A Multi-Agent Model of Workgroup Behaviour in an Enterprise using a Compositional Approach

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ABSTRACT

Fine grained behavioural models of humans in a context, such as associates in an organization or a consumer group may allow us to both better understand existing behaviour as well as what would happen given various situations. We have been working on a behaviour compositional approach to this problem which creates realistic agent behaviour models that when run as a simulation allows us to understand the dynamics of how various behavioural characteristics impact one or more outcome metrics of interest. The compositional approach is founded on a repository of fine grained behavioural relations and elements that have been mined from ongoing and past research in the behavioural sciences as well as data obtained through field studies. The repository, the compositional system and the simulation system are part of an architecture we are developing called the Behaviour Analysis Framework. We demonstrate our approach by showing how we can create a behavioural model of specific aspects of a support team in an enterprise. The goal of our model is to study how individual behavioural dimensions such as emotion and stress impact the macro level outcome metrics of absenteeism and productivity. We use an agent based simulation to implement our behavioural model. We present some experimentation and results obtained from this simulation. Our simulation was able to reproduce various real-world phenomenon such as how absenteeism triggers more absenteeism and slow recovery from workload spikes.

CCS Concepts

•**Computing methodologies → Agent/discrete models**
•**Computing methodologies → Multi-agent systems**

Keywords

Human Behavioural Modelling; Enterprise Modelling; Agent Based Simulation

1. INTRODUCTION

Organizations have been the focus of many research domains at several levels of analyses-the macro or organizational level, the team level and the micro or individual level. Computational modelling of organizations has traditionally focused on modelling of macro-level organizational phenomena such as intra-and inter-organizational networks, with less focus on realistic modelling of micro-level individual behaviour and its impact on team and organizational level behavioural dimensions and outcomes.

The behavioural and social sciences domain have had a long and rich tradition of human behavioural studies focusing on developing theories of behaviour applicable across a wide range of settings such as education, health, society and most significantly, organizations. The methods used in behavioural and social sciences have focused on studying behavioural dimensions of interest using surveys, interviews and experiments with a relatively specific focus on identifying relations among the behavioural variables of interest. These studies use cross-sectional methods, i.e. study of behaviour at a specific point in time, or repeated methods, that study behaviour over a specific time period. However studies of dynamic aspects of behaviour and the impact of behavioural dynamics on outcomes of interest are few and far between. Further, given the complexity, breadth and context sensitivity of human behaviour, it may even be infeasible or inappropriate to conduct experiments and observational studies. In such constrained situations, *in-silico* simulations of human behaviour models become an attractive technique to explore, explain and perhaps predict how behaviour of an individual unfolds over time in a given context.

Given the uniqueness and context-specificity of an individual's actions it is computationally difficult to model all the possible motivations and other behavioural drivers of a given action. For example, a person may respond to stress at work by either putting extra hours into the work or withdrawing from it completely. The drivers for this stress response could range from the person's health status, skill level, reward systems, gender, supervisory support, organizational culture, and many more such dimensions. Simulations of agent based models provide an approach to execute such computational models of human behaviour, such that at every simulation step, an individual agent makes a decision and takes an action considering its own internal behavioural state, behavioural relations and context. In addition, in the presence of a large number of behavioural dimensions or variables, the analysis of their combined effect on outcomes of interest may turn out to be intractable, inconclusive or even impossible. Hence the computational model should find a way to generalize by accepting simplifications and approximations as useful compromises.

This paper describes a framework for human behaviour modelling and simulation in organizations called the Behaviour Analysis Framework (BAF). The BAF makes use of behavioural relations extracted from past research and field studies in organizations to compose a human behavioural model. This model is then used to simulate an enterprise support services team. The simulation allows us to perform experiments on team-level outcomes in the absence and presence of the composed human behaviour.

The rest of the paper is organized as follows: we present an overview of past research in human behaviour modelling and simulation, followed by our study approach, working example, findings, insights and discussion on future work.

2. PAST WORK

Human behaviour has been a topic of continued interest in a wide variety of domains whether it is organizational behaviour or the behaviour of consumers or citizens in society. The domains of behavioural sciences, particularly psychology, sociology and anthropology have offered deep insights into human behaviour in a variety of contexts. . With respect to behavioural sciences, a variety of theoretical and empirical approaches are used to evolve new hypotheses within a context as well as to test and validate them. Empirical techniques in the social sciences range from the quantitative, wherein surveys, experiments, meta-analysis, etc. are used, to the qualitative which involves an in depth examination of text or qualitative data. Within the behavioural sciences, however, the use of computational modelling in studying human behaviour is relatively limited and is emerging as a technique to discover new theoretical relationships only in recent years.

In recent years, there has been an emerging interest in the use of computational techniques to study human behaviour in various contexts such as in an organizational setting [1]. The techniques range from using apps to capture data to simulation engines to simulate behaviour. The mix of computational techniques coupled with the social sciences provides a best of both worlds that can help in modelling and understanding human behaviour in various domains of interest. Our paper uses this stream of literature to guide our overall approach in this study by the application of modelling techniques to understand behaviour in organizational settings at a more granular level. Given the relative novelty of the use of modelling and simulation in industrial and organizational psychology, we demonstrate how dynamic aspects of behaviour can be examined in a specific organizational setting, like a software support services organization.

With respect to the business context, support services are significant drivers of growth and profitability for organizations today. Given the emphasis on business performance, the industry tracks a variety of metrics, most notably client-driven service level agreements (SLAs), process quality standards, other internal organizational data and benchmarks for performance, which makes it a rich context for an empirical investigation. Moreover, being a sector completely driven by its people, the support services industry, and more specifically the support services organization itself, offers a rich canvas for modelling various dimensions of human behaviour, associated task characteristics and their impact on work outcomes such as task completion, absenteeism and productivity.

The quest of bringing the behaviour of simulated agents as close to the reality as possible draws in to account for various human factors such as personality, emotions, relationships with others, stress, goals, standards and preferences, and their impact on the agent's decision making. Silverman et. al. [2,3,4] introduced a performance-centric approach namely 'Performance Moderating Functions', by choosing relevant models from behavioural sciences literature, to be later abstracted, composed and implemented for their computational platform 'PMFServ'. This platform is used as a behavioural engine to drive synthetic agents in a military training simulator [5,6]. However, modelling, representation, simulation and prediction of human behaviour, as individuals and as in groups, still remains a challenge [7]. In addition, we believe that modularity and reusability of these models across various contexts and domains adds a compounding difficulty.

In this work we discuss an approach to computationally model human behaviour by combining results obtained from behavioural research literature and field studies. The approach utilizes the Behaviour Analysis Framework (BAF) for collecting and analysing data, model creation/discovery and simulating a situation of interest. The particular example described here attempts to create a realistic behavioural model of individuals in a software support and maintenance team. We use behavioural insights from a field study of a large support services organization, along with behavioural models extracted from relevant literature to construct an agent based simulation model of a support services team.

We consider behavioural characteristics such as perceived workload, affect and stress on the job; and the individual's perceptions of her own daily productivity as the focus of the present study. We refer to affect as the emotional experience of the individual at the start of the work day and the end of the work day, with respect to their job. We use the positive affect negative affect scale (PANAS) to measure various dimensions of positive and negative affect over the course of the workday for the respondent [8]. Stress at work has been measured using the model proposed by [11]. This model proposes distinct styles of decision making under stress, such as vigilance, hyper vigilance, and defensive avoidance. This model of stress and coping has earlier been implemented in simulators by Silverman et al [3].

To summarize, previously developed approaches such as PMFServ provide ways to model human behaviour in a performance-centric manner. However, considering generality and modularity as essential elements to incrementally develop behavioural models, it prompts us to have a fresh look at the problem and perhaps develop a different approach, such as guided by software engineering methods.

3. OUR APPROACH

As discussed above, the primary focus of this work is to develop a realistic model of human behaviour in the organizational context. Towards this goal, we have designed a computational framework as shown in Figure 1. Behaviour Analysis Framework. The framework is called the Behaviour Analysis Framework (BAF) using which we collect field data, combine it with insights from past research and use the combined behavioural relations in a simulation.

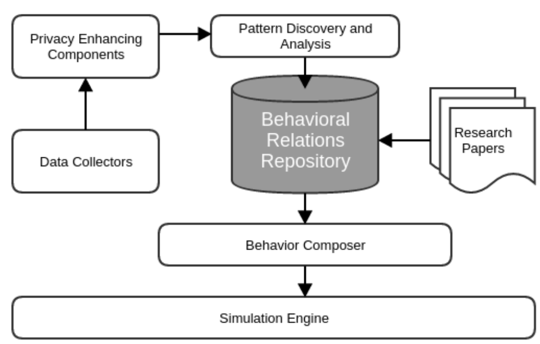

Figure 1. Behaviour Analysis Framework

In the following sections we present our approach in more detail, in terms of data collection from the field, analysis, use of past research insights and simulation.

3.1 Mine Past Research

The core of the BAF is a behavioural relations repository. Relations refer to models of behaviour which link specific behavioural dimensions to specific outcomes (e.g. the relation between affect and productivity) or between one behavioural dimension to another (for example, a relation between Negative Affect and Stress). This is a store of behavioural relations extracted from past research and behavioural studies in the areas of behavioural and social sciences that details the relationship among human behavioural dimensions and outcomes of interest. These dimensions could be aspects of an individual's behaviours such as personality, affect, motivation, performance, productivity, etc. The behaviour repository thus offers us an extensive resource for behavioural insights to be used for modelling and simulation.

3.2 Collect Behavioural Data

Behavioural data collection spans both quantitative (e.g. surveys, secondary data, sensor data etc.) and qualitative methods (e.g. interviews, focus groups, etc.). Duly anonymised, such multi-modal data sources can offer us an in-depth perspective of human behaviour in an organizational setting.

We start the study by exploring a specific organizational context, in this case a support services organization. We carry out in depth interviews with key stakeholders in the organization to get a deeper understanding of the business, its challenges, nature of work and its key deliverables. We also collect existing objective data in the business context such as HR data on employee profiles, metrics on performance, ratings, quality, productivity etc. Based on interview insights and a review of past research, we develop surveys aimed at measuring dynamic aspects of behaviour such as affect, stress and productivity. These surveys are administered at the start and end of the workday to the respondents after seeking their informed consent and after complying with due privacy and confidentiality policies.

3.3 Analyse and Model

Survey data are analysed using standard statistical techniques (e.g. regression, t-test, etc.). Survey data from the respondents and their related organizational data help establish relations between our behavioural dimensions (e.g. affect and stress) and outcomes of interest (e.g. absenteeism and productivity).

Results from the survey data analysis coupled with a related search of past research from the behaviour repository, focused on the same behavioural dimensions, provide us with *relations.* As mentioned above, relations refer to mathematical models of behaviour which link specific behavioural dimensions to specific outcomes. These relations are stored in the behavioural relations repository present in the BAF.

3.4 Behaviour Composition and Simulation

In order to realistically generate human behaviour in a simulated entity (agent) we need a human behavioural model that ties behavioural elements like stress and affect to outcomes of interest like on the job productivity. We use the relations stored in the behavioural relations repository of BAF to compose such human behavioural models for simulated entities. The composition begins with identifying common behavioural elements across relations in the repository. These are then used to combine multiple relations into one composite model of human behaviour for a simulated entity. For example, the three relations, $\boldsymbol{Workload\ perception \rightarrow Affect}$; $\boldsymbol{Affect \rightarrow Stress}$ and $\boldsymbol{Stress \rightarrow Productivity}$ are combined as:

$$\boldsymbol{Workload\ perception \rightarrow Affect \rightarrow Stress \rightarrow Productivity}$$

The composed model can be thought of as an aggregate of multiple relations present in the relations repository of the BAF. The composed model is then used by an agent based simulation engine to generate dynamic behaviour for a set of simulated entities (agents) like, members of a support services team. The simulation engine executes the behavioural model for each agent given a particular simulation scenario. Such simulations enables us to analyse the composed model's behaviour in various scenarios, and reason about the closeness of the simulated behaviour to that observed in the real world. Such a model can be used as a sandbox for discovering the impact of executive policies on important and emergent outcomes like productivity of the work force, thereby making it a useful decision support tool.

4. Working Example

4.1 Context and Goals

The present study was motivated by a request from a support services organization requesting the research team for inputs on behavioural drivers of absenteeism and productivity, which were the primary business priorities to their business leadership. The support services team wished to also explore the dynamics of the impact of various behavioural drivers on absenteeism and productivity.

4.2 Field Study and findings

We started the study by carrying out a preliminary field investigation in the support services organization mentioned above. This enabled us to identify behavioural insights from a real business context, combined with other relevant objective data in the model we developed. Further, we reviewed past research related to the individual, job, absenteeism, stress and productivity which revealed specific behavioural relations. These were used in combination with the insights for the field studies in our simulation model. We discuss each of the specific aspects of this approach in the next section.

4.3 Collect Data

We used a survey based approach for the field investigation where we measured various aspects of individual behaviour using repeated surveys using an Android-based application on the user's smart phone over a two-week period. These surveys sought the individual's response on dimensions such as affect, stress and self-reported productivity.

The survey was complemented by organizational data available from the HR teams of the support services organization. The organizational data provided us information on the individual's demographic characteristics like location, education, skill level, tenure etc., as well as data on process quality, performance ratings and objective productivity.

Together with the field study, we also carried out a review of literature, which demonstrated to us various behavioural relations that we examined in our study. The specific relations we studied are shown in Table 1.

The surveys were administered to a sample of 100 volunteers from the support services organization. Respondents were duly briefed on the survey and their informed consent was sought before they participated in the study. The surveys were administered on the respondents' Android smartphones and they were required to take the surveys measuring affect, stress and productivity at the start and end of their workdays, over a two-week period.

Table 1. Variables of Interest

Variable	Data Sources
Affect	Survey
Stress	Survey
Workload	1-1 interview
Absenteeism	Objective organizational data
Productivity	Survey

The survey and objective organizational data were further supported by 1-1 discussions with delivery heads of sub-teams of the larger sample. This discussion helped us get information on various process level metrics such as workload, hich has been used in the simulation model.

4.4 Simulated Model

We created a multi agent simulation of a software support team using the approach discussed above. We used the GIS and Agent-based Modelling Architecture GAMA [9] as a simulation engine to implement the simulation. The simulation model has two key components: 1) A process model that describes team and task-related metrics for the support services team being simulated, 2) A human behavioural model composed from relations present in the BAF that establishes relationships between a simulated agent's behavioural characteristics and the functional outcomes of interest like productivity and absenteeism probability. We describe each of these components below.

4.4.1 Process Model

The simulated team consists of 50 individuals working in a typical support services workspace. The maximum number of work hours allowed per agent is 10. This includes 8 regular work hours, along with a maximum of 2 hours of overtime. Work is modelled as discrete and independent tasks arriving at the beginning of each work day. The exact number of tasks arriving on a work day is taken from a Normal distribution with a mean and standard deviation of 1000 and 100 respectively. These tasks accumulate in a task pool for the entire team. Individual tasks from this task pool are then uniformly allocated to all the available members (agents) of the support team. An available member is a team member (agent) that is present for work on a particular work day. The initial productivity per agent is set to 2.5 tasks per hour. A task once finished is removed from the task pool.

4.4.2 Human-like Behaviour Model

The following relations were discovered after the analysis of the data collected from the field study and mining of relevant literature:

$$\boldsymbol{Workload\ perception \rightarrow\ Affect}$$

$$\boldsymbol{Affect \rightarrow\ Stress}$$

$$\boldsymbol{Stress \rightarrow\ Productivity}$$

$$\boldsymbol{Stress \rightarrow\ P(Absenteeism)}$$

As discussed in section 3.4, we combine these relations together to come up with a composed human behavioural model. We began by identifying common behavioural variables i.e.: Affect, Stress and used these to combine the four relations above into a composite behavioural model. The relations used in this paper thus have been tested in past research as well as validated in a field study within a real organization. This model takes into account two behavioural variables: Stress and Affect and two outcomes of interest: Productivity and Absenteeism probability.

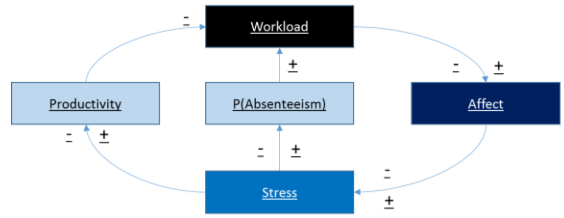

Figure 2. Composed model of human behaviour

The composed model figure 2 above takes the following form:

$$\boldsymbol{Workload\ perception \rightarrow\ Affect \rightarrow Stress \rightarrow Productivity}$$

$$\boldsymbol{Workload\ perception \rightarrow\ Affect \rightarrow Stress \rightarrow P(Absenteeism)}$$

Here, the perceived workload (Workload perception) is defined as the number of extra tasks arriving at the beginning of a work day over and above the mean of task arrival for an individual agent. Affect refers to a general positive or negative emotional experience of the individual at the start and end of the work day. Stress refers to negative behavioural responses to a specific challenging situation or context. In our study, we refer to absenteeism as the number of days the individual goes on unplanned or unscheduled leave from work. Lastly, productivity refers to the number of assigned tasks completed at the end of the person's work day or shift. Table 2 describes the specific equation-based or rule based forms of relations used in the composed human behavioural model for the simulation:

Table 2. Relations used in the composed human behavioural model for simulation

Relation	Model	Source
$Affect\ \leftarrow Workload$	Negative Affect=0.53 (workload)+0.7	Illies et al.[10]
$Stress \leftarrow Affect$	Stress=0.39 (Affect)+0.51	Field Study

$Productivity \leftarrow Stress$	If (Stress <= 0.1) then Productivity= 0.1 * Productivity
	If (Stress > 0.1 && <= 0.25) then Productivity= 0.5 * Productivity
	If (Stress > 0.25 && <= 0.75) then Productivity= 1.25 * Productivity
	If (Stress > 0.75 && <= 0.9) then Productivity= 0.5 * Productivity
	If (Stress > 0.9) then Productivity= 0.1 * Productivity
		Janis Mann (1977) Silverman's PMF Model

$P(Absenteeism) \leftarrow Stress$	If stress>0.9 then N(0.1, 0.1)	Field Study

The composed human behavioural model discussed above is used by the simulation engine to generate human-like behaviour for simulated team members of a support services team constrained by the process model discussed in section 4.4.1. Although the model may seem bounded by fewer parameters and finite value range, it generates interesting dynamics to study spectrum of outcomes. A model with large set of parameters and wide range of values becomes intractable for analysis. Thus this can be considered as a boxed experiment.

The simulation runs for 120 working days (24 work-weeks). A work-week is composed of 5 working days. A spike doubles the number of tasks arriving on a particular work day.

5. FINDINGS

We run two scenarios on the simulation model discussed above. First, we execute the model without taking into consideration the impact of any human behavioural variable on agent behaviour. In the second case, we factor in the impact of two human behavioural variables: Affect and Stress on agent productivity and make observations on outcomes like the state of the task pool for the team and average stress levels for the team.

5.1 Agents as automatons

In the first scenario agent's behave like automatons working on an assembly line. Here, if the number of tasks arriving at the beginning of a day are equal to or less than the combined daily work capacity of all the agents, the task pool is empty by the end of the work day. However, if the number of tasks arriving at the start of a day are more than the combined work capacity of all the agents, the task pool retains some tasks by the end of the workday, which results in task build-up or backlog. Consequently, a spike in task arrival leads to the formation of a substantial backlog. However, the system is able to recover from the backlog because of a work spike in a few days because of buffer staff and regular staff working overtime. Buffer staff refers to extra workers that can support the team operations at a time of crisis or work spike. The amount of buffer staff used in the simulation was 6% of the total staff. Figure 3 shows the task pool for the entire team over simulation time. Here, the horizontal axis represents simulated work hours and the vertical axis represents the number of tasks present in the task pool.

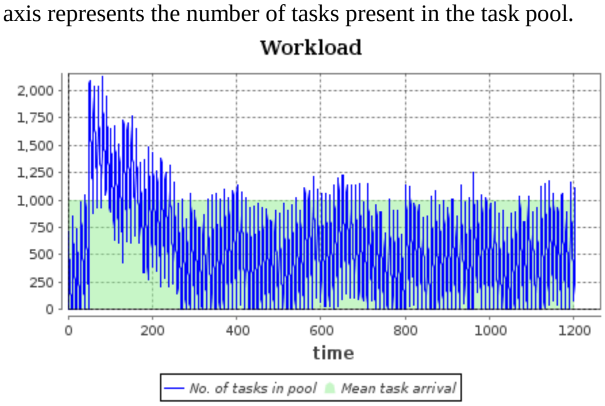

Figure 3. Variations in the team's common task pool over simulation time

5.2 Agents with human-like behaviour

In the next experiment we factor in human behaviour for each agent. We implement workload perception, affect and stress as behavioural variables for each agent, and implement the human behavioural model as discussed in section *4.4.2*. We execute this experiment for the simulation duration of 120 working days and record metrics like: the state of the task pool over time, average stress among the individuals in the support team and number of absentees on a work day. Figures 4 and 5 show the task pool for the entire team over time and average levels of stress for the team over time respectively. For figure 4, the horizontal axis represents simulated work hours and the vertical axis represents the number of tasks present in the task pool. Similarly, for figure 5, the horizontal axis represents simulated work hours and the vertical axis represents the average level of stress in the team. This ranges from 0 to 1.

Figure 4. Variations in the team's common task pool over simulation time

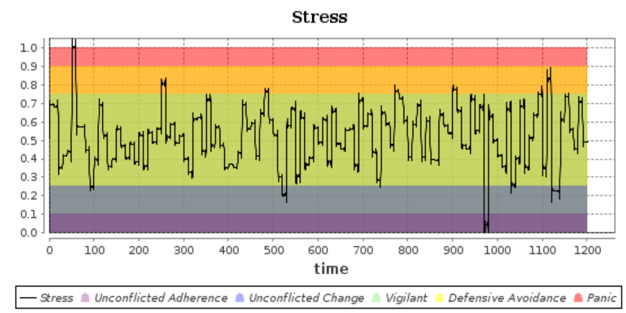

Figure 5. Variations in the team's average stress level over simulation time

Based on the human behavioural model discussed earlier, it is important to highlight that an individual performs optimally only when her stress level lies in the green band of the graph (0.25 to 0.75). If stress for an individual moves out of this band, the individual starts performing sub-optimally leading to low levels of productivity, which leads to backlog and an accumulation of tasks in the team's common task pool.

We observe that the average stress in the team spikes as the workload on individual agents increases because of a spike in tasks, on the second week (after 50 hours on the time axis). However, as the workload stabilizes the average stress level returns to normal. The spike in stress also increases the absenteeism probability of individual agents, causing a spike in the number of absentees on the subsequent days of the spike in average stress. Figure 6 shows the variation in the number of people who are absent with respect to the simulated work days. Here, we observe that absenteeism triggers a vicious cycle, leading to more absenteeism afterwards.

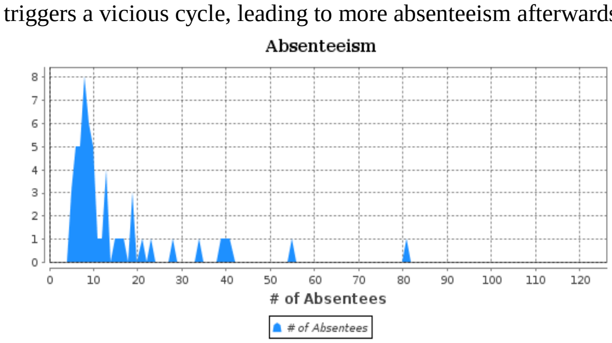

Figure 6. Variations in the number of absentees in the team over the simulation days

This happens because the absence of a team member causes the tasks allocated to the team member to be distributed equally among the rest of the available team members. This causes an increase in the workload of the rest of the team leading to an increased stress among the rest of the team members. Increased stress translates into a greater probability of being absent on the subsequent day for the stressed team members. This leads to a greater number of team members being absent on the subsequent days.

6. FUTURE WORK AND CONCLUSION

In this work we propose a model that incorporates human behaviour into simulated agent's working in an enterprise. We were able to factor in various elements of realism like backlog, absenteeism and spikes in workload. The intent of this work is to demonstrate a possible approach of modelling human behaviour into programmed agents. The human behaviour model presented here is limited when compared to real-world human behaviour in that it includes only bivariate relations. However, this approach allows the modeller to begin with simpler models and then incrementally add more complex behaviour until sufficiently realistic behaviour emerges. The model can then be used to understand a situation and devise interventions if necessary. One dimension for augmenting the current model is to factor in the social environment and social influences. A team would thus be modelled not just as a set of individuals but a network of networks of social and professional relationships. A related area of work which is notably difficult [12] is to extract insights from data generated by simulation of complex networked models with many behavioural variables.

We would also like to increase the number of behavioural variables that are at play. In particular, we would like to use various personality traits and their interplay with agent productivity. This would allow the modeller to compose teams of complex agents having diverse personality traits, which would lead to different behaviours for the organization as a whole. We would also like to model more outcomes of interest, like attrition and change in agent expertise.

7. ACKNOWLEDGMENTS

We are grateful to our group members Sachin Patel and David Clarance for their contributions to this work.

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