Modeling Human Gaming Playing Behavior and Reward/Penalty Mechanism using Discrete Event Simulation (DES)

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Modeling Human Gaming Playing Behavior and Reward/Penalty Mechanism using Discrete Event Simulation (DES)

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Abstract

Humans are remarkably complex and unpredictable; however, while predicting human behavior can be problematic, there are methods such as modeling and simulation that can be used to predict probable futures of human decisions. The present study analyzes the possibility of replacing human subjects with data resulting from pure models. Decisions made by college students in a multi-level mystery-solving game under 3 different gaming conditions are compared with the data collected from a predictive sequential Markov-Decision Process model. In addition, differences in participants' data influenced by the three different conditions (additive, subtractive, control) were analyzed. The test results strongly suggest that the data gathered from the model can possibly represent the ones gathered from the human participants in a practical experiment.

Keywords
Discrete event simulation, game play behavior, game strategy

1. Introduction

The prediction of human behavior is something that is highly required in a variety of fields. Whether one is trying to determine the supply and demand of products in business or anticipate enemy movements in military strategy, being able to infer how humans will respond to future events can be very valuable. However, humans are remarkably complex organisms. Despite leaps and bounds of technological progress, much is still unknown about how the human brain operates. As such, predicting human behavior can be challenging. For example, how does a game player perceive the risks in order to decide what to do next? While it might be impossible to precisely model the details of an individual person's behavior, there are still methods that can be used to predict human behavior in an aggregate level, usually through statistical modeling and simulation.

The use of models exists in virtually every field of study, and has several noted benefits. The most prominent advantage of using models is its claimed ability to facilitate learning and better understanding, which is important when dealing with complex systems [1, 2]. Conceptual models can be used to convey the fundamentals of the system to someone who is new to the idea, as they are high-level, and should be relatively intuitive. Meanwhile, more complex models can be used to simulate the operation of a system. In the empirical case of modeling, simulation refers to the imitation of a real world system and its behavior over a period of time. This emulation is achieved by the use of a model that can serve as a suitable representation of the actual system. There are several different kinds of models, ranging from the very abstract to the very physical − each type having their own strengths and weaknesses. For example, more abstract models are generally less costly and quite easy to create, but tend to have issues with external validity. Conversely, physical mockups tend be of higher fidelity, but can be costly in terms time and money. However, with the rapid advancement of computer technology in recent years, discrete event simulation has become an increasingly prominent method used for imitation of real world settings [3].

Discrete event simulation (DES) stems primarily from mathematical modeling, which describes the given system in terms of state changes (e.g., entities entering or leaving a process) that occur at a specific instance in time [4]. Although this type of simulation can be done by hand, it is typically carried out with the aid of computer software. This is because when the processes are simulated with computer software, some of the validity issues that plague theoretical models can be mitigated more effectively. In a normal mathematical model, the system usually needs to be simplified in order for a person to be able to analyze it adequately. Unfortunately, most real world systems are rather complicated. As a result, such oversimplification can have an understandably detrimental effect on the validity of the model. Luckily, the capabilities of computers are such that the model can remain fairly complex, which allows for a model that can serve as a more realistic representation of the real world system [5]. A typical procedure for DES is illustrated in Figure 1.

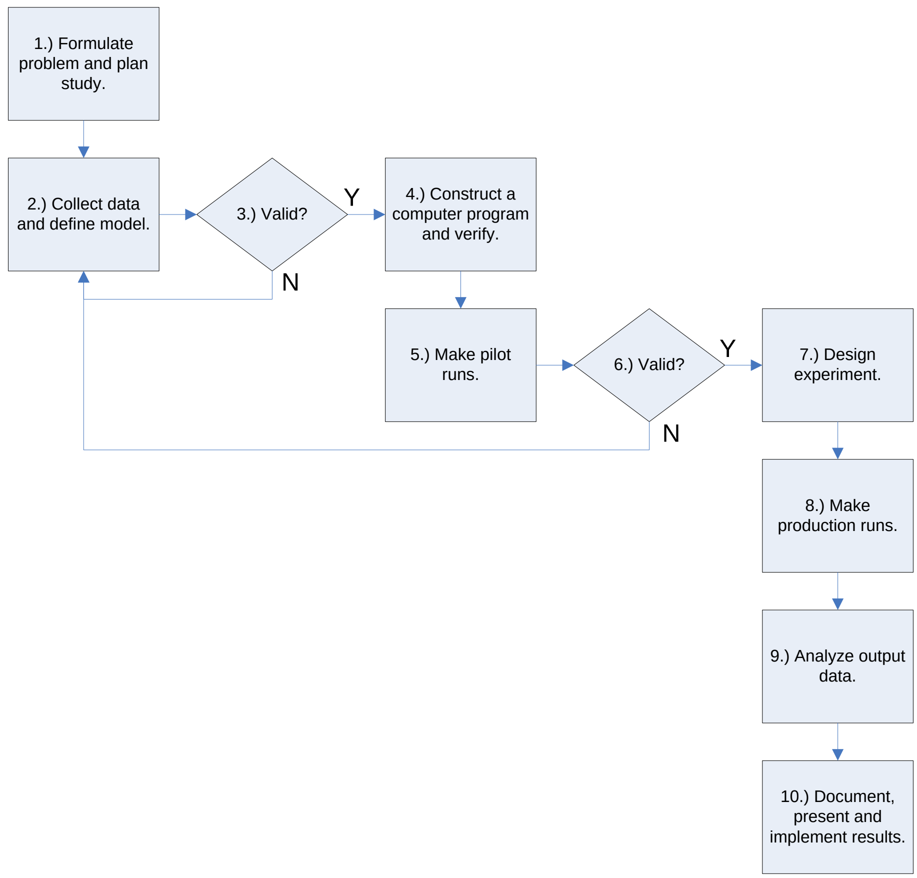

Figure 1: Steps to perform a DES study. Adapted from Law, 1991 [6].

Human game play is one of the complex behaviors that has been studied often [7]. In a game play, a player's ability is often thought to be the primary factor in determining an individual's performance. Other factors, such as motivation, have also had a substantial effect on people's performance. In a study of motivation on human performance impact, Anderson and Butzin [8] proposed a mathematical model in which performance was a function of both an individual's inherent ability and their motivation as well. However, what these effects are, and how they occur, still remains largely unknown. Motivation, itself, is generally broken down into two constructs: extrinsic motivation and intrinsic motivation. Extrinsic motivation refers to external rewards/punishments (e.g., money being given or taken away). Intrinsic motivation refers to things that can be gained or lost, but internally (e.g., feelings of pride or disappointment). For example, Harackiewicz and Manderlink [9] found that using performance-contingent rewards increased motivation, particularly for low achievers (extrinsic focus). Meanwhile, Fortier, Vallerand, and Guay [10] found that autonomous academic motivation had a positive effect on academic performance (intrinsic focus).

The effects of motivation on human behavior are more complex than any analytical model can capture. The effect of motivation on individuals are not uniform and varies a great deal among different people. For example, if a person is financially compensated to perform a task, it may generally be thought that they would have more motivation than someone who isn't offered financial compensation to perform the same task. Other research studies have found that providing incentives can sometimes even do more harm than good; prospective rewards/punishments might actually diminish an individual's intrinsic motivation. It has been argued that such incentives tend to start as reinforcement but are actually weak and short-lived. Results have suggested that these incentives can serve to lower a worker's perception of the given task and/or their own level of competence.

The mechanism and effect of motivation on game play behavior is still very limited. The complex nature of the game play behavior makes it a suitable subject for an empirical study using simulation. This study was intended to develop an empirical simulation model for aggregated game play behavior and investigate the effect of different motivation on game play participants' performance.

2. Method

An iOS-based (i.e., iPad) puzzle game called "100 Floors" was chosen as the game for this study, in which advancement was based on solving some visual challenge at each stage. Each level (or what's called a "floor" in the game) has a varying degree of difficulty. Sixty-nine undergraduate college students were recruited and given 30 minutes to progress as far as they could in this game. The extra credit for their class was used as the motivation for advancing the game level. The participants were randomly split into three groups (Control, Additive, and Subtractive). The control group received no cheats; participants had to solve the puzzles on their own to earn points. The additive group received 1 point after each successful completion of a level. They were also given one cheat at the start of each gaming session to aid the participant in advancing. The subtractive group were given 10 cheats (representing 10 total extra credit points) in the beginning of the game. For both groups, using a cheat would allow the participant to progress to a subsequent level (floor), but using said cheat would also deduct 1 point from the total extra credit the participant received in the beginning of the gaming session. Every participant was required to pass at least 7 levels in order to claim the class extra credits they had earned in their gaming session.

Upon completion of the experiments, each of these three scenarios was modeled in a discrete event simulation (DES) software, ARENA 14, developed by Rockwell Automation. Using data collected from the study, the model can be used to predict player behavior and strategies, including progression and the use of cheats. Data that was collected for each participant and used in the models included 1.) which floors participants used cheats on and 2.) the percentage of participants willing to use cheats or 3.) give up at each level. The total points earned and the final floor that they were able to reach served as the dependent measures for the model validation and experimental analysis.

2.1 Control Model

Figure 2 illustrates the model structure for the control group. In order to keep things simpler, only processes after the 10th floor were modeled, since that is the minimum requirements for receiving any extra credits. First, participants are "created" and a count is taken for passing Floor 1. A Decide module determines whether or not the participant will progress to the next floor based upon the pass percentage data collected for that floor. If the progression is true, the participant adds to the count of participants who reached Floor 2. If the progression is false, and the participant does not continue, then the participant leaves the system. This process repeats itself for all of the following floors until Floor 32 (the highest floor reached by the control group). It is important to note that the pass percentage for each floor wasn't based on the total number of participants in the group but on the number of people who had reached the previous floor. For example, even though the odds of someone making it to Floor 18 were about 24%, the percentage of people to continue from Floor 17 to Floor 18 was modeled 100%, because everyone who reached Floor 17 continued to Floor 18.

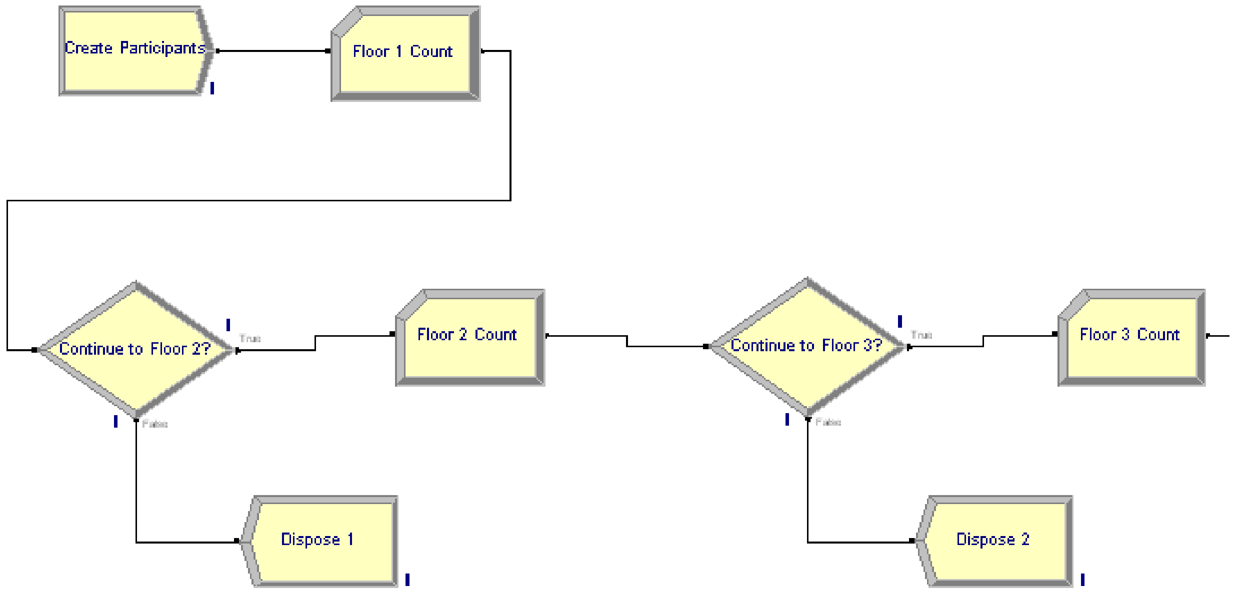

Figure 2: Model structure for the control group.

2.2 Subtractive Model

The subtractive model is based off the control group model, but has several changes. First of all, when participants are created, they are assigned an attribute that keeps track of how many cheats are still available and an attribute that keeps track of their score. The attribute for cheats remaining is initialized with a value of 10, while the attribute for score is initialized at 0 for each participant. The next changes of logic occurs after the Decide module which determines whether or not the participant will progress to the following floor. If the participant did not proceed to the next floor, then the participant's final score is recorded and exits the system; otherwise, they continue to the next level. At this point, the model checks to see if the participant has any cheats remaining. If there are no cheats remaining, the participant goes straight to the next floor to solve it on their own. If there are cheats remaining, the participant goes to another Decide module to determine whether or not they will use a cheat to pass the floor. This percentage to use the cheats was based off the data collected from human subject experiments, and this percentage varies with level of floors and the number of people who reached that floor. If the Decision is a 'yes' to use the cheat, the participant's remaining cheats attribute will be decremented by one, they will add to the count of cheats used on that floor, and they will add to the count of participants who reached that floor. If the answer is no, the participant will simply be added to the count of participants who reached the given floor. This model only went up to Floor 30, as that was the highest floor reached by the subtractive group. The ARENA model of subtractive model is illustrated in Figure 3.

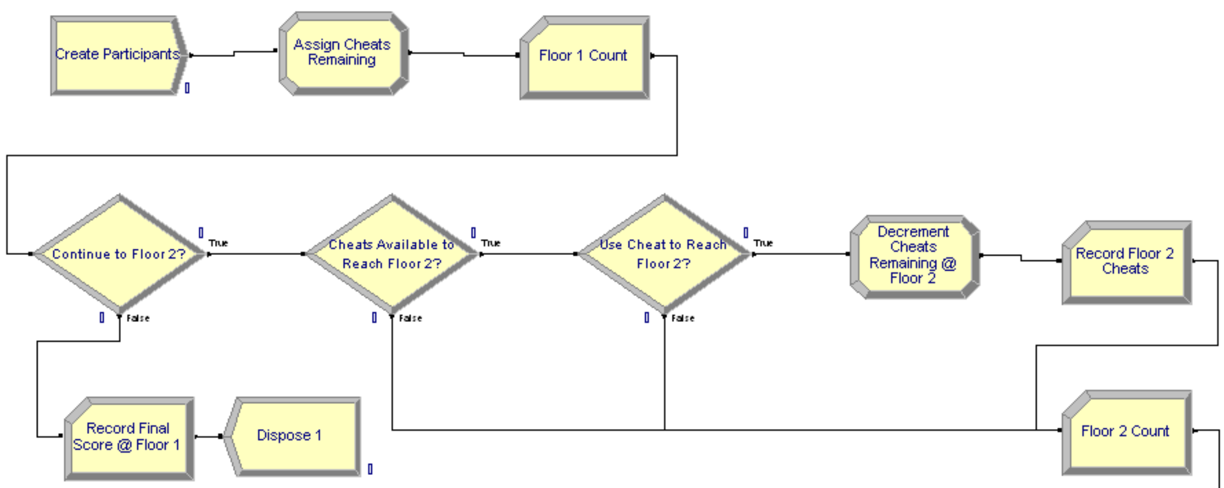

Figure 3: Model structure for the subtractive group.

2.3 Additive Model

The structure of the additive model is very similar to that of the subtractive model. Aside from the data used to calculate whether or not participants will progress or use cheats, there are three variations. First, the attribute for cheats remaining is initialized with a value of 1, instead of 10. Second, the attribute for each participant's score is initialized at 1, instead of 0. Finally, after every third floor (starting with Floor 4), the Decide module that checks to see if the participant has any cheats left is replaced with an Assign module which increments the participant's remaining cheats by one (see Figure 4). This continued until Floor 33, as it was the highest floor reached by this group.

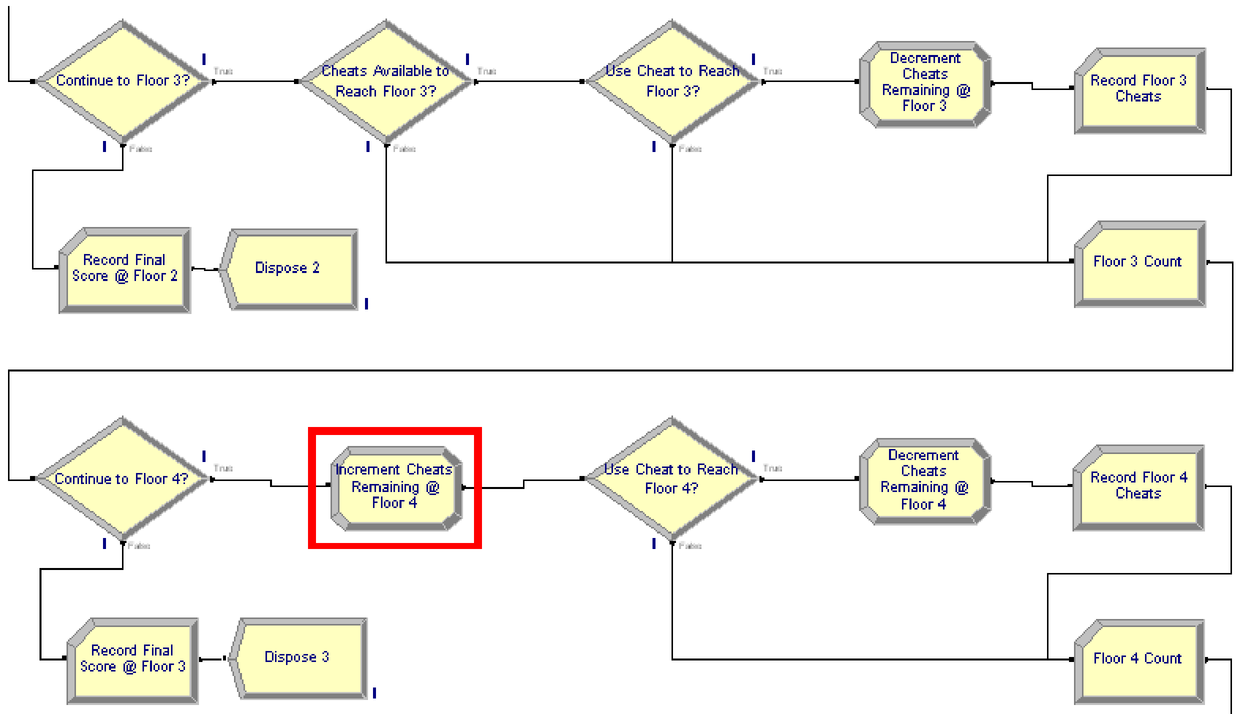

Figure 4: Model structure for the additive group. Note that the Assign module that replaces the Decide module every three floors has been highlighted with a red box.

3. Results

3.1 Model Validation

First, each model was validated by comparing statistics of the dependent measures (floor reached and total score) to those gathered from the models. For the subtractive and additive groups, the floor reached and final score were compared to validate the model. For the control group, only the floor reached was used as the dependent measure, as scores weren't present in the control group.

An independent samples t-test was conducted to determine if there was significant difference in the floors reached by the data collected from the subtractive experiment and the data collected from the subtractive ARENA model. Levene's test for homogeneity of variance was run and was significant, $F = 19.67$, $p < .001$. As such, equal variances were not assumed. No significant difference was found, $t(23.99) = -0.15$, $p = 0.885$. The same procedure was conducted for the final score. The Levene's test was significant ($F = 19.67$, $p < .001$), and the t-test was not significant, $t(24.10) = 0.55$, $p = 0.590$. This implies that two sets of results did not differ significantly.

The same independent samples t-test was run to validate the additive model, that is, to determine if there was significant difference in the floors reached by the data collected from the additive group and the data collected from the additive model. Again Levene's test for homogeneity of variance was found significant, with $F = 56.52$, $p < .001$, implying non-equal variances. No significant difference was found from the t-test, with $t(28.59) = 0.22$, $p = 0.831$. The same procedure was conducted for the final score. The Levene's test was significant ($F = 32.47$, $p < .001$), and the t-test was not significant, $t(28.14) = -0.769$, $p = 0.448$.

For the control model, an independent samples t-test was conducted to determine if there was a significant difference between the floors reached by the data collected from the control group and the data collected from the control model. Levene's test for homogeneity of variance was significant, with $F = 22.90$, $p < .001$. As such, equal variances were not assumed. No significant difference was found in the t-test, with $t(16.59) = -0.03$, $p = 0.974$. All three t-tests showed that the three ARENA models are valid in terms of the output from the model.

Experiment Results

With all simulation models being validated, an independent samples t-test was run to determine if a significant difference in the average final scores between the additive and subtractive groups for the model existed. Levene's test for homogeneity of variance was run and the result was not significant this time, which implies equal variance. With equal variances assumed, a significant difference was found between the average final scores of the additive ($M = 4.92$, $SD = 0.34$) and subtractive groups ($M = 8.88$, $SD = 0.39$), $t(58) = -41.92$, $p < .001$.

In addition, a one-way between-subjects analysis of variance (ANOVA) was conducted to determine whether or not there was a significant difference between the average final floors of the additive, subtractive, and control groups. A significant difference was found, with $F(2, 87) = 113.36$, $p < .001$. This was followed up with a Tukey's post hoc, which showed that the additive group ($M = 20.09$, $SD = 1.17$) had a higher average floor reached than both the subtractive ($M = 15.99$, $SD = 0.94$) and control groups ($M = 16.71$, $SD = 1.25$), both with $p < .001$. It was also found that the control group had a higher average floor reached than the subtractive group, with $p = .041$.

4. Discussions

It should come as no surprise that the subtractive group seemed to outperform the additive group, in terms of score, as seen in the results from the simulation model. Since the subtractive group only needed to reach the tenth floor to reach the maximum number of points. However, if one compares the groups according to progression through the game (average final floor), it can be seen that the additive group clearly did better than the subtractive group. Furthermore, the subtractive group was surpassed (in terms of progression) by the control group, who had no access to cheats. This would seem to suggest that the prospective extra credit was the key motivator; otherwise, participants in the subtractive group should have progressed just as far as, if not further than, the other groups, since they had a significant advantage over the other two groups given that they started with the most available cheats or extra credit. This is particularly interesting, since the amount of extra credit offered was so meager that it would most likely have no effect on a participant's final letter grade in their course. Regardless, participants appeared to value the score (extrinsic motivation) more than the satisfaction that may come from progressing through the game (intrinsic motivation).

From the simulated results, it does appear that external rewards, even minute ones, can indeed undermine an individual's intrinsic motivation, and by extension, alter their performance. However, the degree to which this effect occurs could still use further study. One might consider performing a similar study, but comparing the effects of different types and amounts of rewards. For example, how does performance differ when each point of extra credit is turned into a less nebulous reward, such as money? Also, how would their performance differ according to the size of the reward (e.g., each point of extra credit is changed to be a penny, a dollar, or ten dollars)? Alternatively, how would people respond if the game structure was, instead, more punishment focused? The effects of varying types and severities of punishments could be examined, as well.

5. Conclusions

Humans are complex and thus, to a point, unpredictable; however, this experiment demonstrated that accurate human behavior predictions can be achieved through simple models and simulations. The test results strongly suggested that the data gathered from the model can represent the ones gathered from the human participants in an experiment at an aggregate level. With a valid simulation model, it would make the experiment much easier since it might not need many real human participants, thus saving time and cost. However, there are several limitations with the model. One of the shortcomings of the simulation is that it ignores many of the individual factors in the game play strategy; some individuals are risk-seeking while others might be risk-avoidant. The models are not detailed enough to capture these factors, which makes the models only valid at a very high and abstract level. This is probably the reason that the variance is different from the human performance data and simulation data. These decision factors are very complex and certainly more basic research is needed to incorporate these factors into the simulation model.

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