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A Preliminary Model of Participation

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ABSTRACT: *We present the case for a preliminary organizational model of participation. We review a simulation of the Battle of Medenine with respect to its ability to approximate the historic record. We find that individuals in the actual battle performed with greater variance than the simulation predicted, suggesting that individual differences are important. Using a light-weight simulation, we implement one means of representing these differences based in part upon Grossman's (1995) participation formula. We demonstrate that our preliminary version of the formula can generate individual differences, which in turn have a meaningful impact on group performance. Work remains to improve the formula and its application.*

1. Introduction

In this report, we examine what influence individual variation and psychological distance have on group performance. Over the past decade, interest in individual differences has grown. On the other hand, theories of participation have remained largely descriptive. By participation, we refer to the incidence of a particular and recognizable act by an agent. By a model of participation, we refer to a predictive account describing the reciprocal relationship between individual behavior and group performance, and how that relationship in turn moderates human behavior in a variety of contexts.

To develop these points, we start with a discussion of a validated simulation called Ironside (Harrison, Winters, & Anthistle, 1999). During the course of the validation study (Poncelin de Raucourt, 1997), discrepancies between the simulated and historical outcomes underscored the need to include more accurate human models of individual differences. We next briefly review how agent-based approaches have historically accounted for individual differences in synthetic environments. From there, we discuss in detail the need for a preliminary predictive model describing how organizations influence their members to achieve group goals (we call this an organizational model of participation), and outline its components and an initial implementation. Finally, we conclude by summarizing the model's current development path and implications.

2. Lessons from Ironside

Ironside was an interactive, two sided, closed, stochastic, ground combat simulation developed at the Royal Military College of Science in the UK (Harrison, Winters, & Anthistle, 1999). Ironside's designers sought to produce a battle group simulator that accurately reflected operational doctrine and behavior. To realize this goal, Ironside integrated a representative command and reporting structure with realistic platform engagements. Users could construct command hierarchies for platoon to division-sized elements with corresponding entity level weapon platforms. This feature enabled entities to independently identify and engage targets within a rich simulation environment.

We begin with Ironside for three reasons. First, while Ironside was developed in the 90's, its emphasis on independent entity level activity remains relevant and instructive. Second, the validation and verification study for Ironside is unusually detailed, well documented, and persuasive. Finally, it provides a compelling and early case for not only accounting for low-level group interaction but also individual differences.

Ironside did not determine outcomes by computing relative strengths. Rather, each entity was modeled separately and acted independently. The entities were data driven, dynamic, and constrained by terrain and equipment. Thus, this approach was agent-based, though it lacked either a strong separation between the agent and the simulation or a representation of the constraints imposed by memory or processing limitations.

The validation and verification study of Ironside is unique in that it is available and reflects the combined expertise of an artillery officer and systems designer. Because most military simulations are developed for training or analysis, their emphasis on present or future scenarios and transient effects often obligates their designers to use face and event validation, as well as sensitivity and trace analysis for substantiation. One liability of depending primarily upon these forms of validation is that the influence of individual differences or group interactions on unit performance can remain undefined and thus unaccounted for, leading to unrealistic outcomes. In the past, developers often relied upon Lanchester square and linear models for evaluating attrition rates and performance (Hartely & Helmbold, 1995). Historical data validations, when conducted, indicated that simulations using these methods were unable to replicate historical outcomes, in part because these models failed to account for individual difference or low-level interactions (Hartley & Helmbold, 1995; Gillis, 2000; Sargent, 1999).

In his independent validation study of Ironside, Poncelin de Raucourt (1997) modeled the battle of Medenine. One of the last battles of the North African campaign, Medenine (March 6, 1943) offers the analyst one great advantage—the battle is well documented (Rowland, 1993). Internal memorandums from both sides offer an amazingly consistent step-by-step account of the action. This account coupled with access to original battle maps, equipment, and ammunition allowed Poncelin de Raucourt to implement the battle in Ironside's system with confidence. This study assessed Ironside's ability to model the engagement between the 131st Queens Brigade and the 8th Panzer Regiment lasting from 07:20 to 10:00 hrs, the most significant engagement of the battle. Figure 1 is a map of the Battle of Medenine.

Poncelin de Raucourt's study yielded mixed results. After analyzing ten runs, he found that Ironside's software and engineering supported its designers' intent. On the other hand, Ironside generated outcomes that were reliably different from the historical record when examined on an individual battery level.

Poncelin de Raucourt used the following questions to assess the simulation's validity: (a) Does the duration and distribution of losses in the simulation reflect the historical record? (b) Are the number of casualties, the ratio of shots per kill, the engagement range, and the characteristics of each weapon system consistent with the data?

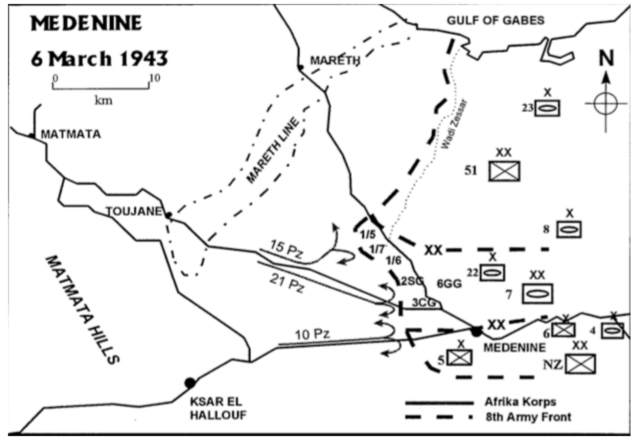

Figure 1: A map of Medenine (Poncelin de Raucourt, 1997).

Though the simulation's number and average distribution of losses, ammunition consumption, and ratio of shots per kill all roughly approximated reality, the simulation's duration, the entities' engagement range, and the individual distribution of casualties per battery did not.

To generate these results, Poncelin de Raucourt first determined which datasets could be characterized as having a normal distribution using the Kolmogorov-Smimov test. He found that the size of the kill zone, the amount of ammunition consumed, and the number of casualties could all be described as having a normal distribution, and thus be analyzed using the student t-test to see if the mean values from the simulation approximated those reported by Rowland (1993).

Table 1 compares the simulated and actual values, as well as showing the results for these tests. For the 14 units involved in the engagement, the actual number of tanks destroyed was not evenly distributed. When we compare the number of tanks on average destroyed across the 10 runs to the actual outcome (25.8 vs. 25 respectively), the simulation closely mirrors Medenine. This consistency most likely reflects the topographical constraints present in the system, particularly the influence of the Wadi Zeuss, Matmata Hills, and Tebaga Gap. On the other hand, the average predicted values across all batteries are different from the simulated values ($p<0.01$) using a Chi-squared test. When the differences are examined individually using tests based on the standard deviations (row 3), the results indicate that several of the batteries performed as expected (within 95% confidence intervals) but several did not. Batteries 6/2, 7/5, and 7/7 are three notable examples. While battery 6/2 in reality immobilized fewer tanks than Ironside's prediction, batteries 7/5 and 7/7 each exceeded the predicted outcome by 1.5 to 2 standard deviations.

Table 1: Consolidated kills report and statistical tests per gun (Poncelin de Raucourt, 1997, Table 7.3).

Gun	6/1	6/2	6/3	6/4	7/5	7/7	7/8	N/1	N/2	R/1	R/2	R/3	R/4	J/2
Tanks Destroyed at Medenine	1	1	0	0	10	10	2	0	0	1	0	0	0	0
Tanks Destroyed by Ironside	2.8	3.2	0.5	1.9	5.4	3.2	4.2	0.9	0.5	0.4	0.6	0.6	1.4	0.2
(STD) of Ironside's Destroyed Tanks	2.86	1.32	0.53	1.37	3.41	2.57	1.81	0.88	0.53	0.52	0.7	0.84	1.96	0.42
Kolmogorov-Smirnov Test	0.24	0.25	0.33	0.14	0.15	0.20	0.17	0.25	0.33	0.38	0.30	0.36	0.26	0.48
Pass/Fail	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Fail	Fail	Fail	Fail	Pass	Fail
Student t-Test	1.89	5.01	-	4.16	4.05	7.93	3.64	3.08	-	-	-	-	2.15	-
Pass/Fail	Pass	Fail	-	Fail	Fail	Fail	Fail	Fail	-	-	-	-	Pass	-

Poncelin de Racourt's analysis (1997) suggests that Ironside's terrain modeling, its lack of a decision-making task model, and its inability to predict the effect of either individual differences or low-level group interactions all significantly impaired its performance. We will discuss each in turn.

Ironside's terrain model was too coarse, resulting in unrealistic firing rates for batteries 6/2, 6/3, 7/5, 7/7, 7/8, and N/1. While Ironside was able to predict the influence of major terrain features (as evidenced by the overall averages), it was unable to predict the influence of minor ones because the elevation matrix's resolution was limited to 100 m. The absence of a decision-making task model had two major consequences. For one, Ironside was unable to predict the delays associated with organizational decision-making or the effects of cognitive constraints. Free of the vagaries of the communication process or the effects of imperfect information, Ironside's agents were, on average, able to prosecute the battle in 31.2 min. vs. the 160 min. it took in reality. In addition, the kill zone was larger in the simulation than at Medenine, 693 m vs. 521 m. This discrepancy is primarily due to the absence of a decision-making task model, but is also a result of faulty assumptions in the agent models. Where the simulation fired at the first opportunity, allied forces chose to hold their fire to deny the enemy maneuvering room once the battle had commenced (weighing the risk to their own troops against a higher probability of success). Finally, in part because it had no means of predicting what influence individual variation or intra-group interactions might have upon group performance, Ironside was unable to replicate the actual distribution of fire (See Table 1).

Like the battles of Decauville (October, 1918) and the liberation of Holtzwihr (January, 1945), the outcome at Medenine appears to have been disproportionately influenced by the actions of a few soldiers, Sergeants Andrew and Vincent (Faulkner, 2008; Rowland, 1993; St. John, 1994). Though the distribution of causalities per gun was normal if the battery fired, weapons fire was not consistent across positions. There are several reasons for this. As noted above, the terrain did favor eight of the fourteen positions. Nevertheless, the concentration of the distribution (where the historic record shows more success than the simulation predicted as in Table 1) suggests that more than terrain effects influenced the outcome. In the final summary of his validation study, Poncelin de Raucourt argued that individual differences and variability across units (heroic or degraded behavior) explained this discrepancy. This hypothesis is strongly supported by both autobiographical accounts (journal entries from the officers of the 6/2 noting the unit's low moral after fierce fighting days earlier), as well as the discrepancies between the historic and simulated outcomes for batteries 6/2, 7/5, and 7/7 (Rowland, 1993).

We believe that theories of individual differences, particularly in respect to participation, if properly implemented would begin to explain and predict the causes for this variation in behavior. In the next section, we will discuss why a theory of participation is necessary by reviewing briefly how agent-based approaches have historically modeled decision-making.

3. Agent-Based Approaches

For our next example, we use agents that operate on the basis of knowledge to take actions in the world. Agents can be seen to run continuously through a cycle of three steps: Perceive -> Decide -> Act, and then perceive again (Newell, 1990). Agents are differentiated from each other on the basis of their capabilities in each of these areas, and intended to describe average or ideal members of a certain class of individual (e.g., fighter pilots).

Modelers have generally accounted for important contextual differences by using agent perception and making rule knowledge highly situational. Such agent-based approaches have become widely recognized and are now finding some success in studying social phenomena (e.g., Norling & Ritter, 2004; Silverman et al., 2002; Taylor et al, 2006). This is particularly appropriate in settings where it is reasonable to consider individuals as essentially similar, and when decisions being made are frequent enough and routine enough that any variations in individuals can be described as statistically similar.

Nevertheless, participation as a phenomenon highlights the limitations of the Perceive -> Decide -> Act cycle. An agent will take the appropriate action as soon as the conditions of that action are met. Humans, however, may hesitate or choose not to act when the stakes are high or emotions are involved. Furthermore, the organizational and local circumstances can affect the quality and severity of that hesitation (which we will illustrate in a simulation); and reciprocally, the severity of that individual hesitation may affect that organization's ultimate outcomes. Drawing from descriptive theories in group psychology and sociology, we further argue that the causes of this hesitation are generalizable and modelable.

4. An Organizational Theory of Participation and its Implementation

Given that variations in individual performance can be important, we start to explore a way to represent these variations as arising from individual responses to situational and organizational factors. Our theory is a preliminary one, a rough sketch indebted to several disciplines but particularly influenced by the work of Grossman (1995). In this section, we discuss in further detail what we mean by a theory of participation and what such a theory entails. After describing the theory generally, we describe a specific implementation domain, specifically modeling combat environments in a light-weight simulation.

Again, we define participation as the incidence of a particular and recognizable act by an agent, generally in response to a change in its environment. We recognize that numerous processes and factors influence this response, and that theories describing these processes can operate at various levels of abstraction. On the other hand, when defined broadly, the concept of participation highlights the underlying reciprocal relationship between individual behavior and group performance. Though we exist in and are influenced by social networks, differentiation between group members can impact group performance. A comprehensive theory of participation would explain this relationship in full and its impact on cognition.

Our current theory falls far short of this. Though it incorporates a primitive notion of individual variation, it is primarily an organizational theory that predicts the effect that group distance and density have upon individual behavior and thus group performance. Nevertheless, it begins to address the modeling challenges Poncelin de Raucourt (1997) identified by offering a theory of group effects and a platform from which to incorporate other micro-theories of cognition.

Our theory of participation rests on three general premises. First, human social networks are complex systems that moderate individual behavior. Second, our awareness of ourselves and our relationships to others is a defining characteristic of the human cognitive architecture. Third, changes to social networks precipitate changes in the agent's state that manifest themselves in divergent outcomes.

A theory of participation is inherently a theory of action. The first premise defines the context of that action, specifically of collaborative activity. Consequently, we must identify and account for the constraints present in social networks. We attempt to model these constraints by using an agent-based approach in a light-weight simulation, dTank (Morgan et al., 2005).

A theory of participation is also inherently a theory of cognition. The second premise posits that modeling the mutual awareness of agents in a network, as well as modeling perception and memory, is necessary for any working theory of participation. This form of awareness is an intrinsic and important aspect of human cognition. The observer effect and its various manifestations, the Hawthorne, Henry, and Pygmalion effects, all attest to this fact. We describe the implementation of this premise in Figure 2.

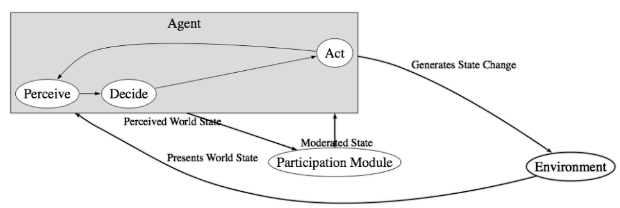

Figure 2: Implementation diagram of a preliminary model of participation.

In Figure 2, we begin with a simple agent diagram. The environment, in this case dTank, generates state changes that the agents respond to, which in turn generates subsequent state changes. The agents' actions arise out of their perception of the environment and reflect human processing and sensory limitations.

Generally, cognitive architectures treat perception and decision making as independent of social influences. Agents perceive the environment and act in accordance to a specified goal hierarchy. In most cases, however, the presence of other agents has no impact upon agent behavior unless their presence or absence impacts the agent's ability to achieve its goals.

Human behavior, on the other hand, is always moderated by presence or absence of others (Haynes & Zander, 1953). Often, our responses to others are unconscious, though we can become acutely aware of them when confronted with unfamiliar or uncomfortable situations. When modeling combat environments, we are able predict these reactions with some confidence because human reactions to tension and fear are generalizable (Collins, 2008). Consequently, we chose combat situations as an initial test case for modeling how an agent's awareness of hostile and friendly observers can complicate its decision-making process, and thus lead to divergent group outcomes. We hope to extend this work to other social contexts in time.

In Figure 2, the arrows leading to and away from the participation model illustrate the influence that others have upon decision-making. The model itself is a representation of inter and intra-group awareness and the management of that awareness (Grossman, 1995; Collins, 2008). The model's relationship to the agent in Figure 2 reflects an interim step rather than a theoretical commitment. Ultimately, a theory of participation should be integrated into the agent's architecture. On the other hand, this modular approach allows researchers using various agent architectures to use and improve upon this approach.

Finally, the third premise of our theory asserts that changes in the social network precipitate changes in the agent's state that manifest themselves in divergent outcomes. The interconnected nature of the system engenders two effects. First, the importance of individual differences is amplified as each node (agent) is connected to more and more edges (relationships)—meaning that not only must military and paramilitary organizations compensate for variation in their daily operations, but also that analysts must account for variation when predicting unit performance. Second, the configuration and composition of a unit directly impacts its performance because these factors influence the ability of leaders and groups to structure behavior.

We account for the first effect by incorporating a score for predisposition and training in our model. Nevertheless, we recognize this area remains underdeveloped. We account for the second effect by implementing a concept of psychological distance that predicts the ability of combat units to moderate behavior.

Human beings react to fear in three general ways: by running, by blustering, and by fighting. Out of the three, fighting is generally the alternative of last resort, and for most human beings, it requires intra-group support to do routinely (Grossman, 1995; Collins, 2008). Accordingly, military and para-military organizations must structure their organizational environments to ensure unit lethality, or the group's ability to engage in repetitive killing by managing the intra and inter-group awareness of its members (Grossman, 1995; Collins, 2008).

Organizations encourage participation in multiple ways including: compartmentalizing decision making, instilling a high sense of group accountability, and instituting a chain of command whose members operate at each organizational level. In our model, organizations moderate individual behavior in two ways: first by distorting the agents' sensory data, and second by ensuring close contact between group members and leaders. The organization's ability to moderate behavior in this simple model is limited by distance and relative size. We will develop these points in reference to Figure 3. In subsequent models, we will also explore the impact that previous outcomes, training, imagery technologies, and changes in a group's composition have on group performance.

Figure 3 depicts a simple squad configuration consisting of two infantry fire teams. In this example, the squad leader is coordinating an attack with the second team leader via radio. The boxes designate two visual groups that in turn represent two organizational environments.

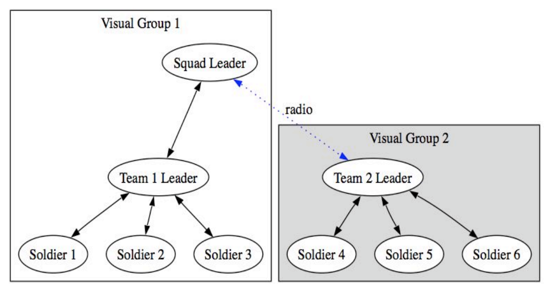

Figure 3: Sparse network of squad interaction.

For this and all subsequent examples, the combatants have equivalent levels of training, conditioning, and intra-group support. In both environments, all team members are in visual range of one another, meaning the ability to engage in deviant behaviors is severely limited. For this example, intentionally misaiming is considered a deviant behavior. In addition to this sense of accountability, team members also benefit from a sense of group absolution. The responsibility for killing is shared by the group, and the group's intersecting fields of fire creates ambiguity, providing group members some sense of plausible deniability (Grossman, 1995). The arrows indicate that all group members share this mutual sense of accountability and anonymity.

Each environment also possesses a definitive leader whose presence further limits the range of acceptable choices and reinforces the group's sense of absolution

(Grossman, 1995; Milgram, 1963). On the other hand, the environments differ in respect to their composition. Team 1 includes not only its team leader but also the squad leader, while team two only possesses a team leader. Our model does not yet predict either how each leader's personal relationship with his or her team might impact their performance, or how they might differ in their ability to compensate for the geographical distance.

We can, however, model the increased load that the geographical distance has placed on the system. This distance limits the ability of both group leaders and members to ensure group accountability or provide absolution. Thus in the model, there is an inverse relationship between intra-group distance and unit lethality.

For example, communications between the two teams can cease entirely if the radio is destroyed. In such an event, the probability of deviant behavior increases throughout the whole system because neither the squad nor second team leader has to respond to the other, meaning one less person to regulate behavior. First squad, however, would be more likely to participate because the squad leader and team leader remain accountable to each other, as well as the rest of the squad. According to the model, we would also predict that this would be the case during routine operations because the second team leader could simply choose to ignore the radio.

The model assigns an initial predisposition value for both moderated and unmoderated agents. The model treats this value as a baseline, and it is the sole representation of intrinsic individual variability. Predisposition is determined randomly, with a weighting that favors higher predispositions.

Where increasing the distance between group members decreases unit lethality by mitigating the group's ability to moderate behavior, increasing the distance between opposing forces (within the limits of the technology available to the unit) raises unit lethality. Again, knowledge of an observer is fundamental to the model. This time, however, increased distance facilitates participation by anonymizing the enemy.

We treat all distances as psychological distances in the model because an agent's knowledge of other entities and its relation to them depends upon its perceptions and its inferences about them. Our model, at this time, does not include notions of cultural or social distance, though we acknowledge that a comprehensive model would. On the other hand, Figure 4 illustrates how, even with a simple model, one can generate a trace of the participation predictions from a system. At this early stage however, this trace is preliminary, in reality the participation score of combat units would most likely be higher than those shown in the figure.

The scenario in Figure 4 and the ten trials summarized in Tables 3 and 4 were conducted using a modified version of dTank 4.5. Though the model is currently best applied to individual soldiers, tanks were used because the simulation environment best supported them. For the purposes of the demonstration, each tank was treated as an individual combatant rather than as a crew-served platform. We conducted all trials on the same 1 x 1 km map for 2,000 s. The map size precluded the possibility of instantaneous kills, and allowed agents to potentially isolate themselves. The length of the trials allowed for the possibility of multiple survivors.

The model generated a participation value for each tank each time the agent moved or shot based upon status reports indicating how many friends and enemies were visible, their distances, and whether team members saw their team leaders. On average, the model generated a participation score every second. If the agent's participation prediction was greater than a linear random number, the agent participated. Otherwise, it hesitated. After another movement or shot, the agent would have another opportunity to participate. If the agent's score again fell below a randomly generated number, it would continue to hesitate. This cycle would persist throughout the life of the agent. We used a random value rather than a participation threshold to reflect the stochastic nature of the system, and to allow for the influence of situational factors not currently included in the model. The model's dependence upon state change poses interesting theoretical questions regarding what qualifies as a meaningful state change, and what implications this might have on behavior.

Figure 4 shows how the probability of participation varies with time as the agents interact in a single sample scenario. These values do not reflect the agent's personal state, but rather reflect the organizational environment's capacity to moderate behavior, i.e. support participation. For this reason, we differentiate our organization model of participation from a comprehensive one. A comprehensive model would also include a representation of the agent's state and how it influences whether agents participate or not. In our model, the organization's capacity to support participation is currently affected by four factors, all of which can be observed in the example trace in Figure 4. These factors are: distance to friend, distance to enemy, relative group sizes, and initial disposition (including training) (Grossman, 1995; Collins, 2008).

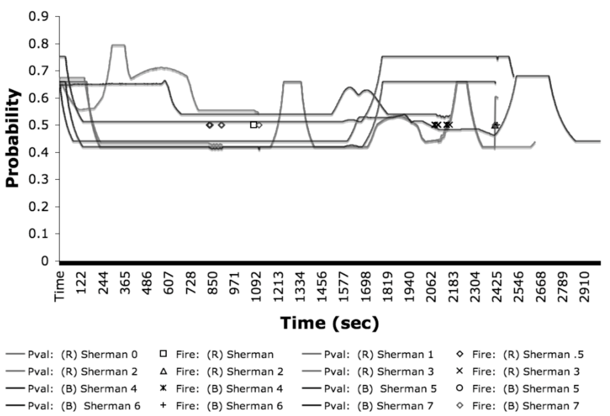

Figure 4: Trace of agents with an implemented model of participation.

In this implementation, the agents' knowledge sets are identical—there are no rules requiring them to stay together. Consequently, allied agents tend to move apart, lowering the team's ability to moderate behavior over time. Agents also tend to engage the enemy immediately once in range. Thus, it is relatively rare for agents to destroy targets at closer ranges. As targets come closer, the willingness to engage the enemy decreases. If more enemies than friends are present, the agent finds it more difficult to participate. Conversely, if the agent's team outnumbers the enemy, the agent is more likely to fire. This effect currently leads to the rather abrupt changes in the participation equilibrium because the agents must *rediscover* their friends. Because they treat each scan as a new state, the agents cannot infer the presence of their friends based upon previous knowledge— this is an implementation effect that we will correct in the future by using more sophisticated agents.

Table 2 indicates the effect of using a participation micro-theory as a moderator of performance. Runs where the model was not used to moderate performance resulted in higher casualties and substantially higher lethality rates. Also in the un-moderated group, there were more shots fired, and less variation in the number of destroyed agents. We found the differences in tanks destroyed is reliably different ($t(8)=-2.36$, $p<0.05$, two-tailed), the other differences are not significant at this number of triasl, but are in the anticipated direction.

Table 2: Averaged (SD) simulation outcomes for agents with and without a participation model (n=5).

Agents	Destroyed	Damaged	Shots	Hesitations
Unmoderated	2.8 (0.45)	0.6 (0.55)	6.2 (3.27)	N/A
Moderated	1.8 (0.84)	1.2 (0.45)	5.6 (2.88)	6.2 (5.40)

Table 3 shows the average participation values for these agents. Values are not calculated for agents that have been destroyed. It also shows the average participation value for agents at the time of shooting, and number of hesitations.

Table 3: Participation values (SD) for agents with and without a participation model (n=5 runs).

Agents	Average Participation Value	Participation Value, Shot	Participation Value, Hesitation
Un-moderated	.53 (.08)	0.55 (.11)	N/A
Moderated	.50 (.05)	0.49 (.08)	0.49 (.08)

5. Discussion and Conclusion

We have discussed how the absence of a model of individual differences can impair the fidelity of agent-based approaches by reviewing a validation study of the battle of Medenine. This study showed that individual performance varied more than would be expected from a homogenous group. We presented a simple organizational model of participation. This model implemented a version of Grossman's (1995) theory of participation. When used to moderate agent behavior, it led to differences in performance on some measures. These results demonstrate that modeling complex environments, particularly combat environments, can be improved by including both a strong theory of individual differences and of teamwork.

This work suggests a principled way to predict the impact of individual variation using agent-based approaches, specifically in regards to their likelihood of participating in combat environments. This theory also suggests that changes in performance might arise from a type of meta-cognition (an agent observing itself). This meta-cognition, if implemented, could help to predict the effects of participation. This reflection arises from theories in social psychology (Lerner, 2003; Morgan, 2007) and military psychology (Grossman, 1995).

There remain many loose ends in this participation model. There are missing terms, and we believe that the constants and relationships are not correct, particularly because the participation value does not yet come close to 1. We have not resolved how to incorporate other models of individual differences, or how to integrate the model into a cognitive architecture. We still must refine our concept of what qualifies as a meaningful change of state to evaluate participation, as well as implementing a more robust notion of hesitation. Though moderated agents do hesitate now, they do not hesitate for very long, not long enough to create the time lags noted by Poncelin de Raucourt. We have yet to incorporate the effects of technology upon human perceptions of distance, or model crew-served weapons. Attempting to replicate the Battle of Medenine will require us to do both. Nevertheless, we now have some encouraging results and useful tools for modeling variability and participation. With these tools, we have shown that individual differences matter, and that it is possible to model the influence of social processes upon the mind.

6. Acknowledgment

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