A HYBRID SIMULATION MODEL OF HELPING BEHAVIOR

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ABSTRACT

Companies in a variety of industries rely on their employees to work together effectively in teams to achieve their objectives. However, finding ways to encourage collaborative behavior to optimize a team's performance is often challenging. In particular, managers would like to be able to increase the likelihood that team members decide to help each other, in the event of workload imbalances. In this paper, a hybrid simulation (ABM-DES) model has been developed to investigate how workers' predisposition to altruistic tendencies, an important personality factor, influences their willingness to help their co-workers on a production task. Model inputs were derived from experimental data, including participants' personalities, perceptions, and decisions regarding whether or not to help team members complete a task. Simulation results suggest that highly altruistic individuals are more likely to help their co-workers.

1   INTRODUCTION

The topic of how production workers' personalities affect team performance is generating increased interest among supply chain scholars. Manufacturing work cells are staffed with production workers who possess a variety of different personalities, and the speed and quality at which they perform job tasks and responsibilities varies as well. If proper attention is not given to these personality differences when addressing human resource staffing and management issues, the firm can be placed at a severe risk of not meeting manufacturing productivity and quality goals. Currently, however, the supply chain discipline lacks a full understanding of how to address the human resource challenges on how to identify, recruit, and motivate workers to become highly productive members on a manufacturing team.

   The research presented in this paper examines the extent to which a non-core team member is predisposed to act altruistically toward a core member of the team. Costa and McCrae (1992) and Cantor and Jin (2017) define altruism as "a trait [that] reflects the extent to which an individual is predisposed to exhibit an active concern for the welfare others; it captures an individual's innate selflessness." The literature further suggests that altruistic individuals are more willing to assist co-workers with no expectation concerning norms of reciprocity (Chattopadhyay and George 2001). The concept of norms of reciprocity refers to the belief that an employee will only help another co-worker because there is the expectation that the co-worker will in turn provide assistance to the original provider of help. The

altruism literature points out that individuals who are predisposed to act altruistically are not concerned with being compensated, rewarded, or acknowledged for their assistance (Morgeson et al. 2005; Prewett et al. 2009; LePine et al. 2011). We seek to contribute to the literature by examining manufacturing situations that would lead to increased levels of altruistic behavior.

To explore the effects of different personalities on team performance, Cantor and Jin (2017) empirically tested the extent to which behavioral and production factors impact helping behavior in situations out of a worker's own discretion (e.g., altruistic personality factor). Their research was motivated by insights from the organizational citizenship behavior literature, which suggest that firms can benefit when their employees are willing to help other workers complete unattended to or unstaffed tasks out of their own volition or discretionary behavior. The ***helping behavior*** theoretical construct has received substantial attention within the business management literature (Bachrach et al. 2001, 2006). Cantor and Jin (2017) described their experiment, which consisted of three workstations, each of which had its own set of: 1) five bins filled with tags that needed to be processed based on predefined orders, 2) five empty bins, 3) a device that processes the tags, and 4) five initial orders. Each participant was randomly assigned to a workstation and was given a set of 25 exogenous orders to complete. All three participants on the team were provided the same set of orders. To complete an order, each participant selected a tag from pre-filled bins, scanned the tag using the processing device, and then placed the processed tag into the corresponding storage bin. The participants were instructed to scan tags according to the predefined sequence specified on the order. Once the order was processed, the participant placed the processed order in the completed orders area and moved on to the next order in the buffer. Two workstations (A and B) operated such that a tag could be scanned in as little as one second, while the third workstation (C) could process a tag only after 12 seconds had elapsed.

Upon completing their 25 orders, the participants could choose to leave, stay and observe the remaining participants, or stay and assist the other participants. No compensation was provided to the participants at the individual or team level; therefore, if a participant decided to stay and help the others, it was assumed that this decision was intrinsically motivated. Data that was captured from the processing devices enabled the collection of measures of performance of interest, including the number of scanning errors, the team's throughput time, and whether or not the participants at workstations A and/or B decided to stay and help the participant at workstation C finish his/her task. Additionally, the participants were given pre- and post-tests to determine measures of their personality traits.

Rather than running additional experiments with human subjects to further investigate the role of the helping behavior construct on team performance, it was decided to develop a simulation model of the experimental setup, using empirical data collected from the original experiment as inputs to the model. The purpose of developing the simulation model was to provide new insight on how a production worker's predisposition to altruistic tendencies, an important personality factor documented in the social psychology literature, influences their willingness to help others on a production task. In so doing, a hybrid agent-based simulation model was developed based on the organizational behavior literature. The specific research question examined in this study is: Do workers who possess a greater predisposition of altruistic personality characteristics exhibit higher levels of helping behavior?

This study makes several contributions to the simulation modeling and supply chain literatures. To the best of our knowledge, this is the first hybrid simulation study that explores how a personality factor predicts helping behavior in a production setting. Prior management research has identified that helping behavior is an important issue in teams (Bachrach et al. 2001, 2006; Podsakoff et al. 2014). However, we are unaware of any research in the simulation modeling literature that addresses the theoretical concept of helping behavior. Therefore, this study contributes to the simulation modeling literature by demonstrating the value of this methodology to the broader behavioral supply chain management discipline. The paper organization is as follows. Section 2 describes the choice of methodology to develop this simulation

model. Next the hybrid simulation model is described, followed by experimentation and results. In Section 5, conclusions from this work and the directions of future work are presented.

2   SIMULATION METHODOLOGY

Discrete event simulation (DES) has been widely used to model the flow of materials in manufacturing operations (see Jahangirian et al. 2010 for a review). In DES, entities are passive objects, and their behaviors are predefined by the modeler (Behdani 2012). However, real-time adaptive decision making by a worker is difficult to realistically incorporate into a DES model (Dubiel and Tsimhoni 2005). In order to integrate human decision making, DES can be combined with an agent-based model (ABM) to form a hybrid simulation (Huanhuan et al. 2013). ABMs simulate unique and autonomous agents that interact with each other and their environment locally (Railsback and Grimm 2012). The agents in an ABM are capable of making complex decisions while engaging in interactions with other agents and objects within their environment. ABM also gives agents the capacity to "learn" from their environment over time and adapt their behaviors accordingly to meet their design objectives (Wooldridge 2002).

Until recently, however, DES and ABM have mainly been used in isolation. In particular, DES has been widely used in manufacturing settings to evaluate system performance (Helal 2007). By contrast, ABM is more commonly used to model organizational behavior (Harrison et al. 2007; Fioretti 2012) and teamwork in which material flows are not explicitly represented, such as design processes in engineering teams (Crowder et al. 2012; Martinez-Miranda and Pavon 2012). However, researchers are increasingly combining these techniques to develop hybrid simulations, which leverage each individual methodology's strengths and enable the analysis of systems that could not be realistically modeled using a single approach (Powell and Mustafee 2014). Hybrid simulation integrates the benefits and capabilities of both modeling methodologies, allowing the modeler to capture the fundamental elements and behavior of the system (Mittal and Krejci 2015; Mittal 2016). For example, Pawlewski and Kluska (2016) developed a hybrid simulation model for assembly line balancing in which DES was used to capture the flow of materials in a bus production plan, and ABM was used represent the assembly operations of the individual workers. Rojas-Villafane (2010) integrated ABM with DES to assess the impacts of team composition, coordination mechanisms, and task characteristics on coordination costs and team performance (e.g., project completion time). Hao and Shen (2008) developed a hybrid ABM-DES model in which DES was used to model a pull-based production line, and ABM was used to model an intelligent kanban-based material handling system.

This paper describes a hybrid ABM-DES model that uses DES to model the flow of tags from the input bins (i.e., queues) to the workers (i.e., resources) and finally to the output bins, and uses ABM to represent the workers' process of deciding whether or not to help each other. DES, which enables the modeling of system state changes at discrete points in time, was well-suited to modeling the flow of the tags. ABM provided a straightforward means of modeling each worker's dynamic and adaptive decision-making process, based on their memories of past events and their observations of other worker agents and the manufacturing environment. In this preliminary hybrid model, ABM serves as a proof of concept for future models that could incorporate more robust empirical agent interaction, whereas a single-method approach with DES would have limited future opportunities to incorporate agent interaction.

3   HYBRID MODEL DESCRIPTION

The hybrid model described in this paper was developed using AnyLogic. Figure 1 shows the relationship between the DES model and the ABM. The DES outputs worker processing rates and worker progress metrics, which the agents in the ABM observe and record. These observations inform the agents' helping decisions. If an agent decides to help, the logic that determines the flow of the tags in the DES model is updated such that tags from workstation C's queue are diverted accordingly. In this section the ABM will be described in detail, followed by a description of the DES.
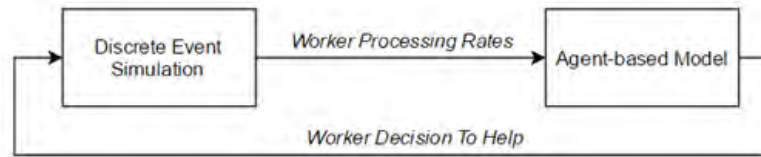
Figure 1: The hybrid simulation (ABM-DES) framework.

3.1 Agent-Based Model

The ABM will be described using the ODD protocol (Grimm et al. 2010). First, an overview of the ABM is provided:

Model purpose – This model seeks to explore the possibility of increasing helping behavior in teams when there is a workload imbalance between members of the team. The possibility of increased helping behavior is investigated by leveraging the inherent characteristics of each individual member rather than incentivizing the decision to help. This will allow experimentation to test the impacts of on helping behavior, with the goal of decreasing throughput time and optimizing team performance.

Entities, state variables, and scales - There are three worker agents (representing the three team members of the experimental setup), and each worker is assigned a role. Workers A and B are team members that process their own assigned tags without any additional responsibilities. These agents are identical in assignment and design. The third worker, Worker C, is the "core member" of the team and is responsible for any extra work that accumulates (e.g., if another team member is absent). Workers A and B have the ability to help Worker C with its additional responsibility once they have completed their assigned tasks. The process for deciding to help is identical for Workers A and B. Worker C does not help Worker A and B, as it is already assuming additional responsibilities. It is assumed that all team members operate within a reasonable line of sight from one another, and it will become self-evident through information cues that the core team member requires assistance from the non-core team members. Further, based on the results from the empirical study, it is assumed that feelings of sympathy for the core worker will tend to manifest among non-core team members who possess higher levels of altruism, increasing the likelihood that they will decide to offer to help the core worker.

Three state variables define the attributes of the worker agents: altruism, memory, and utility. Altruism is defined as a personality trait that demonstrates a person's agreeableness and willingness to do things for others (Costa and McCrae 1992). In the model, altruism is defined on an integer scale from one to five, where five represents the highest possible level of altruism and one represents the lowest. An agent's altruism level is assigned when the model is initialized, and it is assumed that this value does not change over the course of the simulation. Memory is what each helping worker refers to when they reach the point of making the decision to help. This memory is the average of the three most recent observations made by the worker. The workers make observations every 10 seconds, so the agent has 30 seconds of memory to reference. This is consistent with the literature on human decision making and memory, as the length of short-term memory for observations in humans is around 30 seconds (Cowan 2001). Utility for each agent represents the agent's overall level of satisfaction and is represented by a function that is defined on a scale from zero to one. This function is a weighted sum, in which each weighted component of the function represents an individual element of the agent's satisfaction.

Process overview – An overview of Worker A's decision process is shown in Figure 2.
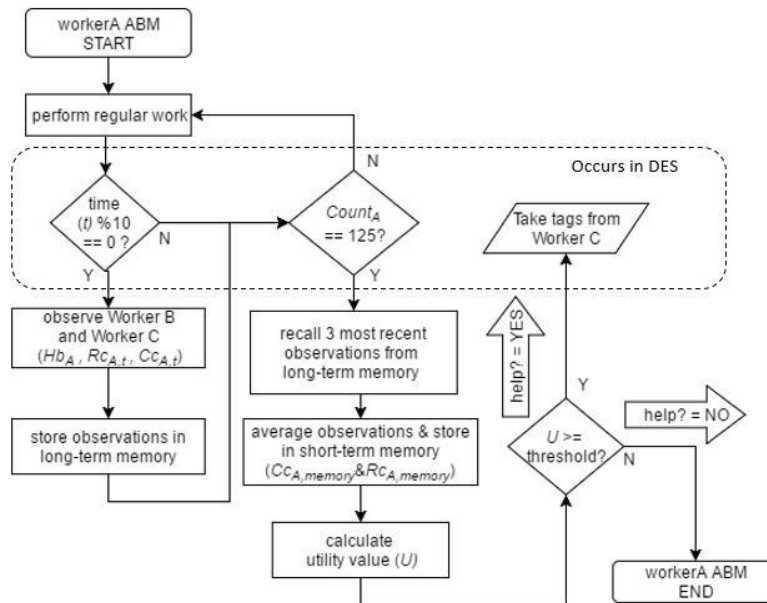

Figure 2: Flowchart of the ABM for Worker A.

As Worker A proceeds to scan the tags in its queue of "regular work", its long-term memory is updated based on the outputs of the DES model. New observations from the DES model are captured every 10 seconds and stored in Worker A's long-memory. After Worker A finishes the work that is in its own queue, Worker A's short-term memory is updated with the average of the three most recent observations stored in the long-term memory. Worker A then decides whether or not to help Worker C. The decision to help is based on the value of Worker A's utility at the time it finishes its own work. If this value is greater than the threshold value, Worker A will decide to help; otherwise, it will decide not to help. Worker A's utility value depends on the values of four different components: its own individual altruism level, whether Worker B has decided to help Worker C, Worker C's processing rate with respect to Worker A's processing rate, and Worker C's percent completed work with respect to Worker A's percent completed work.

Next, the relevant design concepts of the ABM will be described:

Interaction: The interaction between agents occurs when Workers A and B decide to help Worker C and remove tags from Worker C's queue to process.

Stochasticity: The stochastic elements of the ABM are Worker A's and B's decisions to help Worker C, based on their utility values. Worker A's and B's decisions to help are dependent on the other worker's stochastic decision (e.g. Worker A's decision depends on Worker B's decision and vice versa), which are both dependent on identical but separate utility value calculations.

Observation: Worker A periodically observes Worker C's processing rate and then stores that rate in its memory.

Initialization – The model starts at time t=0 and the worker observations begin at t=0. All datasets and variables are initialized immediately.

Input – Outputs from the DES model, including worker processing rate and completion percentage, the number of tags processed by each worker, and the total number of tags processed by the team, are direct inputs to the ABM.

Model outputs – The ABM outputs the results of the decisions of Workers A and B to either help or not help Worker C upon completion of the work in their own respective queues.

Submodels – There are five submodels within the ABM: 1) Utility from individual altruism, 2) Utility from helping sequence, 3) Utility from relative processing rate, 4) Utility from relative percent completed work, and 5) Decision to help. The state variables and decisions of Workers A and B are determined in these submodels. However, for clarity, the submodels are described with respect to Worker A.

1. *Utility from individual altruism*: The utility that Worker A gains from its own individual altruism ($uAlt_a$) is calculated in this submodel. It is a function of its individual altruism (ALT_A), which takes on an integer value between one and five that is assigned at the start of the simulation and remains fixed. This value is then multiplied by 1/5 to represent a linear relationship between ALT_A and $uAlt_a$.:

$$uAlt_a = \frac{1}{5} * ALT_A \tag{1}$$

2. *Utility from helping sequence*: The value of the utility that Worker A gains from Worker B's decision to help/not help Worker C (uHb_a) is determined in this submodel. It is assigned a value of either 0.74 (if Worker B decides to help) or 0.26 (if Worker B does not help). These values were determined from experimental data showing that when one worker helps, the conditional probability that the other worker will help is 0.74 (Cantor and Jin 2017).

$$uHb_a = \begin{cases} 0.74, & Worker\ B\ helps \\ 0.26, & Worker\ B\ does\ not\ help \end{cases} \tag{2}$$

3. *Utility from relative processing rate*: The value of the utility that Worker A gains from Worker C's processing rate relative to its own (uRc_a) is calculated in this submodel. If Worker A perceives that it is on a level playing field with Worker C (i.e., they have similar processing rates), Worker A is more likely to help. However, if the difference in their processing rates is too large, two cases can arise: 1) Worker A's processing rate is much slower than Worker C's, such that Worker A perceives that Worker C is capable of handling its work without assistance, or 2) Worker A's processing rate is much faster than Worker C's, such that Worker A perceives that Worker C is not deserving of help (i.e., a perception of social loafing). The processing rate of Worker A ($R_{A,t}$) and Worker C ($R_{C,t}$) at time t is calculated by dividing the completed tag count ($Count_A$, $Count_C$) by the current time of observation:

$$R_{A,t}, R_{C,t} = \frac{Count_A, Count_C}{t} \tag{3}$$

The value of $R_{C,t}$ is stored in Worker A's long-term memory until the time of the utility calculation. At that point, the average of the three most recent observations with index (i) of Worker C's processing rate will be stored in Worker A's short-term memory for processing rate ($R_{C,mem}$) as shown in (4). The long-term memory is continuously appended with Worker A's observations until the point at which Worker A completes the work in its own queue and evaluates its utility.

$$R_{C,mem} = \frac{R_{C,i-2} + R_{C,i-1} + R_{C,i}}{3} \tag{4}$$

The two cases for calculation of uRc_a are shown in (5) and are graphically represented in Figure 3. The relationship between $R_{C,mem}$ and uRc_a at time t is linear, with a negative slope as $R_{C,mem}$ increases compared to $R_{A,t}$ and a positive slope as $R_{C,mem}$ approaches $R_{A,t}$.

$$uRc_a = \begin{cases} \frac{1}{R_{A,t}} * R_{C,mem}, & R_{A,t} \geq R_{C,mem} \\ \frac{-1}{R_{A,t}} * R_{C,mem} + 2, & R_{C,mem} > R_{A,t} \\ 0, & R_{C,mem} \geq 2R_{A,t} \end{cases} \tag{5}$$
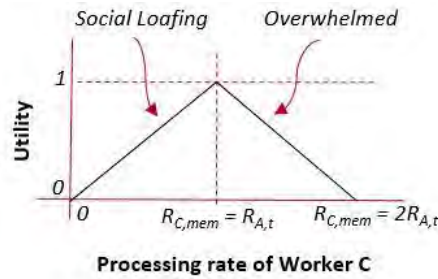
Figure 3: Relationship between the relative processing rates of Workers A and C.

4. *Utility from relative percent completed work*: The value of the utility that Worker A gains from Worker C's percent completed work relative to its own (uCc_a) is calculated in this submodel. The percent completed ($C_{A,t}$, $C_{C,t}$) is calculated by taking $Count_A$ and $Count_C$ and dividing by the remaining tag count ($remCount_A$ and $remCount_C$, respectively).

$$C_{A,t}, C_{C,t} = \frac{Count_A, Count_C}{remCount_A, remCount_C} \tag{6}$$

$C_{C,t}$ is then stored in Worker A's long-term memory. At the time of the utility calculation (i.e., when Worker A completes the work in its own queue), Worker A's short-term memory is updated with the average of the three most recent observations of Worker C's percent completed.

$$C_{C,mem} = \frac{C_{C,i-2} + C_{C,i-1} + C_{C,i}}{3} \tag{7}$$

The value of uCc_A is a function of both Worker A's and Worker's C's percent completed, and its calculation is similar to (5). When $C_{A,t}$ is greater than Worker A's observations of Worker C's percent complete ($C_{C,mem}$), Worker A perceives that Worker C is falling behind (again, a perception of social loafing). Therefore, as $C_{C,mem}$ increases and approaches $C_{A,t}$, uCc_A increases proportionally. When $C_{C,mem}$ is greater than $C_{A,t}$, Worker A perceives that it is falling behind Worker C, and therefore Worker C is not in need of Worker A's help.

$$uCc_a = \begin{cases} \frac{1}{C_{A,t}} * C_{C,mem}, & C_{A,t} \geq C_{C,mem} \\ \frac{-1}{C_{A,t}} * C_{C,mem} + 2, & C_{C,mem} > C_{A,t} \\ 0, & C_{C,mem} \geq 2C_{A,t} \end{cases} \tag{8}$$

5. *Decision to help*: Worker A's decision regarding whether or not to help Worker C is made in this submodel, which is only executed after Worker A has completed all of the work in its own queue. The decision to help is based on Worker A's overall utility (U), which is a weighted sum of the four utility components that were calculated in submodels 1-4:

$$U = w_1 * uAlt_a + w_2 * uHb_a + w_3 * uRc_a + w_4 * uCc_a \tag{9}$$

The weights that are placed on each of these utility components (w) represent the degree of importance that Worker A places on each respective component when deciding to help (where the sum of the four weights is equal to one). If the value of U is at least 0.60, then Worker A will decide to help Worker C; otherwise, Worker A will not help.

3.2   Discrete Event Simulation Model

Each entity in the DES model corresponds to a tag that must be processed by one of the worker agents. A worker is finished once it has processed all of the tags in its own queue. If Workers A or B decide to help Worker C, then they will pull tags from Worker C's queue until there are no tags remaining. Figure 4 provides an overview of the DES model.
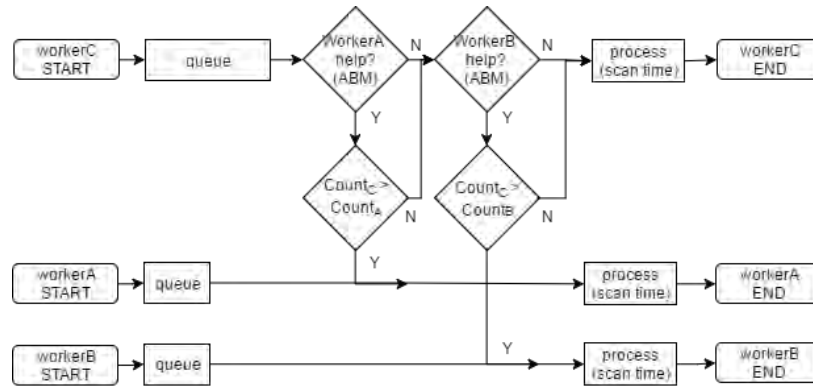

Figure 4: Flowchart of the DES model.

Tag arrival & queueing – All assigned tags arrive at the start of the simulation and are stored in each worker's respective queue. Workers A and B each have 125 tags in their input queues, and 250 tags are stored in Worker C's queue. Tags arriving at the front of the queue seize a worker resource for processing.

Processing – Processing times are stochastic and are drawn from the probability distribution in (10). This distribution was derived from the data collected from the empirical study of Cantor and Jin (2017) and is assumed to be the same for all three workers.

$$scan\ time = F(x; \lambda) \begin{cases} 1 - e^{-0.166x}, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{10}$$

Helping – Any helping behavior that occurs in the DES is triggered by decisions that were made in the ABM. If an agent has decided to help, work from Worker C's queue is diverted to helping workers. However, this only occurs if the number of tags in the helping agent's queue is less than or equal to the number of tags in Worker C's queue. Otherwise, the helping worker waits until the number of tags in Worker C's queue is greater than its own, and at that time it will take work from Worker C's queue.

Output – The DES increments the total number of processed tags and outputs a processing rate and percent complete every time a tag is processed. When the stopping condition of 500 tags is reached, the DES outputs a final count of the total tags scanned for each worker and the total throughput time.

4   EXPERIMENTATION AND RESULTS

This section describes two experimental scenarios that were performed using different versions of the model: a version in which four different personas are developed for Worker A, and a version that incorporates the four personas and varying levels of altruism for Worker A. For both model versions, 50 replications were run. The model initialized at time zero and ran until the stopping condition of 500 tags. The key output metric was the likelihood that Worker A helped Worker C.

Experimental Scenario 1: Personas – The goal of this experimental scenario was to demonstrate the effects of different types of personalities, (i.e., personas) for Worker A on system outcomes.   The personas developed for this experiment serve as examples of some different types of people that could be part of a team in this production system (i.e., they were not experimentally derived). To vary Worker A's

persona, the weights on the four components of Worker A's utility function (*U*) were varied according to persona type, as shown in Table 1.

Table 1: Table of weights assigned to utility function for each persona.

Persona	w_1	w_2	w_3	w_4
1	0.1	0.2	0	0.7
2	0.7	0	0.1	0.2
3	0.2	0.7	0	0.1
4	0	0.3	0.3	0.4

Worker B's weights were held constant at the baseline condition ($w_1 = 0.2$, $w_2 = 0.2$, $w_3 = 0.3$, $w_4 = 0.3$) and ALT_A and ALT_B were fixed at a value of 4. Figure 2 shows that the intrinsically motivated Persona 2 had the highest likelihood of helping.
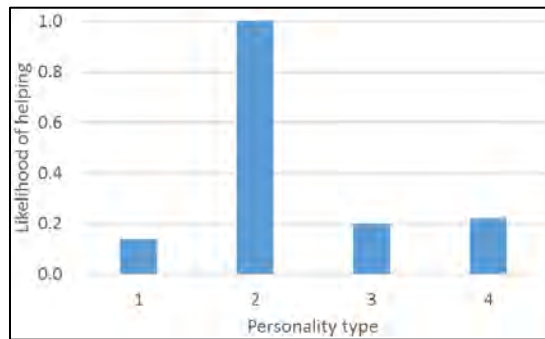

Figure 5: Likelihood of Worker A helping Worker C for the different persona weight values.

Experimental Scenario 2: Varying altruism levels – For this experimental scenario, Personas 1, 2, and 3 were used from the previous experiment, but now Worker A's altruism level was varied from one to five for each persona. Figure 6 shows the relationship between altruism and the likelihood of helping. As altruism increases, the likelihood of helping increases for Persona 1 and Persona 2. Persona 3 exhibited no clear relationship between the likelihood of helping and altruism.
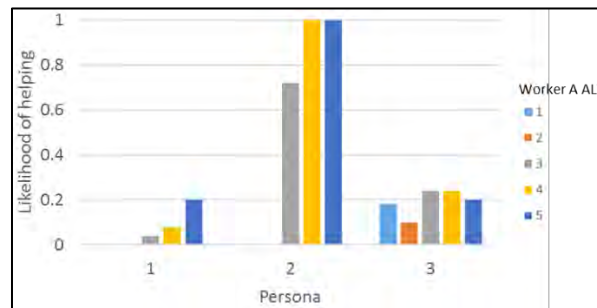

Figure 6: Likelihood of Worker A helping Worker C for three different personas with varying altruism levels.

5   DISCUSSION AND CONCLUSION

This study presented a hybrid simulation model that shows how a non-core production team member's predisposition to altruistic tendencies, an important personality factor, influences their willingness to help a core team member on a production task. In so doing, theory from the social psychology literature was

used to develop the model. Supply chain scholars are interested in this line of research because production environments are often staffed with employees who possess a diversity of personality factors. However, supply chain scholars and practitioners do not have a comprehensive understanding of how individual differences motivate workers to become highly productive members on a manufacturing team.

The first finding from this study is that workers who rely primarily on their individual altruism (ALT_A) to make decisions have an increased likelihood of helping behavior, as shown in Figure 5. We investigated this relationship because the social psychology literature suggests that individuals who are predisposed to act altruistically are not concerned with being compensated, rewarded, or acknowledged for their assistance. Rather, altruistic individuals are more willing to assist co-workers with no expectation concerning norms of reciprocity. The concept of norms of reciprocity refers to the belief that an employee will only help another co-worker because there is the expectation that the co-worker will in turn provide assistance to the original provider of help. In the model presented in this paper, an environment was created without norms of reciprocity expectations.

The results in Figure 5 were then further explored by varying altruism levels. The results shown in Figure 6 underscore the results in Figure 5 – a worker that is highly motivated to help based on individual altruism is highly likely to exhibit helping behavior, which is an intuitive finding. More interestingly, these results suggest that even slight increases in the weight on individual altruism can encourage helping, as demonstrated by the differences in likelihood of helping between Personas 1 and 3 (i.e., an increase in w_I from 0.1 to 0.2). Further, the results for Persona 3 indicate that the influence of social pressure via observations of team helping sequence can push even a non-altruistic worker to exhibit helping behavior.

The next step in this work is to analyze the effects that helping behavior and varying altruism levels have on total system throughput time and other meaningful metrics. Additional predictors, such as team cohesiveness, management policies, task uncertainty, and team consistency, could have impacts on helping behavior and throughput time and will be explored in future work. In order to validate this work, additional empirical studies will be conducted. As the model incorporates more predictors and more accurately represents empirical data, a possible application of the work could be the development of a decision-making tool for managers and other stakeholders to maximize the production of their workforce. Ultimately, the goal of this work is to help people understand and utilize their workforce more effectively for the benefit of both the employees and the firm.

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