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TOWARDS FINE GRAINED HUMAN BEHAVIOUR SIMULATION MODELS

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ABSTRACT

Agent based simulation modelers have found it difficult to build grounded fine grained simulation models of human behavior. By grounded we mean that the model elements must rest on valid observations of the real world, by fine grained we mean the ability to factor in multiple dimensions of behavior such as personality, affect and stress. In this paper, we present a set of guidelines to build such models that use fragments of behavior mined from past literature in the social sciences as well as behavioral studies conducted in the field. The behavior fragments serve as the building blocks to compose grounded fine grained behavior models. The models can be used in simulations for studying the dynamics of any set of behavioral dimensions in some situation of interest. These guidelines are a result of our experience with creating a fine grained simulation model of a support services organization.

1 INTRODUCTION

Agent based simulation has been largely targeted, through a combination of design, necessity and do-ability, towards two classes of systems. The first class which can be called Minimalist Agent Based Systems (M-ABS), was pioneered by Schelling's segregation model (Schelling 1969, Schelling 1971) and continued with the work of other early workers such as Axelrod (Axelrod and Hamilton 1981, Axelrod 1997), Epstein (Epstein 2001), and continued today by works such as (Balaraman et al. 2015, Mahmoud et al. 2012, Katiyar and Clarance 2015). The goal of minimalist ABS is to understand a behavior seen in the real world or to generate hypotheses. Examples of such ABS are formation of ghettos, the spread of ideas among a community and the establishment of norms. These systems use highly abstracted environments and simple rules of agent behavior to see how a behavior may emerge as a consequence of the environment and agent rules. The agent population in such systems is also low, numbering a few score or a few hundred. A second category are agent systems modelling very large human populations situated in the real world to focus on aspects such as traffic modelling, disaster management and urban policy informatics (Hidas 2002, Raney et al. 2003, Eubank et al. 2004, Epstein 2009). Once again the individual models of agents remain relatively simple in this case.

There has been relatively less work on a third class of agent based simulation systems where the agent behavior is more complex and based on multiple drivers of behavior, such as psychological, physiological, cognitive, social and environmental to study their dynamics in specific situations or classes of situations. We call these Fine Grained Agent Based Simulation (FG-ABS) models. These can be of great use in studying real world environments where a person can exhibit a range of behaviors driven by multiple factors. For example, the behavior of a software developer in a software project is complex due to the variety of tasks and a spectrum of factors from skill, motivation, stress, personality, affect, relationships with peers and supervisors, norms as well as ambient factors of the workplace such as noise and temperature. Being able to know the dynamics of individuals in a team may help us to better understand how these impact outcome variables of interest such as individual and group productivity, work completion or schedule slippage. Similar complexities hold for other domains such as consumer behavior or behavior of armed forces in hostile territory. The big challenge has been to build grounded models where each component of the model, is based on real observations, studies or experiments and are not just based on assumptions. Grounded models may allow complex fine grained agent models to be built since each building block, a behavioral relation tying together two behavioral variables (say affect and motivation) or a behavioral variable and an outcome variable (say stress and absenteeism) is based on evidence of such a relation from a study or experiment and its use is thus justified. Our motivation in this work is to be able to build fine grained agent models that will allow complex human systems to be studied and analyzed.

Silverman (Silverman 2004) was the first to propose an approach to enhance realism in non-trivial human behavioral modeling with the PMFServ architecture. As a part of this effort they assessed the state of the practice in human performance moderator functions published in the behavioral sciences literature. It was found that more than 40% of the assessed literature could be directly used for implementing models of human performance called Performance Moderator Functions (PMFs). Based on this best-of-breed PMFs were extracted, composed and implemented in a computational platform 'PMFServ'. This platform is used as a behavioral engine to drive synthetic agents in a military training simulator (Silverman et al. 2009, Silverman et al. 2012). Another effort towards realistic simulated agent behavior is the MAMID methodology and architecture (Hudlicka 2003). The work describes a cognitive-affective architecture capable of producing observable behavior differences emanating from distinct individual profiles.

In this paper, we present an approach to build fine grained models using fragments of behavior, which consists of behavioral relations and patterns been obtained from field studies, mined from literature or other behavioral datasets. We demonstrate this approach using a real example in the organizational domain of a support services unit who wanted to understand the behavioral drivers behind productivity in the workplace and their potential impact on workplace outcomes. We show through two related examples of how such models can be composed and how the simulated results bear close resemblance to real world values.

2 A GUIDELINE FOR BEHAVIOUR COMPOSITION

Before we describe the guidelines, it is necessary that the readers be acquainted with what is involved in a typical behavioral study. A behavioral study usually seeks to test a behavioral relation that has been hypothesized or to prove a behavioral hypothesis in some domain. Many of these studies are empirical in nature and they focus on a specific subset of variables. The choice of which variables to include in the model would be driven by the researcher's own motivation or interest in the problem area or gaps in past research. The study usually begins with an analysis of the past research on the variables of interest. If the researcher wants to test out the role of *additional* behavioral factors, such as the role of the individual's personality or demographic factors for instance, a follow-up empirical study would be conducted. The major tasks in the whole process are selecting the variables to include in the model, discovering relations between the variables, identifying gaps or additional variables with respect to the context being modelled, conducting a field study to measure the additional variables and discovering relationships between the full set of variables. For example, in a study on job characteristics and their relationship with burnout and engagement, (Schaufeli and Bakker 2004) first discuss the gaps in past research on work engagement, which serves as the primary motivation behind the selection of engagement, burnout, job demands and resources as study variables. The authors then hypothesize relations among the above variables. The integrated research model thus links job demands and resources with burnout and engagement. The study variables are measured using a survey of employees in an organization. The results obtained using structural equation modeling thus serve to support the study hypotheses. Behavioral studies thus provide us with the relations that are the fodder to compose models. With this understanding we now propose a set of guidelines to be used for behavior composition.

Step 0: Variable Selection: Given the variables of interest, the first challenge is to decide on the other behavior variables that should be included in the model. Additional variables are included when: a) they feature in past research where they have been measured and tested to have a significant impact on the study variables (e.g. gender, emotion.); b) they feature in past research where they serve as a bridge to tie together two or more variables which are in the variable set; c) they appear in past research but are untested (for example in a study of the impact of personality on productivity, data on variables like gender or age might be collected, but links between them and the outcome variable of interest, namely productivity may not be explicitly tested, which become likely candidates for variable selection as well and d) they are relevant to the context of the study itself.

Step 1: Variable Disambiguation: A major challenge in behavioral research is ambiguity in the definition of variables. The ambiguity arises both due to similar variables being given different names as well as different underlying variables being provided similar names in past research. An example is given in section 3.5. A domain expert would thus have to arrive at a set of ***common*** **definitions** of the variables of interest based on an in-depth understanding of variable definitions and the study context itself.

Step 2: Measurement model: The field of behavioral science research has examined many such relations among behavioral variables across contexts. This has resulted in behavioral variables being defined and measured in several different ways by researchers in the field. For example, the behavioral variable of 'intrinsic motivation' would find several survey measures in the literature. An important challenge therefore, would be evolving **criteria for selection of behavioral relations** of interest from past research. We currently use a *theory-driven approach* for selection of behavioral variables of interest, where the researcher identifies similar variables based on their definition and measurement and then decides on their use in the composition.

Step 3: Behavior Fragment Selection: The researcher could not only use individual studies, but also **meta-analysis**, which offers synthesized effect sizes among behavioral variables, across studies. We suggest that meta-analytic effect sizes or results offer a more robust relationship as compared to individual studies. However, given the challenges in doing valid meta-analysis, results from individual studies are also used. For example, if the researcher wishes to study the link between personality dimensions of neuroticism and conscientiousness with absenteeism, the meta-analysis by Ones et al. (Ones et al. 2003) suggests that the effect of personality on absenteeism is 0.25. Such fragments provide relationships discovered from a large number of studies. Further, we suggest using relations that are tested using statistical tests like multiple regression. This helps us interpret standardized beta coefficients as a measure of strength of impact of the predictor on the outcome variable, and use the overall model fit (Adjusted R^2) as a measure of the strength of the model itself. Thus relations with higher adjusted r^2 would be selected by the researcher in the composition. When the aim of the simulation experiment is to explore unclear or conflicting relations among past research, models with non-significant or lower adjusted r^2 values might also be chosen by the researcher.

Step 4: Connecting the Fragments: These individual relations identified are thus linked theoretically based on common definitions and terminologies. These linked relations are then used in a simulation model to study their dynamics longitudinally in a synthetic environment. The mathematical form of these relations are currently in the form of regression functions and rules.

Step 5: Quantification of the model: There are many fragments that provide qualitative framework for modeling. For example the Inverted-U model (also known as the Yerkes-Dodson law) (Yerkes and Dodson 1908) reinterpreted by Janis and Mann (Janis and Mann 1977) which describes the relationship between stress and performance, but do not provide any numerical thresholds. These numerical thresholds are thus decided by a domain expert based on observations made in the field study. Sometimes, it helps to execute some trial simulation runs to arrive at an appropriate value for these thresholds.

Step 6: Conversion to a Simulation model: A typical simulation model would comprise of the following sub-steps:
Step 6.1: Composing of human behavior for agents: For composing human behavior of individual agents, behavior fragments such as regression functions and rules are connected together to form a linked or combined model where nodes are behavior factors and edges are respective computations, from source nodes to target nodes. Regression functions compute next state of the agent using current state, whereas rules acting as guard conditions during execution, provide threshold values and can also act as a switch between two models of the same relation, different groups of agents can be grouped based on the same grouping variable (e.g. agents high on conscientiousness vs. low on conscientiousness) and alternate scenarios of the same variable (e.g. a model linking stress and productivity, (Janis and Mann 1977, Silverman 2004)).
Step 6.2: Configuring a process model and assigning agents to it and
Step 6.3: Environment Setup: Defining an environment model and inserting the process model into it. The process and environment models are derived from one or more field studies. These help in defining the non-agent aspects of a simulation model, hence imparting realism to the overall system being simulated. These guidelines were developed iteratively through our experience conducting a series of simulation experiments with a support services organization. In the next section we describe the simulation models we had created, experiments conducted using these models followed by analysis of some of the experiment results.

3 CASE STUDY

This study is aimed at modelling a support services organization, understanding behavioral drivers behind productivity and absenteeism of individuals and understanding the implications of these factors on the overall performance of an organizational unit (a team of support service provider agents).

3.1 The Context (Support Services organization)

The support services organization receives service requests (tasks) from its customers in business domains such as mortgage and insurance. Examples of such requests are receiving filled-in application forms from new customers, verifying customer details, flagging incomplete forms and so on. Each request needs to be completed within a stipulated time as per the service-level agreement (SLA) between the customer and the service organization. As the requests arrive, they are added to the task-pool. When the work day begins, the requests in the task-pool are distributed among the team on a first-come-first-served basis. Unfinished tasks are rolled over and become the first tasks in the task-pool for the next day. The workload arrival pattern has variations (including spikes) which are not known in advance. In order to deal with such uncertainties, the organization maintains a separate team of individuals who are called buffers or bench. These individuals are called in to work under two conditions, if there is a big spike in workload and or to compensate for planned or unplanned absenteeism among the regular team. The size of the bench has to be finely calculated since maintaining a large bench would impact profitability while too small a team risks violating the SLA should there be a spike or sudden increase in workload.

3.2 Variable Definitions

Below we define some of the study variables that have been referred to in the following discussion:

Personality is measured using the Big 5 model of personality comprising of five sub-dimensions namely openness to experience, conscientiousness, extraversion, agreeableness and neuroticism.

Emotional state refers to the individual's experience of positive and negative emotion with respect to their work, at a specific point of time during the work day, namely at the start of their work day and at the end of their work day.

Momentary stress refers to the perception of stress related to work at the start and end of the individual's work day.

Workload refers to the number of tasks arriving on a particular day, to be completed by an individual by the end of the day.

Workload spike refers to a 1.75 times increase in workload on a particular day (exceptional day).

Backlog refers to the number of pending tasks for an individual at a particular instance of time.

Crisis point refers to an instance of time after which the simulated team cannot recover from the total accumulated backlog given the remaining simulation execution time.

Risk is the probability that a simulated scenario will reach crisis point. It is defined for a simulation scenario as the number of simulation executions (runs) during which crisis point was reached one or more times during execution divided by the total number of simulation runs.

$$\text{Risk} = \text{Number of runs that reached crisis point} \div \text{Total number of runs}$$

Bench strength refers to individuals in the workforce that are used only during crisis situations like: heavy workload arrival on a particular day, large number of unplanned absentees on a particular day, etc. This is expressed as a percentage of the total available workforce.

Turn-around time (TAT) is the time taken by the simulated team to complete a newly arrived task.

Absenteeism refers to the number of unplanned leaves taken by an individual participating in the study.

Productivity was measured via self-reports, i.e. using a survey where the individual rated themselves in terms of whether they had achieved their daily goals and targets and whether they had achieved all that they had planned to do. Objective productivity metrics were also collected for the participating individuals, from the support services organization in terms of their performance ratings, quality and productivity.

3.3 The Field Study

A field study was rolled out to participants of the support services organization who volunteered to participate in the study. The study comprised of two surveys: a one-time survey that captured the stable aspects of behavior such as personality and job-related factors. The second survey was a repeated survey intended to measure the more dynamic aspects of behavior namely emotion, stress, productivity etc. The survey was administered on the respondents' smart phone and they were sent notifications to participate in the survey at the start and end of the work day over a two week period. The participants' objective data such as their profile data, demographic information and objective productivity measures were also collected. All data was duly anonymized prior to sharing with the research team to adequately address privacy concerns of the respondent. All surveys were in a five-point Likert scale format ranging from 'strongly disagree' to 'strongly agree' except for stress which was on a three-point scale, 'Yes', 'No' and NA. All measures used for the survey were based on existing research and validated survey instruments for e.g. PANAS-X (Watson and Clark 1999). The hypotheses were tested using multiple regression and t-test to test differences among groups based on conscientiousness which is a sub-dimension of personality. Results of the analysis showed that the impact of negative affect on stress was 0.39 ($p<0.05$). Similarly, high stress (>0.9) was correlated with high absenteeism. Further, we found that individuals high on conscientiousness had a lower impact of negative affect on stress (affect=0.35) while those who were low on conscientiousness had a higher impact of negative affect on stress (affect=0.43). Thus conscientiousness played an explanatory role in the relationship between negative affect and stress. Other insights discovered were with respect to the role of engagement and satisfaction on objective and self-reported productivity as well as the role of mentorship and supervisory support on individual work outcomes.

3.4 Process and Environment Models

Given the study's findings the services unit management wanted to find out the implications of these findings on the overall productivity of the unit. To explore this question we used agent based simulation to simulate a prototypical engagement within the services unit. The engagement consists of a team of 50 support service provider agents. At the start of every business day, the team receives workload for that day, as a collection of discrete, independent tasks. We modeled the arrival of tasks as a Gaussian distribution, N (1000, 100). The tasks arrive each day and are gathered in a 'common task pool'. Once the work day begins, the tasks are uniformly assigned to the available team members. Each simulation 'tick' corresponds to an hour in real time. On any typical day, an agent can spend 8 hours for regular work and an additional maximum of 2 more hours as overtime. After work on a task is completed, the task is removed from the pool. The average productivity per agent is 2.5 tasks per hour. Since it is a common occurrence in the unit we also include a day with a spike in task arrival that is 1.75 times the normal task arrival. The task pool is modeled using a synchronous queue to support concurrent execution. Behavior of each agent varies based on environment stimuli, the agent state and specific behavior model. Hence, an agent's stress level, performance, affective state, etc. vary over a simulated day. This change in an agent's behavior is observable at each simulation 'tick'.

3.5 Behavioral Model Composition

We apply the guidelines discussed in section 2, to arrive at composed behavioral models that are capable of generating behavior for synthetic support service provider agents operating in the environment described in section 3.4.

Step 0: Variable Selection: Findings from past research, the field study itself and the study context helped decide the variables to be included in the model. For example, workload and spike were determined based on discussions with stakeholders in the study context, i.e., the support services organization.

Step 1: Variable Disambiguation: The variables defined in section 3.2 were included in the model by identifying relevant variables from a set of theoretically related variables from the behavioral sciences. For example, a variable named *absenteeism* could be named *unplanned leave* in another study or described as *unscheduled leave* in the study context. Similarly another study could use the variable *absence* to indicate the individual's leave either planned or unplanned from work, or in some cases even leave the motivation for the leave from work unspecified. As explained in section 2 this involved the domain expert carrying out an in-depth review of constructs related to absenteeism and productivity, which were the primary challenges of interest to the field study context as well.

Step 2: Measurement model: All measures used for the survey were based on existing research and validated survey instruments for e.g. PANAS-X (Watson and Clark 1999).

Step 3: Behavior Fragment Selection: From the literature survey we identified 2 sources (Ilies et al. 2015) and (Janis and Mann 1977) which had studied the variables of interest. Further there were some variable relations that were discovered through the behavioral study. Table 1 below shows a list of the behavioral fragments that were identified, along with their sources.

Table 1: Behavioral relations and their forms used in behavioral model without individual differences.

Relations	Form	Description	Source
Affect ← Workload	Affect=0.53 (workload)+0.7	Perception of workload has a positive impact on negative affect	Ilies et al. 2015

Stress ← Affect	**If** (Conscientious = TRUE) **then**
	Stress=0.35 (Affect)+0.64
	else
		High conscientiousness had a lower impact of negative affect on stress (affect=0.35) while	Field Study

Relations	**Form**	**Description**	**Source**
	Stress=0.43 (Affect)+0.47	those who were low conscientiousness had a higher impact of negative affect on stress (affect=0.43)	
Stress ← Affect	Stress=0.39 (Affect)+0.51	Impact of negative affect on stress was 0.39 (p<0.05)	Field Study
Productivity ← Stress	<u>Productivity = **M** * Base Productivity</u> **If**(Stress <= 0.1) **then** M = 0.1 **If** (Stress > 0.1 **and** <= 0.25) **then** M = 0.5 **If** (Stress > 0.25 **and** <= 0.75) **then** M = 1.25 **If** (Stress > 0.75 **and** <= 0.9) **then** M = 0.5 **If** (Stress > 0.9) **then** M = 0.1	Stress has an impact on decision making and hence influences productivity. This follows the inverted-U model which suggests that an optimal amount of stress is required for best performance, very low and very high stress degrades performance.	Silverman 2004
P(Absenteeism) ← Stress	**If(**stress>0.9) **then** N(0.1, 0.1)	High stress (>0.9) was correlated with high absenteeism	Field Study

As the source column indicates fragments 1 and 4 are obtained from the literature, whereas 2, 3 and 5 have been obtained from the field study. Behavior Fragments 2 and 3 both are relationships between *Stress* and *Affect*, however relation 2 also comprises of a moderator (explanatory) variable – *Conscientiousness*.

Step 4: Connecting the Fragments:
These set of behavior fragments may be used to compose a number of individual models. At the minimum we have these two relationship chains:

Workload perception→ Affect→Stress→Productivity
Workload perception→ Affect→Stress→P (Absenteeism)

In the above 2 chains, depending upon whether we use relation 3 or relation 2, we can have 2 models, one consisting of fragments 1, 3, 4, 5 which does not factor in conscientiousness and the second 1, 2, 4, 5 which does. Both these models, takes into account two behavioral variables: Stress and Affect and two outcomes of interest: productivity and probability of absenteeism. Figures 1 and 2 below represents the two composed behavioral models using the chains listed above.

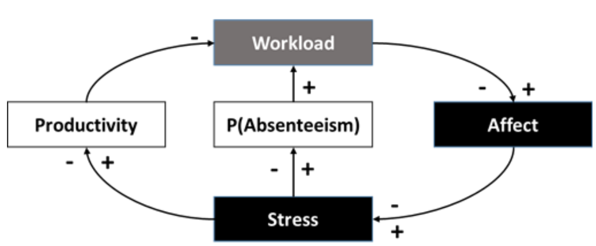

Figure 1: Model without moderation effect caused by a personality trait.

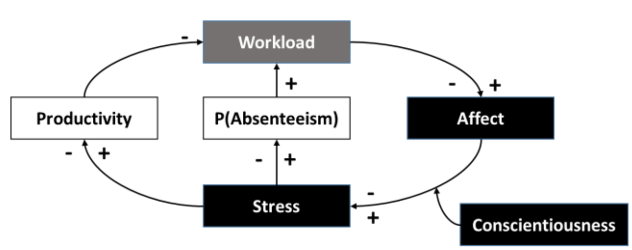

Figure 2: Model with moderation effect caused by a personality trait.

Step 5: Quantification of the model: The behavior fragment number 4, is a theoretical model of the relationship between stress and performance. It suggests that performance is maximized at a particular threshold of stress. As stress reduces or increases beyond the threshold, the performance deteriorates. While this relationship is a useful component of our model, the challenge is that the threshold is not known. A domain expert arrived at this number with the help of the stress data collected in the field study. Also, it is likely that rates of change are different for different behavioral variables but given the current focus of our study we have assumed that the studied behavioral relations operate at a common temporal scale. Therefore, all behavioral relations operate on each simulation clock 'tick'.

Step 6: Conversion to a Simulation model: We use the open source GIS and Agent Modeling Architecture (GAMA) as the simulation engine for simulating the composed models. The composed behavioral models discussed above were used to simulate a team of agents in a support services organization constrained by the process and environment models discussed in section 4.2. The behavior, process and environment models were translated into simulation specifications which are executed by the simulation engine. This execution or simulation run is parametrized and each run simulates 120 days of operation for the team of support service provider agents. In the next section we present some results that were generated by the simulation engine for the behavioral models.

4 EXPERIMENTS AND RESULTS

We conducted three sets of experiments with the models that we have composed. In the first set of experiments we simulated the work environment and monitored backlog and TAT without considering behavioural drivers, i.e. the agents behave like personality less, emotionless automatons unaffected by stress and fatigue. In the second set of experiments, we use the first model discussed in section 3.5 where behavioural drivers exist but without the moderation effects of conscientiousness. In the third set of experiments, we factor in the effect of conscientiousness as well. For this last experiment set we also look at the impact of varying the percentage of conscientious individuals in the agent population and its impact on outcomes of interest. For all experiment sets we study the impact of varying the bench strength on TAT. For each experiment set we also look at the behaviour without a spike in work arrival and with a spike in work arrival. For the last two experiments we also use the concept of *risk* as a measure of goodness of a certain situation, where risk is as defined earlier, the likelihood of a crisis state being reached by the simulated team for a certain simulation setting, averaged over the number of simulation runs for that setting. The results presented in the graphs for each simulation setting below are averaged over 10 repeated simulation runs.

4.1 Turn-around Time for Automaton Agents

We first study how the average TAT varies for the simulated team, when individual agents behave like automatons and how the system reacts to workload spikes for different size of bench strengths. Figure 3, below shows the average TAT in hours along with the presence and absence of a spike in workload. The horizontal axis represents the percentage of bench strength available to the simulated team and the vertical axis represents the average TAT. We observe that as the bench strength increases the average TAT reduces initially steeply and then gradually. Even a 2% bench strength considerably reduces the average TAT. Intuitively, a greater bench strength increases the number of available agents for handling the same number of tasks, thereby reducing the average TAT. We also observe that a workload spike only marginally increases the average TAT for all bench strength values. This happens because with automaton agents, the spike is just additional work and has no other consequences. The spike does not change affect or stress or productivity.

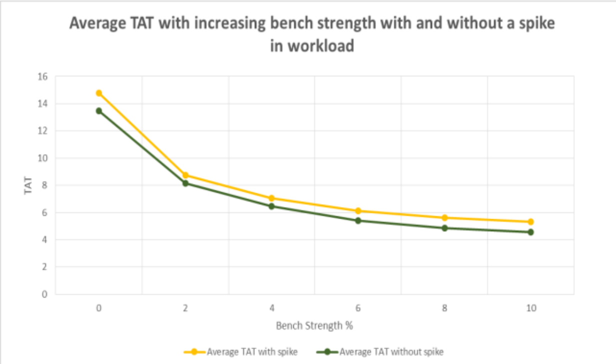

Figure 3: Change in average turn-around time without a behavioral model.

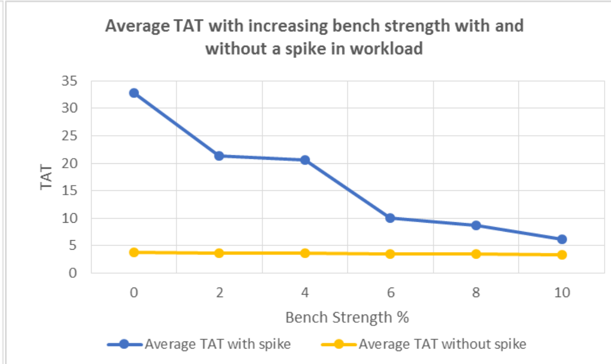

Figure 4: Change in average turn-around time with a behavioral model.

4.2 Turn-around Time for Behavioral Model Agents without Conscientiousness

Next, we factor in the first behavioral model described in section 3.5 for individual agents in the simulated team. We observe that presence of a workload spike heavily influences the TAT achieved by the simulated team. A workload spike acts as a stressor impacting behavior of individual agents in the team. Figure 4 above shows the change in average TAT as bench strength is changed for the simulated team in which each agent's behavior is driven by the first behavioral model described in section 3.5. Without a spike, the peak TAT in figure 3 is approximately 14 hours, while the peak TAT in figure 4 is close to 5 hours. In the presence of a spike, the peak TAT in figure 3 and 4 is approximately 15 hours and 33 hours, respectively. It is evident that behavioral dimensions have a significant impact on the outcome metric of TAT in the presence of an external stressor. The effect of the bench strength is also palpable in both cases. With increase in the bench strength, the average backlog and TAT are reduced, especially when the behavioral model is in place and there is a work spike. From figure 4, we can observe that the average TAT reduces by almost 5 times as the bench strength increases from 0% to 10%.

4.3 Turn-around Time Considering Varying Percentage of Conscientiousness in Population

Within this scenario we had multiple sub-scenarios differentiated by the concentration of conscientious individuals in the simulated team and bench.

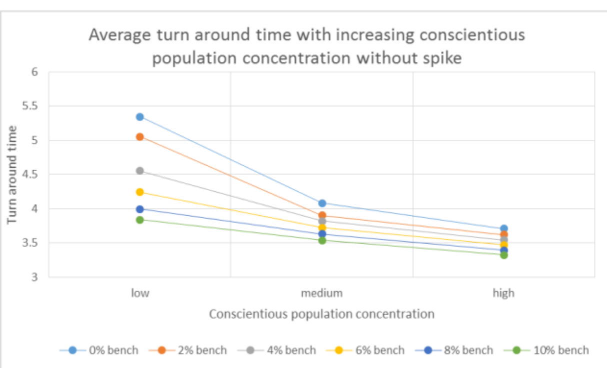

Figure 5: Change in TAT with behavioral model considering conscientiousness without workload spike.

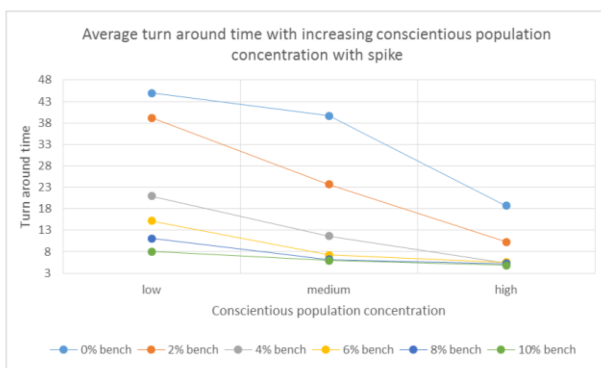

Figure 6: Change in TAT with behavioral model considering conscientiousness with workload spike.

We looked at 3 levels which we called low, medium and high concentration levels corresponding to 10%, 50% and 90% of the agents in the simulated team (and bench) being conscientious. Figure 5, shows the change in average TAT with respect to the different bench strength values and conscientious population concentration levels in the absence of a work spike. The horizontal axis represents the 3 conscientious population concentration levels, and the vertical axis represents the average TAT. The different plotlines represent the behavior of the simulated team for the 6 bench strength values of 0%, 2%, 4%, 6%, 8% and 10%. We observe that, similar to the earlier cases, an increasing bench strength reduces the average TAT. It is also evident from figure 5 that as the concentration of conscientiousness in the population increases the average TAT decreases. However, in the absence of a spike, the total reduction in TAT as a result of increase in bench strength and conscientious population concentration is low. While the maximum TAT is about 5.4 hours the minimum is 3.4 hours, a difference of 2 hours.

Figure 6 shows the same change in average TAT with respect to the different bench strength values and conscientious population concentration levels in the presence of a work spike. The average TAT reduces from 45 hours to 8 hours when the bench strength is increased from 0% to 10%. Also, as the conscientious population concentration increases from low to high, the TAT drops from 45 hours to 18 hours. Another observation is that there is very little change in the average TAT for the medium (50%) and high (90%) conscientious population concentration levels in the simulated team when the bench strength value is 6% or more. It is an insight because the bench strength normally is 6% in the support services organization as we found in our case study.

4.4 A Measure of Risk for the Two Behavioral Models

Finally, we try to assess the risk associated with a simulation scenario using the metric of Risk defined in section 3.2. The simulation scenarios in this case were the 6 bench strength values and the 3 conscientious population concentration levels in the presence of workload spike. For each of the 18 scenarios, 10 simulation runs were executed, and number of runs that reached the crisis point defined in section 3.2, at least once during execution were determined. The number of runs that reached crisis point as a fraction of total number of runs was used to calculate risk associated with a particular simulation scenario. This exercise was done for a simulated team with agents driven by the two behavioral models (without and with conscientiousness).

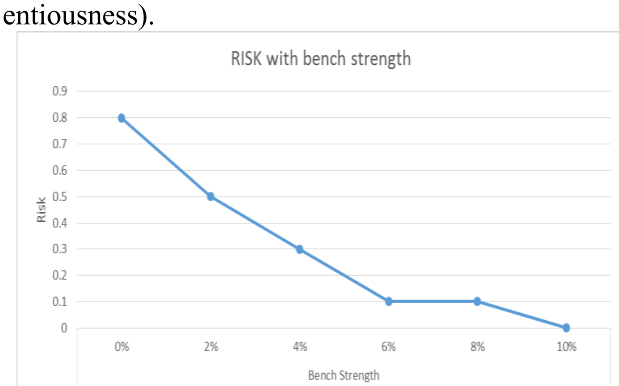

Figure 7: Risk associated with bench strength for the behavioral model not considering conscientiousness.

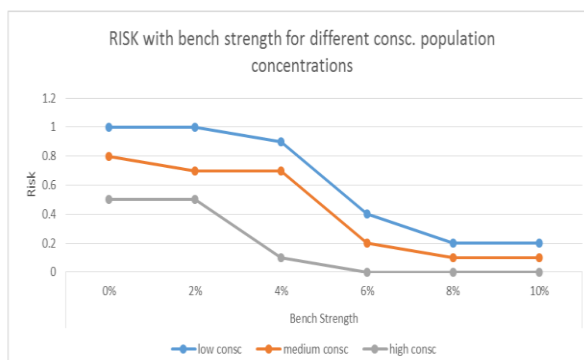

Figure 8: Risk associated with bench strength for the behavioral model that factors in conscientiousness.

Figures 7 and 8 show the impact of bench strength and conscientious population concentration on the associated risk. For both the figures the horizontal axis represents the bench strength from 0% to 10% and the vertical axis represents the amount of risk between 0 and 1. A low value of risk implies that the simulated team is less likely to encounter a crisis situation in the presence of stressors like workload spike. We observe that conscientiousness concentration and bench strength have significant impact on risk. When we do not consider impact of conscientiousness, with increasing bench strength from 0% to 10%, the risk for the team changes from 0.8 to 0 (no risk). For usual 6% bench strength, the risks for an environment with occasional spikes would be 0.1. Considering impact of conscientiousness on the behavior, for low conscientiousness concentration, the risk ranges from 0 to 0.2 whereas for high concentration, it is 0.5 to 0 (no risk). For medium concentration, it lies between these two populations. From this result, one can infer that a high concentration of conscientious agents in the simulated team substantially reduces the risk involved. For such a team, a 6% bench strength would suffice to almost eliminate risk as compared to a team with lesser number of conscientious agents. While at the other extreme of low conscientiousness, even a 10% bench leads to moderate risk (20%). Our model thus is not only in the ballpark but gives us fine grained advice as to the risk with varying bench strengths for different levels of conscientiousness in the workforce.

5 CONCLUSION AND FUTURE WORK

In this paper, we presented a set of guidelines to build grounded fine-grained behavioral models that use fragments of behavior mined from past literature in the social sciences as well as behavioral studies conducted in the field. The behavior fragments are the building blocks to compose grounded fine grained behavior models. We built two models of a support services organization with an aim to study the factors that drive productivity and absenteeism in their workforce. We conducted various experiments with the simulated model and the effects of using the grounded approach are noticeable in the ability of the models to demonstrate behavior that resembles the context being simulated. For example, the simulation model arrived at 6% as the ideal bench strength which will also lead to minimum TAT, this in fact is also the number which the support services organization uses in practice. We incorporated metrics from the context in the development of the model to make it context specific. Also the results of the simulation were in line with past research on the relationship between conscientiousness and productivity, helping us establish that our models were performing as hypothesized. Further, since many of the model variables are derived from a field study the users of the simulation understand the model well and are able to use it themselves to try our various what-if scenarios. For example, if the concentration of conscientiousness people in a team is 20%, then what bench strength should they maintain, or what would be its impact on the TAT and so on. The behavior composition approach is a step in the direction of a larger goal of building a Behavior Analysis Framework (BAF), which will host a repository of behavior fragments mined from research paper corpuses and experiment databases. The BAF will have all the necessary infrastructural elements to compose behavior models in a highly automated manner and use them in simulations.

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