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A Computational Model of Team-based Dynamics in the Workplace: Assessing the Impact of Incentive-based Motivation on Productivity

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A COMPUTATIONAL MODEL
OF TEAM-BASED DYNAMICS IN THE WORKPLACE:
ASSESSING THE IMPACT OF INCENTIVE-BASED MOTIVATION
ON PRODUCTIVITY

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By

Josef Di Pietrantonio

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ABSTRACT

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Thesis supervised by Rachael Miller Neilan, Ph.D., Associate Professor

Large organizations often divide workers into small teams for the completion of essential tasks. In an effort to maximize the number of tasks completed over time, it is common practice for organizations to hire workers with the highest level of education and experience. However, despite capable workers being hired, the ability of teams to complete tasks may suffer if the workers' individual motivational needs are not satisfied.

To explore the impact of incentive-based motivation on the success of team-based organizations, we developed an agent-based model that stochastically simulates the proficiency of 100 workers with varying abilities and motive profiles to complete time-sensitive tasks in small teams. The model is initialized by randomly assigning each of the 100 workers an ability value (1 through 5) and a motive profile from initial probability distributions. A motive profile is a 3-parameter equation that quantifies a worker's tendency to actualize his or her potential based on the individual's motivational needs for affiliation, achievement, and power. The model creates new tasks as workers become available; each new task is assigned a random difficulty value and a team of 2 to 4 workers. During each time step, each worker contributes to their assigned task at a rate determined by the worker's ability

and motive profile. At the end of 365 time steps (1 year), the model outputs the total number of completed tasks, which is the primary measurement of productivity. By simulating the model hundreds of times for different sets of initial distributions and analyzing output, we are able to determine which worker attributes lead to increased team-based productivity. Results aid in understanding optimal hiring and human resource allocation in a team-based organization.

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Contents

Chapter 1

Introduction

Conventional hiring practices focus on knowledge, skills, and abilities (KSAs) as the primary indicator of which workers should be assigned to specific jobs [3]. Human resource management (HRM) practices seek to increase KSA qualities of employees by, for example, screening for more selective staffing [2, 17] or investing in current employees through training and development opportunities [1, 7, 16]. However, staffing a workplace with knowledgeable employees does not guarantee an organization's success. Employees must be both skilled and motivated to contribute to their jobs.

The structure of an organization and its compensation strategy can directly impact employee motivation and engagement levels [4]. Examples of effective compensation strategies include merit pay or incentive compensation systems that provide rewards for goal completion [5]. Examples of organizational structures known to impact employee motivation and increase organization performance include employee participation systems [20], internal labor markets providing employees with internal advancement opportunities [13], and team-based production systems [8]. These organizational structures provide an alternative to hiring employees based solely on KSAs. Instead, employees are hired based on their anticipated fit in the organizational structure and motivational alignment with the compensation strategy [3].

In this thesis, we seek to better understand the potential impact of worker motivation and ability on the productivity of a team-based organization. Towards this goal, we developed an agent-based computational model to simulate teams of workers with various motive profiles and abilities completing tasks of all difficulties. Productivity is measured by the number of completed tasks over the course of one year. In our model experiments, we vary the motivation and ability attributes across the simulated populations and observe the impact of these changes on productivity.

This thesis is organized as follows. Chapter 2 provides a brief introduction to incentive-based motivation theory and defines our mathematical model for individual worker contributions to a task. Chapter 3 describes our agent-based model of an organization in which teams of individuals work together to complete time-sensitive tasks. Chapter 4 presents the results obtained by simulating the computational model hundreds of times for a range of initial conditions. Lastly, Chapter 5 provides concluding remarks and future goals.

Chapter 2

Incentive-based Motivation

2.1 Theory

Motivation is an internal state that arouses us to action, moves us in particular directions, and keeps us engaged in certain activities [12]. It directs goal selection, affects choices, and determines incentive value. An incentive is meant to motivate an individual to action; the individual uses the value of the incentive to determine whether or not to act [18]. Incentive-based motivation depends on an individual's desires and the guarantee of a valuable reward upon behavior completion. An individual's motivation types have different strengths of need fulfillment, which require different incentive schemes in order to motivate the individual to action. Three motivation types in particular have emerged in the study of incentive-based motivation of humans in the workplace. These types (known as the influential trio) are achievement motivation, affiliation motivation, and power motivation [6, 9].

Achievement motivation drives humans to strive for excellence by improving on personal and societal standards of performance [6]. Individuals with a need for high achievement motivation prefer mid-difficulty goals, which have a wide range of probability of success and a reward proportional to difficulty. Based on the incentive value of success, the highest level of motivation for high-need achievement individuals is associated with mid-difficulty goals [18].

Affiliation motivation drives humans to seek social interaction and maintain contact with others in a manner that both parties experience as satisfying, stimulating, and enriching [6]. Individuals with a need for high affiliation motivation prefer easier goals, since they have a higher probability of success despite a smaller reward. Based on the incentive value of success, the highest level of motivation for high-need affiliation individuals is associated with easy goals [18].

Power motivation drives humans to seek advantage in social competence, access to resources, or social status [6]. Individuals with a need for high power motivation prefer harder goals, since they have a lower probability of success but result in a larger reward. Based on the incentive value of success, the highest level of motivation for high-need power individuals is associated with hard goals [18].

In [11], Merrick and Shafi present a mathematical model describing the tendency of an individual to select a goal based on the individual's need for achievement, affiliation, and power. Variables S_{ach}, S_{aff}, and S_{pow} represent the strength of an individual's need for achievement, affiliation, and power, respectively, and define the individual's motive profile. The motive profile is used to quantify the tendency ($Tend$) of the individual to select a goal according to the following equation:

$$\begin{aligned} Tend = &\left(\frac{S_{ach}}{1 + e^{\rho^{+}_{ach}(M^{+}_{ach} - (1 - I_{ach}))}} - \frac{S_{ach}}{1 + e^{\rho^{-}_{ach}(M^{-}_{ach} - (1 - I_{ach}))}} \right) + \left(\frac{S_{aff}}{1 + e^{\rho^{+}_{aff}(I_{aff} - M^{+}_{aff})}} \right. \\ &\left. - \frac{S_{aff}}{1 + e^{\rho^{-}_{aff}(I_{aff} - M^{-}_{aff})}} \right) + \left(\frac{S_{pow}}{1 + e^{\rho^{+}_{pow}(M^{+}_{pow} - I_{pow})}} - \frac{S_{pow}}{1 + e^{\rho^{-}_{pow}(M^{-}_{pow} - I_{pow})}} \right) \end{aligned} \tag{2.1}$$

where ρ^{+} is the gradient of approach, ρ^{-} is the gradient of avoidance for each respective motivation, M^{+} is the approach turning point and M^{-} is the avoidance turning point for each respective motivation. Values of I_{ach}, I_{aff}, and I_{pow} range from 0 to 1 and represent a goal's incentive value of success with respect to each motivation. These incentive values of success are dependent on the probability of success of a task, in which the relationship can be mathematically defined in various ways. As seen in equation (2.1), each pair of terms corresponds to one of three motivation types; tendency is expressed as the sum of these three terms. Higher values of $Tend$ indicate a greater likelihood of the individual selecting the goal.

Each motive profile creates a tendency curve such that for any given incentive value, an individual's tendency to select the goal can be determined. Figure 2.1 is an example of a tendency curve for the motive profile with parameter set $S_{ach} = 2$, $S_{aff} = 1$, and $S_{pow} = 2$. This specific motive profile has been coined as the 'leadership' motive profile [9]. In this example, the individual is more likely to select a goal with incentive value equal to 0.626 than goals with higher or lower incentive values. Equation (2.1) is the foundation to the equation variation that we use to investigate the potential impact of motivation on productivity.

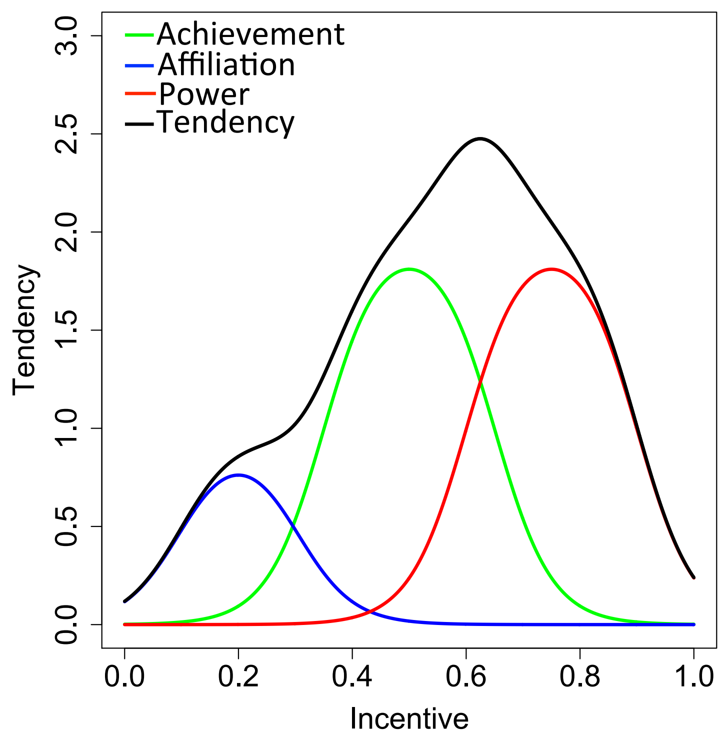

Figure 2.1: Black line shows the tendency (Equation (2.1)) of selecting a goal for an individual with the leadership motive profile. Blue, green, and red lines show the affiliation, achievement, and power motivation components respectively of the tendency curve. Parameter values are $S_{ach} = 2$, $S_{aff} = 1$, and $S_{pow} = 2$; $\rho^+_{ach} = \rho^-_{ach} = \rho^+_{aff} = \rho^-_{aff} = \rho^+_{pow} = \rho^-_{pow} = 20$; $M^+_{ach} = .25$, $M^-_{ach} = .75$, $M^+_{aff} = .3$, $M^-_{aff} = .1$, $M^+_{pow} = .6$, $M^-_{pow} = .9$.

2.2 Mathematical model

An important component of our computational model is the mathematical description of a worker's contribution to his or her assigned task. To quantify the impact of motivation on individual worker productivity, we adopt the tendency model in Section 2.1 and modify it slightly to align with our goals. First, we assume all parameters except S_{ach}, S_{aff}, and S_{pow} are constant for all individuals. These values are

$$\rho^+_{ach} = \rho^-_{ach} = \rho^+_{aff} = \rho^-_{aff} = \rho^+_{pow} = \rho^-_{pow} = 20;$$

$$M^+_{ach} = .25, \quad M^-_{ach} = .75,$$

$$M^+_{aff} = .3, \quad M^-_{aff} = .1, \qquad M^+_{pow} = .6, \quad M^-_{pow} = .9.$$

Second, we assume each individual's motive profile can be expressed in terms of $S_{ach} = 1$ (low) or 2 (high), $S_{aff} = 1$ (low) or 2 (high), and $S_{pow} = 1$ (low) or 2 (high). Third, we include a scaling factor so that the value of $Tend$ is between 0 and 1; this was done by normalizing the values with respect to the maximum $Tend$ value, 3.249629. Thus, in our mathematical model, equation (2.1) is expressed as

$$\begin{aligned} Tend = \frac{1}{3.249629}\Bigg[\left(\frac{S_{ach}}{1+e^{20(.25-(1-I_{ach}))}} - \frac{S_{ach}}{1+e^{20(.75-(1-I_{ach}))}}\right) + \left(\frac{S_{aff}}{1+e^{20(I_{aff}-.3)}}\right. \\ \left. - \frac{S_{aff}}{1+e^{20(I_{aff}-.1)}}\right) + \left(\frac{S_{pow}}{1+e^{20(.6-I_{pow})}} - \frac{S_{pow}}{1+e^{20(.9-I_{pow})}}\right)\Bigg] \qquad (2.2) \end{aligned}$$

where S_{ach}, S_{aff}, and S_{pow} are the three parameters defining the individual's motive profile and I_{ach}, I_{aff}, and I_{pow} represent the incentive of completing a task with respect to each type of motivation. Figure 2.2 shows the tendency curves (Equation (2.2)) for each of the eight different motive profiles.

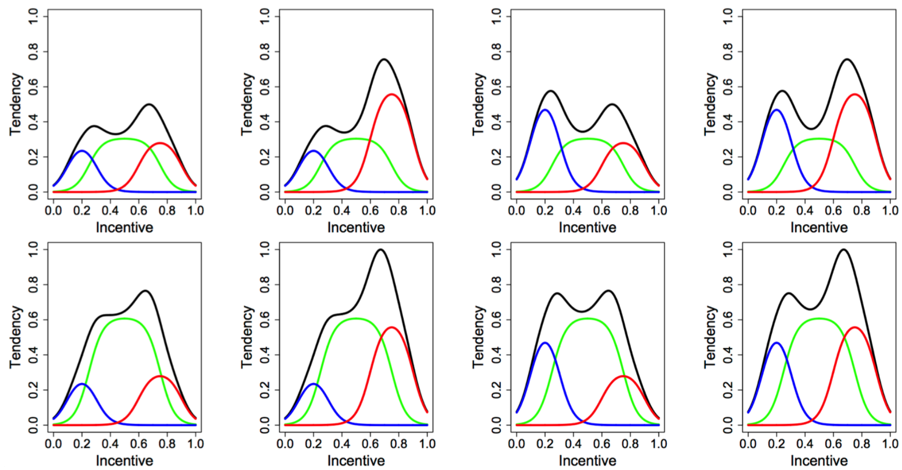

Figure 2.2: For each of the eight different motive profiles, the black line shows the tendency (Equation (2.2)) of a worker to contribute to a task based on the task's inventive value. Blue, green, and red lines show the affiliation, achievement, and power motivation components respectively of the tendency curve.

In our computational model, workers are assigned to a task and therefore the selection of this task is not optional. However, we assume each worker has the option to contribute to the task or not; this depends on the incentive value of completing the task. Therefore, in our model we interpret the tendency value ($Tend$) as a worker's tendency to contribute to a task. As done in [11], we assume the incentive of completing a task (or goal) is determined by the task's probability of success. For each task, we define three probabilities of success:

$$P_1 = \text{probability of success relative to task difficulty}$$

$$P_2 = \text{probability of success relative to worker experience with similar tasks}$$

$$P_3 = \text{probability of success relative to proximity to completion}$$

The incentive of completing a task for each motivation type is calculated as $I_{ach} = 1 - \frac{P_1+P_2+P_3}{3}$, $I_{aff} = 1 - P_1$, and $I_{pow} = 1 - P_1$. Therefore, for both affiliation and power motivation, the incentive of completing a task is determined solely by the difficulty of a task. The incentive value is close to 1 for difficult tasks and close to 0 for easy tasks. For achievement motivation, we use all three measures of a task's probability of success to determine incentive value. This choice is an integration of the multiple methods presented in [9, 10, 11]. The value of I_{ach} is close to 1 for tasks that are difficult, in the beginning stage of completion, and are being worked on by an individual with no experience with similar tasks.

The contribution of a worker to an assigned task is expressed in terms of the worker's tendency and ability. Each worker in our computational model will be assigned one of the eight different motive profiles and an ability value (W_A) ranging from 1 to 5. The worker's contribution to an assigned task (W_C) is expressed as

$$W_C = Tend \cdot W_A \tag{2.3}$$

where $Tend$ is determined by the incentive value of the task using Equation (2.2). Thus, when $Tend = 1$, the worker will contribute a value equal to W_A to the task. When $Tend = 0$, the worker will contribute nothing to the task. In all other cases, the worker will contribute a positive value less than W_A to the task.

Chapter 3

Computational Model

3.1 What is an agent-based model?

Models are developed to represent real systems and used to solve problems and answer questions about these systems [19]. Conventional mathematical modeling uses differential equations to describe systems and methods of calculus to solve the equations or determine optimal inputs. Interpretation of results obtained using this methodology is often limited to system-level analyses.

Agent-based modeling is an alternative methodology that utilizes simulation to describe the individuals (i.e. agents) of the system and allows for observation of collectives formed by agents as well as the emergent properties of the system [15]. A key feature of agent-based models (ABMs) is the ability to define interactions between similar or different agents, as well as between agents and the environment. Additionally, ABMs allow for variation in both the system and the individuals of the system, leading to interpretation of results at all levels.

We developed an ABM to observe how individual worker motivation and ability impact an organization's overall productivity. Sections 3.2 through 3.7 provide a detailed description of the model in accordance with the Overview, Design concepts, and Details (ODD) protocol [15]. The ABM stochastically simulates the proficiency of 100 workers with varying ability levels and motive profiles to complete time-sensitive tasks in small teams. We simulate the ABM hundreds of times across different initializations and analyze output to determine how changes at the individual-level affect productivity of the organization.

3.2 Entities and scales

The model consists of two entities: tasks and workers. Tasks and workers are updated every time step (i.e. tick) over a period of 365 ticks. One time step represents one day and therefore the model simulates task completion by the workers over a period of one year.

Table 3.1 displays all variables assigned to each task in the model. A task is categorized by its status (open, active, or complete). A task is open if it has been created but workers are not yet assigned to the task. A task is active if a team of workers is assigned to the task and the team is contributing to the task workload. A completed task is a task whose workload has been fulfilled and no longer has workers assigned to it.

When a task is created, it is assigned a task number (T_N), a difficulty value (T_{DV}), and a number of workers (T_W). T_{DV} is an integer ranging from 1 to 100 with higher values indicating a more difficult task. Number of workers, T_W, is an integer ranging from 2 to 4 and indicates the number of workers that must be assigned to the task before it becomes active. Both values are randomly chosen for each task from uniform distributions and do not change during the simulation. Each task is assigned a task life variable (T_L) that is initialized to zero and incremented by one every time step while the task is active. Each task is assigned three probability variables P_1, P_2, and P_3 that measure the task's probability of success. P_1 is determined by the task's difficulty value, P_2 is determined by the experience levels of workers associated with the task, and P_3 is updated at each time step based on the proximity of a task to its completion. The value of task workload (T_{WL}) is determined by the task's difficulty value and the length of time the task has been active. Each task has a cumulative team contribution variable ($Team_C$) that is updated at every time step to track progress towards the task's completion. A task is complete when $Team_C \geq T_{WL}$.

Table 3.2 displays all variables assigned to each worker in the model. The model consists of 100 workers, each of which is characterized by an ability value (W_A) and an incentive-based motive profile (denoted by s_1, s_2, s_3 in the agent-based model respectively corresponding to S_{ach}, S_{aff}, and S_{pow} from the mathematical model). Each of the motive profile parameters s_1, s_2, and s_3 has a value of 1 (low) or 2 (high). The ability value (W_A) is an integer ranging from 1 to 5. Values of s_1, s_2, s_3, and W_A are selected for each worker from distributions defined at the initialization of the experiment and do not change during the simulation. Additionally, each worker has several variables that are updated at each time step. A worker's task assignment number is equal to the number of the task to which the worker is assigned (i.e., $W_N = T_N$). If the worker is not currently assigned to a task, then W_N is set to -1. Each worker has a worker contribution variable (W_C) that is updated at each time step and quantifies how much the worker contributes to an assigned task during the time step. Experience variables E_1, E_2, and E_3 are assigned to each worker to indicate the worker's experience with easy, medium, and difficult tasks, respectively. The value of an experience variable is 0 initially and updated to 1 when the worker completes a task with the specified difficulty value.

Notation	Description	Value	Frequency of updates
T_S	Task status	open, active, or complete	Updated each tick
T_N	Task number	positive integer	Fixed
T_{DV}	Task difficulty value	integer (1 - 100)	Fixed
T_W	Number of workers needed for task	2, 3, or 4	Fixed
P_1	Probability of success relative to task difficulty	$[0, 1.0]$	Updated when task becomes active
P_2	Probability of success relative to team experience	$[0, 1.0]$	Updated when task becomes active
P_3	Probability of success relative to task completion	$[0, 1.0]$	Updated each tick
T_{WL}	Task workload	$[0, \infty)$	Updated each tick
$Team_C$	Cumulative team contribution to task workload	$[0, \infty)$	Updated each tick
T_L	Task life	$0, 1, 2, ...$	Updated each tick

Table 3.1: Overview of variables assigned to each task.

Notation	Description	Value	Frequency of updates
s_1	Achievement motivation parameter	1 (low) or 2 (high)	Fixed
s_2	Affiliation motivation parameter	1 (low) or 2 (high)	Fixed
s_3	Power motivation parameter	1 (low) or 2 (high)	Fixed
W_A	Ability of worker	$1, 2, 3, 4$, or 5	Fixed
W_N	Worker's task assignment number	positive integer (or -1 if unassigned to a task)	Updated when assigned to new task
W_C	Individual worker contribution to assigned task	$[0, 5]$	Updated each tick
E_1	Experience with easy tasks	0 or 1	Updated at task completion
E_2	Experience with medium tasks	0 or 1	Updated at task completion
E_3	Experience with hard tasks	0 or 1	Updated at task completion

Table 3.2: Overview of variables assigned to each worker.

3.3 Process overview and scheduling

The model begins by creating 100 workers with initial parameters defined in Section 3.5. Subsequently, one open task is created and randomly assigned T_W workers (called a team). Values of P_1 and P_2 are calculated for the task. This task creation process repeats until either all of the 100 workers are assigned to tasks or there exists one open task such that the number of workers needed (T_W) is greater than the number of unassigned workers. Each task that has been assigned a team is considered an active task.

During each time step, all active tasks are updated one at a time according to the following procedures. At the beginning of the time step, the value of P_3 is updated based on current values of the task workload (T_{WL}) and the team's cumulative contribution to the task workload ($Team_C$). Each worker in the assigned team then calculates it's individual worker contribution (W_C). The individual worker contribution values are added to the cumulative team contribution ($Team_C$), T_L is incremented by 1, and the task is checked for completeness. If a task's cumulative team contribution is greater than or equal to the task workload (i.e. $Team_C \geq T_{WL}$), the task's status is changed to 'complete' and the corresponding experience variable (E_1, E_2, or E_3) of each worker in the team is updated. If a task's cumulative team contribution is less than the task workload (i.e. $Team_C < T_{WL}$), then the task remains active.

At the end of each time step, all workers from completed tasks are unassigned from their task by setting $W_N = -1$ for each of these workers. At the beginning of the next time step, the task creation process is repeated until either all unassigned workers are assigned to an open task or there exists one open task such that the number of workers needed (T_W) is greater than the number of unassigned workers. Therefore, at each time step there will either be 0 or 1 open tasks. The simulation terminates at the end of 365 time steps.

Figure 3.1 shows the history of a single task from its creation to its completion. As seen in the diagram, the active task loop is repeated until $Team_C \geq T_{WL}$.

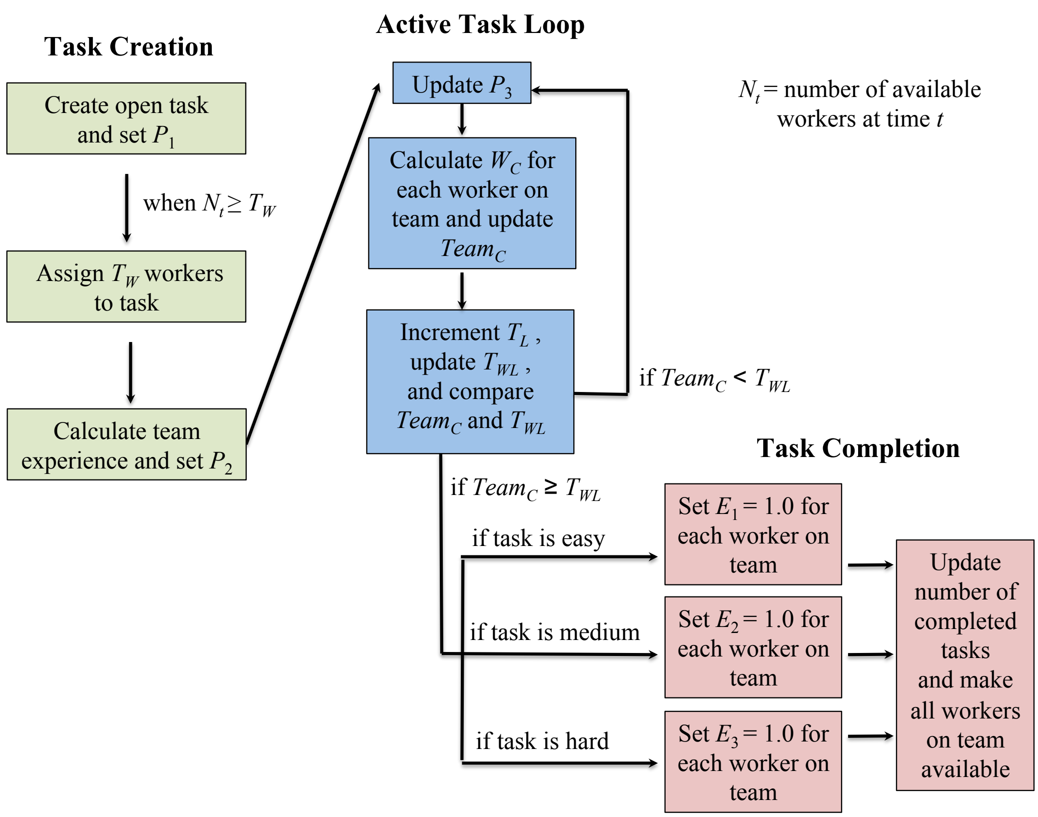

Figure 3.1: Flow diagram illustrating the history of a single task.

3.4 Design concepts

3.4.1 Basic principles

The agent-based model stochastically simulates the proficiency of 100 workers with varying abilities and motive profiles to complete time-sensitive tasks in small teams over the course of one year. New tasks are created as workers become available; each new task is randomly assigned a difficulty value and a team of 2 to 4 workers. Incentive values are associated with each task based on the task's probabilities of success. During each time step, each task workload is updated and workers contribute to their assigned task according to the mathematical model presented in Section 2.2. At the end of 365 time steps (1 year), the model outputs the total number of completed tasks, which is the primary measurement of productivity. By simulating the model hundreds of times for different sets of initial distributions and analyzing output, we are able to determine which distributions of worker motive profiles and abilities lead to increased team-based productivity.

3.4.2 Emergence

The most notable emergent feature of this model is the completion of tasks over time. A task's cumulative team contribution variable increases over time as individual workers contribute to the task. A task is completed when its cumulative team contribution is greater than or equal to the task workload (i.e. $Team_C \geq T_{WL}$).

Another emergent feature of the model is the inability of some teams to complete assigned tasks. A task workload (T_{WL}) grows exponentially at a rate determined by the value of the global penalty parameter α. In some cases, a team's cumulative contribution ($Team_C$) will not increase at a rate needed to surpass (T_{WL}) over time. In these cases, $Team_C < T_{WL}$ at every time step and the task will never be completed.

3.4.3 Sensing

Each worker knows the task it is currently assigned to and can access the attributes of this task only. Each task knows which workers are assigned to it and has access to the attributes of these workers only.

3.4.4 Interaction

Interaction occurs between a task and the workers assigned to it. Workers assigned to a task contribute to the task workload each time step; the task is complete when the team's cumulative contribution equals or exceeds the task workload. When a task is complete, the experience variables of assigned workers are updated accordingly.

3.4.5 Stochasticity

Values of T_{DV} and T_W are randomly assigned to each task from uniform distributions with ranges specified in Table 3.1. Values of s_1, s_2, s_3, and W_A are randomly assigned to each worker from distributions specified at the initialization of the model (see Section 3.5).

3.4.6 Collectives

All workers assigned to the same task form a collective called a team. A team is classified by its size and the attributes of the team's workers, including ability, motive profile, and experience.

3.4.7 Observation

Information about completed tasks is stored at the end of each time step. At the end of each simulation, output displays the total number of completed tasks which we use as the primary measure of productivity. Output also displays the average difficulty value, average life of completed tasks, and the average ability of workers assigned to completed tasks. These secondary outputs were used for validation and explorative insight, but are not further discussed in this paper.

3.5 Initialization

To initialize the model, the user must specify probability distributions for values of the motive profile parameters s_1, s_2, and s_3, and a probability distribution for the value of worker ability W_A. For example, the user must provide a value of $\gamma_1 \in [0, 1]$ such that $Prob(s_1 = 1.0) = \gamma_1$ and $Prob(s_1 = 2.0) = 1 - \gamma_1$. Similarly, values of γ_2 and γ_3 must also be provided. The user must also specify values of $\Psi_i \in [0, 1]$ for $i = 1, 2, 3, 4, 5$ such that $\sum_{i=1}^{5} \Psi_i = 1$. These values determine the ability distribution where $P(W_A = i) = \Psi_i$ for $i = 1, 2, 3, 4, 5$.

The value of α must also be specified at the model's initialization. The global penalty parameter α is used by all tasks to calculate current workload according to the equation $T_{WL} = T_{DV} e^{\alpha T_L}$ where T_{DV} is the task difficulty value and T_L is the task life. To ensure a 20% increase in T_{WL} occurs after $t = 14$ time steps (i.e. 2 weeks), we chose $\alpha = \frac{\ln(1.2)}{14}$.

3.6 Submodels

3.6.1 P_1 calculation

P_1 measures a task's probability of success based on its difficulty value. It is assumed that easy tasks have a high probability of success and difficult tasks have a low probability of success. Accordingly, the value of P_1 is calculated for each task as

$$P_1 = \frac{100 - T_{DV}}{100} \tag{3.1}$$

where T_{DV} is the task difficulty value.

3.6.2 Team experience and P_2 calculation

All workers assigned to the same task have an experience variable E_i where $i = 1$ if $1 \leq T_{DV} \leq 33$, $i = 2$ if $34 \leq T_{DV} \leq 66$, and $i = 3$ if $67 \leq T_{DV} \leq 100$. A worker is either considered experienced if $E_i = 1$ or inexperienced if $E_i = 0$. The team's experience value for the assigned task is calculated as

$$E = \frac{1}{T_W} \sum_{j=1}^{T_W} E_i^j \tag{3.2}$$

where E_i^j is the value of E_i for the j^{th} worker assigned to the task, and T_W is the number of workers assigned to the task.

P_2 measures a task's probability of success relative to the experience of its team and is set equal to E. Therefore, if all workers assigned to the task are experienced, then $P_2 = 1.0$. If all workers assigned to the task are inexperienced, then $P_2 = 0$. Otherwise, $0 < P_2 < 1.0$.

3.6.3 P_3 calculation

P_3 measures a task's probability of success relative to its proximity to being complete. Hence, at the beginning of each time step, P_3 is evaluated as

$$P_3 = \frac{Team_C}{T_{WL}} \tag{3.3}$$

where $Team_C$ is the task's cumulative team contribution and T_{WL} is the task workload.

3.6.4 Worker and team contributions to a task

For each task, the contribution of an assigned worker is denoted by W_C and is updated each time step using the formula

$$W_C = Tend \cdot W_A \tag{3.4}$$

where $Tend$ is the worker's tendency to contribute to the task and W_A is worker's ability. As described in Section 2.2, the value of $Tend$ depends on the worker's motive profile and the task's incentive value according to

$$Tend = \frac{1}{3.249629}\left[\left(\frac{s_1}{1+e^{20(.25-(1-I_{ach}))}} - \frac{s_1}{1+e^{20(.75-(1-I_{ach}))}}\right) + \left(\frac{s_2}{1+e^{20(I_{aff}-.3)}} - \frac{s_2}{1+e^{20(I_{aff}-.1)}}\right) + \left(\frac{s_3}{1+e^{20(.6-I_{pow})}} - \frac{s_3}{1+e^{20(.9-I_{pow})}}\right)\right] \tag{3.5}$$

where the values of incentive for achievement, affiliation, and power are $I_{ach} = 1 - \frac{P_1+P_2+P_3}{3}$, $I_{aff} = 1 - P_1$, and $I_{pow} = 1 - P_1$, respectively.

After the values of W_C have been updated for all workers, a task's cumulative team contribution is updated according to

$$Team_C = Team_C + \sum_{j=1}^{T_W} W_C^j \tag{3.6}$$

where W_C^j is the value of W_C for the j^{th} worker assigned to the task and T_W is the number of workers assigned to the task.

3.6.5 Check task completion

At the end of each time step, each active task is evaluated for completion by comparing the task's cumulative team contribution ($Team_C$) to the task workload (T_{WL}). The task workload is calculated each time step as

$$T_{WL} = T_{DV} e^{\alpha T_L} \tag{3.7}$$

where T_{DV} is the task difficulty, T_L is the task life, and α is the global penalty parameter. If $Team_C < T_{WL}$, then the task's status remains active. If $Team_C \geq T_{WL}$ then the task's status is changed to complete.

3.6.6 Task completion

If a task's status changes from active to complete, then the corresponding experience variable of each assigned worker is updated and workers are unassigned from the task. Specifically, E_i is set to 1.0 where $i = 1$ if $1 \leq T_{DV} \leq 33$, $i = 2$ if $34 \leq T_{DV} \leq 66$, and

$i = 3$ if $67 \leq T_{DV} \leq 100$. The task assignment variable, W_N, for each worker assigned to the completed task is set to -1.

3.7 Implementation

The model was coded in NetlLogo (Version 6.0) [22]. This software has a unique programming language and customizable interface that is designed specifically for ABM development and implementation. NetLogo has an important tool called BehaviorSpace that was used to simulate variations of populations under different parameters. Statistical analyses and graphical displays were conducted in R [14].

Chapter 4

Results

4.1 Impact of motivation on productivity

We first investigated how the total number of completed tasks varies for different motive profile distributions. Each motive profile distribution is described by the values of γ_1, γ_2, and γ_3 where $P(s_i = 2.0) = \gamma_i$ and $P(s_i = 1.0) = 1 - \gamma_i$ for $i = 1, 2, 3$. For each of the 27 different motive profile distributions in Table 4.1, we simulated the model and collected output 100 times. In all of these simulations, the values of worker ability (W_A) were chosen randomly from a uniform distribution.

Figure 4.1 displays box plots summarizing the total number of tasks completed over 100 simulations for each motive profile parameter set. In these simulations, task difficulty values range from 1 to 100. The motive profile parameter sets are numbered in order of descending value for the mean number of completed tasks. Thus, parameter set 1 ($\gamma_1 = \gamma_2 = \gamma_3 = 0.75$) corresponds to the motive profile distribution that yields the greatest number of completed tasks on average. The average number of completed tasks observed with parameter set 1 is 653.52, which is a 44.5% increase over the average number of completed tasks observed with motive profile parameter set 14. Parameter set 14 corresponds to the baseline scenario in which all workers are equally likely to have high or low values in each motivation type ($\gamma_1 = \gamma_2 = \gamma_3 = 0.50$) .

Parameter Set	γ_1 $P(s_1 = 2.0)$	γ_2 $P(s_2 = 2.0)$	γ_3 $P(s_3 = 2.0)$
1	0.75	0.75	0.75
2	0.75	0.50	0.75
3	0.75	0.75	0.50
4	0.75	0.25	0.75
5	0.75	0.50	0.50
6	0.75	0.25	0.50
7	0.50	0.75	0.75
8	0.75	0.75	0.25
9	0.75	0.50	0.25
10	0.50	0.50	0.75
11	0.50	0.75	0.50
12	0.75	0.25	0.25
13	0.50	0.25	0.75
14	0.50	0.50	0.50
15	0.50	0.75	0.25
16	0.50	0.25	0.50
17	0.25	0.75	0.75
18	0.25	0.50	0.75
19	0.50	0.50	0.25
20	0.50	0.25	0.25
21	0.25	0.25	0.75
22	0.25	0.75	0.50
23	0.25	0.50	0.50
24	0.25	0.75	0.25
25	0.25	0.25	0.50
26	0.25	0.50	0.25
27	0.25	0.25	0.25

Table 4.1: Parameter sets defining each of the 27 different motive profile distributions.

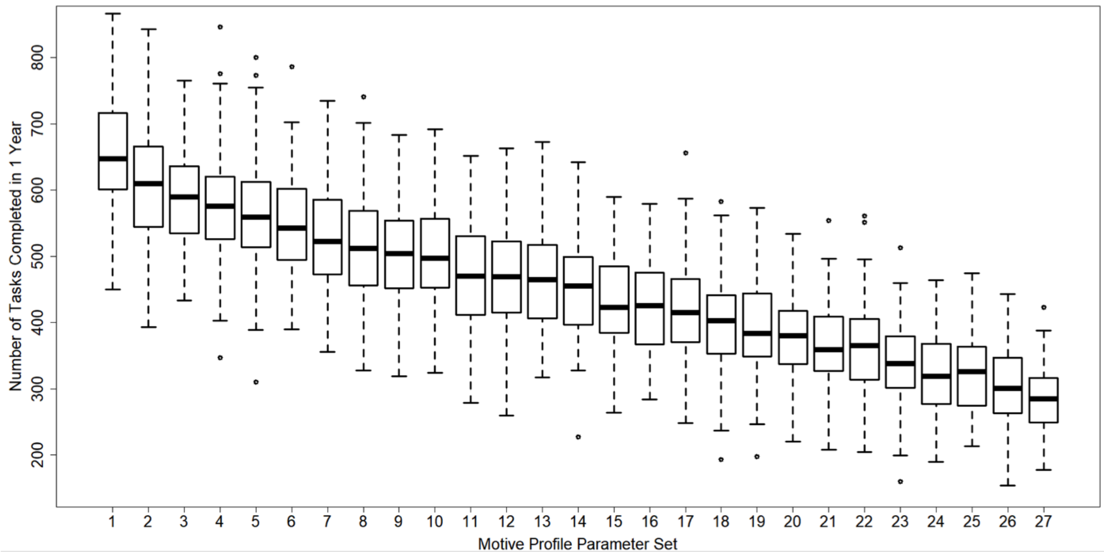

Figure 4.1: Statistical summary of the number of completed tasks from 100 model simulations for each motive profile distribution. Task difficulty values range from 1 to 100.

Motive profile parameter sets 1 through 6 correspond to the motive profile distributions that yielded the highest values of productivity on average. These six parameter sets have one thing in common; they all assume the probability of selecting a worker with high achievement motivation is maximized (i.e. $\gamma_1 = 0.75$). Values of γ_2 vary between 0.75 and 0.25, while values of γ_3 vary between 0.75 and 0.50 in these six motive profile parameter sets. These results suggests that if task difficulty values span the full range (1 to 100) then hiring workers with high achievement motivation should be a top priority in order to maximize productivity.

It is also worth noting that motive profile parameter sets 15, 17, 18, 21, 22, and 24 all include $\gamma_2 = 0.75$ and/or $\gamma_3 = 0.75$, but these sets do not correspond to high productivity. These five parameters sets maximize the probability of selecting workers with high affiliation motivation, or high power motivation, or both (as seen in parameter set 17). However, each of these parameter sets yields an average number of completed tasks that is less than that of the baseline scenario. This result indicates that if task difficulty values span the full range (1 to 100) then hiring workers with high motivation of any type is not sufficient to maximize productivity. Furthermore, profile parameter set 17 highlights the impact of achievement motivation on productivity, since despite this parameter set including $\gamma_2 = \gamma_3 = 0.75$ the average number of completed tasks that is less than that of the baseline scenario due to $\gamma_1 = 0.25$.

To further explore the impact of motive profiles on productivity, we repeated the above experiment using model simulations with only hard tasks ($67 \leq T_{DV} \leq 100$) and model simulations with only easy tasks ($1 \leq T_{DV} \leq 33$). Figure 4.2 displays box plots corresponding to the motive profile parameter sets that perform better than the baseline set (parameter set 14). When all tasks are difficult (Figure 4.2 A), the three best motive profile parameter sets (4, 2, and 1) correspond to those having $\gamma_1 = 0.75$ and $\gamma_3 = 0.75$. This result suggests that, in situations where tasks are consistently difficult, it is important to hire workers with high power motivation in addition to high achievement motivation. When all tasks are easy (Figure 4.2 B), the three best motive profile parameter sets (3, 8, and 1) correspond to those having $\gamma_1 = 0.75$ and $\gamma_2 = 0.75$. In fact, the first six parameter sets in Figure 4.2 B correspond to those with $\gamma_2 = 0.75$. This result suggests that, in situations where tasks are consistently easy, hiring workers with high affiliation motivation should be a top priority in order to maximize productivity.

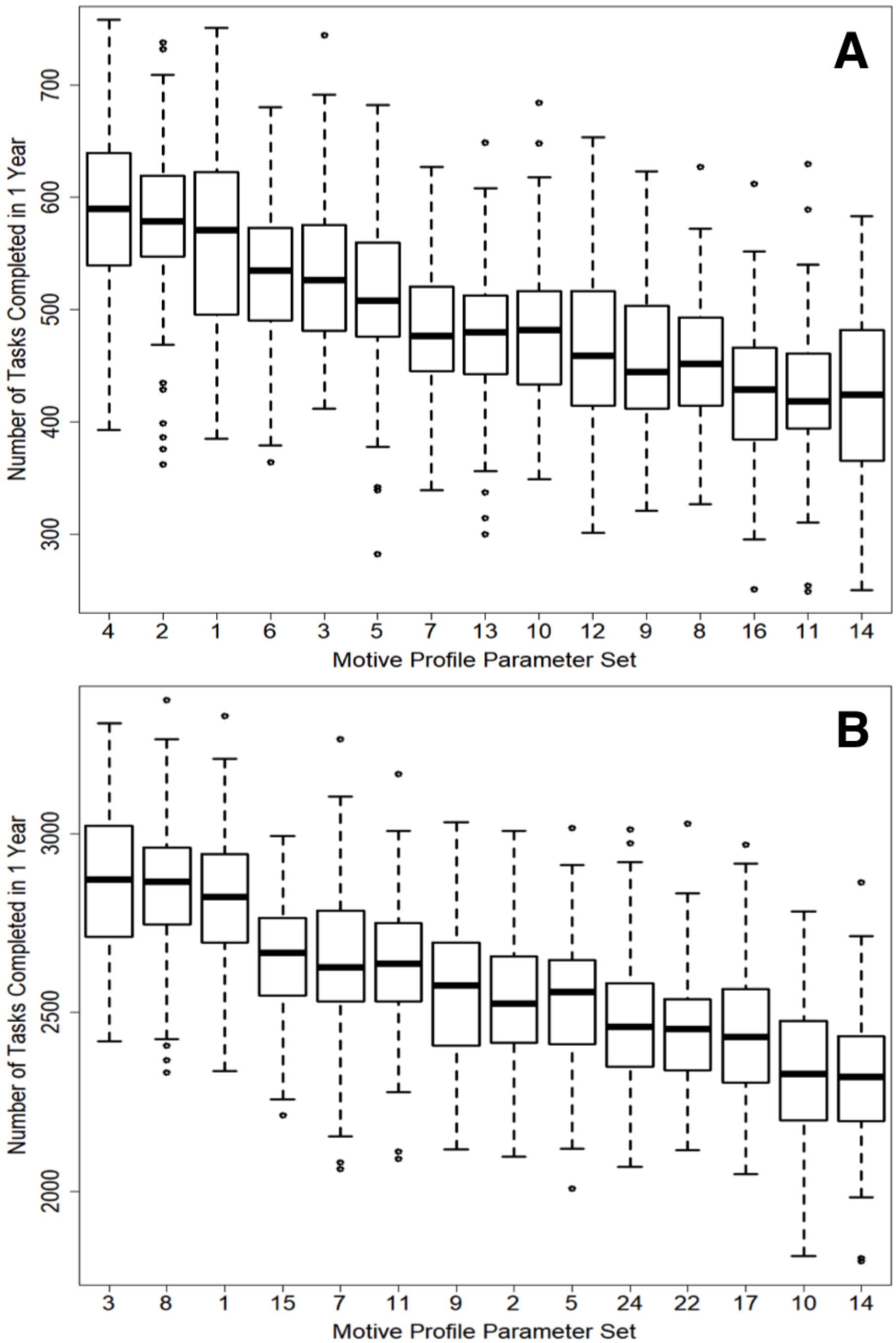

Figure 4.2: Statistical summary of the number of completed tasks from 100 model simulations for each of the top performing motive profile distributions. Top: Panel A displays results obtained with simulations using task difficulty values between 67-100. Bottom: Panel B displays results obtained with simulations using task difficulty values between 1-33.

4.2 Impact of ability on productivity

We next investigated how the total number of completed tasks varies for different ability distributions. Each ability distribution is described by the values of ψ_1, ψ_2, ψ_3, ψ_4, and ψ_5 where $P(W_A = j) = \psi_j$ for $j = 1, 2, 3, 4, 5$. We considered five different ability distributions (Table 4.2): two bimodal distributions (parameter sets A and D), two normal distributions (parameter sets C and E), and one uniform distribution (parameter set B). All ability parameter sets have a distribution mean value of 3. For each of these five ability distributions, we simulated the model and collected output 100 times. In all of these simulations, motive profiles were selected from the distribution defined by parameter set 1 in Table 4.1.

Figure 4.3 displays box plots summarizing the total number of tasks completed over 100 simulations for each ability distribution. In these simulations, task difficulty values range from 1 to 100. The ability parameter sets are lettered in order of descending value for the mean number of completed tasks. Thus, parameter set A corresponds to the ability distribution that yields the greatest number of completed tasks on average. The average number of completed tasks observed with the ability distribution defined by parameter set A is 730.61, which is an 11.8% increase over the average number of completed tasks observed with the ability distribution defined by parameter set B. Parameter set B defines the uniform ability distribution and corresponds to the ability distribution used in the experiments in Section 4.1.

The average number of completed tasks observed with each of the ability distributions decreases as the value of ψ_5 decreases. The average number of completed tasks is at its smallest when the ability distribution defined by parameter set E is implemented. Parameter set E assumes all workers have ability 2, 3, or 4. Hence, the corresponding distribution has no workers with ability 5. On the other hand, the most productive distribution, defined by parameter set A, corresponds to the bimodal ability distribution classifying workers as having either ability 1 or 5 with equal probability. Parameter set A assumes all workers have the highest ability or the lowest ability value. These results highlight the value of high-ability workers in maximizing productivity, and suggest hiring as many high ability workers as possible even if it results in the remaining workers having low ability.

Parameter Set	ψ_1 $P(W_A = 1)$	ψ_2 $P(W_A = 2)$	ψ_3 $P(W_A = 3)$	ψ_4 $P(W_A = 4)$	ψ_5 $P(W_A = 5)$
A	0.50	0.0	0.0	0.0	0.50
B	0.20	0.20	0.20	0.20	0.20
C	0.10	0.20	0.30	0.20	0.10
D	0.0	0.50	0.0	0.50	0.0
E	0.0	0.30	0.40	0.30	0.0

Table 4.2: Parameter sets defining each of the five different ability distributions.

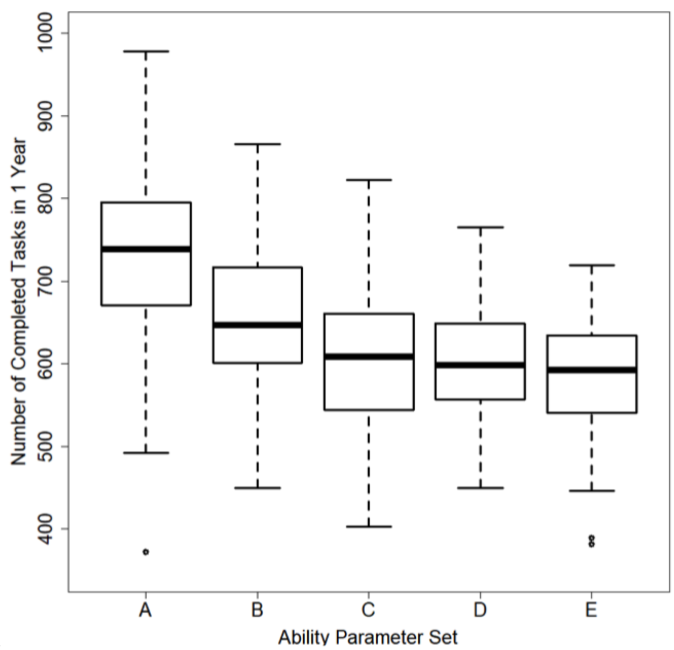

Figure 4.3: Statistical summary of the number of completed tasks from 100 model simulations for each ability distribution. Task difficulty values range from 1 to 100. The motive profile distribution is defined by parameter set 1 in Table 4.1.

4.3 Task Failure Detection

In the model, it is possible for an active task to never be completed during a simulation if the task workload (T_{WL}) increases faster than the team's cumulative contribution ($Team_C$). These are called failing tasks. In all of the model experiments discussed thus far, failing tasks remain active until the end of the simulation and the assigned team continues to contribute to the task even though it is impossible for the team complete the task.

To mitigate the negative impact of failing tasks on productivity, we designed a model feature called Task Failure Detection (TFD). During the simulation, TFD assesses whether a task is failing or not and allows for a new team of workers to be assigned to failing tasks as they are identified. At every time step, TFD assesses each task by comparing the current value of $\frac{Team_C}{T_{WL}}$ to the value obtained during the previous time step. If it is the case that

$$\left(\frac{Team_C}{T_{WL}}\right)_{i-1} > \left(\frac{Team_C}{T_{WL}}\right)_i \tag{4.1}$$

where i denotes the tick, then the task is deemed a failing task. If inequality (4.1) holds true for at least one time step i, then it remains true at all subsequent time steps and $Team_C < T_{WL}$ for the entire simulation. This is due to the fact that T_{WL} grows exponentially with time while $Team_C$ increases by an additive amount each time step. Thus, inequality 4.1 is an accurate indicator of a failing task. Once a task is marked as failing, the workers are immediately removed from this task. The task is randomly assigned a new team of workers when they become available.

Figure 4.4 displays box plots summarizing the total number of tasks completed over 100 simulations with TFD and without TFD. In these simulations, task difficulty values range from 1 to 100. The motive profile of each worker is selected from the distribution defined by parameter set 1 and the ability of each worker is selected from the distribution defined by parameter set A. On average, the number of completed tasks in simulations with TFD is 838.71, which is a 14.8% increase over the average number of completed tasks in simulations without TFD. These results suggest that evaluating task progress on a frequent basis and reassigning a new team to a failing task can substantially increase productivity.

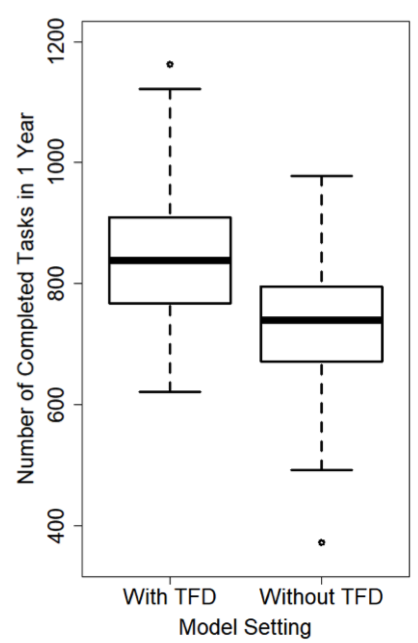

Figure 4.4: Statistical summary of the number of completed tasks from 100 model simulations with TFD and without TFD. Task difficulty values range from 1 to 100. The motive profile distribution is defined by parameter set 1. The ability distribution is defined by parameter set A.

Chapter 5

Conclusions

In this thesis, we present one framework for evaluating optimal hiring guidelines for a team-based organization based on the abilities and motivational preferences of workers. Our agent-based model (ABM) can be easily modified to accommodate organizations of any size and tasks that range between any difficulty values. The ABM offers the flexibility of simulating team-based dynamics over any time frame and under any set of initial conditions. The main use of the ABM is to compare productivity across different pools of workers and quantify the impact of hiring workers with certain attributes.

In the experiments presented here, we found that both motivational profiles and ability substantially impact productivity in a team-based organization. In experiments that included tasks of all difficulty values, we found that the optimal distribution of motive profiles among workers can increase productivity by 44.5% on average compared to baseline values. Furthermore, when the optimal distribution of ability values was implemented, average productivity increased by an additional 11.8%. These results suggest that both characteristics (ability and motive profile) should be considered during the hiring process.

The results highlighted in this thesis are dependent upon the difficulty of the organization's essential tasks. Our framework requires an organization's essential tasks be defined by difficulty values ranging from 1 to 100. When difficulty values span the entire range, our results shows that hiring workers with high achievement motivation is critical to maximizing productivity. When tasks were limited to only difficulty tasks, we observed a need for workers with both high achievement and power motivation. This was different from the results found when only easy tasks were considered. In this case, the optimal results suggest hiring practices prioritize selecting workers with high affiliation motivation.

In working with the model we noticed some tasks remained incomplete for the duration of the simulation due to an underperforming team. In looking more closely at the properties of these tasks, we realized these tasks could be recognized in real-time. We developed a new model feature to recognize failing tasks as they emerge and immediately re-assign a new team of workers to the failing task. By implementing this new feature, we found a 14.8% increase in average productivity at the organizational level. This feature is not only important to maximizing productivity, but it is also important to maximizing worker motivation. A worker assigned to a failing task will exhibit decreasing tendencies to contribute to their work, which is a sign of an unmotivated employee.

Future work includes conducting a sensitivity analysis to determine which of the model parameters have the greatest impact on our results. Parameters such as the number of workers, the size of the teams, and the penalty value will be investigated. Other parameters to investigate include the parameters defining the motive profiles, specifically the gradients and turning points to approach or avoidance. Additionally, in the future we will use the model to investigate scenarios of dynamic parameter perturbation during simulation under known conditions. One such scenario involves introducing a worker (or group of workers) with known attributes that are vastly different from other workers into the system to observe outcomes that deviate from expected results. It is also possible for us to consider implementing variations in the organizational structure (e.g. employee participation programs) that might better represent certain sectors of industry.

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