches the start button, and the first game begins.
4. The participant observes how the cells form dynamic patterns and interact by changing the color of any cell as they prefer.
5. Each game takes one minute with 15 seconds interval.
6. Each game starts after resetting all states of the previous game to non-color states.
7. Each rule is played for five games.
8. The next rule is set after five games.

This session continues until all rules have been played five times.

Play Session 2

In the second play session, the participant could freely choose the game to play and switch among them for 10 minutes in total. The experimenter instructed the participant to select the rule for the first game by touching a rule number button on the screen. The procedure was the same as steps 2 to 4 for play Session 1. The participant could change the rule by touching the rule button and reset all status of the cells by touching the end button. This session continued until 10 minutes passed or until a participant made no interaction for 5 minutes during the session. In the latter case, the session ended automatically.

After the three sessions were over, the participant was required to answer the questions in the questionnaire. The questionnaire form is attached as Appendix C.

At the end of an experiment, the experimenter told the participant more details about the purpose of the study.

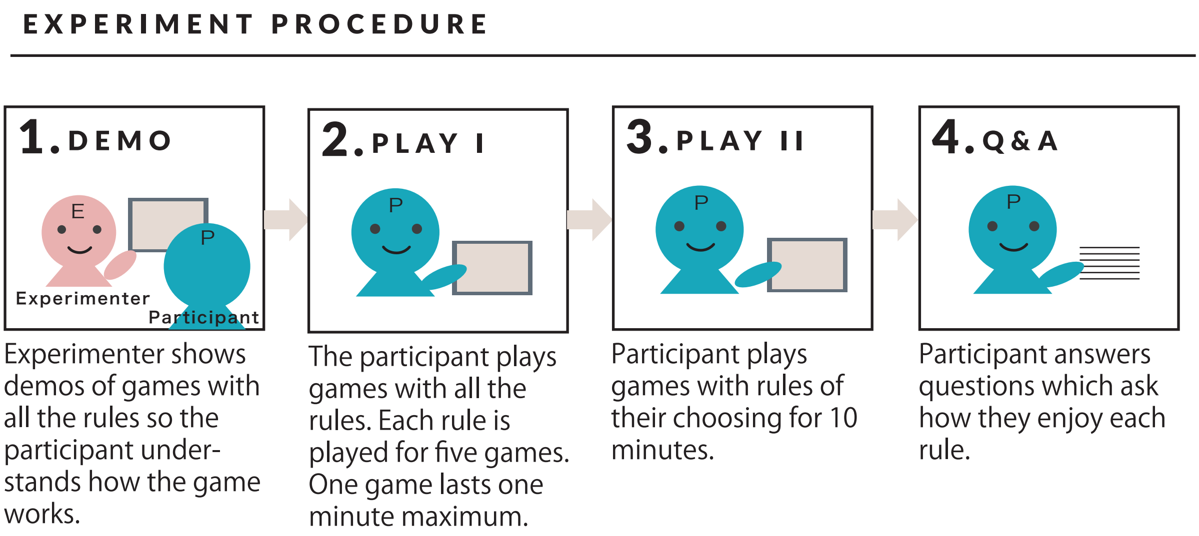

Figure 2.2: Procedure of the experiment
The experiment contains four parts. First, the experimenter demonstrates how to play with the game. In the second and third, participants play in different settings of playing time restrictions. In the end, participants fill out a questionnaire for mainly collecting information on how they enjoy each rule.

2.3.5 Questionnaire

Both the English and Japanese questionnaires were prepared and provided based on the participants' choices. The questionnaire comprised of questions regarding subjective scores that measure:

1. How much participants enjoyed the rules.
2. How simple/complex participants perceived each rule was.
3. How much variety participants perceived for each rule.

The whole list of questions is included in Appendix C. The Likert scale method of the scale of 1-7 was used for the three qualities above, with 1 being not enjoyable and 7 being very enjoyable, 1 being simplest and 7 being the most complex, and 1 being less varied, and 7 being most varied, respectively. Besides the questions, free comments about the game were also collected. The subjective scores were applied subject-wise standardization for the analyses.

The question for asking intrinsic motivation was "How much did you enjoy the game with each rule?" and participants marked a number as they intuitively evaluated. As the feature of intrinsic motivation, I focused on "enjoyment," i.e., how much participants had fun with the task. To find out, I simply asked how much they enjoyed the task. Regarding the simplicity/complexity of the rule they used, the question was, "How did you think each rule was simple or complex?". To measure the variety of expression, I asked, "How did you think the pattern transition with each rule was interesting?".

In the preliminary study, I first used the question: "How did you think the pattern with each rule had more variety?". However, most participants did not understand the question and asked the experimenter the meaning of the varieties of patterns. Therefore, in realizing that the question may not be straightforward enough, I changed the question to ask how much the participants saw the variety in the patterns with their interest. However, the question did not explicitly ask the variety of expression and had a confound with the measure of intrinsic motivation itself. Accordingly, as described later in Chapter 3, the score of this question was analyzed to see its correlation with the score of intrinsic motivation but was not used for further analyses.

2.4 Data analysis

There is no established quantitative measure of neither "variety of expression" nor "simplicity/complexity of a rule." To measure the variable for variety, I designed the task with discrete grid patterns as output to quantify the participants' expression by counting the number of colored grid cells and their distribution. Also, cellular automata rules allow us to control the simplicity/complexity with its λ parameter of complexity. However, the parameter is simply an index to categorize the rules into four groups, and the numerical value of the parameter does not stand for a variable of rule complexity. The concept of empowerment is also used to measure rule complexity in terms of changeability and controllability of rules for the analysis. Details of the variables are described in table 2.2.

2.4.1 Variables for intrinsic motivation

Intrinsic motivation inventory (IMI)(Ryan, Mims, and Koestner, 1983) is a multidimensional measurement method to assess the subjective experiences of participants in intrinsic motivation. IMI features subscales of participants' interest/enjoyment, perceived competence, effort, value/usefulness, felt pressure and tension, and perceived choice while performing the given activity for assessment. However, the validity of the subscales has yet to be established, and it is recommended to perform appropriate factor analyses depending on data sets. Although multiple item subscales tend to perform better than a single scale, fewer items are also reliable if appropriately selected. According to its guideline, the interest/enjoyment subscale is only considered the self-report measure of intrinsic motivation.

In this experiment, intrinsic motivation was measured by the scale of enjoyment and perceived behaviors. The task was not long enough for the subject to perceive competence or value/usefulness. The differences between the rules were not significant enough for participants to perceive the difference of choice, effort, and pressure/tension. Due to these features of the present task, participants were asked only the subscale of interest/enjoyment in the questionnaire.

Since the activity in this experiment was playing a game of cellular automata with different parameters, participants may have an interest in the cellular automaton system itself. Therefore, I simply asked how much participants "enjoyed" playing with each rule in a questionnaire as the major measurement of intrinsic motivation.

Instead of relying on questionnaires like those from IMI, the degree of intrinsic motivation was also measured by the behaviors such as playing time before boredom sets in and frequency of touch interaction. All measurements were compared between the four rules (Rules 1 to 4) with different complexity and variety of expression.

2.4.2 Variables for the variety of expression

To measure the variable "variety of expression," I measured the number of live cells, the number of cell state transitions, the entropy of the distribution of local patterns observed by each participant, and the subjective scores of a variety of expressions. Other possible measures of a variety of expressions include symmetries, particular shapes of patterns, and semantic interpretations. However, the measures based on the distribution of the numbers, such as entropy, are the most fundamental.

2.4.3 Variables for the simplicity of the rule

The simplicity of rules was measured by Langtonns' lambda parameter as the complexity measures defined by cellular automaton. In addition, to measure the categorical simplicity by lambda, empowerment was computed as the amount of control or influence the agent has over the environment. If the rule is easier to control or influence, the rule can be defined as simpler. Subjective scores of rule complexity were also collected in the questionnaire.

Table 2.2: Description of the variables measured in the experiment

Variables Measure	Description
Intrinsic motivation	
Subjective scores of enjoyment	Subjective scores of enjoyment were collected by asking, "How much did you enjoy the game with each rule?". The Likert scale method on a scale of 1 -7 with 1 being not enjoyable and 7 being very enjoyable are used in the questionnaire.
Playing time	The length of time in seconds participant used for each rule. The mean of each game in each rule was used for the analysis.
Frequency of touching interaction	The number of interactions is represented by the frequency of touch by participants during the games. The mean of each game in each rule was used for the analysis.
Variety of expression	
Number of live cells	The number of cells that are alive in transitions. Mean of numbers counted in every transition in each rule was used for the analysis.
A number of cell state transitions	The number of how many cells transit their state in transitions. Mean of numbers counted in every transition in each rule was used for the analysis.
Entropy	Entropy of the distribution of live cells (2 states of alive or dead) is computed in each game. The mean of all games in each rule was used for the analysis.
Entropy of 2 by 2 square grid pattern	Entropy of 2 by 2 square grid pattern ($2^4 = 16 components$) computed in each game. The mean of all games in each rule was computed and used for the analysis.
Subjective scores of a variety of expressions	Subjective scores of a of expressions collected by asking, "How much did you think the pattern transition with each rule was interesting?". The Likert scale method on a scale of 1 -7 with 1 being very boring and 7 being very interesting is used in the questionnaire.
Simplicity/complexity of the rule	
Empowerment	Empowerment is computed as the amount of control or influences the agent, i.e., participant of the experiment has over the environment defined by the equation (3.4).
Subjective scores of rule complexity	Subjective scores of rule complexity collected by asking, "How much did you think each rule was simple or complex?". The Likert scale method on a scale of 1 -7 with 1 being very simple and 7 being very complex is used in the questionnaire.

Chapter 3

Results: Factors influencing intrinsic motivation

3.1 Participants

Forty-two adults ages 20-56 (average 36.6±8.07(s.d.), 29 females and 13 males) were recruited by the Neural Computation Unit at Okinawa Institute of Science and Technology Graduate University (OIST). Recruitment was conducted by email to OIST members and poster/leaflet distributed on campus and the OIST internal website. The experimenter started the experiment after participants read and signed a consent form to participate in the experiment with the option to drop out of the project at any point. The experiments were conducted during the participants' working hours without any extra compensation. No incentives for participation in this experiment were given. All participants fulfilled all experiment procedures, and none of the participants were excluded from the analysis. All participants completed two sessions and a questionnaire.

3.2 Questionnaire: Subjective scores

All participants thoroughly answered all of the questions. Standardized subjective scores were computed within each participant by subtracting the mean and dividing by the unbiased standard deviation. If a subject gave the same score for all four rules, the standardized score was set as zero.

3.2.1 Ranges of subjective scores

Subjective scores of enjoyment are collected using the Likert scale method on a scale of 1 -7 with 1 being not enjoyable and 7 being very enjoyable in the questionnaire. Figure 3.1 shows the mean of scores. As described in the caption of the figure, average scores of 4.63±1.61(s.d.) for all rules are over 3.5, which is the neutral point on the scale 1-7, which identifies that participants generally enjoyed playing the task in the experiment. As shown in Figure 3.1, the average score of every rule is over 3.5, which also indicates those participants enjoyed the game.

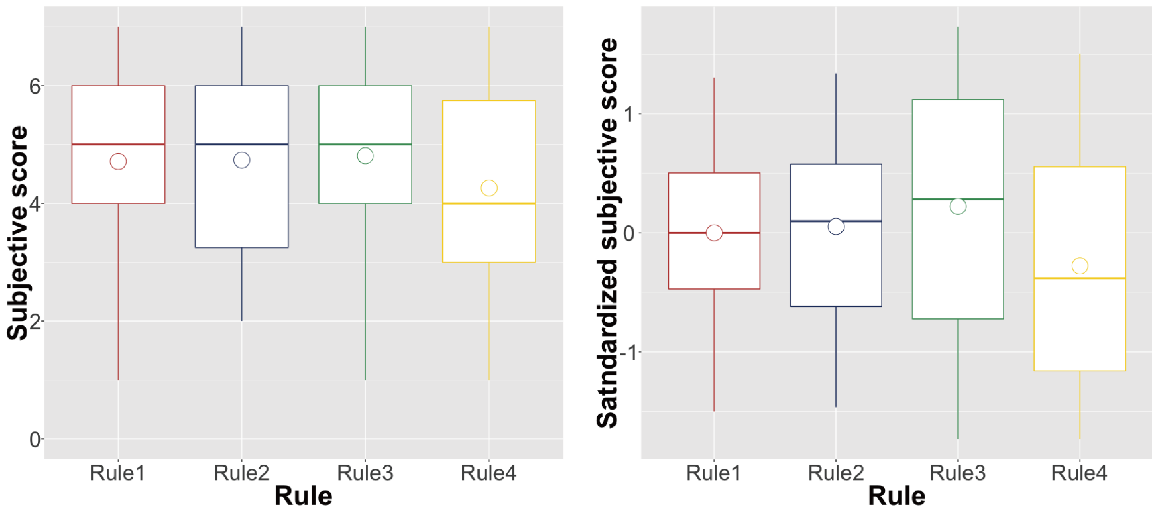

Figure 3.1: Mean of subjective scores of enjoyment
LEFT: Subjective score of enjoyment on the scale of 1 - 7. Mean of scores of all participants. The mean of all rules was 4.63±1.61(s.d.) over a neutral point at 3.5. Overall scores showed that participants enjoyed the task in the experiment. The white dots plot the mean of scores in each rule. In each rule, the mean is 4.71±1.47(s.d.) in Rule 1, 4.73±1.61(s.d.) in Rule 2, 4.81±1.57(s.d.) in Rule 3, and 4.26±1.80(s.d.) in Rule 4. On average, the mean score identifies that participants enjoyed playing the game in every rule. RIGHT: Mean of standardized subjective scores of the LEFT figure. The white dots plot the mean of scores in each rule. In each rule, the mean is 0.001±0.67(s.d.) in Rule 1, 0.053±0.80(s.d.) in Rule 2, 0.22±0.98(s.d.) in Rule 3, and -0.277±0.98(s.d.) in Rule 4.

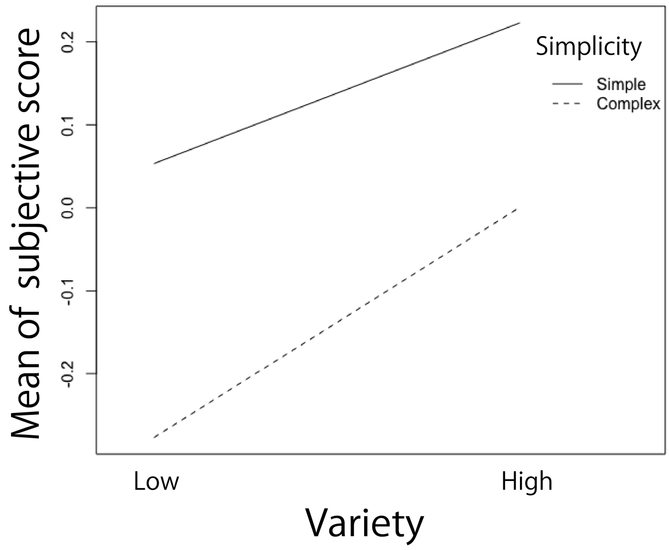

Figure 3.2: Result of two-way ANOVA by variety-complexity
The measurement of objective variety is represented on the horizontal axis, and a subjective score of enjoyment is represented on the vertical axis. The objective variety of expression was measured by the parameter in this analysis. The subjective enjoyment was measure by the scores from the questionnaire and standardized within the subjects.

3.2.2 ANOVA by variety-complexity

Figure 3.1 shows the standardized mean of subjective scores. Standardization is applied individually. The scores given by participants who marked identical scores to all rules are standardized as 0 (zero). As shown in the figure, Rule 3 is subjectively evaluated as the most enjoyable rule. Rule 4 is evaluated as the least enjoyable rule, while Rule 3 and Rule 4 have more significant variation with standard deviation, indicating a subtypes of participants favoring different components of intrinsic motivation. This insight leads to deeper analyses in Chapter 4.

The proposed hypothesis is that a learning environment with more variety of expression by simpler rules makes people more intrinsically motivated. For the subjective scores of intrinsic motivation, two-way ANOVA showed a statistical difference both in condition (simple or complex) ($F(1, 41)=4.252$, $p<0.05$) and between variety (varied or monotonous) ($F(1, 41)=2.786$, $p<0.1$). No interaction was detected between simplicity of rule and variety of expression ($F(1, 41)=0.163$, $p=0.687$) (Figure 3.2). For applying two-way ANOVA, I categorized four rules into matrix by two factors, simplicity of rule and variety of expression as described in Table 2.1. This result strongly supports our hypothesis that higher variety with simpler rule intrinsically motivates people.

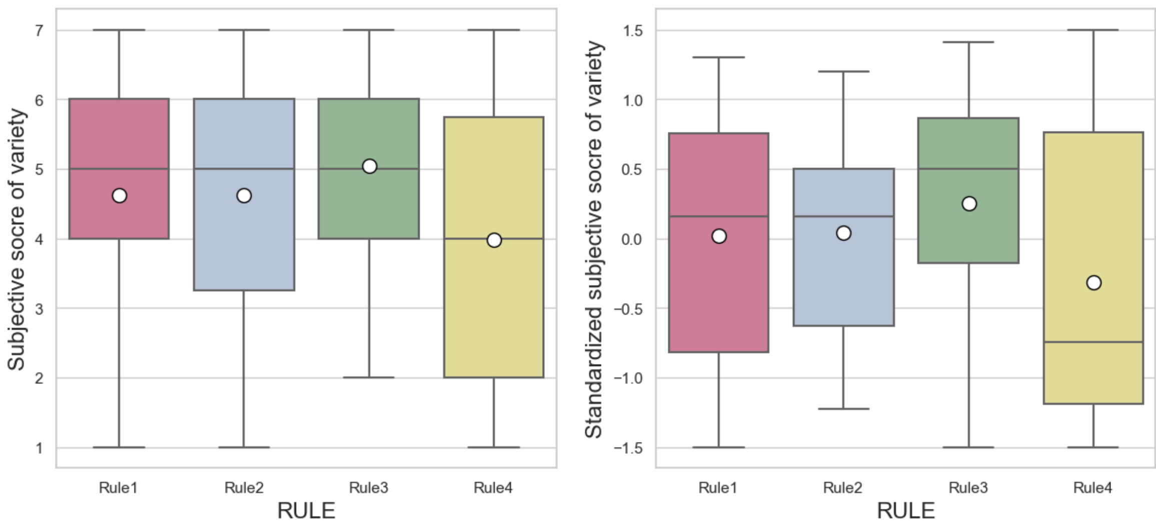

Figure 3.3: Subjective scores of variety of expression
The white dots plot mean of scores in each rule. LEFT : mean of scores on a scale 1 - 7 (mean and s.d., Rule1: 4.62±1.73(s.d.), Rule2: 4.62±1.63(s.d.),Rule3: 5.05±1.31(s.d.),Rule4: 3.98±2.00(s.d.)). RIGHT: mean of standardized scores by individuals. (mean and s.d., Rule1: 0.02±0.78(s.d.), Rule2: 0.34±0.68(s.d.), Rule3: 0.25±0.76(s.d.), Rule4: -0.31±0.98(s.d.)).

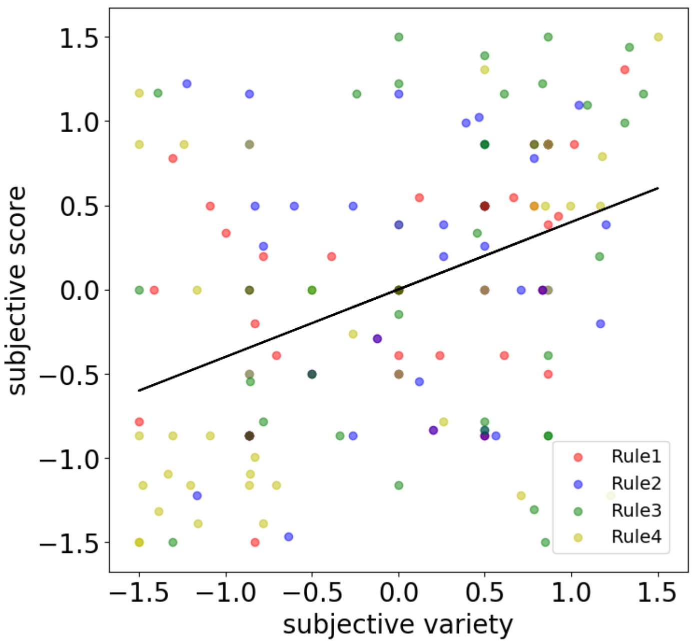

Figure 3.4: Subjective variety vs. subjective score of intrinsic motivation (slope=0.400, R^2=0.165, p<0.001.) Both variables are standardized by individuals. The data from participants who gave the same scores to all rules were standardized as 0 (zero).

3.2.3 Subjective enjoyment, variety and complexity

As an average of whole participants, the ANOVA results support our hypothesis. Nevertheless, what each participant observed and was impressed by could be different with defined categorical variety and complexity. Therefore, an analysis of the subjective simplicity/complexity of rule and variety of expression was conducted. The subjective measures which were asked after the two sessions were only used.

Figure 3.3 shows the mean and distribution of subjective scores of a variety of expressions. The left figure plots the raw score that participants gave in the questionnaire on a scale of 1-7, and the right plots the standardized scores. The mean illustrated in the right figure corresponds to Figure 3.1 in terms of the ranking between rules. Rule 3 is subjectively measured as the most intrinsically motivated and highest between the rules, and Rule 2 is the second most. Rule 4 is subjectively measured as less intrinsically motivated and lowest variety, and Rule 1 is the second least. This result corresponds to our hypothesis that higher variety positively influences intrinsic motivation.

The mean illustrated in the right figure corresponds to Figure 3.1 in terms of the ranking between the rules. Rule 3 is subjectively measured as most intrinsically motivated and highest varied between the rules, and Rule 2 is the second most. Rule 4 is subjectively measured as less intrinsically motivated and lowest varied, and Rule 1 is the second least. This result corresponds to our hypothesis that higher variety positively influences intrinsic motivation.

Figure 3.4 illustrates a correlation between a subjective variety of expressions and subjective scores. There is no significant correlation between subjective scores, and the variety of expression is not strong.

By contrast, the result in Figure 3.5 contradicts the hypothesis. Higher complexity of a rule also positively influences intrinsic motivation, while the hypothesis posits that more simplicity positively influences intrinsic motivation.

As shown in Figure 3.5, which illustrates the mean and distribution of the subjective scores of rule simplicity/complexity regarding raw scores on the left and standardized scores on the right, Rule 3 is subjectively measured as the most intrinsically motivated and highest complexity between the rules and Rule 2 is the second most. Rule 4 is subjectively measured as less intrinsically motivated and lowest complexity, and Rule 1 is the second least.

Figure 3.6 illustrates the correlation between subjective simplicity/complexity and subjective scores. There is no significant correlation between the subjective scores and the simplicity/complexity of rules is not strong.

Both regression lines in Figure 3.4 and Figure 3.6 show a positive correlation. In terms of the complexity of rules, the regression result is contrary to the hypothesis. A focus on the single variable seems to strengthen the complexity of the rule to motivate participants proportionally. This result might be because participants did not distinguish between the complexity of the four rules, as some mentioned to the experimenter. Eight participants gave the same scores of complexity to all four rules. Some were also confusing complexity with variety when they filled out the questionnaire. Individually, twenty participants showed a positive correlation between complexity and subjective enjoyment, and ten participants showed a negative correlation. The rest marked the

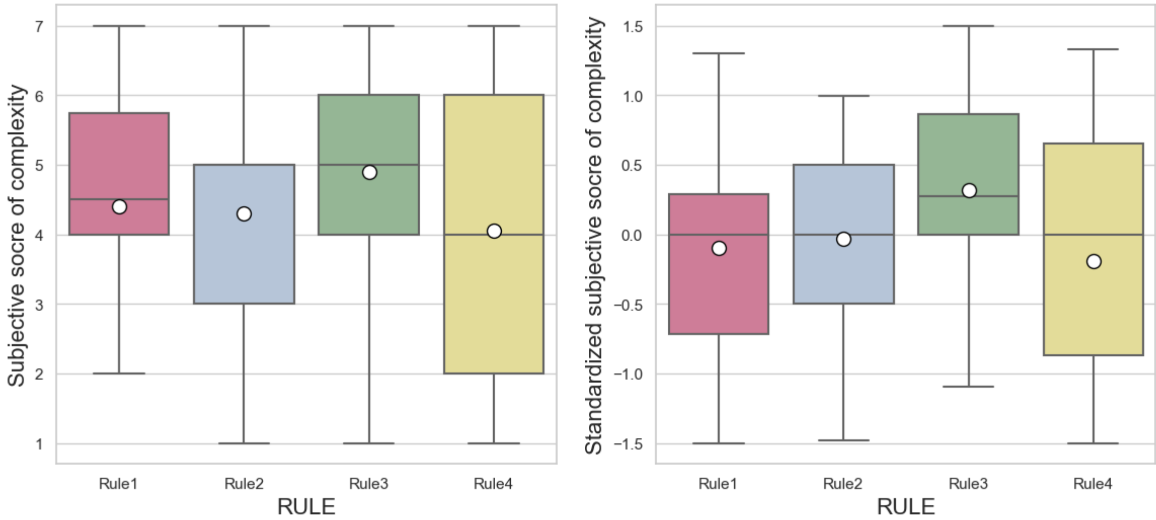

Figure 3.5: Subjective scores of complexity of rules
The white dots plot mean of scores in each rule. LEFT : mean of scores on the scale 1 - 7 (mean and s.d., Rule1: 4.40±1.75(s.d.), Rule2: 4.31±1.79(s.d.), Rule3: 4.90±1.60(s.d.), Rule4: 4.05±2.21(s.d.)). RIGHT: mean of standardized scores by individuals. (mean and s.d., Rule1: -0.10±0.68(s.d.), Rule2: -0.03±0.66(s.d.), Rule3: 0.32±0.68(s.d.),Rule4: -0.19±0.88(s.d.)).

same scores for either complexity or subjective scores for all the rules. In terms of variety, the positive correlation slightly supports the hypothesis with an unconvincing r-squared (R^2=0.165). Hence, both subjective complexity and variety were not used as variables for the multiple regression in Section 3.6.

3.3 Behavioral measures for intrinsic motivation

The degree of intrinsic motivation is measured by the subjective scores in the questionnaire, the playing time before getting bored, and the frequency of touching interaction. All measurements are compared between the four rules (Rules 1 to 4) with the different complexities and varieties of expression.

Playing time

We spend more time on what we are motivated to do than what we are not. In Session 1 where participants can play for 60 seconds per game, most of the participants fully used the maximum time as the average playing time of all four rules was almost 60 seconds (Figure 3.7). A few participants quit a game very quickly, but they are a minority among the participants. In Session 2 where participants can use the time freely for 10 minutes, there is no significant difference for the mean of playing time among the four rules (Figure 3.8). In anecdotal observation, participants tended to try playing with all the rules equally rather than only playing with their favorite rules.

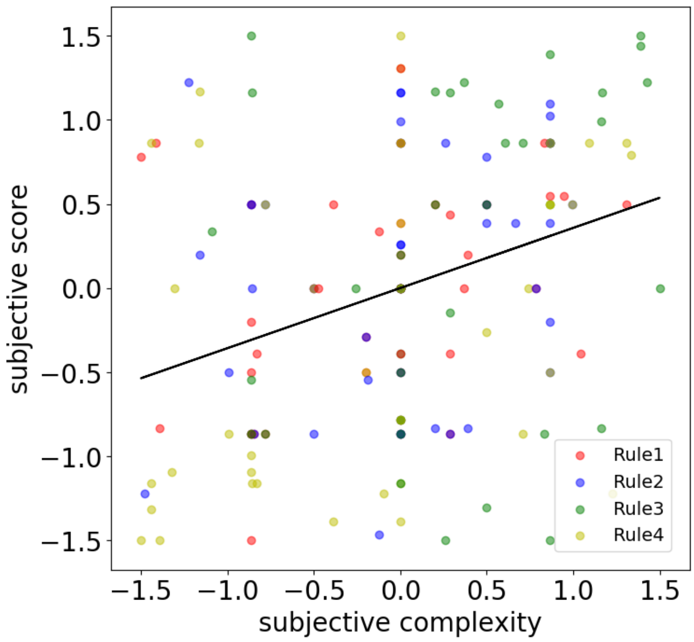

Figure 3.6: Subjective complexity vs. subjective score of intrinsic motivation. (slope=0.358, R^2=0.108, p<0.001.) Both variables are standardized by individuals. The data from participants who gave the same scores for all the rules were standardized as 0 (zero).

Frequency of touch interaction

Motivation activates behavior; in other words, behavior is a consequence of motivation. In the experiment, behavior is observed as interaction through touching to change the states of the cells, which is the only input in the game. Figure 3.7 shows the mean of touching frequency in each rule in Session 1. Rule 4 has the most frequent interaction in Session 1. In anecdotal observation, live cells easily die in Rule 4, so that participants tried to add more live, colored cells by touching cells more frequently than with the other rules. Once participants had made up patterns to entertain themselves, they stopped their interaction and watched the patterns. In this sense, the frequency of touching interaction seems not to be simply responding to participants' intrinsic motivation.

3.4 Behavioral measures for variety of expression

Given the dimension of each session, data from Session 1 is used for overall analysis. Data from Session 2 is used mostly for analyzing how participants responded to the questionnaire and evaluated the rules. In Session 2, as the game program allowed participants to change rules without clearing all the states, the observed variables are strongly dependent on initial states when the rule had changed rather than consistent behaviors in each rule among the participants. The design was to produce more variety for the patterns; However, it resulted in an episodic experience for each participant.

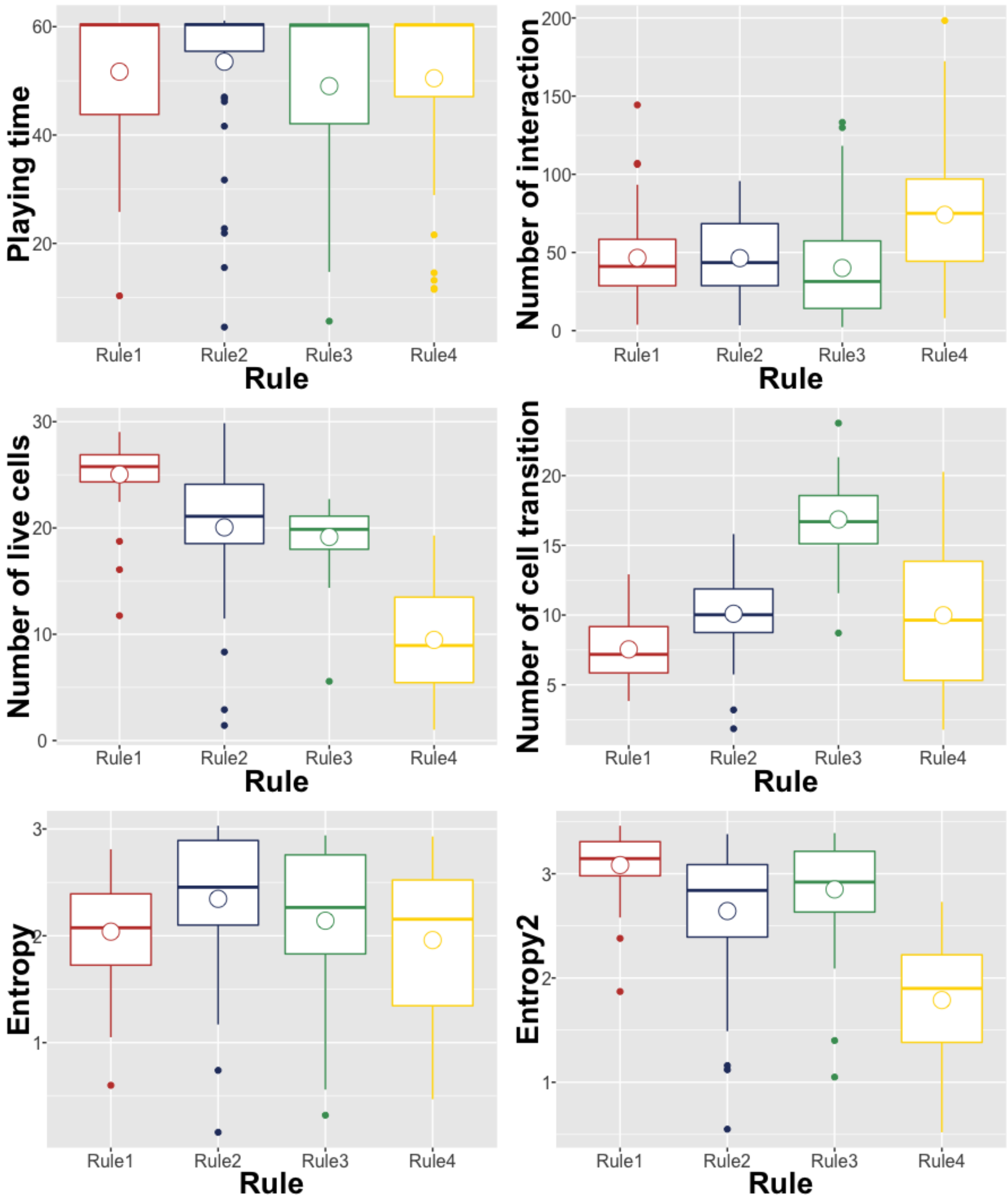

Figure 3.7: Mean of playing time; Number of interaction; Number of live cells; Number of cell transitions; Entropy; and Entropy of local patterns(Entropy2) in Session 1

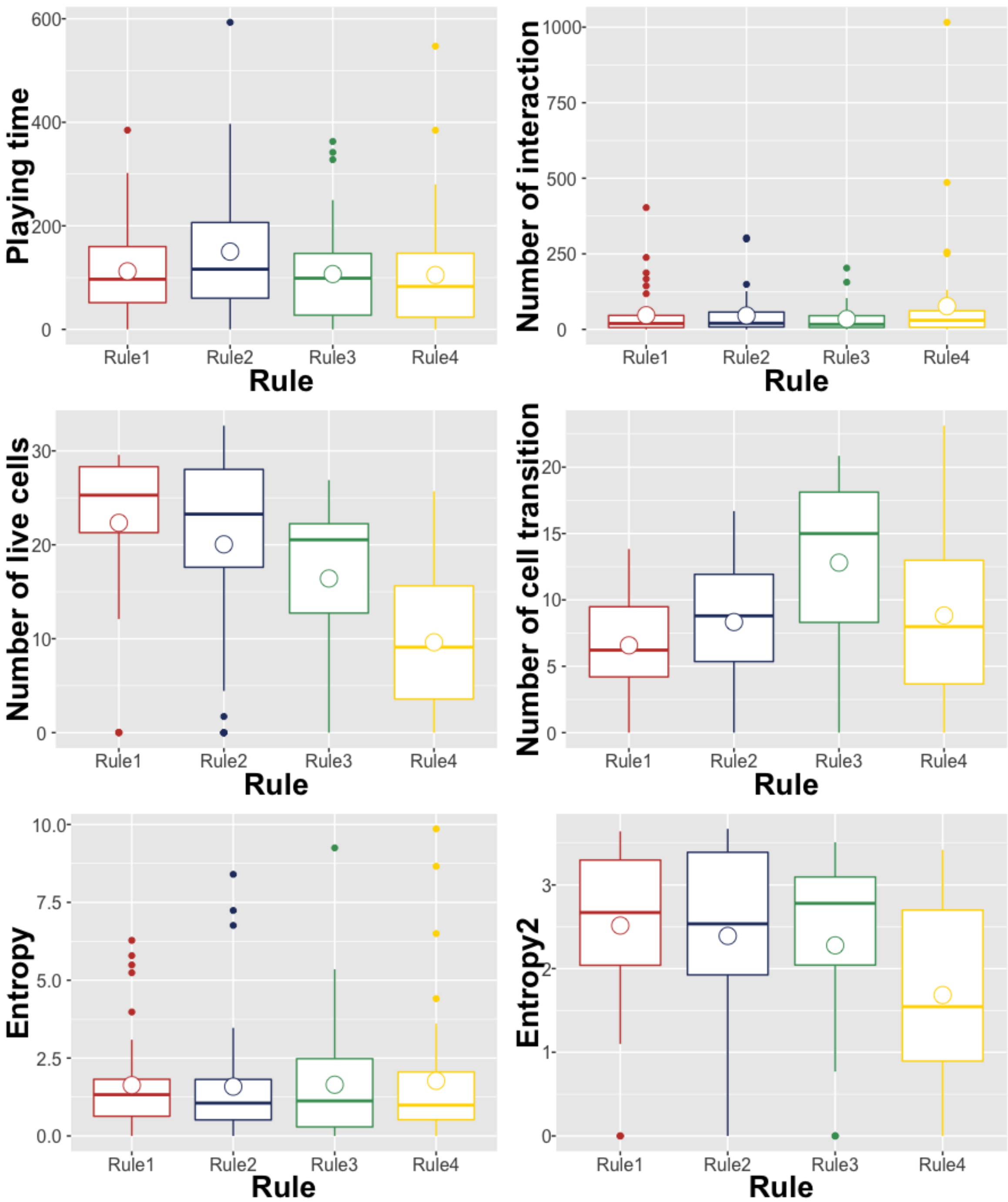

Figure 3.8: Mean of playing time; Number of interaction; Number of live cells; Number of cell transitions; Entropy; and Entropy of local patterns(Entropy2) in Session 2

Since experiences of GOL can be infinite, not resetting states when changing a rule provides distinct patterns to each participant, which complicated the analysis of dependent variables. For statistical analysis to compare with the hypothesis, subjective scores were only used as a measurement of intrinsic motivation.

Number of live cells

As the first index for measuring variables for variety of expression, the number of live cells (colored cells) was counted in each generation during the games. The left in Figure3.9 is an example from a participant which shows how the number changes for each rule, and the right side in the figures shows distributions of counted numbers for the four rules. The upper figure which illustrates data from Session 1 is a typical example over 42 participants for which the lower number is generally observed for Rule 4, and the higher number is observed in Rules 1 and 3. In Rule 2, the higher number is instantaneously observed, but the mean of the numbers is lower than for Rules 1 and 2. Interestingly, cyclic patterns are observed in both Rules 1 and 3, which might have induced participants to evaluate the variable over the chaotic patterns observed for Rule 2. The bottom figures illustrating data from Session 2 are sampled from different time durations of time among the rules by each participant. The total number of live cells generally tended to increase depending on the time duration of time; therefore, I focus on the data from Session 1 for this measure.

Number of cell state transitions

The number of live cells demonstrates how variable the patterns are straightforwardly, but it does not show how transient the patterns are, which is also an important index regarding variety. The number of cell state transitions represents how each cell changes its state as represented by a color. Figure3.10 is an example from a participant which shows how the number changes for each rule, as shown in the left of the figure and the distributions of the number for each rule in the right. This data is from the same participant in Figure 3.9. It shows that a relatively less stable number was observed for Rules 2 and 4 while a constant number was observed in Rule 1 and 3. In the first trial of Rule 3, which is the first game of green area before the first green line on the upper figure, cyclic patterns are observed, which gives the most variable behavior among the session as far as I observe the shape of waves.

Entropy of the number of live cells

The number of live cells and the number of transition cells indicate the primal behavior of the patterns. However, human recognition is assumed to be more organized, for example, the human ability of object recognition rather than just capturing and storing a bunch of pixels of perceived images. It was impossible for the participant to count the exact number of live cells. Instead, they observed the dynamic patterns shaped by live cells. To capture the feature of the dynamic patterns, the concept of information theory and distributional models are among the approaches we used to discuss the human perception for variety.

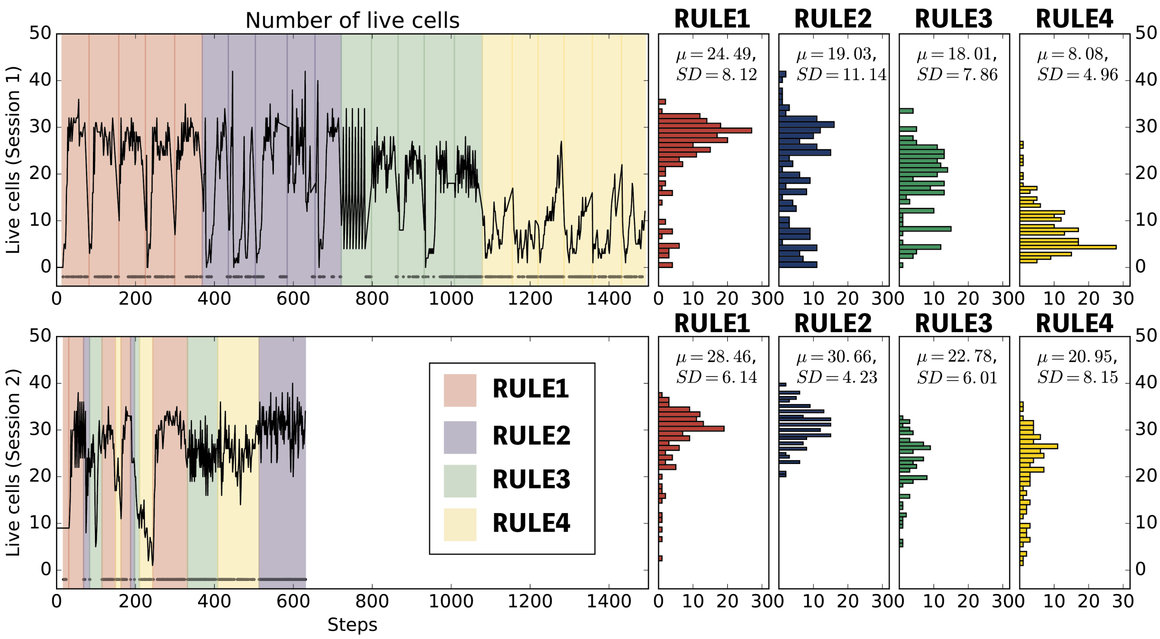

Figure 3.9: Timeline of the number of live cells during the sessions
The time series of the number of live cells in Session 1 (TOP, LEFT) and Session 2 (BOTTOM, LEFT). The background color represents which rule the participants played. The horizontal axes are the time steps when a generation changes by the rule of cellular automata rule. One generation steps forward for every one second. The small dots under the plots illustrate touching interactions by each participant. The histograms show the distributions of the number of live cells that appeared in all steps for Session 1 (TOP, 1st to 4th RIGHT) and Session 2 (BOTTOM, 1st to 4th RIGHT).

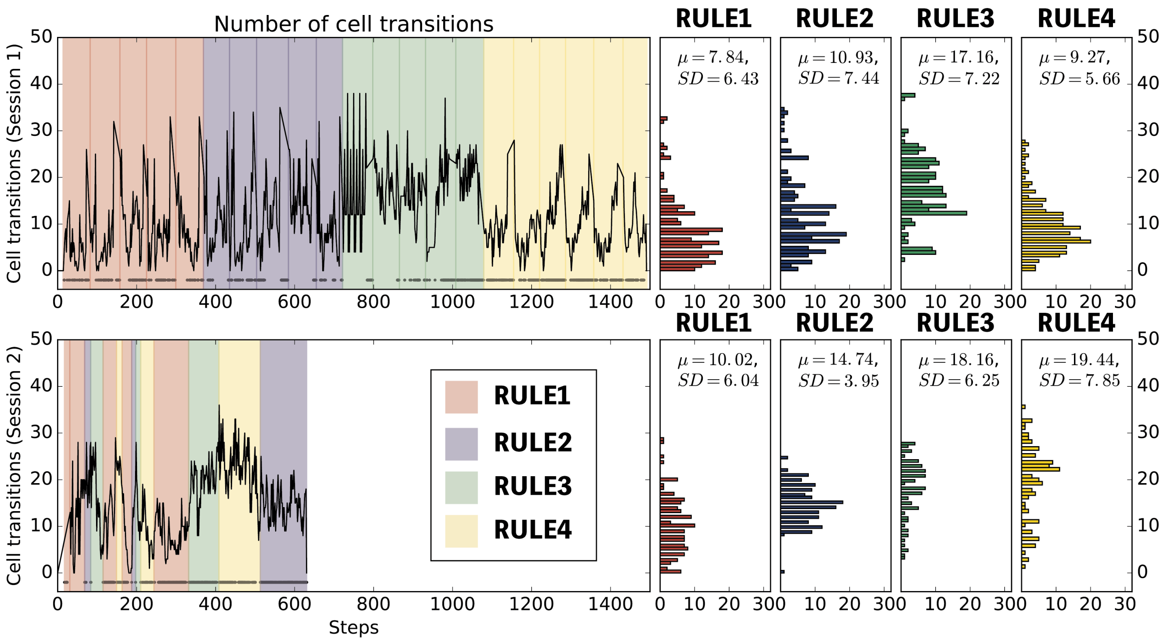

Figure 3.10: Timeline of the number of transition cells during the sessions
The time series of the number of cell transitions in Session 1 (TOP, LEFT) and Session 2 (BOTTOM, LEFT). The background color represents which rule the participants played. The horizontal axes are the time steps when a generation changes by the rule of cellular automata rule. One generation steps forward for every one second. The small dots under the plots illustrate touching interactions by each participant. The histograms show the distributions of the number of cell transitions that appeared in all steps for Session 1 (TOP, 1st to 4th RIGHT) and Session 2 (BOTTOM, 1st to 4th RIGHT).

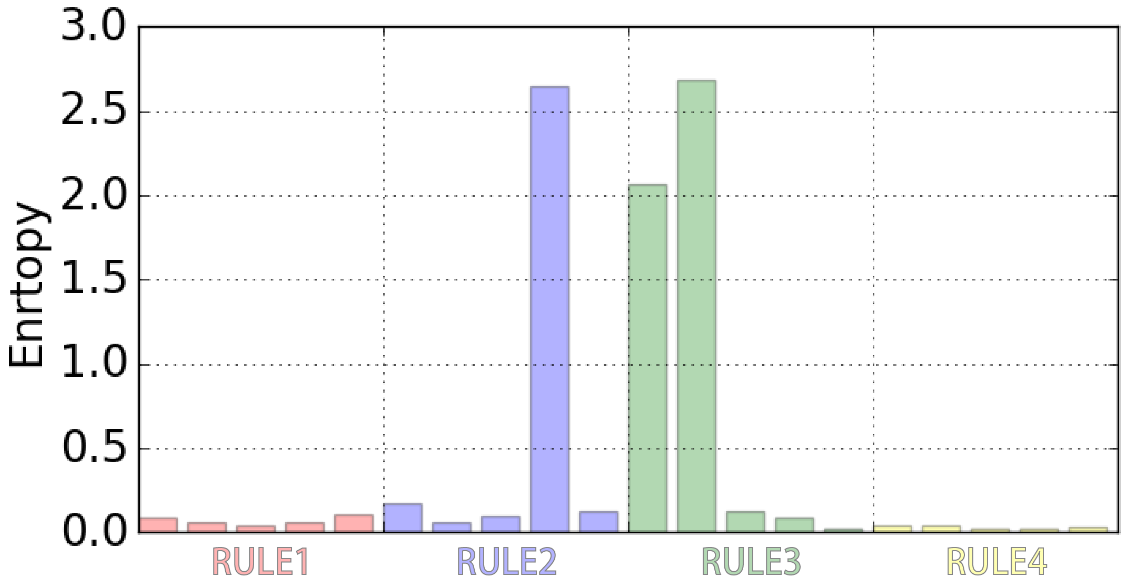

Figure 3.11: Entropy of each game in four rules
The bars illustrate the amount of entropy in each game in Session 1. All rules are played five times. In the fourth game of Rule 2 and the first and second game of Rule3, larger values of entropy are observed, which means the participant developed the patterns with the variety of the numbers of live cells.

First, the entropy of the distribution of the number of live cells in each generation was computed in each game using the equation , where $n(k)$ is the number of live cells in each generation and 0 $\quad 0 \leq n(k) \leq 8^2$. Figure 3.11 shows the example of entropy of one participant in Session 1. In the fourth game for Rule 2 and the first and second games for Rule3, larger entropy values were observed, which means the participant developed the patterns with variety for the numbers of live cells. The mean of all the games for each rule in each session is used as the representative value for the variety of the patterns. The top-left area in Figure 3.12 displays the mean of entropy for each rule in Session 1. Rule 2 and Rule 3 exhibited relatively higher entropy than Rule 1 and Rule 4. Overall, there was a significant difference in the mean entropy between the rules ($F(3,168)=3.011$, $p<0.05$). Figure 3.13 shows the mean of entropy for each rule in Session 2, which has a higher variance than Session 1. There was no significant difference in mean entropy between the rules ($F(3,164)=0.074$, $p=0.97$).

Entropy of local patterns

To collect comprehensive information on pattern formation for measurement purpose, the entropy of a two by two square grid pattern is computed. The entropy of the distribution of live cells in a two by two square grid has $2^4 = 16$ pattern components. The mean of entropy in all generations is computed for each game, and the mean of all games for the four rules in each session are computed as representative values of Entropy 2. The top-right area in Figure 3.12 shows the mean of Entropy 2 in each rule of Session 1, and the top-right area in Figure 3.13 shows that of Session 2.

Higher Entropy 2 is observed for Rule 1 and Rule 3 than for Rule 2 and Rule 4, which corresponds to our initial design of parameters as shown in Figure 2.1 and Table 2.1.

For more information on the entire pattern represented by the eight by eight grid, the entropy of the three by three grid pattern and that of the four by four grid pattern were also computed. Entropy of the three by three has $2^9 = 512$ components and entropy of the four by four grid pattern has $2^(16) = 65,536$ components. Both results show the same tendency as the entropy of the two by two grid pattern in terms of the comparison of mean between the four rules for all participants (Figure3.12 and Figure 3.13). Therefore, the entropy of the two by two grid pattern is only used for further analysis to make the calculation simpler and faster.

A subjective scores of a variety of expression

The details of the result were described in Section 3.2.

Correlation with subjective scores of enjoyment

Figure 3.14 and Figure 3.15 show the correlation coefficient between variables. All variables are standardized. As shown in the top lines of the Figures, no variable for the variety of expression (Number of Live cells, Number of cell transitions, Entropy, and Entropy2) has a strong correlation as a single variable with the subjective scores for both sessions. Although the correlation is not strong, all variables for a variety of expression has a positive correlation with the subjective score. I will investigate the relationship by multiple regression analysis in Section 3.6.

3.5 Behavioral measures for simplicity/complexity of rules

The measurement for a variety of expressions is collected from observed data caused by the participants' behavior. The measurement for simplicity/complexity of rules is manipulated by the parameter of cellular automata and measured by the concept of empowerment and by subjective questionnaire.

Empowerment

To clarify, a major reason why empowerment is included to measure of simplicity/complexity of rules is that empowerment is defined as the amount of control or influence the participant has over the environment (grid) by the equation B.5 in Appendix B. In this sense, the higher empowerment corresponds to the higher capacity for control, which makes the rule simpler.

According to the description of computation in Appendix B, empowerment of each rule is computed as in Figure 3.16. Rule 4 had the highest level of empowerment, while the other three rules had much lower levels of empowerment. This was accounted by how some of the participants marked the highest scores for Rule 4, while the observed

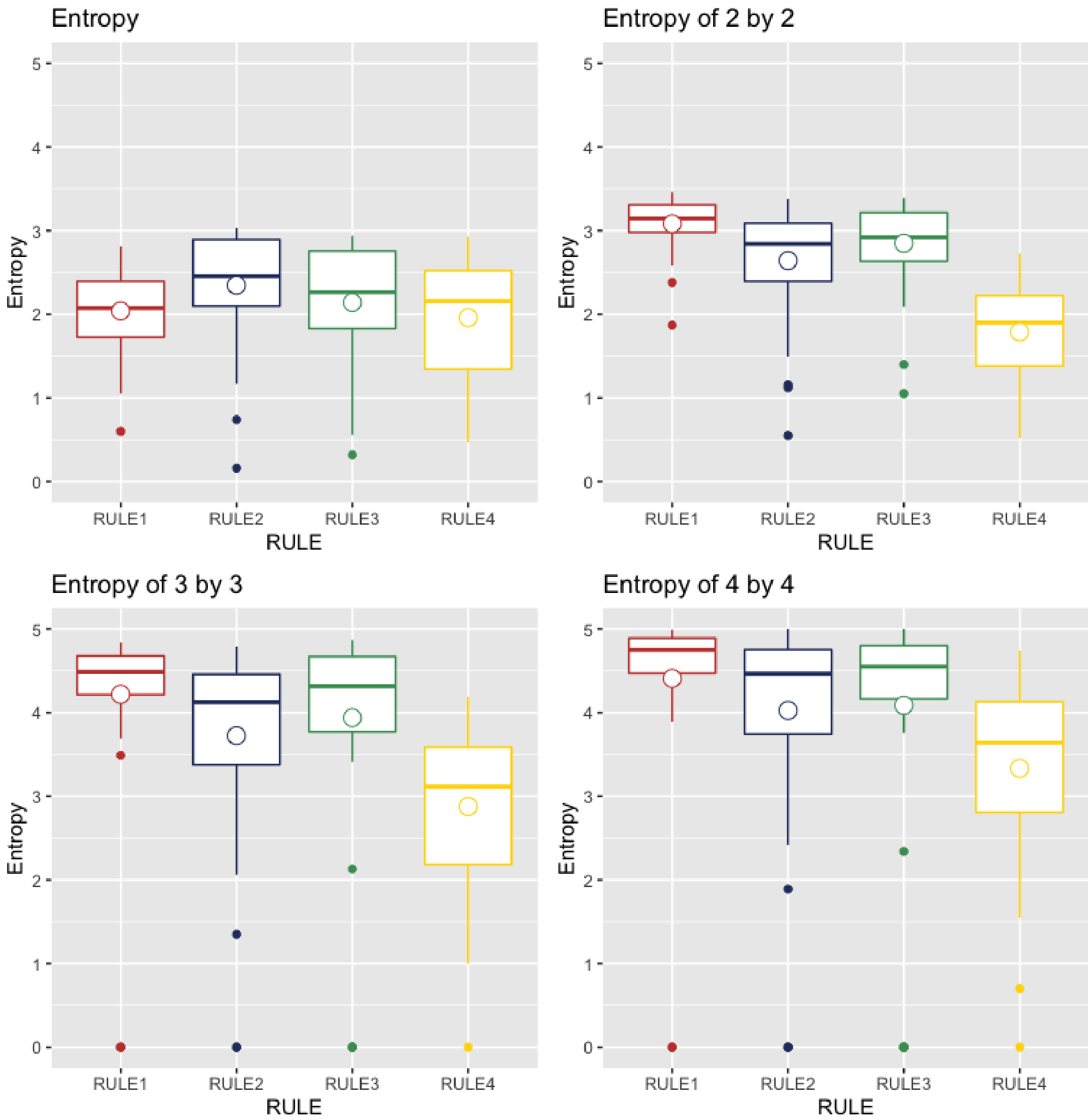

Figure 3.12: Mean of entropy with different resolutions in Session 1
Mean in Rule1, Rule2, Rule3, Rule4
Entropy: 2.05±0.47(s.d.), 2.36±0.66(s.d.), 2.15±0.70(s.d.), 1.97±0.71(s.d.)
Entropy of 2 by 2: 3.08±0.33(s.d.), 2.58±0.71(s.d.), 2.82±0.49(s.d.), 1.74±0.61(s.d.)
Entropy 3 by 3: 4.23±0.99(s.d.), 3.73±1.13(s.d.), 3.95±1.21(s.d.), 2.89±0.96(s.d.)
Entropy 4 by 4: 4.55±1.07(s.d.), 4.08±1.19(s.d.), 4.25±1.30(s.d.), 3.33±1.09(s.d.)

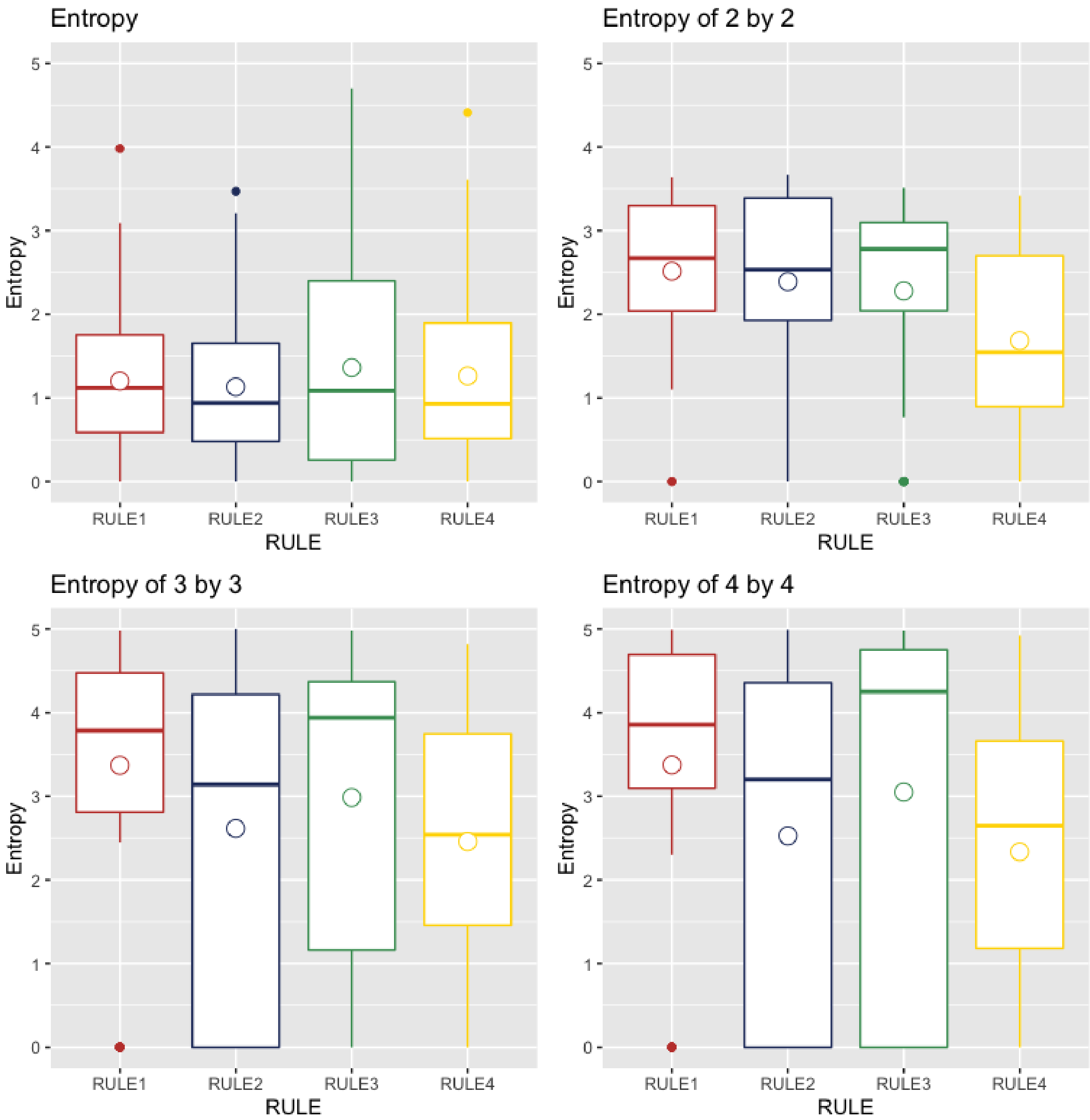

Figure 3.13: Mean of entropy with different resolutions in Session 2
Mean in Rule1, Rule2, Rule3, Rule4
Entropy: 1.63±1.58(s.d.), 1.58±1.89(s.d.), 1.64±1.84(s.d.), 1.77±2.17(s.d.)
Entropy of 2 by 2: 2.51±0.95(s.d.), 2.39±1.12(s.d.), 2.28±1.20(s.d.), 1.68±1.11(s.d.)
Entropy 3 by 3: 3.45±1.50(s.d.), 2.61±1.91(s.d.), 3.03±1.90(s.d.), 2.46±1.61(s.d.)
Entropy 4 by 4: 3.79±1.61(s.d.), 2.90±2.08(s.d.), 3.29±2.07(s.d.), 2.66±1.76(s.d.)

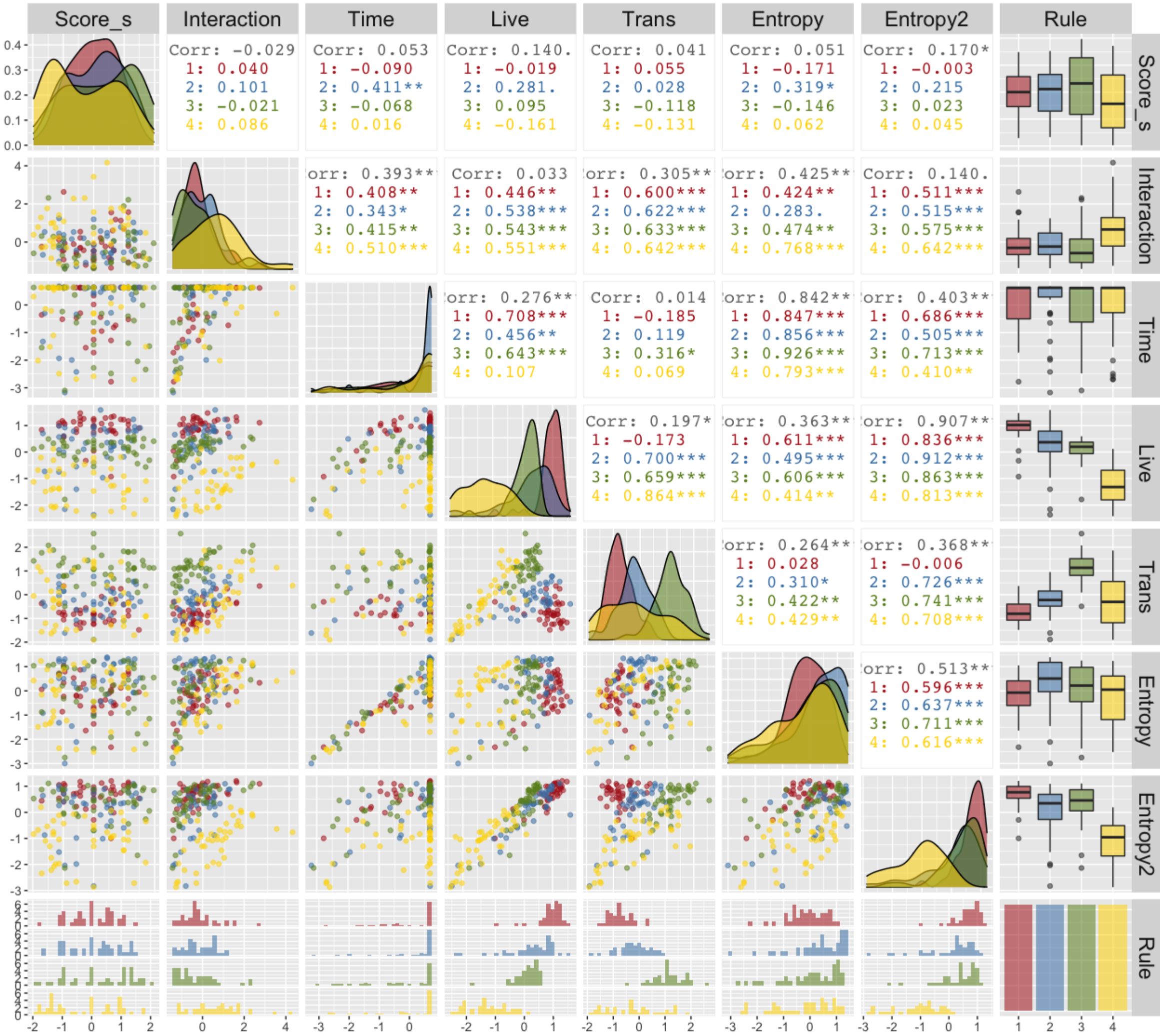

Figure 3.14: Relationships between subjective and behavioral measures in Session 1 The plots show the correlation between all variables of intrinsic motivation and variety of expression in Session1 with four rules (Red: Rule1, Blue: Rule2, Green: Rule3, Yellow: Rule4). There is no strong correlation between the variables except between the time the participant spent with each rule since entropy tends to increase over time. In the figures regarding Time have lines on the right edge, which tells that many participants spent the maximum time they were given for 60 seconds.

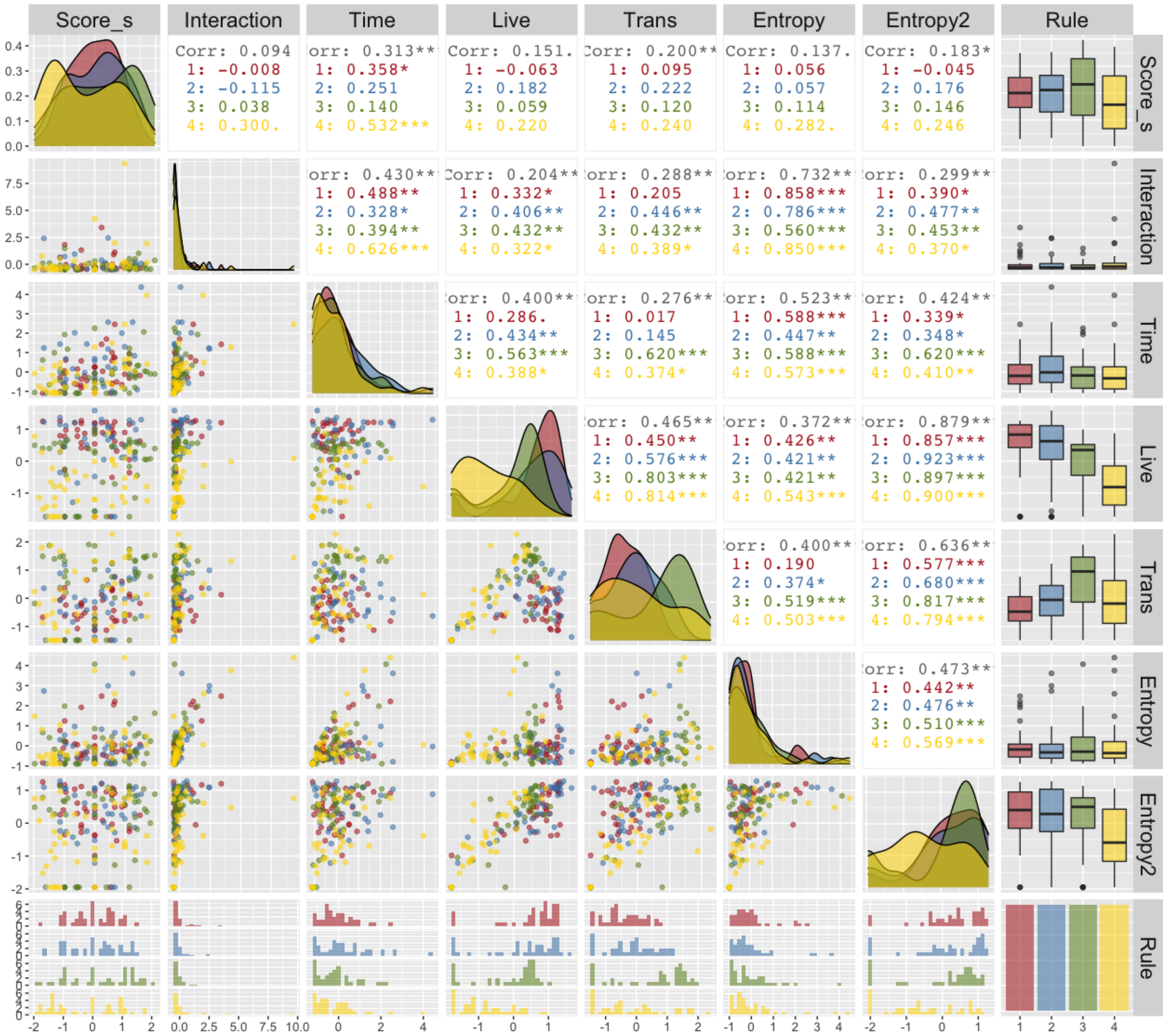

Figure 3.15: Relationships between subjective and behavioral measures in Session 2 The plots show the correlation between all variables of intrinsic motivation and variety of expression in Session 2 with four rules (Red: Rule1, Blue: Rule2, Green: Rule3, Yellow: Rule4). There is no strong correlation between all variables. However, in Session 2, there are no lines in the figures regarding Time. Participants spent time as they preferred.

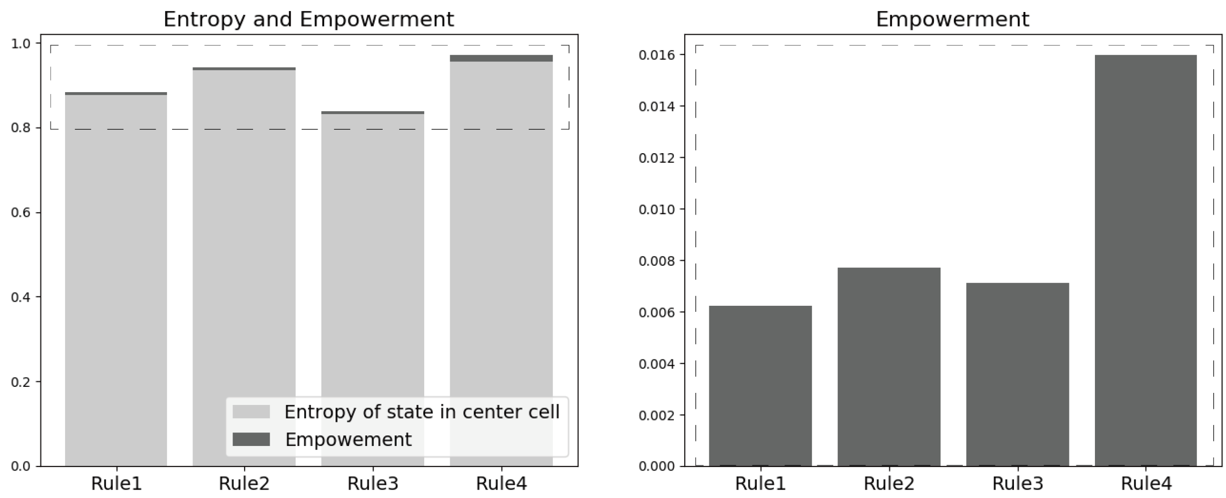

Figure 3.16: Empowerment in four rules
Empowerment is computed as the amount of control or influence that the agent can take action. Rule 4 has the highest empowerment, while the amount of empowerment is relatively smaller than that of entropy of each rule.

behavior of patterns produced by Rule 4 had less variety than other rules. Although the parameters for Rule 4 are supposed to provide complex rules, the higher level of empowerment implies that Rule 4 is the simpler rule among the four rules.

The impact that participants influence on "the universal world of cellular automata" is still small, as seen by the tiny part of the dark grey area, which illustrates the degree of empowerment, compared with the bright grey area, which is the entropy of all possible behavior of automata, in Figure 3.16.

Subjective score of simplicity/complexity of rules

The details of the result were described in Section 3.2.

3.6 Relationships between subjective and behavioral measures

For multiple linear regression, subjective scores were only used for the analysis as a single variable of intrinsic motivation. Interaction frequency and playing time were not used for multiple linear regression.

No single variable for a variety of expressions has a strong correlation with the subjective score of enjoyment, which is the main measurement for intrinsic motivation. Multiple linear regression was carried out to investigate whether multiple variables for a variety of expressions could produce a model to predict the subjective score, using lm function in R. The result of the regression is not a significantly good model ($R^2_{Adjusted}$= 0.01 ,p=0.219). There is also no variable that contributes significantly to the regression model as the p-values of each variable indicates in Table 3.1.

Figure 3.17 shows coefficient estimates of the regression. The contribution of all variables is low, but Entropy2 has the largest coefficient estimate among the variables. The VIF of predictor variables are 6.89(Live), 1.32(Trans), 1.47(Entropy), 8.70(Entropy2). Both Live and Entropy2 have larger VIF, which corresponds to the correlation between these variables in Figure 3.14 and Figure 3.15. Multiple regression excluding Live or Entropy2 was conducted; however, none of the regression results produced a better model.

In searching for the best model using these variables, using the only Entropy2 is the best fit model from all the combination of variables according to the minimum AIC ($R^2_{Adjusted} = 0.0232$, $p < 0.05$). Figure 3.18 shows plots and regression results depicting increasing linear trends, with participants marking higher scores when they observed more variety of expression represented by entropy 2, although the increasing trends were very small.

3.7 Canonical Correlation Analysis

As an index of intrinsic motivation, only the subjective score was used for statistical analysis and multiple linear regression analysis. In this section, other dependent variables such as the frequency of interaction and playing time were also included for the analysis using Canonical Correlation Analysis (CCA). CCA is a multivariate extension of correlation analysis through searching for components that have a maximum correlation between two sets of variables. To explore linkages between measures of intrinsic motivation and variables for a variety of expressions, CCA was performed using the scikit-learn package in Python.

In this analysis, I looked into the first two-component pairs according to the correlation level as below. The first singular vector (canonical correlation coefficient Session 1:0.87, Session 2: 0.77) resulted in a strong correlation, although there is a bias of variable time caused by the limitation of playing time (60 seconds) in Session 1. Most participants had used the maximum time that they were given in Session 1. The second singular vector (canonical correlation coefficient Session 1:0.37, Session 2: 0.29) did not indicate a strong correlation between the variables.

I also computed the cross-loadings in the set of variables (Figure 3.19). The cross-loadings, also called structure coefficients, measured the linear correlations between two original observed independent variables and the component score of canonical dependent variates and vice versa. There are no clear guidelines on how to interpret cross-loadings. However, a higher cross-loading generally can be interpreted as higher relative contribution of each variable to each canonical function since the larger the coefficient, the more important the original variable deriving the canonical variate. The result of CCA in Session 1 was strongly impacted by a bias of playing time (Time), which increased the amount of Entropy and Entropy2, especially in the first singular vector (blue bars in Figure 3.19). According to the second vector (green bars in Figure 3.19), the frequency of interaction (Interaction) is related to the number of cell state transitions (Trans). Interactions that make more changes to the state of cells can make participants more intrinsically motivated to reinforce an interaction. The result of CCA for Session 2 shows that Entropy seems to be a dominant factor in fostering

Table 3.1: Result of multiple linear regression

	coefficient	std. error	t value	p value
Live	-1.515e-01	2.021e-01	-0.750	0.454
Trans	-4.269e-02	8.827e-02	-0.484	0.629
Entropy	-6.615e-02	9.343e-02	-0.708	0.480
Entropy2	3.572e-01	2.270e-01	1.574	0.118
(Intercept)	-2.219e-16	7.674e-02	0.000	1.000

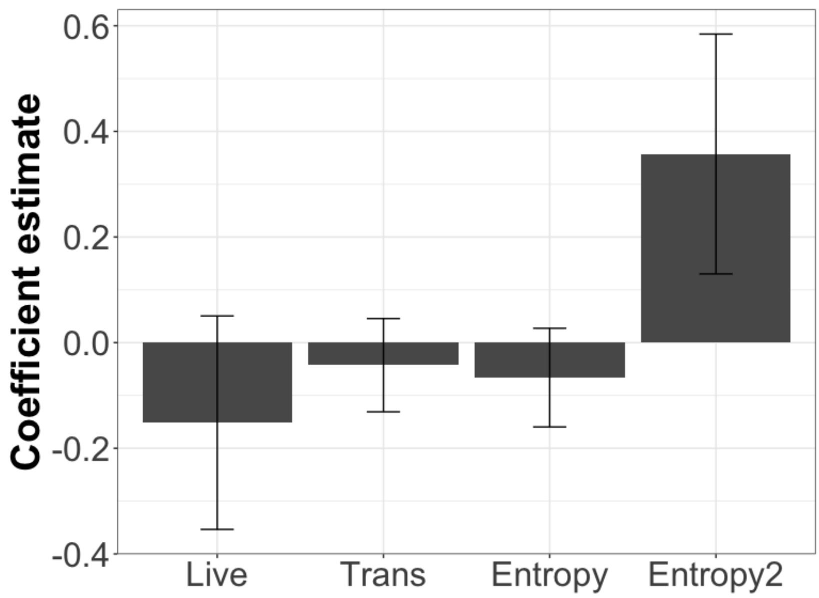

Figure 3.17: Coefficients of regression result
The bars represent the linear regression coefficient estimate with standard errors. The coefficients show Entropy2, which stands for the entropy of two by two grid has the largest positive coefficient. This result is consistent with the best-fit regression model. The more entropy 2 are observed, the more intrinsically motivated as hypothesized.

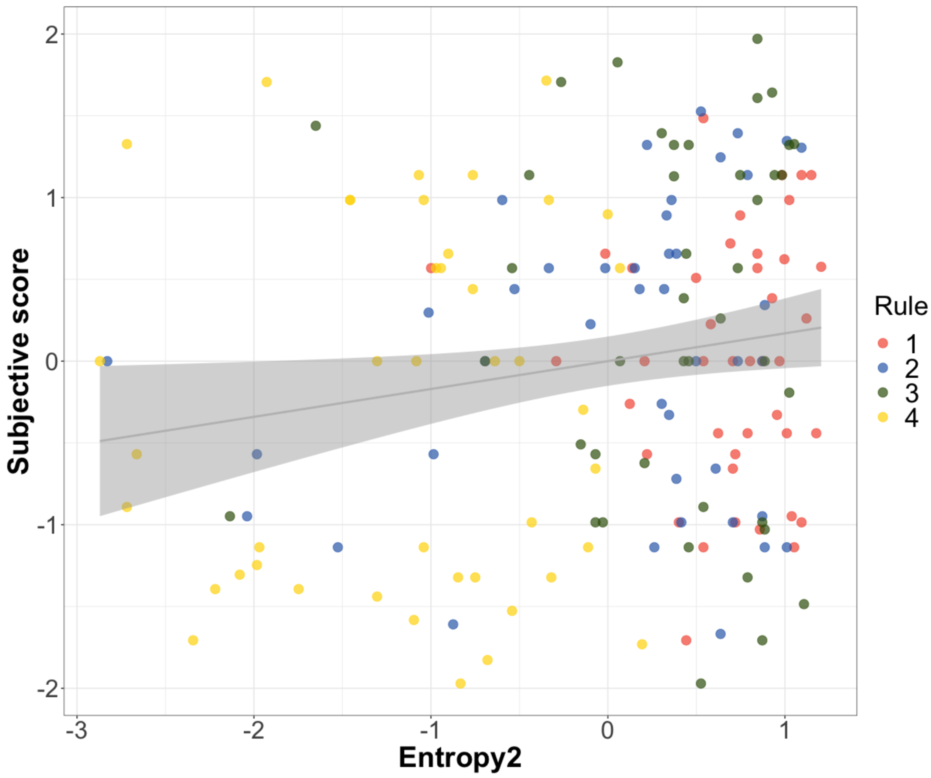

Figure 3.18: Plot of subjective scores and entropy of two by two square grid pattern(Entropy2)

The line shows the result of the linear regression model with confidence interval in Session1 ($R^2 = 0.01$, $p < 0.05$). Both variables are standardized before regression. The regression slope is almost zero but positive, as shown.

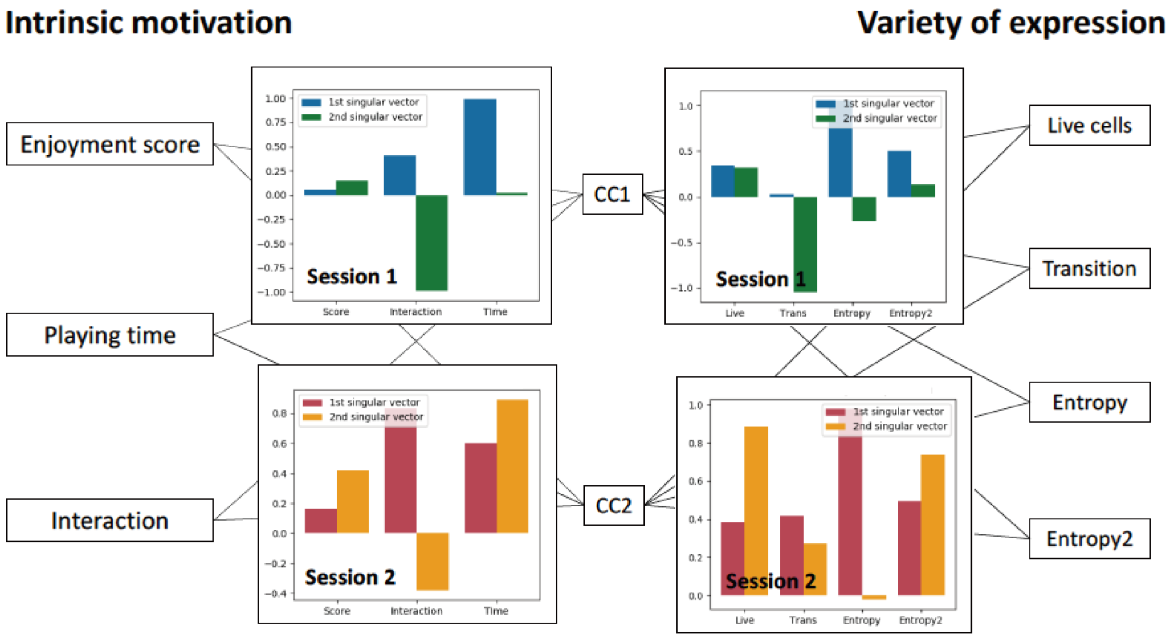

Figure 3.19: Cross-loadings of variables by CCA in Session1 and Session 2
The upper figures show the cross-loadings of CCA from session 1, and the lower ones show session 2. The cross-loadings figured by blue bars and red bars from the first singular vector are all positive, which indicates the positive correlation between the measurements. In the second singular vector, the interaction has negative loadings, which implies that participants enjoyed both cases where frequent interaction produced more variety of patterns and cellular automaton works enough to show some variety automatically without frequent interaction. The first singular vectors are 0.87 in Session 1 and 0.77 in Session 2. The second singular vectors are 0.37 in Session 1 and 0.29 in Session 2.

intrinsic motivation, which is related to the frequency of interaction (red bars in Figure 3.19). This first vector most supports the overall correlation between independent and dependent variables. In the second vector for Session 2 (orange bars in Figure 3.19), the number of live cells and the entropy of two by two grid pattern that participants observed presumably influenced the time participants spent for each rule. It is interesting that the second vector interaction has negative loadings, which implies that participants enjoyed both cases where frequent interaction produced more variety of patterns and cellular automaton works enough to show some variety automatically without frequent interaction.

3.8 Discussion

The results of the experiments suggest that participants are more intrinsically motivated when they observe the higher variety of expressions and use simpler rules. This is consistent with the hypothesis that more variety by simpler rules makes people more intrinsically motivated.

Participants subjectively evaluate the more various and simpler rule as the most enjoyable rule. Two-way ANOVA strongly supports our hypothesis by analyzing the effect of two factors on the subjective score of intrinsic motivation. Interestingly, participants did not correctly evaluate the degree of two factors influencing intrinsic motivation as were implemented, while their evaluation for intrinsic motivation did meet my expectation. A significant feature of our experimental design was the ability to measure abstract factors presumably important for creativity. To our knowledge, the hypothesis has not been tested while controlling for the variables as measurements of these essential factors, especially in creative activity. Therefore, this study advances the design of such experiments. Additionally, the results provide evidence that interaction between the two fundamental factors can be significant for creativity. This suggests that humans do not regard features of intrinsic reward independently but consider the variety of different features dependently to perceive and experience a variety of information by interacting with the environment. That might be the reason why the majority of participants preferred simpler rules for greater control in order to induce the highest variety by controlling the rules.

Through the analyses, however, I acknowledged that individuals were unique in their respective playing. Our results did not formally model the intrinsic motivation, but the factors remain powerful candidates for modeling. If I can model the individual intrinsic motivation can be modeled by measurable input, a better environment can be designed for learning and play using intrinsic motivation.

In summary, my findings show that more variety of expression intrinsically motivates human participants. Besides, participants were more motivated when they can manipulate a simpler environmental rule, which suggests that humans try to make more variety in the given environment through initiating interactions. This could be a very important factor for understanding creativity. There are, however, several limitations in the present study. First, among multifaceted aspects of intrinsic motivation, the major findings in this study was based on the subjective measure of enjoyment collected by the questionnaire. The original plan was to utilize multiple behavioral measures of intrinsic motivation for the analyses, but behavioral measurements did not necessarily correlate with the score of enjoyment. Participants did not necessarily spend more time with the enjoyable rules. The frequency of touching interaction largly depended on the participants traits. Some more questions from IMI may be better asked in the future experiments even if focusing on a single subcale of enjoyment.

Second, the behavioral measures for the variety of expression captured a limited aspect of variety. It is desired to develop additional measures related to how participants actually appreciate and interpret the patterns.

Despite these limitations, this novel framework of the experiment using the games can contribute to the research on creativity and intrinsic motivation.

Chapter 4

Subgroup analysis: Preferences for passive viewing and active control

I hypothesized that more variety of expressions by a simpler rule motivates humans intrinsically. The significant differences in the degree of intrinsic motivation for the four different levels of a variety of expressions and simplicity/complexity of rules strongly support this hypothesis; However, the experiment revealed considerable individual differences in the participants' behaviors and preference for the task parameters. The results suggested that there were subgroups among the participants with marked preference, especially for Rule 4. In this chapter, I examine whether and what kind of subgroups the participants exist and perform subgroup analyses accordingly.

4.1 Existence of subgroups

Figure 4.1 shows that the individual slopes of the subjective score for Entropy 2. There are groups of participants with positive or negative slopes. The subjective scores for Rule 4 (upper left corner in Figures 3.14 and 3.15) also suggest bimodality. Because Rule4 was designed to be less motivating with lower variety and more complex (Figure 2.1), it is intriguing that some participants gave higher scores for Rule4. Both the distributions of the slopes of the subjective scores for Entropy 2 (Figure 4.2 LEFT). The subjective scores for Rule 4 (RIGHT) suggest bimodal distributions, which suggests that subgroups of participants favored different components of our intrinsic motivation models.

Figure 4.3 shows the distribution of the slope for Entropy 2 and the subjective score for Rule 4 of each participant. This also suggests there exist two subgroups of participants; one favors the variety of local patterns and does not enjoy Rule 4, and the other favors the variety of local patterns and enjoyed Rule 4.

To statistically test whether the distributions are bimodal, I applied the Silverman test for multimodality. Figure 4.4 reports the statistical significance levels for the null hypothesis tests that the distribution has at most $i(\leqq 4)$ modes against the alternative of more than i modes. The p-value for the slope for Entropy 2 is 0.17 for the null hypothesis that the distribution has one mode. However, the p-value for the null hypothesis that it has two modes is 0.76, suggesting that the null hypothesis of two

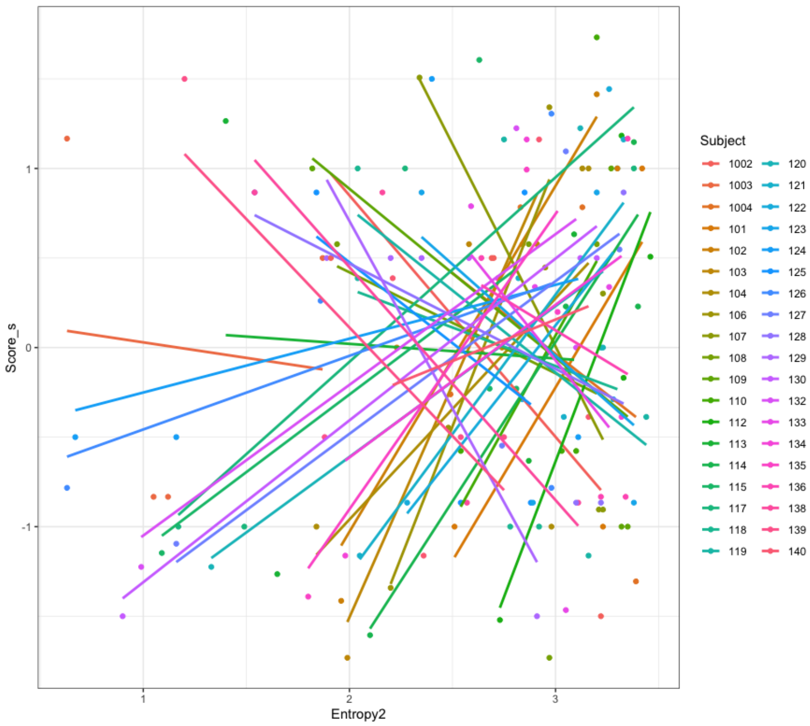

Figure 4.1: Plot of entropy of two by two grid square(Entropy2) vs. intrinsic motivation with individual slopes

Table 4.1: The Silverman test for multimodality of the two distributions

Distribution	p-values	
	H_0: One mode H_1: More than one mode	H_0: Two modes H_1: More than two modes
Gradient	0.17 (H_0 not rejected)	0.76 (H_0 not rejected)
Preference for Rule4	0.11 (H_0 not rejected)	0.79 (H_0 not rejected)

modes is harder to reject than that of one mode. The same tendency can be observed for the distribution of the preference for Rule 4. The p-value for the null hypothesis of one mode is 0.11, and that of two modes is 0.79 (Table 4.1). Figure 4.4 also shows lower p-values for the hypothesis with three and four modes. Even though the test results were not decisive, considering the sample size of the data, I judge that it is sensible to perform group-wise analysis based on the presumption that participants can be classified into two subgroups.

4.2 Intrinsic motivation of subgroups

As the next step toward understanding the mechanism of intrinsic motivation, I performed linear regression analysis, assuming participants were grouped into two subgroups. The subtypes used to group the participants were the gradients of the regres-

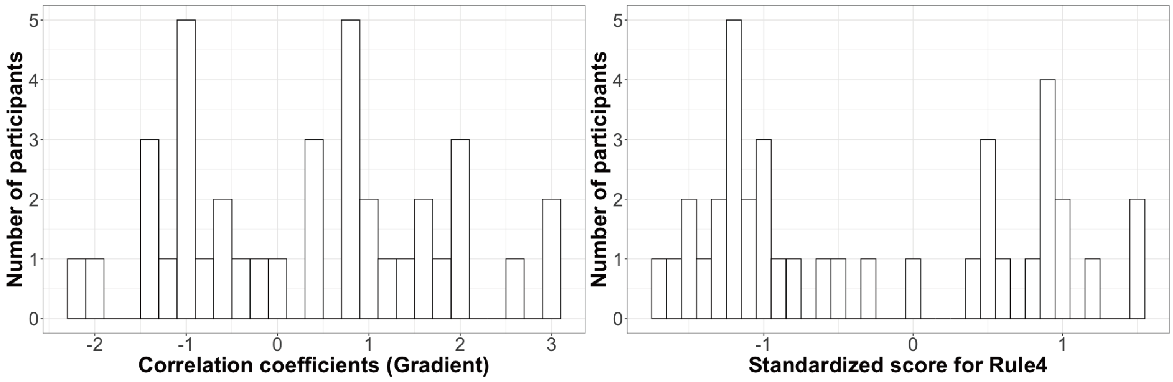

Figure 4.2: Distribution of participants in two measurement
The distributions of line gradients of lines between Entropy 2 and subjective score (LEFT) and preference for Rule 4 represented by subjective score (RIGHT).

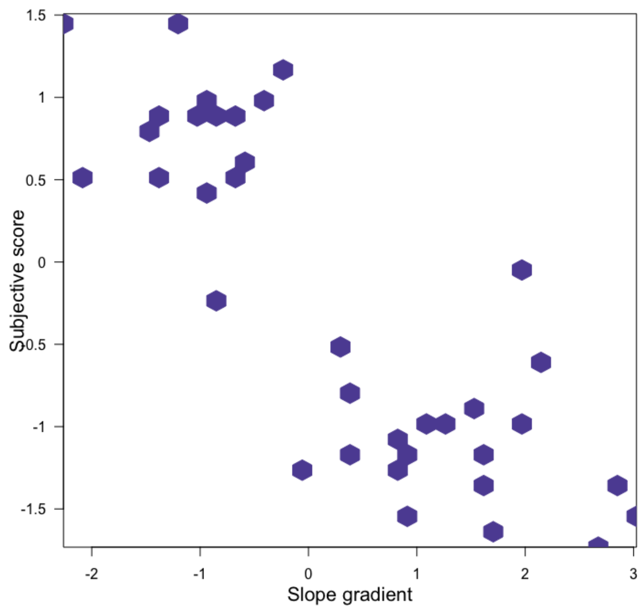

Figure 4.3: Scatter plot of the slopes of the subjective score for Entropy 2 and subjective scores for Rule 4.

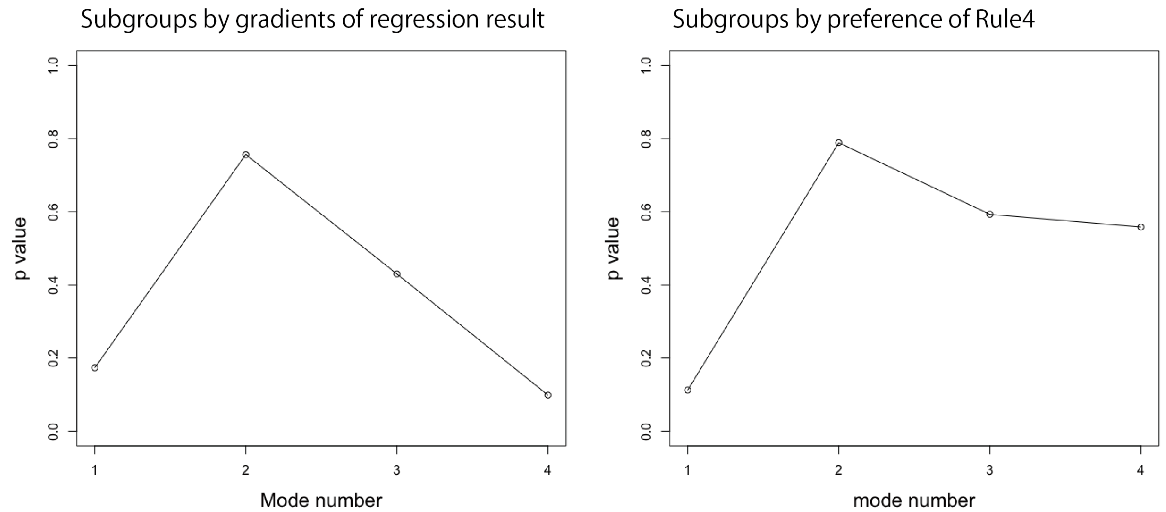

Figure 4.4: P-values by a number of modes in Silverman test.
Plots of the p-values of a sequence of the Silverman test in the distribution of the number of participants by subjective scores for Rule 4.This visualization is an easy way to find the smallest number of modes where the null hypothesis of the Silverman test can be rejected. The p-value at each mode is 1 mode: 0.12, 2 modes:0.79, 3 modes:0.59, 4 modes:0.56.

sion result between the subjective scores and Entropy2, as shown in Figure 3.18, which provides the best fit model. Four participants who gave the same scores to all the rules are excluded in the figure. Group 1 had positive slopes of the subjective score for Entropy2, and Group 2 had negative slopes. Figure 4.5 show the regression results of the group of participants labeled as Group 1, which preferred higher entropy (21 participants, $R^2 = 0.336$, $p < 0.001$) and those of the group of participants labeled as Group 2, which preferred lower entropy (17 participants, $R^2 = 0.119$, $p < 0.01$).

The multiple linear regression was performed by groups. This classification of participants by their preferences for the entropy of local patterns (Entropy2) provides a better fit analysis than in the single regression with subjective score and Entropy2 and multiple regression. Figure 4.6 plots coefficient estimates of multiple regression. In Group1, Live, Trans, and Entropy2 have positive coefficients while Entropy has negative coefficient ($R^2 = 0.386$, $p < 0.001$). In contrast with Group 1, Live, Trans, and Entropy2 for in Group 2 have negative coefficients while Entropy has a positive coefficient ($R^2 = 0.199$, $p < 0.01$).

Based on AIC, the best multiple regression model for Group 1 is the model using Trans, Entropy, and Entropy2 as a predictor ($R^2 = 0.382$, $p < 0.001$). The best multiple regression model for Group 2 uses the same predictive variables as Group 1. ($R^2 = 0.196$, $p < 0.01$). Interestingly, as shown in Table 4.3 and Figure 4.7, Trans and Entropy2 for Group 1 have positive coefficients while Entropy has a negative coefficient. Group 2 is the opposite in that only Entropy has a positive coefficient. The comparison between two groups in terms of variables affecting intrinsic motivation might provide insight regarding individual differences in intrinsic motivation models in further studies.

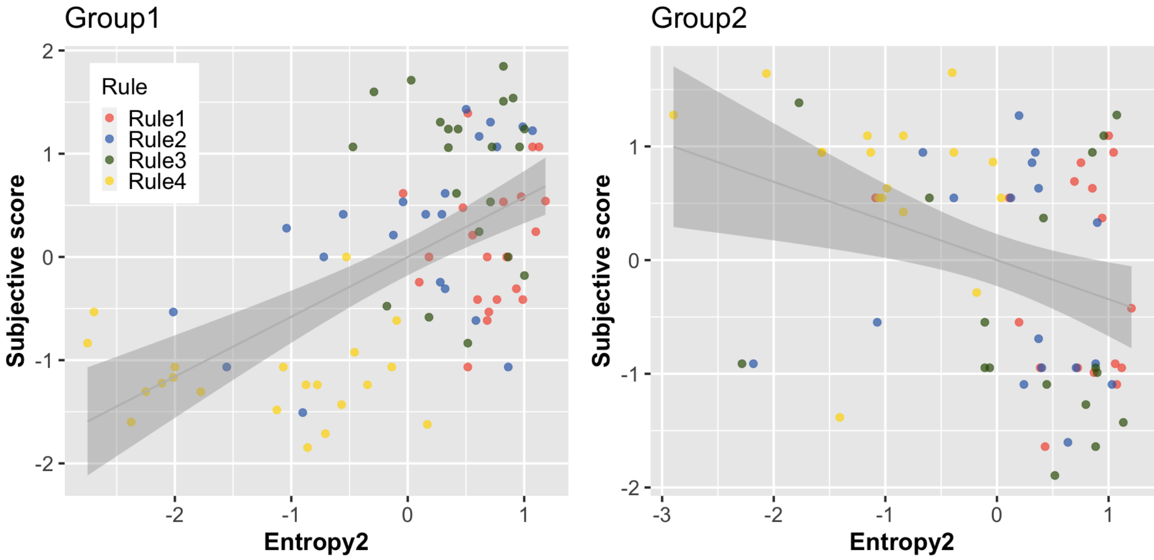

Figure 4.5: Linear regression results by subgroups
Left: Plots and result of regression analysis of Group 1 ($R^2 = 0.336$, $p < 0.0001$) in which participants preferred higher entropy two by two grid square, Right: Plots and result of regression analysis of Group 2 ($R^2 = 0.119$, $p < 0.01$) in which participants preferred lower entropy two by two grid square. The color shows the rule number of the data. (Red: Rule 1, Blue: Rule2, Green: Rule 3, Yellow: Rule4)

In addition to the regression analyses, the subjective scores are compared between the two groups. The mean of subjective scores for Group 1 is significantly different from that for Group 2 in Rule 3 ($p < 0.001$) and Rule 4 ($p < 0.001$) (Figure 4.8. This difference corresponds to how the rules were designed. Parameters of Rule 3 were designed to have a higher variety of expression, represented by Entropy2 as one of the measurements. Parameters for Rule 4 were designed to have a lower variety of expressions. In fact, as seen in the yellow plots on the left side of Figure 4.5, participants in Group 2 assigned higher scores to Rule 4 even as they were with observed lower entropy of two by two grid square. This implies that participants in Group2 prioritized another factor over the variety of expression. This other factor might be empowerment, as described in Section 3.5.

4.3 Discussion

The results of the subgroup analysis reported in this chapter have important implications to understanding differences in the intrinsic motivation models of the participants. Classification of the participants by their preference of the entropy of local patterns did not only provide better fits in regression analysis but also revealed other factors affecting the subjective scores.

The first group had a positive correlation between the variety of expression measured by entropy of local patterns for their intrinsic motivation, while the second group

	Group1				Group2			
	coefficient	std. error	t value	p-value	coefficient	std. error	t value	p-value
Live	1.774e-01	2.439e-01	0.727	0.4693	-1.292e-01	2.722e-01	-0.474	0.6368
Trans	1.958-01	1.079e-01	1.814	0.0735	-2.673e-01	1.246e-01	-2.146	0.0358
Entropy	-1.889e-01	1.070e-01	-1.766	0.0813	1.913e-01	1.399e-01	1.368	0.1763
Entropy2	4.386e-01	2.743e-01	1.599	0.1139	-2.346e-01	3.064e-01	-0.765	0.4468

Table 4.2: Result of multiple linear regression by group with all variables

	Group1				Group2			
	coefficient	std. error	t value	p-value	coefficient	std. error	t value	p-value
Trans	1.610e-01	9.650e-02	1.669	0.0991	-2.548e-01	1.210e-01	-2.106	0.03917
Entropy	-2.090e-01	1.030e-01	-2.028	0.0459	2.109e-01	1.329e-01	1.587	0.11739
Entropy2	6.227e-01	1.054e-01	5.906	8.13e-08	-3.648e-01	1.356e-01	-2.690	0.00911

Table 4.3: Result of multiple linear regression by group of the best fit model

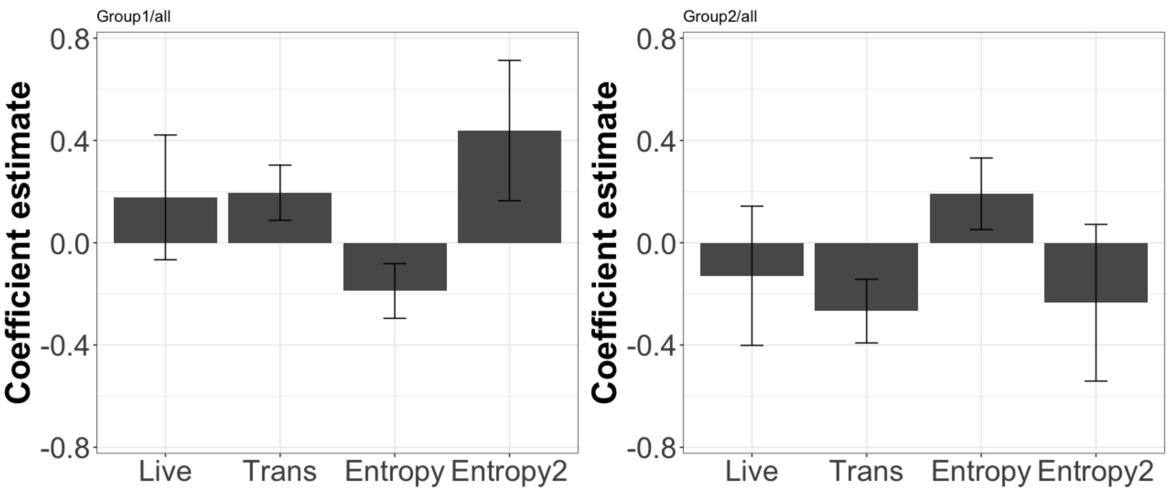

Figure 4.6: Coefficients of regression result with all variables
The bars represent the coefficient estimates with standard errors.

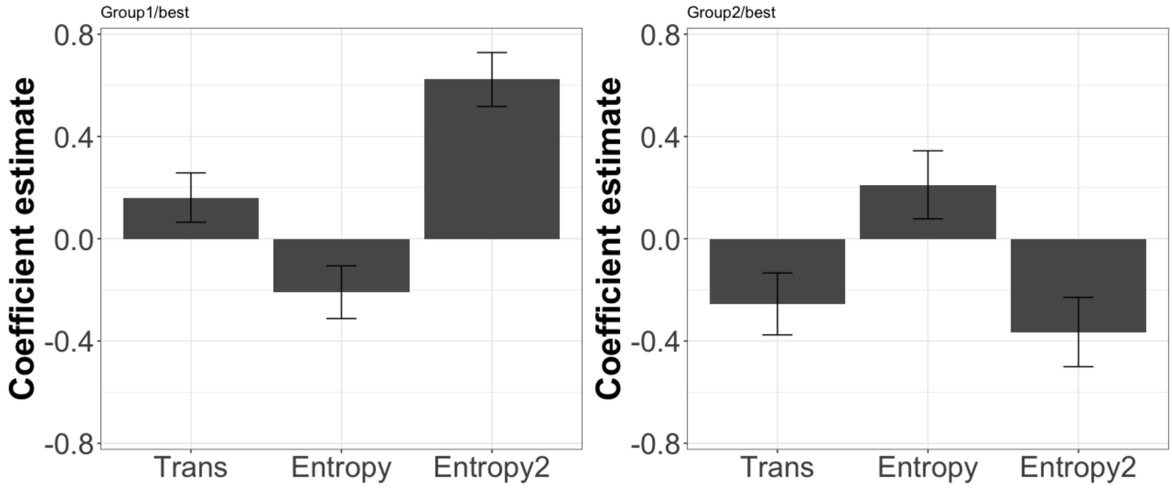

Figure 4.7: Coefficients of regression result of the best model
The bars represent the coefficient estimates with standard errors.

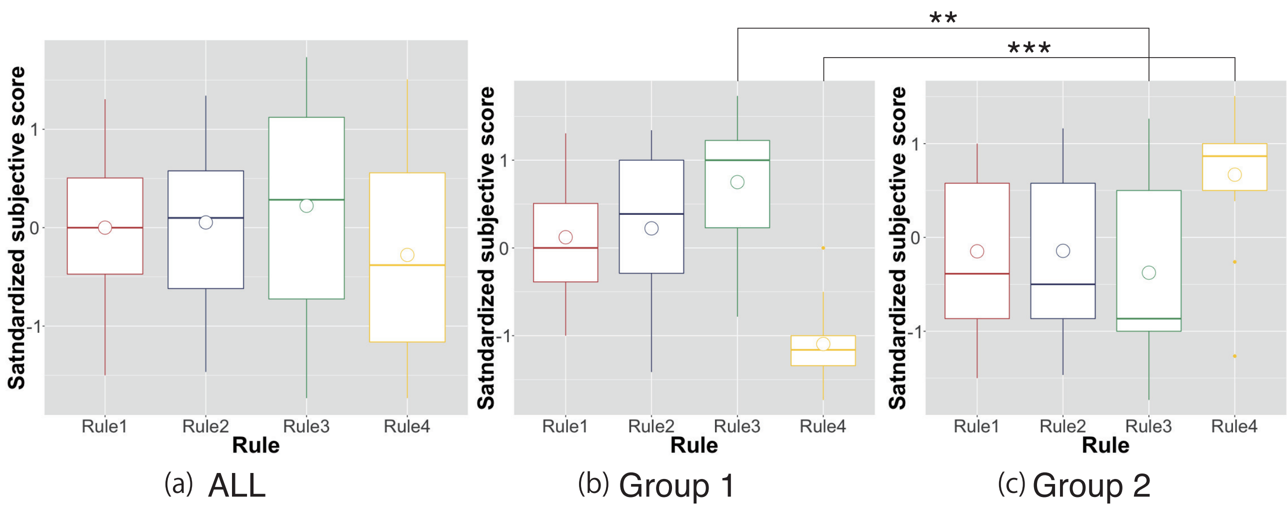

Figure 4.8: Normalized mean of subjective scores for the four rules in two groups of (a) all participants, (b) participants with positive slop (c) Participants with negative slope. Significant differences of subjective scores between the two groups for Rule 3 and Rule 4.

was the opposite. Interestingly, the multiple regression for the second group resulted in the entropy of distribution as the dominant predictor for intrinsic motivation. The participants were encouraged to change the number of live cells due to interactions rather than producing various patterns. Further investigation of interactions could explain how much each participant made changes to the environment through their interactions. As discussed in Chapter 3, empowerment is the proper index here, representing how much participants can make changes in the environment.

Our data indicate that it is premature to conclude that humans by nature seek richer expressions with limited physical resources, which is one of the key factors of creativity. It is important to note that creativity is not stationary, is highly context-dependent, and even mood-dependent. An individual analysis is necessary for the study of creativity by behavioral analysis, which calls for better personalization to maximize individual creativity by learning through interacting. However, the sample size of the subjects turned out not sufficient for the subgroup analysis. This was mainly because of the time constraint and some changes in experimental procedures during the preliminary experiments. More samples can be available if the task is put online to hire participants remotely. The more sample size will allow to analysis for subgroup and individual analyses with more statistical reliability. Moreover, the larger sample size may enable personalization to estimate individual intrinsic motivation models to design the learning environment for each person optimally.

In summary, the classification of the participants depending on the preference for the variety of local patterns did not only provide better fits of regression but also revealed other features of the subgroups. The result suggests that investigating personal features of intrinsic motivation, mechanisms can provide better models to help humans to be more intrinsically motivated for creative activities.

Chapter 5

Conclusion

I demonstrated that the intrinsic motivation of humans in creative activity represented by subjective evaluation correlates with how varied the expressions can be and how simple the rule being employed is. Speaking more broadly, I have shown that, when intrinsically motivated, humans would try to generate richer expressions by selecting simpler rules, which presumably is optimal for maximizing reward with the limited resources of our memory and this can explain one of the inherent characteristics of creativity.

In Chapter 3, the ANOVA for subjective scores of enjoyment for the four rules, which was the major index of intrinsic motivation in the analysis, showed significant differences between the two factors, variety of expressions and simplicity of rules. The result supported my main hypothesis. In contrast, the analysis of the subjective variety of expression and subjective simplicity/complexity of rules resulted in a weak correlation to the subjective score. It might be because participants accounted for the two factors implicitly rather than consciously. Analysis of behavioral measures, the playing time, and frequency of touch interaction did not show a significant correlation with subjective intrinsic motivation. Among the behavioral measures for the variety of expression number of live cells, number of cell state transitions, the entropy of the number of live cells, and entropy of local patterns the entropy of two by two square grid pattern had a significant correlation with the subjective score of enjoyment and a positive coefficient in multiple regression analysis. This result leads to further analysis in Chapter 4. Canonical Correlation Analysis (CCA) was performed to investigate which measure of the variety of expression is related to intrinsic motivation. In CCA, with measures for a variety of expression including playing time and frequency of touch interaction, two components had positive loadings for subjective enjoyment and the entropy of local patterns. Interestingly, the first and second components had positive and negative loading for the frequency of interaction, which suggests that participants enjoyed both cases where frequent interaction produced more variety of patterns or the cellular automaton showed variety automatically without frequent interactions. Rule 4 had the highest level of empowerment among the four rules, which might explain why some participants marked the highest score of enjoyment for Rule 4.

Although the ANOVA of the mean of subjective scores supports the hypothesis, some participants preferred Rule 4 in an apparent contradiction to the hypothesis as this rule was designed as a complex rule with a lower variety of expression. In fact, the distributions of participants in two measurements, their preference for Rule 4 and the entropy of local patterns, seemed to have two modes. Although the Silverman tests for each of these measures did not reach significance, the results combined suggest bimodality. The subgroup analyses based on participants' preference of the entropy of local patterns did not produce not only a better fit in multiple regression but also revealed opposite preferences for Rule 3 and Rule 4. The result suggests that my hypothesis that higher variety of expression by simpler rules promotes intrinsic motivation holds well in a subgroup of subjects (21 out of 42). However, others had the opposite preferences for these features.

The results of this human behavioral experiment have important implications for the hypothesis that more variety of expression by simpler rules promotes more intrinsic motivation. Based on the designed features of the four rules, subjective scores of enjoyment support the hypothesis. To be clear, the data obtained in this study do not demonstrate that what condition is better for being more creative. It does, however, strongly indicate what condition is good for intrinsic motivation in creation. Most of the researchers in creativity have struggled to quantify creativity through measurements, which is too subjective and too context-dependent to measure uniformly. Instead, this study focused on measuring intrinsic motivation, which was simply defined as the enjoyment level in creative activity.

Based on this study, I claim that the enjoyment rate in expressing something in a varied manner by the combinations of simple elements is precisely the intrinsic motivation for creative activity. The more elements are learned and available, the more variety of expression can be created. A learner tries to learn effectively by selecting a better environment for various expressions due to the learning cost. Alternatively, the environment in which a learner can enjoy a creative activity is a good environment for creation. The results may also provide specific suggestions beyond understanding the mechanisms of intrinsic motivation regarding the conditions that promote more creativity in general and impressive values in artworks. All of this can serve as the basis for modeling creativity with effective key factors.

Practically, many other factors, including task components, acquired skills, and reward function that might change after learning, need to be considered to understand mechanisms of intrinsic motivation. Especially, time restrictions may affect the way participants allocate their time for playing. Intrinsic motivation is molded by the sequence of actions, environment experienced, and people with whom the person interacts. It may be causally related to life experiences, "connecting the dots" to new creation and innovation. However, I strongly believe that the findings from this study can be practically applied. For instance, the original game that I designed using a touch panel can be extended to a tangible digital toy like the photo in Figure 5.1. Applying the framework in three-dimensional cellular automata, the toy is designed as a set of digital building blocks. Children can learn the rules of cellular automata implicitly and how to use the rule to build what develops their motivation through playing. Suppose the intrinsic motivation level can be measured from their behaviors. In that case, it might be possible to detect children's preferences and provide a better environment (rule) to motivate them intrinsically. To understand the motivations of individuals and how they explore, learn, and use knowledge, I must investigate the sequence of behavior and its effect, subjective goals, and the accomplishment and assessment of

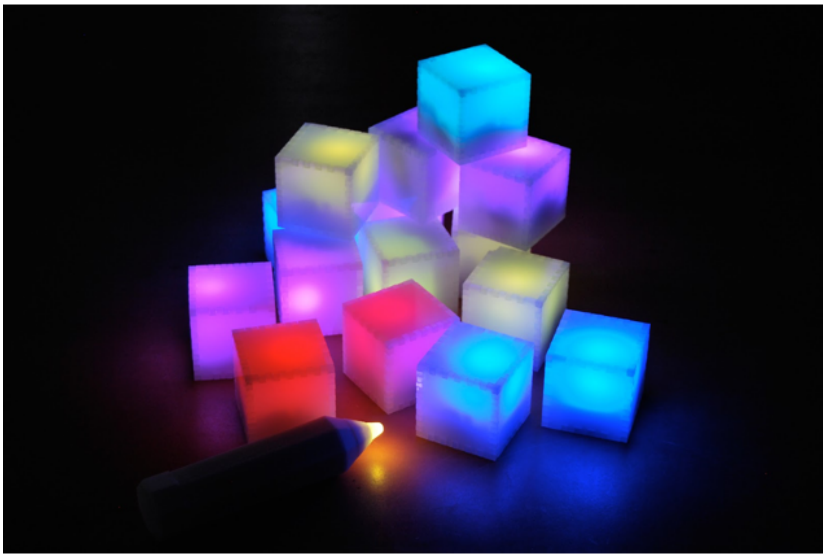

Figure 5.1: "bit world" designed and created by Tomomi Kasahara

output in more detail, which will be my next challenges.

Intrinsic motivation is influenced by many factors which are correlated or dependent upon one another to some extent. The factors for intrinsic motivation can be extensive such as an inherent ability, age, generation, experience, timing, culture, context, and synergy with others. The two hypothesized factors in this study seem essential for understanding the intrinsic motivation for creativity, which I believe is the primary drive or passion for creators, including scientists and artists.

As an example of more variety of expressions by a simpler rule, a well-known haiku (i.e., a type of Japanese short-form poetry consisting of three phrases in a 5, 7, 5 character pattern) is cited as follows.

Yukitokete Muraippaino Kodomokana

(The snow thaws, and a village is filled with children.)

Written by Issa Kobayashi, 1814

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Appendix A

The life of game cellular automata

The rule of cellular automata

As described in Section 2, the original game was developed as a behavioral experiment to collect data from human subjects. Using the framework of cellular automata (CA) in the original game, the interface has a grid cell in which the color of each cell changes about the colors of the neighboring cells and rules being applied at the time.

CA (Von Neumann, 1951; Wolfram, 1984a) is represented as an array of cells, and each cell is updated via a rule which determines how the state of the cell, i.e., 0 or 1, and its colors change. Its state updates depend on the current state of a cell itself and its neighbors' states. Figure A.1 shows examples of a template of the neighborhood in one-dimensional and two-dimensional spaces.

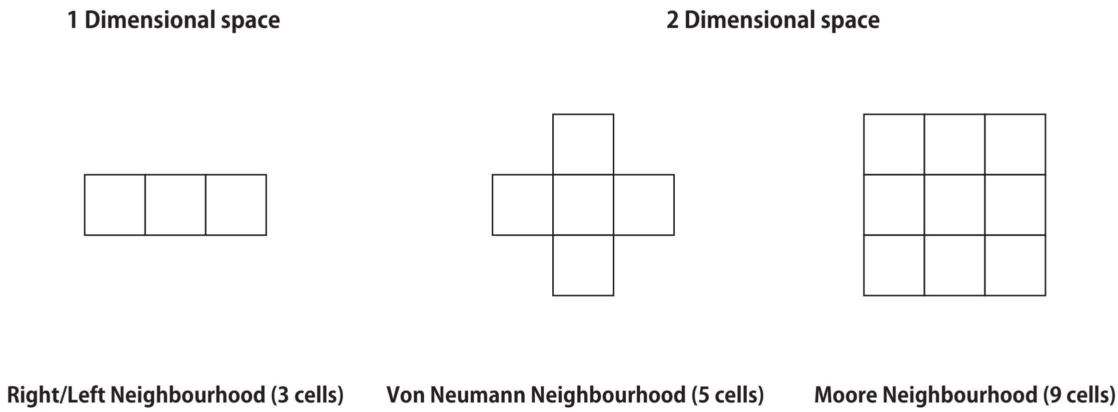


Figure A.1: Neighbors in CA: The center cell is sometimes included as part of the neighbourhood and sometimes not.

The principles of CA rules are as follows to implement the cell grid system.

1. The environment is described as discrete space and discrete time.

2. Cells are uniform in shape and size.

3. The state of a cell changes discretely.

4. State updates are synchronized for all cells.

The transition of ϕ rules of certain CA in one dimension is defined as:

$$S_{t+1}^{i} = \phi(S_t^{i-r}, S_t^{i-r+1}, \cdots, S_t^{i}, \cdots, S_t^{i+r-1}, S_t^{i+r}) \tag{A.1}$$

where S is the state, i is the position of the cell, t is the discrete time step, and r is the number of cells included as neighbors on one side.

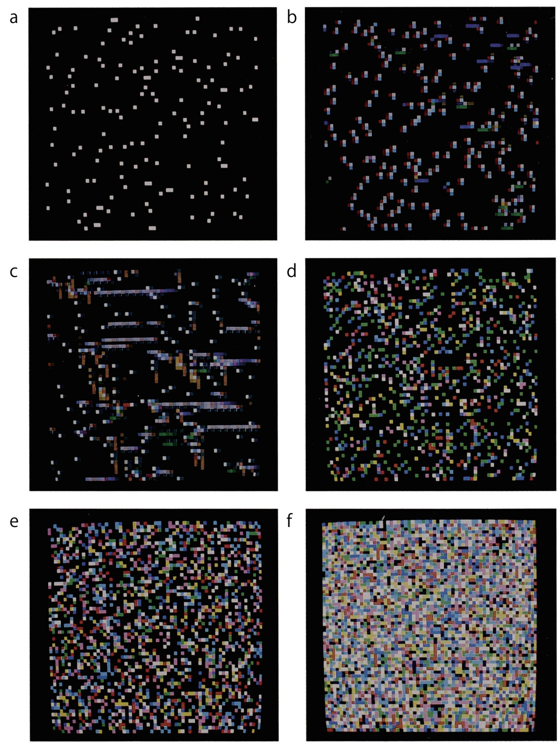


Figure A.2: Two dimensional CA representative configurations with different λ parameters
a) $\lambda = 0.17$; b) $\lambda = 0.19$; c) $\lambda = 0.22$; d) $\lambda = 0.33$; e) $\lambda = 0.45$; f) $\lambda = 0.86$ (Langton, 1986).

The pattern generated is determined by the given CA rule and the initial setting of cell states. The possible pattern variations of the patterns are much larger than the number of neighborhoods. Wolfram (1984b) qualitatively categorized the patterns into four qualitative classes:

Class 1 converges to a stable state in which almost all cells are dead. (Fixed)

Class 2 leads to a set of simple periodic patterns. (Periodic)

Class 3 results in unified chaotic periodic patterns. (Chaotic)

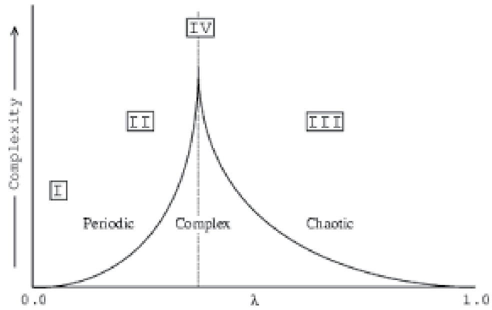


Figure A.3: Location of the Wolfram classes in lambda space (Langton, 1990).

Class 4 results in complex patterns that are partially structured. (Complex)

Langton (1986) proposed the λ parameter, which can be a rough index of Wolfram's classes. The λ parameter is defined as:

$$\lambda = \frac{K^N - n}{K^N} \tag{A.2}$$

where K^N is the total number of cell states in the neighborhood and $K^N - n$ is the number of cell states in the neighborhood that maps to a non-quiescent state. K is the number of possible states, and N is the number of the neighborhood. Quiescent state means an arbitrary state from K states. Figure A.2 shows how representative configurations vary in various settings of λ. Image a is categorized Class 1, b is Class 2, c is Class 4, and d,e, and f seems to belong to Class 3. The λ parameter can be used to generate transition function ϕ (Langton, 1990). The λ parameter can also be an index of the complexity of environmental behaviors. Complexity is measured by mutual information derived by Shannon's entropy. Mutual information detail the correlations between the states of two cells. The mutual information $I(A;B)$ between cell A and cell B is calculated by Shannon's entropy of $H(A)$ as a combination of the entropies of each cell and joint entropies::

$$H(A) = -\sum_{i=1}^{K} p_i \log p_i \tag{A.3}$$

$$I(A;B) = H(A) + H(B) - H(A,B) \tag{A.4}$$

The larger $H(A)$, close to 1, means that the environment dynamics are more complex. The smaller $H(A)$, which is close to 0, indicates that the environment has a more regular pattern. Figure A.3 shows how complexity derived by $I(A;B)$ changes along the λ spectrum.

The game of life cellular automata

The game of life is a two-dimensional cellular automaton invented by John Conway (1970), in which some life-like interesting patterns are created. IN this cellular automaton, each cell has two potential states, referred to as dead or live. It also uses the Moore neighborhood. A live cell stays alive when it has two or three alive neighbors; otherwise, the cell turns to becomes dead. A live cell emerges from a dead cell if it has exactly three alive neighbors. This simple rule leads to interesting life-like patterns, such as when a pattern repeats itself infinitely or moves by repeating itself. For the pilot test, the rule of the original game of life and the altered rules will be applied. Details of the rule set are described in Chapter 2.

Appendix B

Formulas for calculating entropy and empowerment

Entropy

The probability distribution of the observed numbers of live cells $n(k)$ is represented by using the concept of entropy:

$$P(k) = \frac{n(k)}{N} \tag{B.1}$$

$$H(E) = -\sum_{k \in E} P(k) \ln P(k), \quad 0 \leq n(k) \leq N \tag{B.2}$$

Entropy indicates a variety of patterns as a series of expression by quantitatively showing a distribution of the different numbers of live cells.

Although entropy shows observed features of patterns as dynamics, it does not include information of how each pattern is formulated.

Variables for the simplicity/complexity of the rule

The measurement "simplicity/complexity of a rule" is controlled by parameters of the state transition function and quantified by the complexity measures formulated in the theory of cellular automaton. The complexity of the rule is measured by empowerment and subjective scores of the complexity of the rule.

Table 2.2 provides the list of the measured variables. How the variables were computed is described as follows.

Empowerment

A temporal reduction of entropy after event n^k happens is defined as the information gained motivation:

$$r(n^k, t) = C \cdot (H(E, t) - H(E, t+1)) \tag{B.3}$$

C is a constant number. It defines the decrease of uncertainty in the agent's knowledge as rewarding. Another examples of the measurement of reward as an independent variable is empowerment (Capdepuy et al., 2007), which encourages an agent to maximize the amount of information in the environment with sensory perception. It uses the concept of a channel capacity through the series of actions A_t^n=$(A_{t,}A_{t+1},\cdots,A_{t+n-1})$ to the perceptions S_{t+n}:

$$r(A_t^{n-1} \rightarrow S_{t+n}) = \max_{p(a_t^n)} I(A_t^n, S_{t+n}) \tag{B.4}$$

where $p(a_t^n)$ represents the function of probability distribution in the series of actions, and I represents mutual information. Empowerment is measured as 0 when an agent has no control over the environment, and its measured result is higher when an agent has stronger control.

Empowerment of four rules is computed as the amount of control or influence the agent,i.e., the participant of the experiment, has over the environment (Klyubin, Polani, and Nehaniv, 2005) defined by equation (B.5).

$$MI(s'|a,s) = H(s'|s) - H(s'|a,s) \tag{B.5}$$

Here, $H(s'|s)$ represents entropy of the distribution of all possible states for a particular center cell, and $H(s'|a,s)$ represents entropy of the distribution of the states for the center cell after an agent takes action (including not touching the cell).

Each possible action is assumed to occur with the same probability as in Table B.1. The options of action are to touch or not touch a certain cell, and the option to touch has nine choices in which the agent can touch one of the surrounding eight cells or the center cell. Therefore, the total number of action options is ten, and thus, the probability of each action (p) is calculated as 0.1.

The concepts of changeability (δ) and controllability (κ) as defined by equations (B.6) and B.7 are introduced to compute empowerment. κ is separately calculated when the agent touch one of the neighboring cells (κ_n) or the center cell (κ_c).

$$\delta = \frac{N_{new\,birth/death}}{N_{all}} \tag{B.6}$$

$$\kappa = \frac{N_{new\,birth/death\,affected\,by\,action}}{N_{all}} \tag{B.7}$$

N_{all}: Number of all possible states
$N_{newbirth/death}$: Number of states causing new birth or death
$N_{newbirth/deathaffectedbyaction}$: Number of states where an action affects new birth or death

$$\begin{aligned} H(s'|s) &= -\sum p(s'|s) * log(p(s'|s)) && \text{(B.8)} \\ &= \underbrace{-p_a * log2(p_a)}_{alive} - \underbrace{p_d * log2(p_d)}_{dead} && \text{(B.9)} \end{aligned}$$

Here, the probability for being alive is calculated as: $p_a = \delta * p_a + \kappa_n * p_a * 8 + \kappa_c * p_a$,

Table B.1: Calculation of empowerment

State of center cell	Action		
	No action	on neighbor cell	on center cell
Alive	δ	κ_n	κ_c
Death	1 - δ	1 - κ_n	1 - κ_c
Probability of action	0.1	0.8	0.1

and the probability for death is calculated as: $p_d = (1 - \delta) * p_a + (1 - \kappa 0) * p_a * 8 + (1 - \kappa 1) * p_a$.

$$\begin{aligned} H(s'|a, s) &= -\sum p(s'|a, s) * log(p(s'|a, s)) && \text{(B.10)} \\ &= p * (H_{na} + 8 * H_a + H_{ac}) && \text{(B.11)} \end{aligned}$$

$$\begin{aligned} H_n a &= -\delta * log_2(\delta) - (1 - \delta) * log_2(1 - \delta) && \text{(B.12)} \\ H_a &= -\kappa_n * log_2(\kappa_n) - (1 - \kappa_n) * log_2(1 - \kappa_n) && \text{(B.13)} \\ H_a c &= -\kappa_c * log_2(\kappa_c) - (1 - \kappa_c) * log_2(1 - \kappa_c) && \text{(B.14)} \end{aligned}$$

where $H_n a$: Entropy after no action, H_a: Entropy after an action in surrounding cells, and H_{ac}: Entropy after an action in center cell.

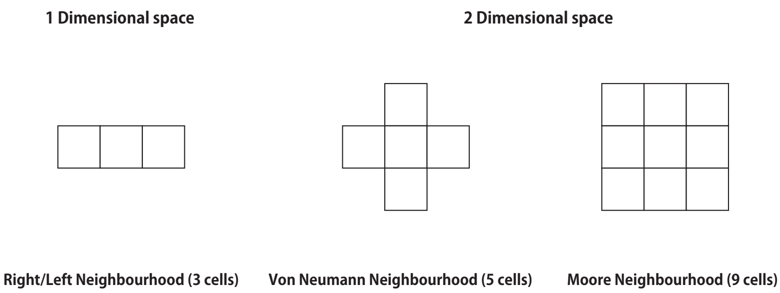
Appendix C

Documents of experiment

How to Play the game of life program

■ What is the game of life?

The game of life is the computer simulation of the “live” and “death” of living organisms. The environment is designed as a grid world and each cell on the grid represents an organism. The state of “live” is shown by a particular color and “dead” is shown by uncolored (white). The organisms can be born, alive and dead through generations by following the given rule. The rule in the game of life determines the next states of each organism according to its neighbourhood states such as over populated or under populated. The neighbourhood has two variations in 2 dimensional space in this game.



The most basic rule of the game of life is as follows.

a. Each cell with three neighbours becomes alive.
b. Each live cell with two or three neighbours stays alive. Otherwise it dies because of over populated or under populated environment.

In this experiment, the environment is designed by 8 times 8 grid world. The edges on top and bottom/ left and right are virtually connected for applying the rules. The cells on top have neighbors on the bottom and the cello on left edge have neighbours on right edge. There are four rules from RULE 1 to RULE 4 to play and each rule has different color of representing a live cell.

Figure C.1: Instruction to be given to participants before starting demos and games.

SUBJECT NO. ☐ Experimenter ____ Date / / 2019

'Intrinsic motivation in learning and play' **Experiment Questionnaire**

Thank you for participating in our experiment. Please answer all questions about the experiment.

1. How much did you enjoy the game with each rule?

	not enjoyed 1	2	3	neither 4	5	6	very enjoyed 7
RULE1	☐	☐	☐	☐	☐	☐	☐
RULE2	☐	☐	☐	☐	☐	☐	☐
RULE3	☐	☐	☐	☐	☐	☐	☐
RULE4	☐	☐	☐	☐	☐	☐	☐

2. How did you think each rule was simple or complex?

	very simple 1	2	3	neither 4	5	6	very complex 7
RULE1	☐	☐	☐	☐	☐	☐	☐
RULE2	☐	☐	☐	☐	☐	☐	☐
RULE3	☐	☐	☐	☐	☐	☐	☐
RULE4	☐	☐	☐	☐	☐	☐	☐

3. How did you think the pattern transition with each rule was interesting?

	Very boring 1	2	3	neither 4	5	6	very interesting 7
RULE1	☐	☐	☐	☐	☐	☐	☐
RULE2	☐	☐	☐	☐	☐	☐	☐
RULE3	☐	☐	☐	☐	☐	☐	☐
RULE4	☐	☐	☐	☐	☐	☐	☐

4. What kind of pattern did you try to draw? (If you had a particular image)
Ex.) Stripe pattern, Single colored, Symmetry

5. Please tell us more opinion in your own words about the game.

Figure C.2: Questionnaire to distribute after the games.

Appendix D

Examples of the patterns with interactions based on the four rules

Here are examples of how dynamic patterns are created. All rules initially start with the same pattern (a cross shape) and then interacted twice. The numbers each marked on each pattern represent the order of the patterns that appeared. "Stable" means that the pattern gains equilibrium with the rule so that no changes happen without interaction. "Interact" means that the player has touched the cells. When all cells are dead (uncolored), the game ends.

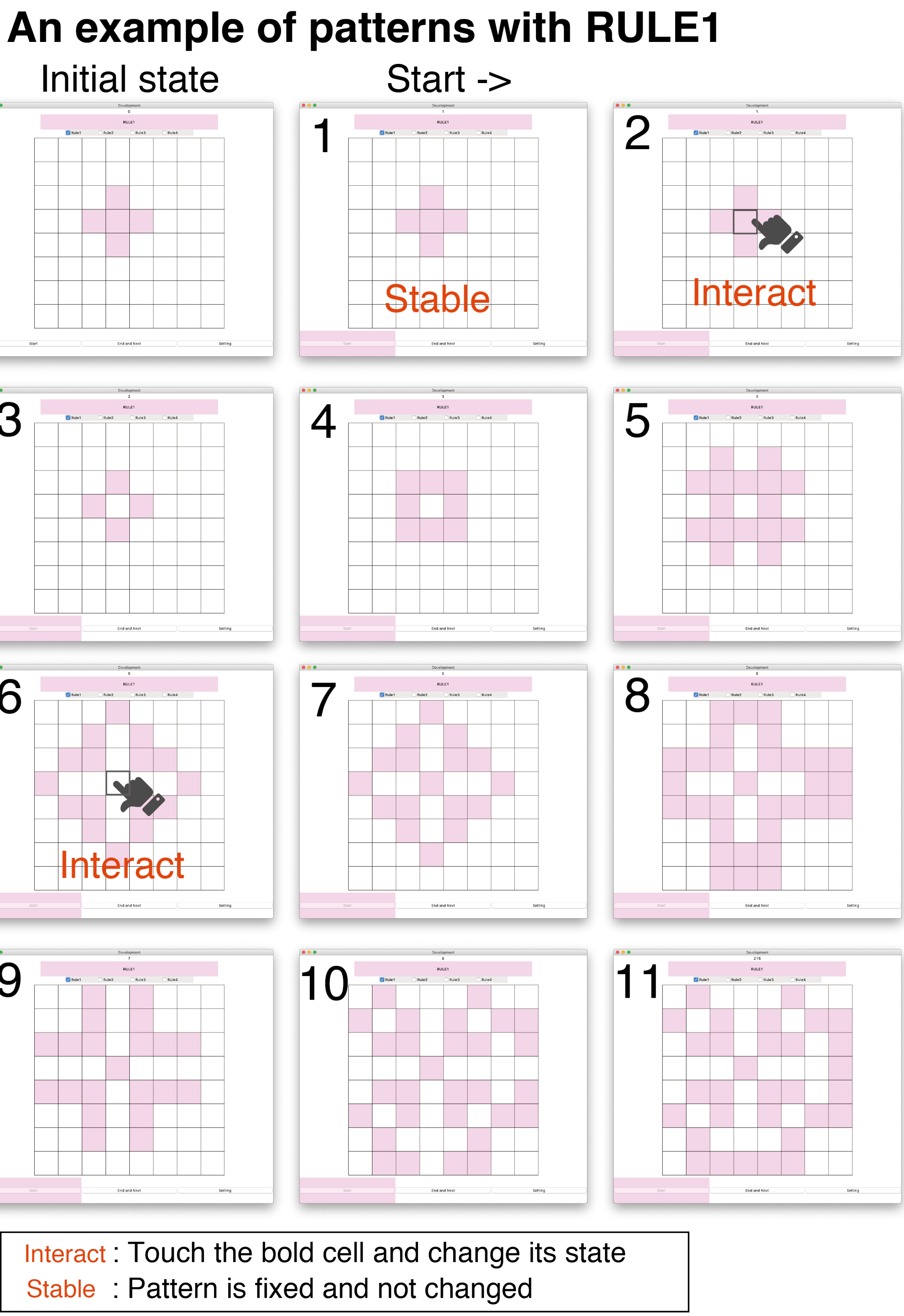


Figure D.1: An example of changing patterns during the game with RULE1

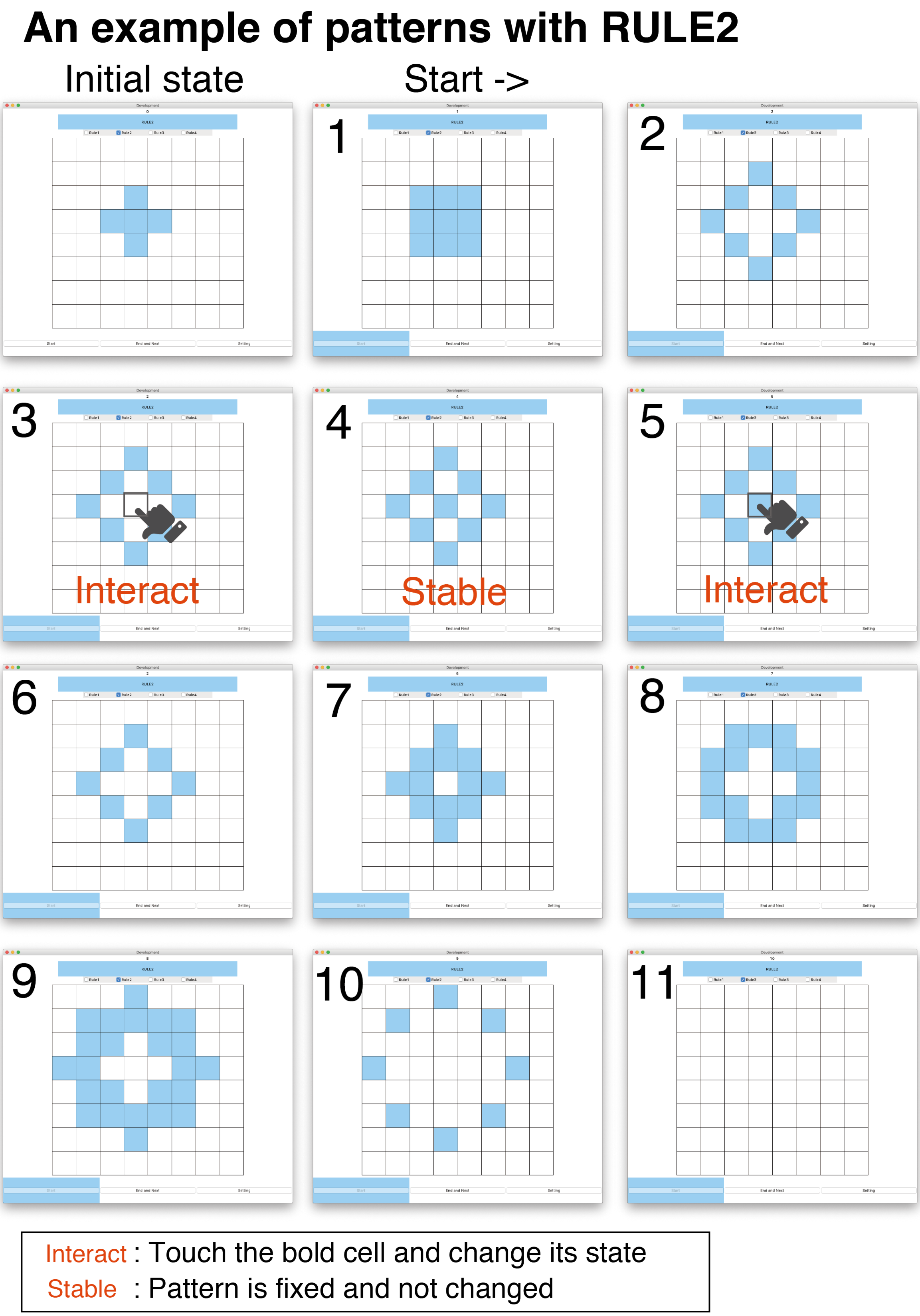


Figure D.2: An example of changing patterns during the game with RULE2

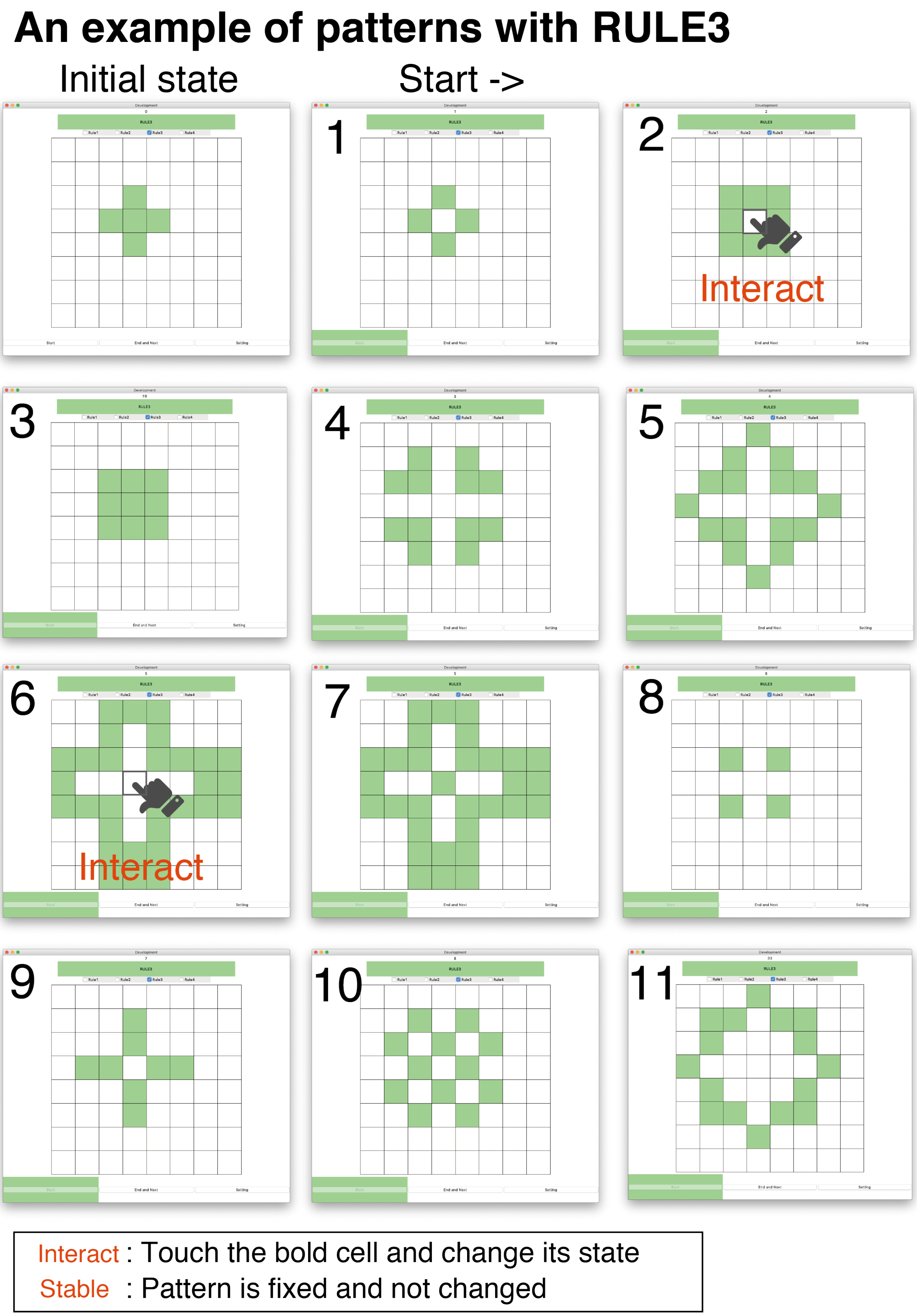


Figure D.3: An example of changing patterns during the game with RULE3

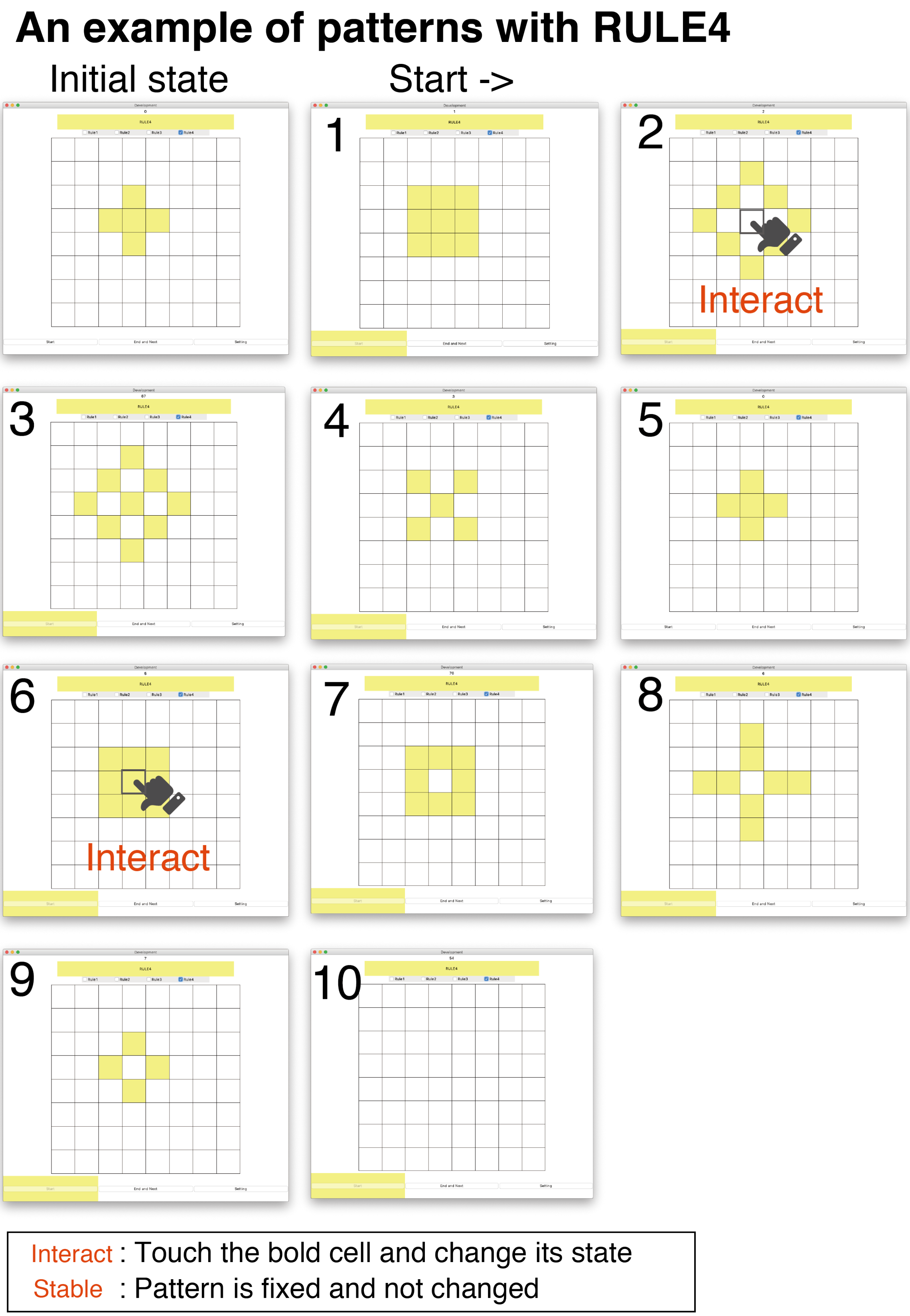


Figure D.4: An example of changing patterns during the game with RULE4