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A HUMAN EXPERIMENT USING A HYBRID AGENT-BASED MODEL

Andrew J. Collins
Sheida Etemadidavan
Pilar Pazos-Lago

Department of Engineering Management and Systems Engineering
Old Dominion University
Norfolk, VA 23529, USA

ABSTRACT

Agent-based modeling (ABM) provides a means to investigate the emergent phenomenon generated from interacting autonomous agents. However, there are some concerns with this modeling approach. One concern is how to integrate strategic group formation, into ABM, without imposing macro-level aggregation rules. Another concern is whether the computerized agents' behavior is reflective of actual human behavior. Collins and Frydenlund developed a hybrid modeling approach to address the first concern in 2018. The focus of our paper is on the second concern, in the context of the hybrid model. An experiment was conducted to help determine whether a person's experiences affect their behavior and whether their behavior is similar to those generated by the hybrid model. The experimental results confirmed these two assertions. Our experiment used a standard cooperative game-theoretic game, called the glove game, as its base scenario.

1 INTRODUCTION

Agent-based models can give insight into macro-level phenomena through the modeling of the behavior of heterogeneous interacting agents at the micro-level (Epstein 2007; Miller and Page 2007). A classic example is Schelling's segregation model, where Schelling was able to explain why segregated neighborhoods still form even though the population showed a willingness to live in non-segregated communities (Schelling 1971). ABM differs from multi-agent modeling because its problems are rooted in real-world social systems, like the housing market, whereas multi-agent modeling focuses on the artificial environments to test software agents (Collins et al. 2015). As ABM is used to model social systems, it has been suggested that improving ABM's ability to model human behavior is an important next step (Cheng et al. 2016). Before we can improve ABM's ability to model human behavior, we must first know our starting point; that is, how do computerized agent's behavior compare to actual human behavior.

Our research aims to explore whether a heuristic algorithm for strategic group formation conforms to human behavior. This paper shows the initial results from an experiment to compare human behavior to those of simulated agents in the context of strategic group formation. Strategic group formation was chosen as our focus area, for behavioral modeling, because, we believe, that it represents another important future advance for agent-based modeling and simulation (ABMS): the ability to allow agents to form coalitions strategically; that is, in certain situations, agents work together because it helps them individually. Several algorithms have been developed that simulate strategic group formation within an agent-based simulation (Collins and Frydenlund 2018; Vernon-Bido and Collins 2020). These algorithms have been applied to different problem domains, including farming cooperatives (Collins and Krejci 2018) and group formation in minority games (Collins 2019). It is the latest version of these algorithms that we apply in our research, which we call the ABMSCORE algorithm.

The experiment, described in this paper, was created to compare the outputs from the algorithm to actual human behavior. Ligtenberg et al. (2010)'s validation approach to ABMS inspired our experimental approach. Ligtenberg et al. suggested that validation of an ABMS can be achieved by comparing its outputs to those generated by human participants role-playing the simulated agents. Thus, our experiment compares the decisions made by human participants to simulated agents in the context of strategic group formation. Each trial involves one human replacing a simulated agent with all other agents' behavior being governed by the ABMSCORE algorithm.

Traditionally, strategic group formation is modeled using cooperative game theory (Chakravarty et al. 2015). The ABMSCORE algorithm incorporates concepts from cooperative game theory into an agent-based model (Collins and Frydenlund 2018). This type of hybrid modeling is called enhancement (Brailsford et al. 2019). We believe that using the ABMSCORE algorithm within a hybrid model overcomes some of the computational issues associated with cooperative game theory. The ABMSCORE algorithm finds a reasonable solution much faster than solving a cooperative game numerically, though it is a heuristic (Vernon-Bido and Collins 2020). The ABMSCORE algorithm works by iteratively searching, in a stochastic manner, for better coalitions that a given agent can join.

We believe that our experimental approach advances hybrid modeling because it outlines a method to compare a hybrid simulation's outputs with human behavior. As Nav Mustafee points it: "a hybrid approach, a using game theory, and M&S will enable the development of models which may better represent the actors in a service system" (Eldabi et al. 2016). We believe that our hybrid modeling approach does just that, and our experiment is the evidence to support this claim.

The next section gives some background into the use of humans in experiments in game theory and agent-based modeling. A detailed description of our experiments follows the background section. The final sections discuss the implications of our results and conclusion.

2 BACKGROUND

This section discusses human experiments in the context of our hybrid modeling approach. Since our approach is a hybrid of cooperative game theory and agent-based modeling, we discuss each approach in turn. There was no other research found which combines both in an experiment, as we do in this paper.

2.1 Human Experiments in Cooperative Game Theory

Cooperative game theory is a type of game theory that focuses on games involving three or more players. Cooperative game theory, or n-person game theory (Shapley 1953; Rapoport 1970), studies self-interested agents' behavior when agents' can form coalitions (aka strategic groups), and binding agreements are possible between them (Chalkiadakis et al. 2011). There exists a small number of recorded human experiments that use cooperative game theory in the extant literature; we believe that this limited number is due to the difficulty of implementation because cooperative games tend to be complicated. In this section, we present some of the handful of works that conducted human experiments in the area of cooperative game theory.

In the literature, the authors have used human experiments, with cooperative game theory, as a catalyst to understand human behavior better. This usage differs from our research intent, which is to see if a cooperative game theory (hybrid) model actually models human behavior. The extant studies focus on several different phenomena: cost reduction, impacts of communication, and impacts of power. We will briefly discuss some examples of each in turn.

Beimborn (2014) used cooperative game theory to understand competing firms' willingness to use "shared-service processing in order to leverage economies of scale and skill." They used a bargaining game, a type of cooperative game, to study firms' behavior regarding merging similar processes. They used a human experiment to understand what aspect of their theoretical model was important in a real-world context. The study also looked at the impact of communication through the use of incomplete information.

Other studies that focused on the impact of communication include Murnighan and Roth (1977) and Bolton et al. (2003). The intent of both studies was to determine what circumstances affect strategic decision-making and are needed to reach a precise prediction of the outcome found through cooperative game theory. Murnighan and Roth (1977) used the shoe game in their research, which is a variation on the glove game that we use in our experiment. Bolton et al. (2003) considered five types of communication alternatives to see which one predicted the formation of the grand coalition.

Another use of experimentation using cooperative game theory is to investigate the impacts of power. Montero et al. (2008) conducted a human experiment to understand the effect of a player's power on the final player's payoff. Their experimental game was based on unstructured bargaining protocols to measure the power of voters in the voting environment. Their experiment tested the relationship between voting weights and voting power of players. These experiential results, from human players, conformed the power expectations predicted by the game theory model.

The examples of the use of cooperative game theory in a human experiment differ from our experiment in a number of ways. As previously mentioned, the intent is different, but also the experimental game design is different. Our hybrid model uses computerized agents which allows a larger number of players to be considered in each game; the studies discussed above used games of three players whereas we used games of upto seven players (with only one human-controlled agent). In our research, all players have equal roles in being able to form coalitions. We are not focused on the game's outcome but the differences between human and simulated agent behavior, from the rationality point of view.

2.2 Human Experiments in Agent-based Modeling

Agent-based modeling and simulation (ABMS) provides a natural step toward understanding and managing the complexity of today's business and social systems (Macal and North 2009). ABMS is applicable where the individuals and their interactions are a vital aspect of the system under consideration, like organizational psychology, supply chain, consumer market, etc. Researchers face three significant challenges when modeling human behavior in an agent-based model; these are (1) understanding humans, (2) data collection, and (3) validation & verification (Kennedy 2012). Gu et al. (2016) believed that to overcome some of the limitations of agent-based models, empirical data generated from human experiments are needed to ensure that the agent-based model delivers a rigorous and realistic outcome. There are a few studies that have incorporated human experiments into their ABMS development process; these studies come from a host of different application domains.

One use of human experiments is to support the validation of an agent-based model. For instance, in a supply-chain context, Utomo et al. (2020) designed a scenario-based questionnaire to extract participants' stated preferences, and they used this data to create behavioral rules; these rules were used to validate their agent-based simulation. Another example is Coen (2006), who studied human behavior in a social dilemma environment by conducting a human experiment. Their experimental results were used to validate their agent-based model. Their empirical study looked at how people make decisions while their simulation was used to explore which decisions (strategies) are more effective than others. In terms of consumer markets, Rouchier and Robin (2006) studied individual rational behavior in a competitive continuous double auction market environment. They were interested in investigating the effect of market price perception on an individual's strategies and collective behavior. As such, they built an artificial market and incorporated some observed laboratory data into an agent-based simulation. They used results from a behavioral experiment to validate the simulation. In the context of emergency evacuation, Lee (2009) studied characteristics of human behavior in decision-planning, decision-making, and dynamic learning to develop a comprehensive model of human decision architecture. They did a human experiment to use the data for the development and validation of their proposed model. Finally, they constructed an agent-based simulation to demonstrate, test, and validation of propose model and several factors which affect evacuation performance.

We used a computerized game in our human experiment; Gu et al. (2016) also used a computerized game in their research. They validated their agent-based simulation using data collected from an online computerized gaming human experiment. They used this data to show the efficiency of their model at the system level, and they used real human behavior data to enhance the model at the individual level. They were using an agent-based model to study the creation of value in the organization as a complex adaptive system based on evolutionary knowledge management. Also, they were capturing factors that affect human decision-making and organizational performance. The game configuration and flows follow the flows in their agent-based model, which is similar to what we have done. They believed that ABMS needs to learn from human experiments to make its models more robust and enable its models to more rigorously reflect human decision-making behavior.

Beyond validation, the outputs of human experiments have been used as inputs to the agent-based model development process. To model crowd panic, Ji et al. (2018) used agent-based model, human experiment, and theory to understand human behavior patterns. Their aim was to reveal a state equation to improve crowd safety by optimally designing room exits. In a traffic network context, Dal Forno and Merlone (2013) replicate human interaction. They ran a human experiment to collect different human behaviors when adding a new road to a traffic network. They used this collected experimental data to model different human behavior into artificial populations using ABM so that they could replicate human behavior in a non-homogenous human population.

In the discussed papers, researchers try to validate the result from ABM by conducting a human experiment and vice versa. We are simply trying to determine if the hybrid algorithm makes the simulated agents behave like humans; we are not making any validation claims in this paper.

To the best of our knowledge of human experiments in the literature, researchers have only used either cooperative game theory or ABM to get data and validate their results, while we have incorporated cooperative game theory into ABMS as a hybrid approach. Hybrid model can give a better understanding of the system (Eldabi et al. 2016). We believe that our approach will overcome the computational complexity of cooperative game theory and compensate for the lack of ABMS ability to reflect human decision making in the context of strategic coalition formation.

3 EXPERIMENT

Our experiment focuses on determining if there is a difference between human behavior and the behavior of our simulated agents, in the context of coalition formation. We are also interested in the differences between the coalitions formed by human agents and simulated agents; however, for this experiment, we focus on whether the human players' previous experience affects their behavior. The ABMSCORE algorithm governs the simulated agents' behavior. The algorithm creates coalitions amongst the agents in an agent-based simulation through agents suggesting and joining new coalitions.

In our experimental design, one of the simulated agents is replaced by a human player. The human player can suggest coalitions, and they can join coalitions suggested by the other agents. The simulated scenario is the glove game, a simple exchange economic game used in the study of cooperative game theory (Hart and Kurz 1983; Hart 1985). Our experiment was intended to determine whether human players respond in a similar way to computerized agents, i.e., does the human suggests coalitions that strategically is better for them? Do they accept invitations to coalitions that strategically make sense? We call an action strategic if it leads to an increase in utility for that decision-maker, at least in the short-term myopic sense. If the human player's behavior is similar to the computerized agents, governed by the algorithm, then this is an indicator that the ABMSCORE algorithm replicates human behavior, at least for the glove game and, potentially, in other scenarios.

The motivation behind this experiment is a desire to compare the ABMSCORE algorithm of coalition formation to actual human behavior. The ultimate purpose of the experiment was to examine the fidelity of the algorithm when compared to what a human player will do. This is important because identifying this similarity is a first step in building valid simulated scenarios that can be used to study strategic coalition formation.

An initial prototype of this experiment was conducted and reported in Saolyleh et al. (2019). This prototype revealed several issues on our original design: the glove game was too complex to be explained through a web interface, looking only at the end coalition structures did not give insight, and a lot more training games were required for participants to understand the glove game. As a result of these weaknesses, the prototype did not produce any meaningful or significant results. All these issues have been addressed in the experiment presented in this paper.

Though the glove game is simple, in cooperative game-theoretic terms, it was clear that some participants, in the prototype, did not understand the mechanics of the game without supervisory support. As such, a decision was taken to introduce a human moderator into an experiment protocol, who would follow a predetermined script. Also, more training games were included (going from three to five). Each trail was split into two phases; one phase where the experiment moderator explains the game and its rules to the single human player, and another phase where the human player interacts with the computer simulation.

During the computer simulation phase of each trial, the human player was presented with different glove games to play. The initial training games are relatively simple (involving a relatively small number of players) to test whether the player understands the game and its rules. The games increase in complexity as the trail progresses. The subject will end up playing seven games during the experiment, namely:

- Two verbally presented training games which visually represented by using a slide deck.
- Three computerized training games
- Two computerized games of interest

During the games, the actions of the human subject participants are collected for later comparison with human-equivalent simulated agents' choices in a similar situation. By human-equivalent, we mean that the simulated agent player has exactly the same initial conditions, i.e., the same initial endowment. By the same game, we mean that all the rules, the number of players, and the initial endowments are the same. Endowments in the glove game are the number of gloves that each player has at the start of the game.

Our human subject population consisted of a wide range of individuals, not just university students. The demographic questionnaire included two types of information: personal information like age, gender, level of education, and experience information like experience in game theory, video game, and board gaming. The experience information was measured by selecting from the following choices: "Never heard of" to "High" in game theory category and "None" to "Almost every day" in video and board games categories. In the result section, we will discuss how we measured the level of experience for each individual.

Our research hypothesis was that humans that played board games would behave more like what simulated agents do:

H_0: Playing board games regularly (have experience) has no impact on whether the human players will act like simulated agents.
H_1: Human players who play board gaming regularly (have experience) act and decide more like simulated agents than a human with no experience.

The next section describes the games used in the experiment and introduces some fundamental concepts of the experiments. The algorithms that govern the simulated agents' behavior are then described, followed by a discussion on the simulation environment used to generate the computational results.

3.1 Game Design

The game type used in our experiment is called the glove game, which was initially designed by Hart and Kurz (1983). The glove game is a simple exchange economy game where there are two commodities: left-hand gloves and right-hand gloves. This game was chosen because it is a game that involves coalition formation that is easy for the experiment participants to understand or, at least, less complicated than other cooperative games. An easily understood game is essential as the participants will need to learn the game in a short span of time.

The game involves the players forming coalitions to maximize their payoff from selling pairs of gloves. Each player starts with a different initial endowment of left-hand gloves and right-hand gloves. All the left-hand gloves are identical and, similarly, the right-hand gloves; however, only pairs of gloves are worth anything. The players in a coalition pool their gloves to form the maximum number of pairs, and the revenue generated is shared equally amongst the coalition members.

The coalition's payoff is the number of pairs of gloves the coalition has once all the gloves, from all players in the coalition, has been pooled. For simplicity, a pair of gloves was assumed to be worth one dollar. The member's payoff of the coalition is this total number of pairs divided by the number of members of the coalition. This payoff is a slight departure from the usual payoff for an exchange economy where the agents would get a payoff that is proportional to the number of necessary gloves they bring to the coalition; however, this approach would involve calculating a price system which, we felt, overcomplicates the game. The risk-neutral utility function for a given coalition "S" and member "a" is:

$$U(a,S) = {min\left(\sum_{b\in S} L(b), \sum_{b\in S} R(b)\right)}\Big/{|S|}$$

where L(.) is the number of left-gloves of a player, and R(.) is the number of right-gloves. Thus, each player of a coalition gets an equal share of the number of glove pairs sold as a payoff. Players cannot share the payoffs with other players; as such, we are considering the games of nontransferable utility (NTU).

A simple example is given to help the reader understand the glove game better. Consider a game with three players: X, Y, and Z. X has one left-glove and two right-hand gloves, represented as <1, 2>. Y has <5, 0> and Z has <0, 5>. If all the players formed the grand coalition {X, Y, Z}, then they would have six left-hand gloves and seven right-hand gloves, resulting in six pairs. As the profits are equally shared, each player would get two (dollars). If Player X choose to remain on their own (X), called the singleton coalition, they would have one pair to sell and no one else to share it with; thus, they would receive a payoff of one (dollar). If either player Y or Z chooses to remain in their singleton coalition, {Y} or {Z}, neither would have any pairs and would receive no dollars. If Y and Z joined to form a pair coalition, they would receive a payoff of 2.5 (dollars). The (core) to this game is {X} {Y, Z} using the core concept.

3.2 Simulation Design

The simulation recreates the game with computerized agents. The human player plays the role of one of those agents. The simulation endows the agents (players) in the game with a certain number of left and right gloves then recreates the dynamic process of coalition suggestion and its resultant decision. There are two decisions that needed to be simulated: coalition suggestions and acceptance of a suggested coalition. The coalition suggestions are based on a heuristic algorithm that tries to emulate the core concept form cooperative game theory. This ABMSCORE algorithm cycles through the following possibilities for the suggested coalitions: the coalition formed when an agent leaves their coalition to form a singleton coalition, the coalition formed when a coalition kicks out one agent, the coalition formed from two coalitions joining, the coalitions formed when a coalition splits, the coalition formed when a single agent joins a coalition, and the coalition formed when two agents form a new coalition. In all cases, the agent and coalitions under consideration are selected randomly. If the new coalition suggestion is acceptable to all the agents involved, then it forms (i.e., if all the agents in the new suggested coalition would see an increase their utility, then they will form a new coalition). The ABMSCORE algorithm was developed by Vernon-Bido and Collins (2020), which is an improvement on the algorithm developed by Collins and Frydenlund (2018). Others have used agent-based modeling to simulate cooperative game theory (Bonnevay et al. 2005), whereas the ABMSCORE approach enhances ABMS with cooperative game theory.

The simulation itself was built in NetLogo, an agent-based simulation engine (Wilensky 1999). A screenshot of the simulation is shown in Figure 1.

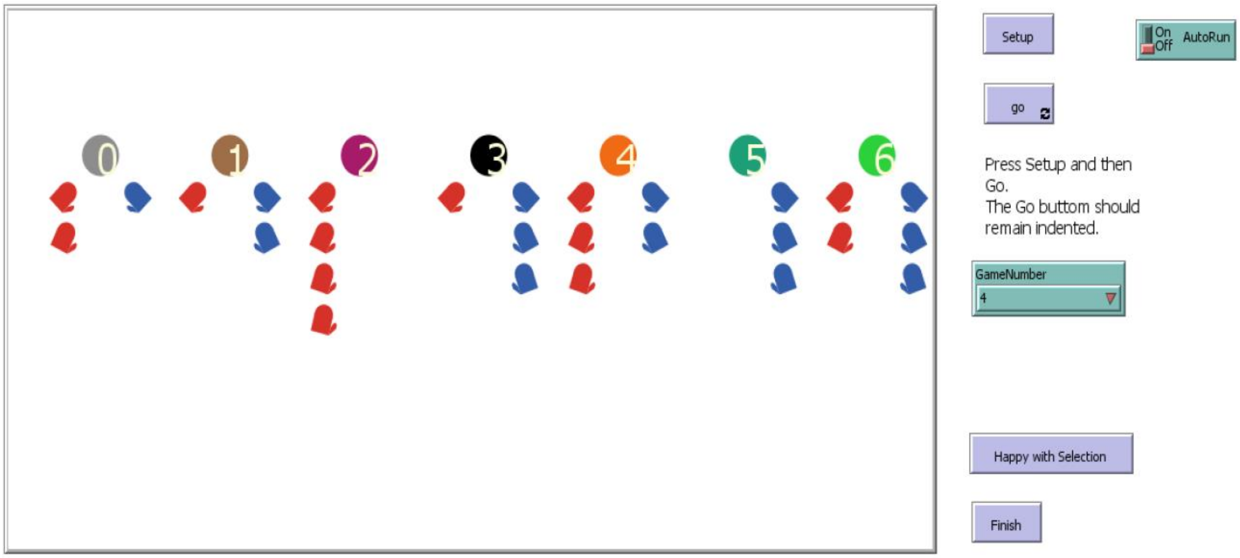

Figure 1: A screenshot of the simulation interface used in the experiment.

3.3 Data Collected

The data collected was whether human player decisions would be possible by the simulated agents. There are numbers of possible decisions that a human player could make during the game, and different types of data were collected for each:

- The decision to join a coalition offered to a human
  - Data Collected 1: Would the computerized agents make the same decision as humans to join the coalition or not?
- The decision on what coalition to suggest to the other simulated agent players
  - Data Collected 2: Would the computerized agents have made the same coalition suggestion?

Determining whether the computerized agent would have made the same decision or not is equivalent to determining whether the decision would increase the agent's utility. In each individual game, these two decisions could have happened multiple times, and the appropriate data points were collected for each.
As such, in the experiment's output (which was generated using a specially designed Netlogo model (Wilensky 1999)), we capture the consistency of human behavior with the simulated agent by a binary indicator. One indicates that humans and simulated agents behave the same in the same situation, and zero indicates that the human and simulated agents did not behave the same. Note that due to the game setup, each player will make multiple decisions per game, and the number of these decisions will differ between players.

4 RESULTS

As we mentioned in previous sections, we consider seven types of games, each with a different number of players, in a single trial. The first five training games were only used to see if the player understands the glove games and their rules; if the human player had experienced difficultly understanding the game, then their input was ignored; this was not the case in our experiment as all players readily understood the game.

The two final games are the games that analyzed their output; in each trial, we let the human player play each game for as many game rounds as they wanted; a game round is defined by a collection of coalition suggestions. A single round consists of one coalition suggestion by the human player and a limited number of coalition suggestions by the simulated agents. We felt that allowing the humans flexibility in the number of rounds they played made the experiment more realistic than restricting each player to play a certain number of rounds in the game.

In the data collection, we captured the consistency of human and simulated agent players by means of “does the human behave the same as a simulated agent in the same situation and vice versa?”. So, as we mentioned before, the main goal of this research is to help explore whether our heuristic algorithm for strategic group formation conforms to human behavior.

This experiment conducted by a population of 31 volunteers; each volunteer acted as the human player for one trial of all seven games. Conducting a simple descriptive analysis of the data, we found that the human’s decision was consistent with the simulated agents the majority of the time (239 of 297 decision data points).

The immediate next question is: what effects consistency? To investigate this, we looked at some of the demographic information of the players. Before each trial was conducted, we asked the human player to fill out a demographic survey, which included information questions on expertise in the game theory, video games, board games, and the glove game.

By reviewing the demographic survey, we understand that 13 out of 31 players played board games regularly, and 18 of them had never play board games or seldom played it. We classified the population of individuals into two groups based on frequency (experience) in board games. An experienced individual is a person who answered “sometimes,” “frequently,” and “almost every day” in the multi-choice question, and an individual with no experience is a person who chose “never” and “seldom.” Based on the characteristic of the problem of study and research assumption, a chi-square test was a suitable approach to check the significance between the two categorical variables, using contingency tables. The results of the chi-squared test are shown in Table 1.

Table 1: Results from a chi-squared test.

Board gaming experience	Human/Simulated agent consistent behavior	Human/Simulated agent, not consistent behavior
Experience	72	8
No experience	167	50
Chi-squared = 6.33	df =1	p-value = 0.01

The p-value gives us information about the evidence’s weight against the null hypothesis (Montgomery et al. 2009). We assumed a 95% confidence level, which means a p-value less than the significance level (0.05) implies that the null hypothesis would be rejected (Fisher and Yates 1938). The result from Table 1 shows a p-value less than this significance level. The statistical test shows evidence against the null hypothesis, which indicates that board game experience does matter. We decided to compare the percentage of consistent/not consistent behavior to reach a better understanding of the results. We used the bar chart in Figure 2 to show the percentage of behavior which is consistent/not consistent in each individual category (humans with/without experience).

The experimental result, illustrated in Figure 2, shows that humans with experience in board gaming have a more consistent behavior (90%) in contrast to humans with no experience in game theory (77%). The human behavior with/without experience in board gaming can behave like a simulated agent, but a human with experience are more likely to behave like a simulated agent. It means that the ABMSCORE algorithm can conform to actual human behavior in the context of strategic group formation because, in general, the total percentage of consistent behavior is higher than not consistent behavior. We conducted simple one-tail t-tests for both groups, and the results supported this finding.

However, there still exists humans without board gaming experience that behaves like a simulated agent and humans with a board gaming experience that does not behave like a simulated agent in a strategic group formation context. To make our findings more robust, we need to consider other variables that may affect the way a human makes a decision in a strategic coalition context. This has been left for future study.

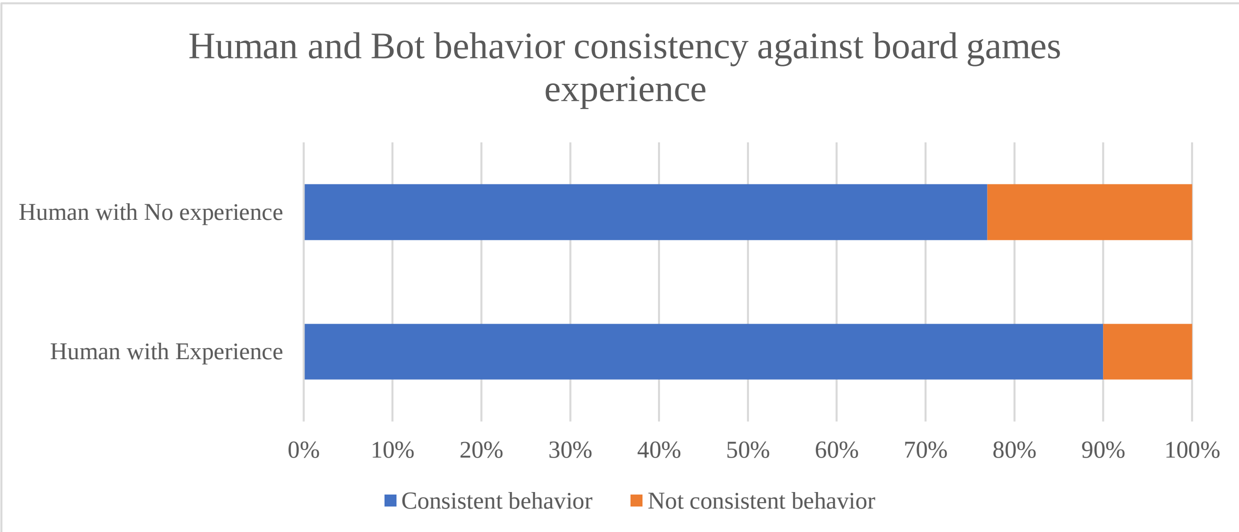

Figure 2: Consistency in human/simulated agent behavior with/without board gaming experience.

5 LIMITATIONS

In the time while our experiment was being conducted, the COVID-19 pandemic started. As such, we were required to conduct the experimentation using a teleconferencing approach instead of an in-person approach. Comparing the results, we did not notice any difference in the two data collections approaches (in-person vs. teleconferencing).

Another limitation is related to our data collection approach, in which we collect multiple behaviors data points from a single individual. That is, we have 297 data points from 31 individuals. This has the potential to introduce a bias in our data analysis because there is a clear interdependency between specific data points (of a given player). This bias could be overcome by introducing a single measure for each participant (e.g., percentage of consistent decision).

The effect of both these limitations could be reduced by collecting a larger sample size, which is the next step of this investigation. Due to the limitations described here, our results should be taken as a potential indication as opposed to definite conclusions.

6 CONCLUSIONS

This paper describes a human experiment, and its outputs, to investigate the difference between human behavior and those of simulated agents, in terms of coalition formation. The experimental approach involved humans playing the part of simulated agents in a series of glove games. The results indicate that there are slight differences between the human and the simulated agent's behavior. This difference was lower for human players that regularly play board games. The results did confirm that the humans were consistent with simulated agents for the majority of the time.

We believe that there exists a potential capacity to use ABM to investigate systems that involve strategic coalition formation. We believe that this paper represents the first step in demonstrating the validity of such an investigation.

Ideas for future studies include using different statistical tests and measures, for example, comparing the payoffs at the end of each game, that the human earned, with that of a simulated agent taking their place. This comparison could give insight into which type of player plays the game better. Other studies could employ a higher number of human players in the experiment to get more accurate findings from the experiment's outcomes.

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AUTHOR BIOGRAPHIES

ANDREW COLLINS is an assistant professor at Old Dominion University in the Department of Engineering Management and Systems Engineering. He has a Ph.D. in Operations Research from the University of Southampton, and his undergraduate degree in Mathematics was from the University of Oxford. He has published over 80 peer-review articles. His projects have been funded to the amount of approximately $9 million. Dr. Collins has developed several research simulations, including an award-winning investigation into the foreclosure contagion that incorporated social networks. His email address is: ajcollin@odu.edu. His website and full resume are at www.drandrewjcollins.com.

SHEIDA ETEMADIDAVAN is a Ph.D. student at Old Dominion University in the Department of Engineering Management and Systems Engineering. Her research interests are the use of agent-based modeling to explore enterprise-level problems. Her email is setemadi@odu.edu.

PILAR PAZOS-LAGO is an associate professor at Old Dominion University in the Department of Engineering Management and Systems Engineering. She received her Ph.D. from Texas Tech University (2005) in Industrial Engineering with a focus on Engineering Management and a minor in Applied Statistics from the Rawls School of Business. She also earned an M.S. degree in Systems Engineering from Texas Tech University. Her main areas of research interest are high-performance collaborative work structures, virtual teams, team decision-making, and collaborative learning. She has an extensive publication record and a funded research program in the areas of team research, collaborative learning, management information systems, and training. Her email is mpazosla@odu.edu.