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Methodology for Extracting Knowledge from a Gaming Simulation Using Data Envelopment Analysis

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***Abstract*—In this study, we propose a methodology for extracting knowledge about which play logs are superior (inferior) to other play logs under certain criteria from the results of a gaming simulation. Previous research has enabled facilitators to know where players' play logs output from gaming simulations are positioned in all possible scenarios. However, facilitators have no valid solution to encourage players to change their behavior in gaming simulations. The proposed methodology enables a facilitator to identify the players who show similar behavior and performance to the target player under certain criteria, and to present to the play logs which show superior performance than the target player's play log to the target player. In order to achieve our research objective, we created several software agents instead of human players to play a gaming simulation for career education, and analyzed the output play logs using data envelopment analysis. As a result, the desired knowledge was extracted. We argue that the extracted knowledge should be applied for debriefing. The proposed methodology is flexible enough to work under both conditions where all players are human and where human and machine agents are mixed as players.**

***Index Terms*—Gaming simulation; data envelopment analysis; knowledge extraction; debriefing; facilitation.**

I. Introduction

The objective of this study is to propose a methodology to extract knowledge about which play logs are superior (or inferior) to other play logs under certain criteria from the results of a gaming simulation. In order to achieve our research objective, we use a gaming simulation that is a modified version of the Shin-Life Career Game [1] presented at eKNOW 2021, and the Data Envelopment Analysis (DEA) [2]. A gaming simulation is a simulation in which humans participate in the simulation situation as players and are influenced by the decisions of those players [3]. DEA is a method that uses linear programming to measure the efficiency of a decision-making unit (DMU) by enveloping the observed input-output vectors as tightly as possible [4].

Facilitation and debriefing are important in gaming simulations [5]. Facilitation is that a facilitator takes care of everything related to the progress of the game [6]. Debriefing is learning by reflecting on the simulation experience [7]. However, it is said that the effectiveness of facilitation and debriefing depends largely on the experience and skills of a facilitator [6].

According to Kikuchi et al. [8], in order to evaluate a player's behavior in a gaming simulation, it is common to focus on individual play logs, track a player's decisions and actions, and observe them in detail (e.g., [9], [10]) . The approach of analyzing individual play logs requires a great deal of effort and cost. It is therefore difficult to compare and evaluate the play logs of a large number of different players.

In contrast to the approach of analyzing individual play logs, there is an approach of comprehensively analyzing the results of gaming simulations. Kikuchi et al. point out the following challenges in comprehensively analyzing the results of business games [8]: (1) the collection of a large number of play logs, (2) the possibility of a biased sample, and (3) the difficulty of creating a list that covers all possibilities. Business games are a type of gaming simulation. Business games are a common means of studying business and management principles under controlled and virtual situations [11]. Kikuchi et al. point out that because of the difficulty in overcoming issues raised above, methods for evaluating gaming outcomes based on game wins and losses are overused.

Based on these arguments, Kikuchi et al. proposed a framework for properly evaluating the behavior of players in computer-based business games [8]. In the framework proposed by Kikuchi et al., the following steps are taken: (1) Agent-based Model is constructed based on the target business game, computer simulations are run thoroughly, and the logs are classified. (2) Identify the behavior of players in gaming by locating the experimental results (play logs) generated by players in the classified computational results. Kikuchi et al. argue that by following these steps of analysis, it is possible to visualize and present to the players and facilitators the position of the players in the possible outcomes of business games.

The analytical framework proposed by Kikuchi et al. is applicable to all gaming simulations. This is because the arguments of Kikuchi et al. are derived from a structure that is common to all gaming simulations, not just business games. By applying the framework proposed by Kikuchi et al. to a gaming simulation, players can know in which pattern their behavior in their playing experience is included in all possible gaming scenarios. This method provides an opportunity for players to recognize what differences there are between their own behavior and that of other players.

However, previous approaches are unlikely to encourage players to improve their play. This is because even if players know the position of their gaming outcome in possible scenarios, they do not know what they can refer to for changing their behavior in their gaming.

Based on the above, we propose a methodology for acquiring knowledge that facilitates a player to change his/her behavior in a gaming simulation. Specifically, the following steps are taken: (1) have players play the gaming simulation and collect play logs, (2) classify the play logs, and (3) evaluate the superiority or inferiority of the play logs under the criteria specific to each group. By following these steps, we can acquire knowledge, which play logs are superior (inferior) to others under the same criteria. As a result, a facilitator will be able to use the acquired knowledge to narrow down the play log that can serve as a model for the players to be instructed, and to give appropriate advice to the players. In addition, players can learn effectively and efficiently by referring to the facilitator's advice. The above analysis procedures are also valid if some of the players are replaced by machine agents.

The differences between our analytical approach and that proposed by Kikuchi et al. [8] are as follows: (1) the players in the gaming simulation can be either human-only or a mixture of human and machine agents, (2) when the players are human-only (which limits the number of experiments), the superiority or inferiority among play logs among a limited number of play logs can be helpful to the players. Of course, in conditions where both humans and software agents are mixed, a large number of play logs should be collected by computer simulation, as in the study by Kikuchi et al..

In this study, we demonstrate our proposed methodology with solving a example problem. Specifically, we assume software agents to be human players, have them play a gaming simulations, collect play logs, classify the play logs using Charnes-Cooper-Rhodes model (CCR model) [2], which is the basic model of DEA, and extract knowledge about which play logs are better than other play logs under a specific objective function, or which play logs are worse than other play logs under the same objective function. The gaming simulation to be used in this demonstration is the Shin-Life Career Game version 2 developed for career education [12]. The Shin-Life Career Game version 2 is a kind of typical life game that allows players to experience a virtual life as a worker. The Shin-Life Career Game version 2 consists of multiple rounds, and in each round, players are forced to make life choices and solve resource allocation problems according to their own will. The details of this gaming simulation are described in Section 2.

The rest of this paper is organized as follows: First, related research (Sections 2 and 3) is described. Section 2 provides a detailed description of the Shin-Life Career Game version 2 used in this research and Section 3 describes DEA. Sections 4 through 6 provide an example of applications of the proposed methodology and finally, a summary and conclusions are provided.

II. The Shin-Life Career Game

In this study, a gaming simulation named the Shin-Life Career Game version 2 [12] is used in the experiments. This game was developed by adding new functional elements to the original Shin-Life Career Game [1]. In the following, we first describe how and why the original Shin-Life Career Game was developed, and then describe the Shin-Life Career Game version 2.

A. *The Shin-Life Career Game (Original Version)*

The Shin-Life Career Game is an updated version of the Life Career Game developed by Boocock [13][14] that reflects modern work elements. To overcome the discrepancy between the career world as seen by secondary school youth and the career world as seen by adults, Boocock developed the Life Career Game, which plays much like the original Life Game [15]. The players of the game experience a hypothetical life, playing various roles and spending their resources (money, time, etc.) on various activities with the aim of maximizing their present satisfaction and the possibility of a good life in the future. As a result, they acquire knowledge related to career development and develop understanding and confidence. These characteristics have been partially inherited by serious games for career education that have been developed since then (e.g., [1], [16] [17] [18]).

Resource Variable	Conventional Games	The Shin-Life Career Game
Number of labors a player can have at the same time	One	Multiple
Diversity of labor forms	Low	High

TABLE I: Difference in characteristics between the Shin-Life Career Game and traditional gaming simulations (Reprinted from [1])

The situation that the Life Career Game developed by Boocock offers to players is somewhat unrealistic in today's working society. In the game, players are required to make a living from only one job, and they cannot choose the type of work they do when they enter the profession. It is natural for a modern worker to have a variety of options, such as working as an employee or as a freelance worker.

The Shin-Life Career Game was developed to solve this problem. It is a modern version of the Life Career Game in which players can choose any number of activities such as work and skill development at the same time, as long as the constraints are satisfied. Specifically, in the Shin-Life Career Game, players can choose from various types of work, such as permanent work, freelance work, and simple work. And, they can also choose learning to develop their ability.

In the Shin-Life Career Game, players are asked to live out their lives as virtual workers through game play. In the course of their virtual lives, players determine their own goals in life, decide what and how to spend their resources: earn money, improve their abilities, and sometimes take a break. Just as in real life, players may lose money or get into trouble. A table describing the differences in characteristics between the Shin-Life Career Game and previous career education games from the study [1] is reproduced above (see Table I).

Munsen et al. is skeptical that the experiences of players who participated in gaming simulations that imitate the life of a worker adequately reflect real-life [19]. In response to these negative views, Duke, the founder of the International Society for Simulation and Gaming, said the following [20]: gaming simulation is a useful method for representing dynamic models that abstract complex realities; gaming simulation is appropriate for gaining a holistic understanding of complex situations, and; it helps to deepen the contemplation of multiple futures by considering multiple alternatives in a gaming simulation. We have supported Duke ' s position and developed the Shin-Life Career Game (and version 2). Players who participate in the Shin-Life Career Game will be assigned the role of a worker, experience a virtual life from the perspective of a worker, and interpret the life of a worker from their perspectives in the course of the experience, gaining new knowledge and perspectives through the exchange of opinions among the players and facilitators.

B. The Shin-Life Career Game version 2

In this study, we use the Shin-Life Career Game version 2 [12], which is an extension of the original Shin Life Career Game described above. In the Shin-Life Career Game, players have a total of four types of resources (money, ability, time, and health), which they can freely distribute among five types of activities (permanent work, freelance work, simple work, learning, and leisure). The main differences between Shin-Life Career Game version 2 and the original Shin-Life Career Game are: (1) the number of resource variables the player has been increased by one (the health resource variable has been added), (2) the number of activities that can be selected has been increased by one (Leisure has been added), and (3) the health resource variable affects the performance of work and learning activities. With these new elements added to the game model, the decision-making problem regarding the allocation of resources handled by players becomes more complex, and the behavior of the game system becomes more dynamic. The differences in the specifications of the two games are summarized in Table II.

Figure 1 depicts a model that represents which resources are gained (or lost) when a player allocates certain resources for his activities in the Shin-Life Career Game version 2. This model, called MATH model, describes the four basic resource variables of an agent: monetary assets (M: money), ability (A: ability), time (T: time), and health and fitness (H: health), in N^2 diagram (duality) form, with each variable as input and output [21]. This is a logical model in which the agent's activity is described as a region that crosses the corresponding rows and columns [21].

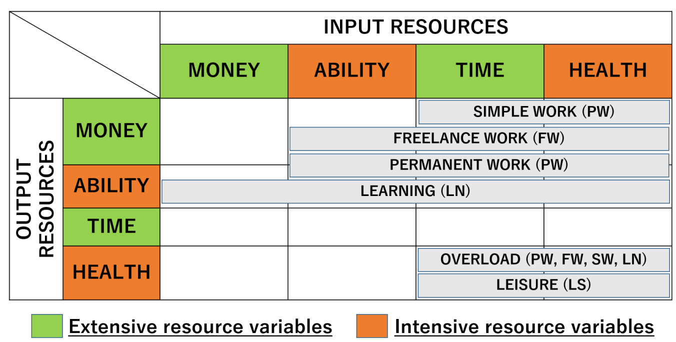


Fig. 1: This figure shows the relationship between the resources input to each activity and the resources output from each one in the Shin-Life Career Game version 2. For example, players input time resources and health ones to SW, and they acquire money resources. In a given round, if a player inputs extensive resources, such as money and time, into multiple activities, the resources decrease with each resource input because extensive resource is allocated competitively and additively. Also, in a given round, if a player inputs intensive resources, such as ability and health, into multiple activities, the same amount of the resources are allocated to the target activities because intensive resource is non-competitively and multiplicatively. The amount of extensive and intensive resources increase, decrease, or remain the same depending on a result of a target activity. A detailed description of the properties of resource variables and activities can be found in "1) Resource Variable" and "2) Activity", respectively.

Category	Elements	The Shin-Life Career Game†	
		Original Version	Version 2
Resources	Money	◯	◯
	Ability	◯	◯
	Time	◯	◯
	Health	×	◯
Labors	Permanent work (PW)	◯	◯
	Freelance work (FW)	◯	◯
	Simple work (SW)	◯	◯
	Learning (LN)	◯	◯
	Leisure (LS)	×	◯
Efficiency‡	Money	×	◯
	Ability	×	◯

† ”◯” means that the element is integrated into the game model. ”×” means that the element is not integrated into the game model.
‡ Efficiency of increasing resources through activities.

TABLE II: Difference in composition elements between the Shin-Life Career Game (Original version) and the Shin-Life Career Game version2

This logic diagram is interpreted as follows. When ability resources, time resources, and health resources are input to permanent work (PW), freelance work (FW), and simple work (SW), money resources are output, and the player obtains money resources. For permanent work (PW), ability resources are also output, and the player's ability increases. When ability resources, time resources, and health resources are input to learning (LN), ability resources are output, again increasing the player's ability. When time and health resources are input to leisure (LS), health resources are output, and the player's health is restored. The last resource input/output to overload (OL) means that when time and health resources are input to permanent work, freelance work, simple work, and learning, health resources are reduced. A detailed description of each resource variable and each activity is left to the subsequent sections.

1) Resource Variable: In the following, we explain the resource variables according to the studies [12][21]. The resource variable has two properties.

The first property is whether a resource variable is extensive or intensive. Extensive resource variables are additive and competitively allocated in resource allocation. If a player allocates his/her extensive resources for one objective, the resources reduce. And then, there are fewer resources available to allocate for other objectives. On the other hand, intensive resource variables are multiplicative and allocated non-competitively in resource allocation. If a player allocates his/her intensive resources for multiple objectives at the same time, unlike extensive resources, his/her intensive resources have the same effect on all objectives.

The second property is whether or not there is an upper bound on the value of a resource variable. If there is no upper limit to the value of a resource variable, it means that the resource is able to increase without limit. On the other hand, if there is an upper limit to the value of a resource variable, it means that the resource is not able to increase beyond a certain level. Here, a resource variable with no upper limit on its value is called an unbounded resource variable, while a resource variable with an upper limit on its value is called a bounded resource variable.

In the Shin-Life Career Game version 2, a player has a total of four types of resources (money resource, ability resource, time resource, and health resource). Money resource corresponds to an asset in the real life. Human beings use monetary assets to support their lives. Money resource is extensive and unbounded. Ability resource corresponds to knowledge and skills for work in the real life. Human beings use their skills and knowledge to engage in labor and get paid for it. Ability resource is intensive and unbounded. Time resource corresponds to time for real life. Human beings live their lives by spending their time in a variety of activities. Time resource is extensive and bounded. Health resource corresponds to health or physical fitness for real life. Health and physical fitness are the foundation of real life. Health resource is intensive and bounded. Table III summarizes the characteristics of these resource variables.

2) Activity: In the following, we describe the activities of the agents according to the cited research [12]. In this game, the player allocates his resources to several activities (permanent work (PW), freelance work (FW), simple work (SW), learning (LN), and leisure (LS)) in each round according to the constraints of the game and his own will. The individual activities are described below. Table IV summarizes the definitions and characteristics of the various types of activities in the Shin-Life Career Game version 2.

Permanent work (PW) is a labor form in which workers are employed by an organization until they reach retirement age and receive remuneration for their labor. The characteristics of permanent work are described below. First, the remuneration for permanent work is stable. In reality, formal workers are

Resource Variables	Properties Extensive / Intensive	Upper limit	Descriptions
Money resource	Extensive	No	The variable of money resource corresponds to an asset in the real life.
Ability resource	Intensive	No	The variable of ability resource corresponds to knowledge and skills for work in the real life.
Time resource	Extensive	Yes	The variable of time resource corresponds to time for real life.
Health resource	Intensive	Yes	The variable of health resource corresponds to health or physical fitness for real life.

TABLE III: Properties of resource variables

Activity	Symbol	Definition
Permanent work	PW	Permanent work (PW) is a way of working in which a person is employed by an organization until retirement and receives remuneration for providing labor power.
Freelance work	FW	Freelance work (FW) is a form of work in which a worker is independent of a particular organization and is paid for providing specialized knowledge and skills to a contractor.
Simple work	SW	Simple work (SW) is a form of work in which a worker provides labor time to an employer or contractor and is paid for it.
Learning	LN	Learning (LN) is the act of taking extra time to develop one's skills in order to develop one's ability to do a job.
Leisure	LS	Leisure (LS) is an activity that workers set aside to restore their physical and mental health.

TABLE IV: Definition of activities implemented in the Shin-Life Career Game Version2

less likely to experience unemployment due to the effects of the economy than non-formal workers [22]. Second, the remuneration for formal labor is higher than that for simple labor. In reality, the income of full-time workers is much higher than that of part-time workers [23]. Third, as a player's ability resources increase, his/her rewards of permanent work become higher. In the personnel evaluation system of a company, it is customary to reflect the medium- to long-term accumulation of capabilities by permanent workers in the increase of their basic salary and the promotion of their qualification grade [24]. Fourth, engagement in permanent work increases a player's ability resources. Firms provide formal workers with education or special jobs that encourage their growth [25]. Fifth, a player needs to provide a certain amount of time resources for permanent work. In general, the law sets minimum and maximum working hours for permanent workers. Sixth, a player cannot decide the amount of time resources to be allocated to permanent work at will. In general, in formal employment, workers are obligated to engage in overtime and holiday work according to the orders of their supervisors.

Freelance work (FW) is a labor form in which workers are independent of a particular organization and is paid by providing expertise and skills to a contracted party. Freelance labor has the following characteristics. First, the income of workers who engage in freelance work is unstable. The income of actual freelance workers is unstable as well [26]. Second, as a player's ability resources increase, the reward for freelance labor increases. In the online job brokerage services used by real freelance workers, workers with high value-added skills have a chance to get high-paying jobs [27]. Third, a player's ability resources do not increase when the player engages in freelance labor. Employers spend less time on training self-employed workers than employees do [28]. Our model have not been designed to take into account the experience through freelance work based on the views obtained from interviews with a real freelance worker. But, it is debatable whether the experience of engaging in freelance work should be included in ability resource. Fourth, the player is free to decide the amount of time resources to be allocated to freelance labor. Since freelance workers do not have an employment contract, they do not have the obligation or responsibility to have their working hours controlled by others [29].

Simple work (SW) is a labor form in which workers provide their time to their employers or contractors and are paid for it. In this game, simple work is the kind of work that manual workers do in the real world, such as part-time jobs, day labor, and gig work, which do not require any special skills or qualifications. Simple work has the following characteristics. First, the reward (the money resource) increases in proportion to the amount of time resource the player allocates to simple work. In general, the wages of part-timers are determined by the length of time they work. Similarly, the wages of day laborers and gig workers are determined by the unit cost and number of jobs that can be completed in a relatively short period of time. Regardless of the type of labor engaged in, the longer the time spent in labor, the more the worker's income is expected to increase roughly proportionally. Second, the amount of players' ability resources does not affect the amount of compensation for simple work. In fact, many managers do not require part-time workers to have special job performance skills [30]. Third, the income of players who engage in simple labor is unstable. When economic conditions are favorable, the income of simple workers is stable, but when economic conditions worsen, simple workers' jobs are reduced or they are laid off [31]. Fourth, players' ability resources do not increase when the players engages in simple work. Many firms keep the training costs they pay for part-timers to a minimum [30]. Finally, workers have the flexibility to adjust their working hours to engage in simple labor. Workers who earn money from one-time jobs, such as on-call work or gig work, and part-time workers can flexibly manage their working hours [32].

Learning (LN) is the act of taking extra time to develop competencies in order to nurture one's work capacity. People who hold core positions in organizations and those who do business with expertise as freelancers engage in lifelong learning to develop the professional skills needed to maintain their employment status [33]. Self-employed individuals with unstable incomes devote more time to work-related learning than employees of firms [28].

Overload (OL) is an activity that involves an involuntary phenomenon in which agents automatically lose health resources in return for choosing to engage in these activities (PW, FW, SW, and LN). In general, overwork in labor and study impairs human health, which in turn leads to lower labor productivity and reduced effectiveness in learning. OL is not an activity to which the player directly allocates resources, but executes automatically as a consequence of the allocation of resources to activities (PW, FW, SW, and LN).

Leisure (LS) is an activity that workers engage in to restore their physical and mental health. In general, workers use their leisure time for rest and recuperation to maintain their health condition.

Based on the characteristics of each activity described above, equations (1) through (8) were designed to describe the relationship between input and output resources for the activities in the Shin-Life Career Game version 2 [12]. The following sections describe the characteristics of the changes in each output.

The amount of remuneration for permanent work is considered to increase monotonically in proportion to the product of the length of working hours, the amount of basic wage, and the level of a worker ‘ s ability (corresponding to Equation (1)). We set up Equation (1) from the following idea: the higher the basic wage, the more a employer pay permanent workers in his/her organization; the higher the level of permanent workers' professional competence, the more they earn; the longer permanent workers work, the higher their income is; and permanent workers are less likely to be dismissed if their health suffers unlike other types of work (as they are protected by law, and therefore their health status does not affect their income).

The ability of permanent workers is considered to increase monotonically in proportion to the product of the length of the working hours, the level of ability, the learning effect per working time, and the degree of influence from health conditions (corresponding to Equation (2)). We set up Equation (2) from the following idea: the better permanent workers are at learning through engagement in their work, the faster they grow; the higher the competence level of permanent workers, the more they grow on the job; the longer permanent workers are on the job, the more experience and educational opportunities they have, and the more they grow; and the worse permanent workers' health, the slower their growth.

The amount of remuneration for freelance work increases monotonically in proportion to the product of the length of working hours, the degree of influence from the worker's ability, the amount of the basic compensation per working time, health condition, but there is uncertainty in the income side. (corresponding to Equation (3)). We set up Equation (3) from the following idea: freelance workers earn more if they take on jobs with higher base compensation; if freelance workers have higher job skills, they can get higher-paying jobs and their income goes up; the more time freelance workers spend on a job, the more income they earn; freelance workers may not earn enough money due to unforeseen problems at work, or maybe lucky enough to get a job that pays well; and when freelance workers' health deteriorates, they cannot work efficiently and their income decreases.

The amount of remuneration for simple work is considered to increase monotonically in proportion to the product of hourly pay rates, the length of working hours, and the degree of influence from the state of health (corresponding to Equation (4)). We set up Equation (4) from the following idea: simple workers earn income more by working with a good basic wage; simple workers earn more if they work longer; and when simple workers' health deteriorates, they cannot work efficiently and their income decreases.

The degree of growth of a worker's ability is considered to increase monotonically in proportion to the product of the length of learning time, the learning effect per learning time, n power of learning cost, the level of working ability, and the degree of influence from health conditions (corresponding to Equation (5)). We set up Equation (5) from the following idea: the efficiency of workers' skill development depends on whether they are good at it or not; money supports the growth of workers (For example, it would be more effective to spend the same amount of time at a preparatory school and receive instruction from a professional teacher than to study for a qualification by oneself. However, the higher the amount invested in education, the more effective the education becomes, but at the same time, the worse the cost effectiveness becomes. The quality of lectures offered by prestigious universities that require students to pay very high tuition fees is not necessarily better than the quality of lectures offered by ordinary universities.); it is easier to grow if a worker's ability at the time of skill development is high (For example, if an expert software engineer and a beginner spend the same amount of time studying, the former will acquire much more knowledge and skills than the latter.); the more time a worker spends on skill development, the more he/she grows; and health status generally affects the efficiency of a worker's performance.

The degree of deterioration in health status is considered to increase monotonically in proportion to the time of the activity (corresponding to Equation (6)). The more a worker devote themselves to work and learning, the worse the worker ' s health becomes. This is expressed in Equation (6).

The degree of recovery of the health state is considered to increase monotonically in proportion to leisure time (corresponding to Equation (7)). The more time a worker take to rest, the better the worker's health becomes. This is expressed in Equation (7).

The degree of influence from the health condition will be influenced by the past health condition after a time delay (corresponding to Equation (8)). It takes a certain amount of time for ordinary people without medical expertise or skills to become aware of the deterioration of their own health condition. Equation (8) expresses this.

The values of each resource variable are updated in Equations (9) through (12). The variables and constants used in the equations are summarized in Table V. Range of values for resource variables is listed in Table VI. Each equation is explained the followings.

The amount of money resource in the latest round is determined by adding the amount of money resource obtained in the latest round to the amount of money resource in the previous round and subtracting the amount of money resource used in the latest round (see Equation (9)). A person's wealth can change depending on his/her financial situation.

The amount of ability resource is determined by adding the increase in ability resources in the latest round to ability resources in the previous round (see Equation (10)). Everyone grows after he/she has learned.

There is an upper limit to the time a worker can spend on activities (see Equation (11)). For any human being, time is finite.

The amount of health resource in the latest round are determined by subtracting the amount of decreasing health resource in the latest round from the amount of health resource in the previous round and adding up the amount of increasing health resource in the latest round (see Equation (12)). Real workers take care of the negative health effects of high-impact activities such as work by resting and treating illness.

$$I_{PW}(t) = c_{PW} \times A(t-1) \times T_{PW}(t) \quad (1)$$

$$G_{PW}(t) = \gamma_H(t) \times cg_{PW} \times T_{PW}(t) \times A(t-1) \quad (2)$$

$$I_{FW}(t) = \gamma_H(t) \times \epsilon_{FW} \times c_{FW} \times T_{FW}(t) \times A(t-1) \quad (3)$$

$$I_{SW}(t) = \gamma_H(t) \times c_{SW} \times T_{SW}(t) \quad (4)$$

$$G_{LN}(t) = \gamma_H(t) \times cg_{LN} \times T_{LN}(t) \times M_{LN}(t)^n \times A(t-1) \quad (5)$$

Symbol	Description
$M(t)$	Player's money resource as of round t
$A(t)$	Player's ability resource as of round t
$T(t)$	Player's time resource as of round t
$H(t)$	Player's health resource as of round t
$I_{PW}(t)$	Reward for PW in round t (money resource)
$I_{FW}(t)$	Reward for FW in round t (money resource)
$I_{SW}(t)$	Reward for SW in round t (money resource)
$G_{PW}(t)$	Reward for PW in round t (ability resource)
$G_{LN}(t)$	Reward for LN in round t (ability resource)
$H_{RCV}(t)$	Reward for LS in round t (health resource)
$H_{BRDW}(t)$	Penalty for activities (except LS) in round t (health resource)
$M_{LN}(t)$	Money allocated to LN in round t by a player (money resource)
$T_{PW}(t)$	Time spent working as a permanent worker in round t (time resource)
$T_{FW}(t)$	Time spent working as a freelance worker in round t (time resource)
$T_{SW}(t)$	Time spent working as a simple worker in round t (time resource)
$T_{LN}(t)$	Time spent developing ability in round t (time resource)
$T_{LS}(t)$	Time spent recovering health in round t (time resource)
$\epsilon_{FW}(t)$	A random number generated according to a continuous distribution whose probability density function is constant on a finite interval (α,β) and zero outside the interval.
$\gamma_H(t)$	Influence of health status on performance of each activity ($0 \leq \gamma_H(t) \leq 1$)
T_{MAX}	Initial value of a player's time resource (time resource, constant)
H_{MAX}	Initial value of a player's health resource (health resource, constant)
c_{PW}	Reward per unit time for PW (constant)
c_{FW}	Reward per unit time for FW (constant)
c_{SW}	Reward per unit time for SW (constant)
cg_{PW}	Growth per unit time for PW (constant)
cg_{LN}	Growth per unit time for LN (constant)
c_{BRDW}	Amount of health resources lost per unit of time (constant)
c_{RCV}	Amount of health resources recovered per unit time (constant)

TABLE V: Variables and constants composing Equations (1)-(12) (Reprinted from [12] and modified the table)

$$H_{BRDW}(t) = c_{BRDW} \times (T_{PW}(t)+T_{FW}(t)+T_{SW}(t)+T_{LN}(t)) \quad (6)$$

$$H_{RCV}(t) = c_{RCV} \times T_{LS}(t) \quad (7)$$

$$\gamma_H(t) = \begin{cases} 1 & (1 \leq t \leq 2) \\ \frac{H(t-2)}{H_{MAX}} & (2 < t \leq 40) \end{cases} \quad (8)$$

$$M(t) = M(t-1) + I_{PW} + I_{FW} + I_{SW} - M_{LN} \quad (9)$$

$$A(t) = A(t-1) + G_{PW} + G_{LN} \quad (10)$$

Range of values
$0 \leq M(t)$
$0 \leq A(t)$
$0 \leq T(t) \leq T_{MAX}$
$0 \leq H(t) \leq H_{MAX}$

TABLE VI: Range of values for resource variables

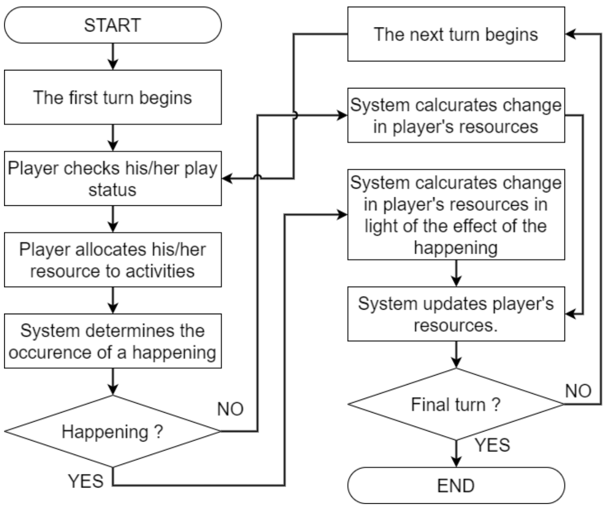


Fig. 2: Flowchart for gameplay (Reprinted from [12])

$$T(t) = T_{MAX} - (T_{PW} + T_{FW} + T_{SW} + T_{LN} + T_{LS}) \quad (11)$$

$$H(t) = H(t-1) + H_{RCV}(t) - H_{BRDW}(t) \quad (12)$$

3) Unexpected Happenings: The Shin-Life Career Game version 2 implements an event called an economic depression event. An economic depression event is a phenomenon designed based on real-world global financial crises such as the Lehman Bankruptcy and the Pandemic Shock. A player may experience an economic depression event. The occurrence of an economic depression event is unpredictable and occurs randomly in each round with a predetermined probability. When an economic depression event occurs, it affects the amount of resources the player allocates to various types of labor. The amount of time resources allocated to PW, FW, and SW is forcibly reset to the minimum amount, and all surplus time resources are allocated to LS. In this study, the minimum amount of time resources that a player can allocate to PW is seventy, and the minimum amount of time resources that a player can allocate to FW and SW is zero.

4) Instructions for Gameplay: In this section, we describe the procedure for playing the game (see Figure 2), referring to the description of the Shin-Life Career Game version 2. In each round, a player make decisions and allocate resources to activities. First, when a round starts, the player has the opportunity to check the game information (history of the amount of each resource, of the amount of resources allocated, and of the occurrence of economic recession events). At this phase, the player considers the policy of resource allocation for the current round and subsequent rounds. Next, the player allocates resources to each activity. After completing the screen operations for resource allocation, the game system updates the game information. At this time, if an economic depression event occurs, the effects of the event are reflected in the game information. Finally, the player is notified of the updating game information, and the round ends. Thereafter, the above procedure is repeated until the player has experienced all rounds.

III. DEA

DEA, proposed by Charnes, Cooper, and Rhodes in 1978, is an approach comparing the efficiency of organizational units such as local authority departments, schools, hospitals, shops, bank branches, and similar instances where there is a relatively homogeneous set of units[4]. In an analysis using the DEA, the observed input-output vectors are enveloped as tightly as possible using linear programming to measure the efficiency of decision-making units (DMUs) and compare the efficiency of DMUs with each other. As a result, each DMU is characterized by a reference set consisting of DMUs with more optimal efficiency. In addition, the envelope generated by connecting the reference sets reveals the relative positions of each DMU. In addition to empirical studies of organizational efficiency, the DEA has been applied to simulation studies such as optimization of production systems (e.g., [34], [35], [36], [37]).

In the following, we describe CCR model, which is the basic model of the DEA. In the analysis using CCR model, the following procedure is followed: first, the input and output of each DMU is observed and the data is collected; second, the weights of the input and output vectors of each DMU are optimized to obtain the efficiency; thirdly, which is then compared among DMUs; and finally, the inefficient DMUs are characterized by a reference set of DMUs with higher efficiency. One of the advantages of the DEA is that it automatically solves the problem of weighting when measuring the efficiency of multi-input multi-output systems.

In the following explanation, we denote the N DMUs to be evaluated by $DMU_j(j = 1, 2, \ldots, N)$. DMU_j has M input variables $\mathbf{x_{mj}}$ and L output variables $\mathbf{y_{lj}}$ that have already been observed. When these are described by matrix equations, they can be regarded as data stored in an M by N matrix X and an L by N matrix Y (see equations (13) and (14)).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & & \vdots \\ x_{M1} & x_{M2} & \cdots & x_{MN} \end{bmatrix} \quad (x_{mj} > 0 \quad (\forall j, \forall m)) \tag{13}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1N} \\ y_{21} & y_{22} & \cdots & y_{2N} \\ \vdots & \vdots & & \vdots \\ y_{L1} & y_{L2} & \cdots & y_{LN} \end{bmatrix} \quad (y_{lj} > 0 \quad (\forall j, \forall l)) \tag{14}$$

First, we briefly define the efficiency of the simplest input-output system with one type of input data and one type of output data; the efficiency when $M = 1$ and $L = 1$

is expressed by the following equation, and the system is evaluated as efficient in the order of increasing efficiency value.

$$Efficiency = \frac{output}{input}$$

More general input-output systems are characterized by multiple input terms, output terms, or both. The efficiency under such complex conditions is defined as follows

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs}$$

In the above definition, a set of weights should be defined, but this is difficult. In contrast, in CCR model, the efficiency of DMU_j, Θ_j, is formulated as the following fractional programming problem. By solving this fractional programming problem, the efficiency score of DMU_j can be easily obtained.

$<FP_j>$

$$\text{maximize} \quad \Theta_j = \frac{\sum_{l=1}^{L} u_l y_{lj}}{\sum_{m=1}^{M} v_m x_{mj}} \tag{15}$$

$$\text{subject to:} \quad \frac{\sum_{l=1}^{L} u_l y_{lj}}{\sum_{m=1}^{M} v_m x_{mj}} \leq 1 (j = 1, 2, \ldots, N) \tag{16}$$

$$v_m \geq 0 \quad (m = 1, 2, \ldots, M) \tag{17}$$

$$u_l \geq 0 \quad (l = 1, 2, \ldots, L) \tag{18}$$

In this case, since the weights $\mathbf{u_j}$ and $\mathbf{v_j}$ can be moved in any way, the value of the efficiency Θ_j also changes depending on the values of the weights $\mathbf{u_j}$ and $\mathbf{v_j}$, and is not uniquely determined. Therefore, after commonizing the upper limit of efficiency Θ_j at 1 ($\Theta_j \leq 1$), we select the weights $\mathbf{u_j}$ and $\mathbf{v_j}$ that maximize the value of efficiency Θ_j for each DMU_j. If DMU_j is efficient compared to other $DMUs$, the value of Θ_j is 1; conversely, if it is not efficient, it takes a value smaller than 1.

Here suppose that DMU_o is inefficient. Let the optimal weight of the input of DMUo is v^*, the one of the output is u^*, and the input-output efficiency calculated from v^* and u^* is Θ^*. If DMU_j ($j \neq o$) for which the left and right sides of the equation (19) are equal exists, DMU_j is called the reference set of DMU_o. This reference set E_o can be used as a reference to improve the efficiency of DMU_j.

$$E_o = \left\{ j \left| \sum_{l=1}^{L} u_l^* y_{lj} = \sum_{m=1}^{M} v_m^* x_{mj}, j = 1, 2, \ldots, N, j \neq o \right. \right\} \tag{19}$$

The optimization of efficiency in DEA that we have described so far is formulated as a fractional programming problem (see equations (15) through (18)). However, in practice, it is solved by converting it into an equivalent linear problem (see equations (20) through (24)).

$<LP_j>$

$$\text{maximize} \quad \Theta_j = \sum_{l=1}^{L} u_l y_{lj} \tag{20}$$

$$\text{subject to:} \quad \sum_{m=1}^{M} v_m x_{mj} = 1 \tag{21}$$

$$\sum_{l=1}^{L} u_l y_{lj} \leq \sum_{m=1}^{M} v_m x_{mj} (j = 1, 2, \ldots, N) \tag{22}$$

$$v_m \geq 0 \quad (m = 1, 2, \ldots, M) \tag{23}$$

$$u_l \geq 0 \quad (l = 1, 2, \ldots, L) \tag{24}$$

One of the advantages of using the DEA is that the problem of how to determine weights when comparing the efficiency of multiple-input multiple-output systems is automatically solved in the optimization process described above.

In the following, we will discuss DEA as a data classification method. As a methodology for data classification, DEA takes a different approach from distance-based classification methods such as cluster analysis.

In DEA, the reference set E of an inefficient DMU is a target that should be referred to in order to improve the efficiency of the DMU. Also, the reference set of an efficient DMU is itself. If we draw a scatter plot of DMUs in the space of input/output variables, the envelope of DMUs is formed by all the efficient DMUs (see Figure 3). The smallest convex region containing the efficient DMUs and the origin also contains the inefficient DMUs whose reference set is the efficient DMUs. Therefore, this set of DMUs is considered to share the same reference set and is classified into the same group.

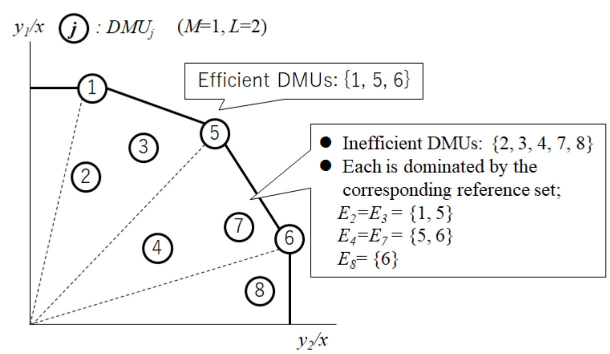


Fig. 3: Dividing the envelope by efficient DMUs (reference set) allows classification of inefficient DMUs by common reference sets. (Reprinted from the study by Kunigami et al.[38])

Kunigami et al. list two advantages of using the DEA as a classifier [38]. One of the advantages of using the DEA as a classifier is that the superiority and inferiority relationships between DMUs belonging to a certain group can be extracted mechanically and endogenously. When an analyst uses the DEA to optimize the efficiency of each DMU that has the same reference set, a set of DMUs with weight sets that are

Agent ID	Action #	Orientation	Allocated Resources †,*,**					Outcome‡		
			T_{PW}	T_{FW}	T_{SW}	T_{LN}	T_{LS}	M	A	H
A1	0	Money-making	RD^1_{PW}			Rest^2	Rest^2	+	(+)	+/-
A2	1	Money-making		RD^1_{FW}		Rest^2	Rest^2	+	(+)	+/-
A3	2	Money-making			RD^1_{SW}	Rest^2	Rest^2	+	(+)	+/-
A4	3	Money-making	RD^1_{PW}, RD^1_{FW}, or RD^1_{SW}			Rest^2	Rest^2	+	(+)	+/-
B1	4	Ability Development	RD^1_{PW}			Rest^2	RD^1_{LS}	(+)	+	+/-
B2	5	Ability Development		RD^1_{FW}		Rest^2	RD^1_{LS}	(+)	+	+/-
B3	6	Ability Development			RD^1_{SW}	Rest^2	RD^1_{LS}	(+)	+	+/-
B4	7	Ability Development	RD^1_{PW}, RD^1_{FW}, or RD^1_{SW}			Rest^2	RD^1_{LS}	(+)	+	+/-
C1	8	Enjoying Leisure	RD^1_{PW}			RD^1_{LN}	Rest^2	(+)	(+)	+/-
C2	9	Enjoying Leisure		RD^1_{FW}		RD^1_{LN}	Rest^2	(+)	(+)	+/-
C3	10	Enjoying Leisure			RD^1_{SW}	RD^1_{LN}	Rest^2	(+)	(+)	+/-
C4	11	Enjoying Leisure	RD^1_{PW}, RD^1_{FW}, or RD^1_{SW}			RD^1_{LN}	Rest^2	(+)	(+)	+/-

† RD_{PW}, RD_{FW}, RD_{SW}, RD_{LN}, and RD_{LS} are randomly determined in increments of 10, from 70 to 100, 50 to 100, 90 to 100, 50 to 100, and 50 to 100 respectively.

‡ "M" stands for money resource, "A" for ability resource,and "H" for health resource."+" means resource increase, "-" means resource decrease, and "+/-" means one of the two can happen. "(+)" means resource may increase.

* "Rest" is the maximum value of time resources available to the player in each round minus the total value of time resources allocated to other activities. For example, if software agent A1 first decides the amount of time resources to allocate to PWs, and then decides to allocate resources to LNs, all remaining time resources are allocated to LNs.

** The player performs resource allocation in two steps. First, the player executes the resource allocation action^1; if there are two actions with ^{1}, the player randomly executes one of them. Next, the player executes resource allocation action^2. If there are two actions marked with ^{2}, the player executes one of them at random.

TABLE VII: List of Resource Allocation Actions to Be Selected by Software Agents

similar in composition to each other is mechanically output. As a result, a relation representing the dominance of efficient DMUs belonging to a certain group (which is the reference set and has the optimal weight set) and other inefficient DMUs is endogenously extracted. This is an advantage in using the DEA as a classifier.

Another advantage of using the DEA as a classifier is that it is easy to determine the similarity of groups. The number of overlapping DMUs between DMUs belonging to two reference sets indicates the high degree of similarity between the two groups. The more reference sets in common between the two groups, the closer the two groups are.

IV. Demonstration

In this section, we explain how to conduct a demonstration experiment.

A. Gaming simulation

For this demonstration experiment, we decided to use the Shin-Life Career Game version 2. This game is a gaming simulation with a multi-input multi-output system. See Section 2 for details of the game.

B. Analysis Tools

To analyze the play logs output from the gaming simulation, we use CCR model, which is the basic model of DEA; for more information on DEA, see Section 3.

C. Participants

We made twelve software agents play the Shin-Life Career Game version 2 in place of human players. Each software agent chooses the same resource allocation rule for all rounds. The characteristics of each software agent's play policy and resource allocation rules are described below. In addition, Table VII summarizes the characteristics of the behavioral rules of the software agents.

Software agents A1, A2, A3, and A4 always choose money-making oriented behavioral rules. They always allocate resources to labor every round, and allocate the extra time resources to either learning or leisure. A1, A2, and A3 always engage only in a specific type of labor, while A4 randomly chooses one of the three types of labor in each round. Second, software agents B1, B2, B3, and B4 always choose growth-oriented behavioral rules. These software agents always allocate resources to learning each round, and allocate the surplus resources to either labor or leisure. When software agents B1, B2, and B3 choose to allocate resources to labor, they always engage in a specific labor only, while B4 randomly chooses one labor among the three. Finally, the software agents C1, C2, C3, and C4 always choose health-oriented behavioral rules. When the software agents C1, C2, and C3 choose to allocate resources to labor, they always engage in only one specific labor, whereas C4 randomly chooses one labor from among the three. These software agents always allocate resources to leisure each round, and allocate the surplus resources to either

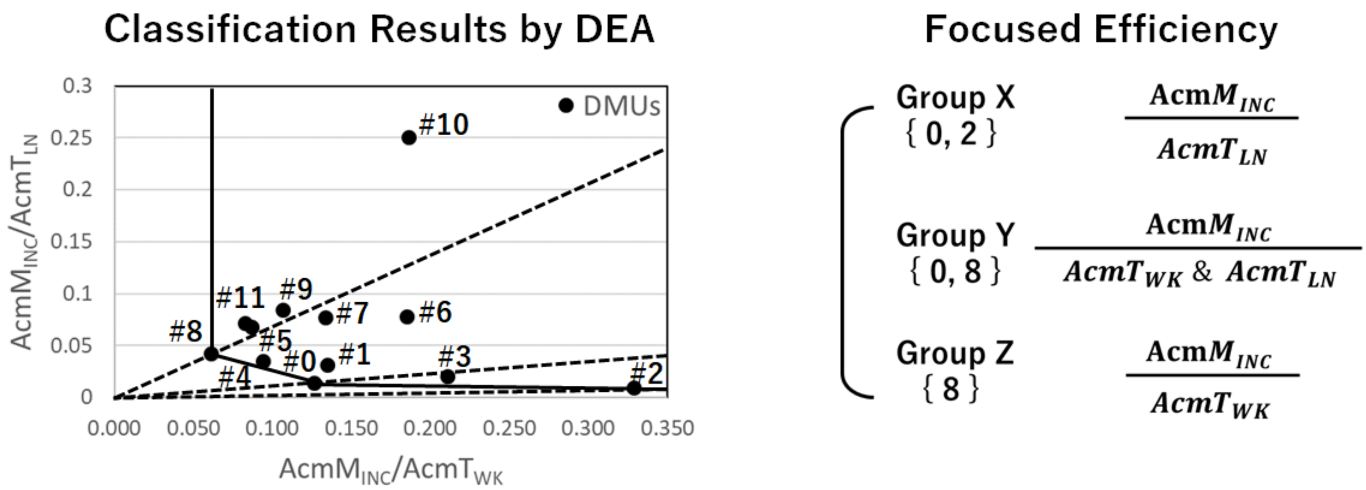


Fig. 4: Classification Results

labor or learning.

D. System

The software for gaming is written in python. The gaming simulation was carried out using Intel(R) core(TM) 4600U CPU @ 2.10GHz PC with 16GB RAM, Windows10 Pro, 64bit OS.

E. Procedures

The software agent was given 40 opportunities (rounds) to make a decision per gaming session. For each gaming session, the incidence of economic recession was fixed at 10 percent. In all gaming rounds, a common random seed and random number generator were used to determine the choice of activities for resource allocation by each software agent, the amount of resources allocated to each activity, whether an economic depression event occurred, and the FW reward correction rate. Each software agent played the game one time. The initial values of the parameters common to all gaming are listed in Table VIII.

Parameter	Initial Value	Parameter	Initial Value
$M(0)$	0	cg_{PW}	2.0E-4
$A(0)$	1	cg_{LN}	2.0E-4
T_{MAX}	100	c_{RCV}	2.8E-1
H_{MAX}	100	c_{BRDW}	5.0E-2
c_{PW}	5.5	n	0.50
c_{FW}	5.5	α	2.5E-1
c_{SW}	5.5	β	2.0

TABLE VIII: Initial values of parameters

V. RESULTS

The input and output data of each software agent are summarized in Table IXa. Basic statistics of input and output are summarized in Table IXb. Note that $AcmT_{WK}$ represents the accumulated value of time resources allocated to labors, $AcmT_{LN}$ represents the accumulated value of time resources allocated to learning, $AcmT_{LS}$ represents the accumulated value of time resources allocated to leisure, and $AcmINC$ represents the accumulated value of money resources acquired. In addition, a DEA tool pyDEA [39][40] was used to generate the following DEA results (See Table IXc).

According to Table IXc, the most efficient software agents (DMUs) were DMU#0 and DMU#8. The DEA also classified the play logs into Group X, Group Y, and Group Z. Group X consisted of only DMU#3 with DMU#0 and DMU#2 as the reference set. Group Y consisted of DMU#1, DMU#4, DMU#6, and DMU#7 with DMU#0 and DMU#8 as the reference set. Group Z consisted of DMU#5, DMU#9, DMU#10, and DMU#11 with DMU#8 as the reference set. The software agents (DMUs) belonging to each group are summarized in Table IXd.

The results of the analysis using DEA (Table IXc) are schematically summarized in Figure 4. As a result of the analysis by DEA, the value of the weight of the accumulated value of time resources allocated to leisure for all play logs was zero (this means that this factor has no effect on the evaluation of the efficiency of each play log.), so the data was plotted on a two-dimensional plane (see Figure 4). In Figure 4, multiple groups consisting of efficient DMUs (reference sets) and inefficient DMUs that refer to them are depicted. The similarity between the groups was easily determined by whether or not the reference sets were shared. Specifically, it was found that the similarity between Group X and Group Y, which share the common reference set DMU#0, is higher than the similarity between Group X and Group Z. Similarly, we found that the similarity between Group Y and Group Z with the common reference set, DMU#8, was higher than the similarity between Group X and Group Z. Therefore, we also found that Group Y is the group that was in the middle of Group X and Group Z.

DMU #	Agent ID	Gaming Result[†]			
		INPUT			OUTPUT
		$AcmT_{WK}$	$AcmT_{LN}$	$AcmT_{LS}$	$AcmINC$
0	A1	3.39.E+03	3.60.E+02	2.50.E+02	2.67.E+04
1	A2	2.62.E+03	6.10.E+02	7.70.E+02	1.94.E+04
2	A3	3.61.E+03	1.00.E+02	2.90.E+02	1.10.E+04
3	A4	3.29.E+03	3.20.E+02	3.90.E+02	1.56.E+04
4	B1	1.89.E+03	7.00.E+02	1.41.E+03	2.01.E+04
5	B2	1.23.E+03	9.50.E+02	1.82.E+03	1.41.E+04
6	B3	1.41.E+03	5.90.E+02	2.00.E+03	7.60.E+03
7	B4	1.32.E+03	7.60.E+02	1.92.E+03	9.86.E+03
8	C1	1.84.E+03	1.28.E+03	8.80.E+02	3.01.E+04
9	C2	1.63.E+03	1.28.E+03	1.09.E+03	1.52.E+04
10	C3	1.31.E+03	1.76.E+03	9.30.E+02	7.04.E+03
11	C4	1.64.E+03	1.41.E+03	9.50.E+02	1.97.E+04

[†] $AcmT_{WK}$ and $AcmT_{LN}$ are the accmulated value of time resources allocated to works (PW, FW, and SW) and learning, respectively. $AcmINC$ is the accumulated value of income (money resource).

(a) Gaming Results (Input-output data)

$Statics$	$AcmT_{WK}$	$AcmT_{LN}$	$AcmT_{LS}$	$AcmINC$
Mean	2.10.E+03	8.43.E+02	1.06.E+03	1.64.E+04
S.D.	8.86.E+02	5.01.E+02	6.16.E+02	7.22.E+03
Variance	7.85.E+05	2.51.E+05	3.79.E+05	5.21.E+07
Median	1.74.E+03	7.30.E+02	9.40.E+02	1.54.E+04
Max	3.61.E+03	1.76.E+03	2.00.E+03	3.01.E+04
Min	1.23.E+03	1.00.E+02	2.50.E+02	7.04.E+03

(b) Basic statistics of input/output data

DMU #	Agent ID	DEA Score Θ	Reference sets	Weights			
				INPUT			OUTPUT
				$v_{T_{WK}}$	$v_{T_{LN}}$	$v_{T_{LS}}$	u_I
0	A1	1.00	{0, 8}	2.38.E-04	5.38.E-04	0.00.E+00	3.74.E-05
1	A2	0.765	{0, 8}	2.50.E-04	5.66.E-04	0.00.E+00	3.93.E-05
2	A3	1.00	{0, 2}	1.21.E-04	5.63.E-03	0.00.E+00	9.12.E-05
3	A4	0.646	{0, 2}	5.51.E-05	2.56.E-03	0.00.E+00	4.15.E-05
4	B1	0.910	{0, 8}	2.88.E-04	6.51.E-04	0.00.E+00	4.53.E-05
5	B2	0.700	{8}	8.13.E-04	0.00.E+00	0.00.E+00	4.97.E-05
6	B3	0.436	{0, 8}	3.64.E-04	8.24.E-04	0.00.E+00	5.73.E-05
7	B4	0.510	{0, 8}	3.29.E-04	7.44.E-04	0.00.E+00	5.18.E-05
8	C1	1.00	{0, 8}	2.11.E-04	4.78.E-04	0.00.E+00	3.32.E-05
9	C2	0.571	{8}	6.13.E-04	0.00.E+00	0.00.E+00	3.75.E-05
10	C3	0.328	{8}	7.63.E-04	0.00.E+00	0.00.E+00	4.67.E-05
11	C4	0.736	{8}	6.10.E-04	0.00.E+00	0.00.E+00	3.73.E-05

(c) Analysis results by DEA

Groups	Reference sets	DMUs
X	{0, 2}	3
Y	{0, 8}	1, 4, 6, 7
Z	{8}	5, 9, 10, 11

(d) List of software agents (DMUs) belonging to each group

TABLE IX: Input-output data and basic statistics, and results of analysis by DEA

VI. Discussions

As a result of DEA analysis of the play logs obtained from the Shin-Life Career Game version 2, the play logs were classified into three groups, and the reference sets and DMUs composition of each group were revealed. The reference sets of each group can be used as a reference to improve the efficiency of inefficient DMUs belonging to the same group. In the following, we will clarify the structure of the evaluation criteria for each group and discuss what methods can be used to improve the evaluation of inefficient DMUs belonging to each group.

First, we discuss the experimental results for Group X. The value of the weights of $AcmT_{WK}$ ($v_{AcmT_{WK}}$) and of $AcmT_{LN}$ ($v_{AcmT_{LN}}$) of DMU#3 (inefficient DMU belonging to Group X) are both positive. However, the value of the weight of the former is about 2% of the one of the latter, and the effect of $v_{AcmT_{WK}}$ on the evaluation criteria is small. Thus, it was found that in Group X, DMUs were evaluated based on the efficiency of the accumulated income amount (output) relative to the accumulated learning time (input).

The criterion for evaluating the efficiency of DMU#2, the one of reference sets of group X, was similar to that of DMU#3. As in the case of DMU#3, the value of $v_{AcmT_{WK}}$ and $v_{AcmT_{LN}}$ in DMU#2 were both positive. However, the former was only about 2% as large as the latter. Therefore, the effect of $AcmT_{WK}$ is very small. In other words, DMU#2 was evaluated by DEA to be optimal in terms of its efficiency under the same evaluation criteria as Group X.

In contrast, the evaluation criteria for DMU#0, the other reference set of Group X, was different from the one for DMU#2. For DMU#0, the value of $v_{AcmT_{WK}}$ was about 44% of $v_{AcmT_{LN}}$. In other words, the effect of $AcmT_{WK}$ on AcmINC for DMU#0 was larger than the one for DMU#2. Thus, DMU#0 was highly valued by DEA as having made a lot of money despite the fact that the player had spent less time on working and learning.

Given the above discussion on Group X, we found that there were two options to improve the efficiency of inefficient DMU#3 belonging to Group X. The first option is to learn from the behavior of DMU#2 that performed better without changing its current policy on resource allocations. The second option is to modify the current policy on resource allocations by referring to DMU#0 and change it to one that takes into account the allocation of resources to both work and learning.

Next, we discuss the experimental results for Group Y. The values of $v_{AcmT_{WK}}$ and $v_{AcmT_{LN}}$ of the DMUs belonging to Group Y were both positive. The value of the former was about 44% of the one of the latter, indicating that the influence of $AcmT_{WK}$ and $AcmT_{LN}$ on $AcmINC$ was not negligible in both factors. Therefore, it was found that in Group Y, DMUs were evaluated based on the efficiency of $AcmINC$ with respect to $AcmT_{WK}$ and $AcmT_{LN}$. In other words, in Group Y, DMUs that earned a lot of money while spending less time working and learning through gaming were highly valued.

In contrast, the efficiency metric of DMU#8, the one of reference sets of Group Y, is different from that of Group Y. For DMU#8, the value of $v_{AcmT_{LN}}$ is zero, while the value of $v_{AcmT_{WK}}$ is positive. Thus, DMU#8 was highly valued because he made a lot of money through gaming, even though he did not spend much time on labor.

Given the above discussion on Group Y, we found that there were two options to improve the efficiency of inefficient DMUs belonging to Group Y. The first option is to learn from the behavior of DMU#0 that performed better without changing the current course of action. The second option is to change the current course of action by referring to DMU#8 and orienting to a more active allocation of resources to labor.

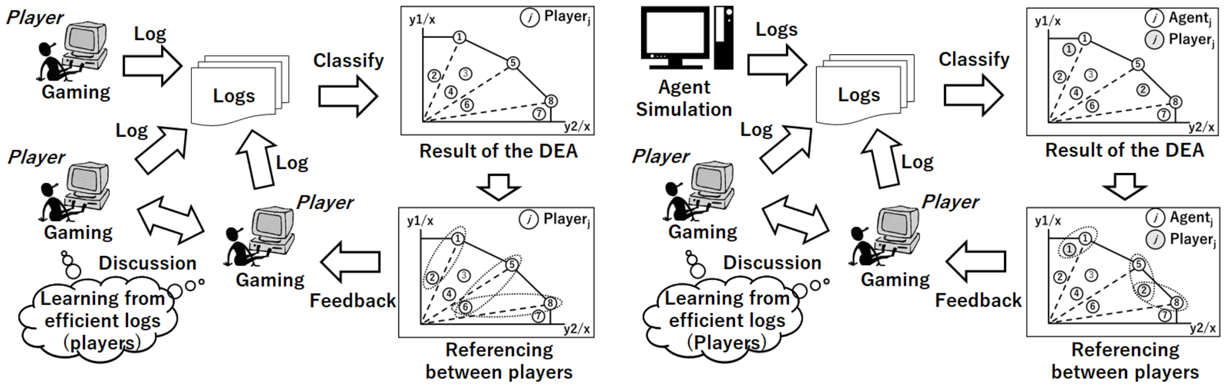
Finally, we discuss the experimental results for Group Z. The value of $v_{AcmT_{WK}}$ for DMUs belonging to Group Z was positive, while the value of $v_{AcmT_{LN}}$ was zero. Therefore, we knew that in Group Z, DMUs were evaluated based on the high efficiency of $AcmINC$ relative to $AcmT_{WK}$. In other words, in Group Z, DMUs that earned a lot of money through gaming, even though they spent less time on labor, were highly valued.

From the above discussion, by using DEA to analyze the 12 play logs output from the gaming simulation, it became clear which play logs were superior to other play logs under the same evaluation criteria. Based on the extracted knowledge, the facilitator can develop instruction that encourages players to improve their behavior. In addition, players can use the facilitator's guidance to narrow down the behaviors and performances of others in the game that they need to learn, and learn more efficiently (See Figure 5a).

As shown in the explanation of the example above, by applying DEA to the analysis of the play logs output from a gaming simulation, multiple play logs are automatically classified under various criteria, and the superiority or inferiority of the play logs within each group is revealed. Based on the above knowledge obtained from the analysis, facilitators will be able to provide specific guidance to players in debriefing to improve their behavior. And at the same time, the players will be able to focus on specific play logs to learn effectively and efficiently (see Figure 5a and Figure 5b). In order to propose a new analysis methodology, we have presented an example of analysis using a gaming simulation, the Shin-Life Career Game version 2, and DEA, but this analysis methodology can be applied to any gaming simulation that its players operate a multiple-input, multiple-output system, and the tools used in the analysis are not limited to DEA. In addition, this analytical methodology can be applied to both gaming simulations consisting only of humans and gaming simulations in which humans and software agents are mixed (see Figure 5a and Figure 5b).

VII. Concluding Remarks

In this study, we proposed a methodology to extract knowledge from the results of a gaming simulation that explains which play logs are superior (inferior) to other play logs under a specific objective function. In order to propose the new methodology, we had multiple software agents play the gaming simulation instead of human players, and analyzed



(a) Gaming simulation with only human players **(b)** Gaming simulation with human players and software agents

Fig. 5: Conceptual diagram of the proposed method: Play logs are collected in a gaming session with a large number of players, and DEA is used to identify the superiority or inferiority among the play logs, so that each player has the opportunity to learn from the play logs of players whose behavior is similar to and superior to his own.

the output multiple play logs with DEA to extract the desired knowledge. As a result, the desired knowledge was obtained. Finally, we proposed supporting players' learning of gaming by facilitators' presenting the extracted knowledge to players in debriefing.

In past research, it was pointed out that life simulation games such as the Life Career Game developed by Boocock and the Shin-Life Career Game developed by us may not express human decision-making problems in real life properly [19]. Munson et al. pointed out that the social properties and attitudes of players may affect the results of gaming simulations. Based on Munson et al.'s consideration, we are considering using the Shin-Life Career Game to analyze the relationship between the lifestyles of people who have proven to be successful in real life and the results of their gaming (input-output efficiency). We think that lifestyle of people is a reflection of their policies in their resource allocation in life. This new approach may provide a new answer to the long-standing criticism of gaming simulations.

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