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APPROACHES FOR MODELING INDIVIDUALS WITHIN ORGANIZATIONAL SIMULATIONS

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ABSTRACT

The human behavior modeling community has traditionally been divided into those addressing *individual behavior models*, and those addressing *organizational and team models*. And yet it is clear that these extremes do not reflect the complex reality of the mutually-constraining interactions between an individual and his/her organizational environment. In this paper we argue that realistic models of organizations may require not only models of individual decision-makers, but also explicit models of a variety of individual differences influencing their decision-making and behavior (e.g., cognitive styles, personality traits, and affective states). Following a brief review of individual differences and cognitive architectures research, we describe two alternative approaches to modeling the individual within an organizational simulation: a cognitive architecture and a profile-based social network. We illustrate each approach with concrete examples from existing prototypes.

1 INTRODUCTION

The human behavior modeling community has traditionally been divided into researchers and practitioners addressing *individual behavior models*, and those addressing *organizational and team models*. And yet it is clear that these extremes do not reflect the complex reality of the mutually-constraining interactions between an individual and the organization environment within which s/he operates. We cannot effectively model the individual if we ignore the organizational constraints within which s/he operates, nor can we effectively model an organization if we abstract away the behavioral idiosyncrasies of the individuals who make up that organization.

The purpose of this paper is twofold: first, to motivate the need for modeling the individual within an organization, in particular, the need to explicitly represent a variety of individual differences or behavior moderators to assure adequate model fidelity; and second, to provide examples of two approaches to modeling the individual within an organizational context: a c*ognitive architecture human behavior model*, and a *profile-based social network model*.

The paper is organized as follows. Section 2 provides a brief summary of relevant background research, focusing on the effects of individual differences on decision-making (section 2.1), and existing cognitive architecture models (section 2.2). Section 3 then describes the two alternative modeling approaches, and section 4 provides examples of each approach. Section 5 briefly outlines how these approaches could be integrated within organizational models. The paper concludes with a brief summary of the utility of these models and organizational simulation in general.

2 RELATED RESEARCH

2.1 Effects of Individual Differences on Decision-Making and Behavior

Individual behavior is determined by range of internal and external factors, and by the interactions among them. Depending on the breadth of focus, these have variously been termed *behavior determinants* (Hudlicka et al. 2002; 2004), *behavior moderators* (Pew and Mavor 1998), and *individual differences* (Revelle 1995)). These factors include a variety of static and dynamic factors, most notably cognitive factors (baseline attention and working memory speed, capacity and accuracy; skill level; cognitive style), stable personality characteristics (traits such as the "Big 5" (openness, conscientiousness, extraversion, agreeableness, neuroticism) (Matthews and Deary 1998), and transient emotions and moods (states such as joy, sadness, fear, anger, disgust) (Ekman and Davidson 1994).

These factors, along with the decision-maker's individual history and cultural context, in turn determine the individual's internal mental dynamic context consisting of activated beliefs, expectations, attitudes and goals, which eventually lead to the selection of a particular observable behavior. Variability among these factors then causes the types of behavior variability observed in humans (but generally not represented in models).

Traits and states affect observable behavior via a variety of distinct influences on perception, cognition, and motor processes, both transient and long-term. A number of these influences have been identified, at varying levels of specificity and generalizability, both at the "lower" levels of processing (e.g., attention orientation during an acute fear episode, increased working memory capacity correlated with positive affect), and at "higher" levels involving goals, situation assessments, expectations, and self schemas (e.g., complex feedback relationships between affective state and self-schemas).

As might be expected, traits tend to exert their influence via more stable structures (e.g., types of schemas stored in LTM, preferential processing pathways among functional components), whereas states tend to produce transient changes that influence the dynamic characteristics of a particular cognitive or perceptual process (e.g., attention and WM capacity, speed, and accuracy). Traits also contribute to the dynamic characteristics of the affective states themselves, particularly their generation, intensity, duration, and expression.

Table 1: Examples of Trait and State Effects on Cognition and Behavior

Anxiety and Attention & Working Memory Reduction in capacity Faster threat detection / slower otherwise
Obsessiveness and Performance Delayed decision-making Excessive 'checking' behaviors
Affect and Judgment & Perception Negative affect lowers estimates of degree of control Anxiety bias towards threat interpretation Positive affect increases estimates of degree of control
High Neuroticism and Attention / Perception Preference for self and affective state stimuli Bias toward negative appraisal (self and non-self)
High E / High N and Behavior Preferences High extraversion preference for approach behavior High neuroticism preference for avoidance behavior
Traits and Reward / Punishment Behaviors High extraversion and reward seeking High neuroticism and punishment avoidance

Last, but not least, we mention cultural factors as additional behavior determinants (Matsumoto 2001; Hofstede 1991; Klein et al. 2002). In spite of the vast literature addressing cultural issues, there is relative paucity of attributes defined at a sufficient level of specificity to enable computational modeling and inferencing; that is, cultural characteristics which could be operationalized to enable computational models of the effects of culture on individual (and organizational) decision-making, culture-based profiling, and, more importantly, likely to yield useful behavior predictions for particular individuals, groups, and organizations.

Recent attempts to address these issues, and to develop a practical cultural-profiling approach, have explored a notion introduced by Karabaich (2004) that proposes to consider each group to which an individual belongs as representing a distinct culture; that is, the assumption that *every group creates its own culture* (Hudlicka et al. 2004). This approach is motivated by the observation that national and ethnic groups are in fact not as diagnostic with respect to behavior prediction as are smaller groups to which an individual belongs (e.g., student group, social group, political group, family, etc.).

It should also be noted that any cultural influence ultimately functions at the individual level, and must therefore be translated to one or more of the individual behavior determinants outlined above. Thorough understandings of the critical behavior determinants, and a determination of the mappings of the cultural factors onto these behavior determinants, are therefore critical to the effective modeling of cultural differences.

2.2 Modeling the Individual

Computational cognitive models have a long history in artificial intelligence and cognitive science, going back to the seminal work of Newell on the general problem solver (which led to the Soar architecture (Newell 1990)), and Selfridge's Pandemonium in the 50's (Selfridge 1959) (which laid the foundation for the now-popular blackboard systems and blackboard cognitive architectures.

Recently, the integrated-architecture approach, which aims to model end-to-end information processing required for intelligent adaptive behavior, has become the most prominent method, and forms the basis for intelligent behavior in synthetic agents and robots. Associated developments in virtual environments and robotics have further motivated the development of intelligent agents, capable of functioning in simulated or real environments.

Below we provide a brief overview of several representative cognitive architectures, including also recent attempts to model individual differences and emotions. For more extensive and detailed reviews of existing cognitive architectures see Pew and Mavor (1998) and Ritter et al. (1999).

Among the first implemented cognitive architectures were Soar (Newell 1990), and ACT (Adaptive Character of Thought) (Anderson 1990). Soar's original aim to model learning and intelligent behavior and uses rules and rule chunking as the primary representational and inferencing mechanisms. ACT was initially aimed to model lower-level memory processes, and account for observed empirical data, but was later developed into a full-fledged agent architecture, using a combination of rules and semantic nets.

Originating from a different tradition, and built for a different purpose, is the Sim_Agent architecture. Sim_Agent was developed by Sloman and colleagues in the 1980's, with the objective to explore the architectural components and processes necessary to exhibit adaptive behavior, including emotions, and address the fundamental questions of what specific architectural features are necessary for different types (and complexity) of cognition, emotion, and behavior (Sloman 2003).

Over the past decade, a number of new architectures have been developed, including: OMAR, focusing on modeling multi-tasking and multiple operators in the air traffic control domain, and using a hierarchical representation of procedures; MIDAS (Man-machine Integrated Design and Analysis System), used for human-machine system design, primarily within the commercial aviation cockpit; COGNET, used to model multitasking, interface design and adversary models and uses a blackboard architecture; SAMPLE, focused on modeling recognition-primed decision making in a variety of settings, including piloting and air traffic control and uses a combination of, fuzzy logic, belief nets, and rules (Pew and Mavor 1998). Many other architecture-based models have been developed in academic laboratories, as research vehicles, as components of synthetic virtual agents, or in the context of robotics.

2.2.1 Modeling Individual Differences and Emotions

With increasing awareness of the effects of individual differences on behavior, and increasing need for more realistic simulations, attempts have begun to incorporate individual differences effects within cognitive architectures and agents (Hudlicka 1997; 2003; see also Pew and Mavor 1998). Models that focus on modeling individual differences range from individual processes to integrated architectures. The most frequently modeled process has been *cognitive appraisal,* whereby external and internal stimuli (emotion elicitors) are mapped onto a particular emotion. A number of models have been implemented, both as stand-alone versions, and integrated within larger agent architectures (e.g., Scherer 1993; Bates et al. 1992; Elliot et al. 1999; Andre et al. 2000). Other emotion model implementations include models of emotions as goal management mechanisms (Frijda & Swagerman 1987), models of interactions of emotion and cognition (Araujo 1993), and effects of emotions on agent belief generation (Marsella and Gratch 2002). Examples of *integrated architectures* focusing on emotion include most notably the work of Sloman and colleagues (Sloman 2003), and more recent efforts to explicitly model the effects of a range of interacting individual differences on cognition and behavior (Hudlicka 2002; 2003), and efforts to integrate emotion effects in Soar (Jones et al. 2002) and in ACT (Ritter et al. 2002).

3 TWO APPROACHES FOR MODELING THE INDIVIDUAL DECISION-MAKER

In this section we describe two approaches suitable for modeling the individual within an organizational context: a *cognitive architectur*e and a *profile-based social network model*. We also briefly outline the knowledge and data requirements for each approach.

The objective of the *cognitive architecture approach* is to emulate the structures and processes used by the human decision-maker. The resulting architecture can then function in a simulation environment to represent the individual decision-maker's behavior for training purposes, and can also help in behavior prediction. In contrast to this, the *profile-based approach* does not require knowledge that allows emulation of the actual decision processes. Instead, these models require knowledge that enables automatic inferencing by a decision-aid (e.g., an expert system) *about* the decision-maker, to derive additional knowledge about the decision-maker's profile, and to predict likely decisions and behavior, within a particular context.

The distinguishing characteristic of the *cognitive architecture approach* is thus the need to identify the internal structures and processes mediating the performance of interest, and to capture these in terms of the architecture components; that is, the *architecture modules*, the *mental constructs* manipulated by these modules, and the algorithms comprising processing within these modules. Typically the performance of interest will be a set of concrete tasks within the domain of interest.

In contrast, the *profile-based approach* requires knowledge and data characterizing a decision-maker and predicting his/her behavior, and the knowledge of how to use the available data to derive the information of interest (e.g., particular unknown characteristic or likely behavior).

Ideally, a profile would consist of a small set of factors from which all other characteristics and likely behaviors could then be predicted. Unfortunately, the complexity of human personality and decision-making precludes its characterization in terms of a single set of orthogonal covering dimensions. To obtain a detailed characterization of an individual, and to define the behavior determinants, it is therefore necessary to analyze the individual from a variety of perspectives, and at varying levels of abstraction. This requires the use of multiple sets of profile attributes, whose relative importance for particular behavior predictions may vary, depending on the operational context.

There are thus overlapping but distinct requirements for the types of knowledge necessary to construct these two types of models, for the data required to populate the model structures, and for the data required to support dynamic simulations. For example, the individual profile may include the individual's situations, expectations, and goals. However, while in the cognitive architecture approach these situations, expectations and goals are *derived by the architecture* via the emulated decision-processes, in the profile-based approach they are either provided directly by the modeler (as input data), or derived via some inferencing mechanism that makes no attempt to emulate human decision-making, but instead simply captures the observed regularities (e.g., situation A frequently leads actor X to generate behavior B).

3.1 Knowledge and Data Requirements

There are three primary sources of knowledge and data for developing individual models: (1) existing empirical literature; (2) task analysis and knowledge elicitation interviews; and (3) empirical studies collecting specific required data. These serve as the basis for the following aspects of the models: (1) theories of decision-making to emulate within the cognitive architecture approach; (2) the long-term memory schemas used in the cognitive architecture approach; (3) the mappings among these schemas that enable the actual transformation of incoming data to selections of particular adaptive behavior within the architecture approach; (4) the structure and contents of the individual profiles used in the profile-based approach; and (5) data necessary for the dynamic simulation of the evolving context during model execution. A detailed analysis of these sources can be found elsewhere (Hudlicka & Zacharias 2005).

4 EXAMPLES OF ALTERNATIVE APPROACHES TO INDIVIDUAL MODELING

Below we present examples of the the *cognitive architecture* and a *profile-based social network model* approaches, highlighting in each case the means and ability of representing individual differences, and the ability to model the influence of those differences on decision-making and behavior.

4.1 Modeling the Individual in Terms of a Cognitive Architecture

There are a number of possible architectures that could be used to model the individual within an organizational simulation (see partial review earlier). Given the critical role that individual behavioral variations may play in organizational behavior, it is important to select an architecture that is capable of representing these variations, in a rapid and empirically justified manner. Below we describe an architecture developed specifically to address the modeling of a range of multiple, interacting individual differences: MAMID (Methodology for Analysis and Modeling of Individual Differences), developed by Psychometrix Associates (Hudlicka 2002; Hudlicka and Billingsley 1999).

The initial MAMID prototype demonstrated an ability to model the effects of selected individual differences within an Army peacekeeping demonstration scenario (Hudlicka 2003). Below we describe the individual differences modeling methodology, outline the key components of the MAMID cognitive architecture, and illustrate its operation and results from an initial evaluation.

4.1.1 MAMID Modeling Methodology

MAMID is a *generic methodology* for modeling a range of multiple, interacting individual differences within symbolic cognitive architectures, via parametric manipulations of the architecture *processes* and *structures*. The underlying thesis of the approach is that the combined effects of a broad range of cognitive, affective, and trait individual differences, as well as a variety of cultural and individual history factors, can be modeled by varying the *values of these parameters*, rather than the architectural components themselves (Hudlicka 1997; 2002). This then allows a rapid specification of cognitive architecture configurations capable of modeling a wide range of individual stereotypes, represented by distinct individual differences profiles.

The architecture parameters control speed of module processing, capacity of working memory associated with each module, and structure and contents of long-term memories mediating perceptual and cognitive processing. They also determine the values of the attributes of internal mental constructs such as cues, situations, expectations and goals (e.g., threat level of cues, salience of situations, desirability of goals, etc.), thereby controlling when a particular construct will be processed (e.g., cue attended, situation derived, goal selected, etc.).

Distinct individual types (e.g., normal, anxious, aggressive) are represented by distinct individual profiles, which are then mapped onto specific configurations of the architecture parameters. The parameters cause 'micro' variations in architecture processing, (e.g., number and types of cues processed by the attention module, number and types situations derived by the situation assessment modules; focus on goal A vs. goal B), which then lead to 'macro' variations in observable behavior (e.g., high trait-anxious team leader requires more time and resources for a particular operation than a low trait-anxious; high-anxious operator misses a critical cue on operating console due to attentional narrowing, failing to diagnose an electrical malfunction, etc.). Figure 1 illustrates the general relationship between a representative set of individual differences, the architecture parameters, and the architecture itself. Figure 2 shows an expanded view of the MAMID architecture.

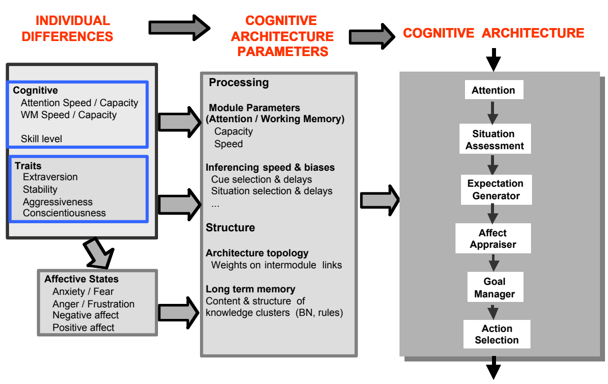

Figure 1: Schematic Illustration of MAMID Behavior Moderator Modeling Approach and Architecture

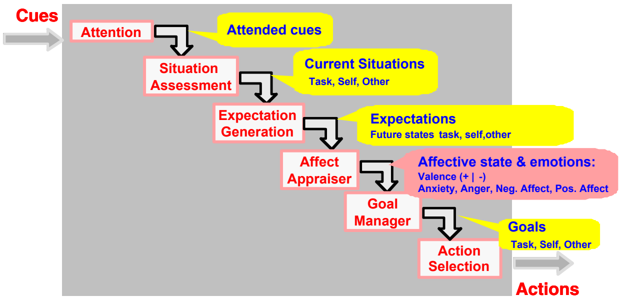

Figure 2: MAMID Cognitive Architecture and Mental Constructs that Comprise Input / Output of the Architecture Modules

4.1.2 MAMID Architecture

MAMID is a sequential 'see-think-do' cognitive architecture, consisting of six processing *modules* which map the incoming stimuli (cues) onto the outgoing behavior (actions), via a series of intermediate internal representational structures (situations, expectations, and goals). We term these internal structures *mental constructs*. The remainder of this section describes the MAMID cognitive architecture and the parameter space available for encoding behavior moderators.

The MAMID modules consist of the following: *sensory pre-processing*, translating the incoming raw data into high-level task-relevant perceptual cues; *attention*, filtering the incoming cues and selecting a subset for further processing; *situation assessment*, integrating individual cues into an overall situation assessment; *expectation generation*, projecting the current situation into one or more possible future states; *affect appraiser* deriving the affective state from the variety of influencing factors: static (traits, individual history) and dynamic (current affective state, current situation, goal, expectation); *goal selection*, selecting the most relevant goal for achievement; and *action selection,* selecting the most suitable action for achieving the current goal within the current context. Figure 2 illustrates the MAMID cognitive architecture, its constituent modules, and the mental constructs that comprise the input and output of these modules; that is, cues, situations, expectations, goals and actions.

4.1.3 MAMID Evaluation Results

The MAMID prototype was evaluated in the context of a peacekeeping scenario, where separate instances of the architecture controlled the behavior of simulated battalion commanders, moving through an unsecured territory. During the evaluation experiment, the simulated commanders encountered a series of surprise events (e.g., destroyed bridge, enemy illumination rounds, hostile crowd.

Several 'stereotype' commanders were defined (anxious, aggressive, normal, obsessive) and MAMID generated distinct internal processing and differences in observable behavior, as shown in figures 3 and 4.

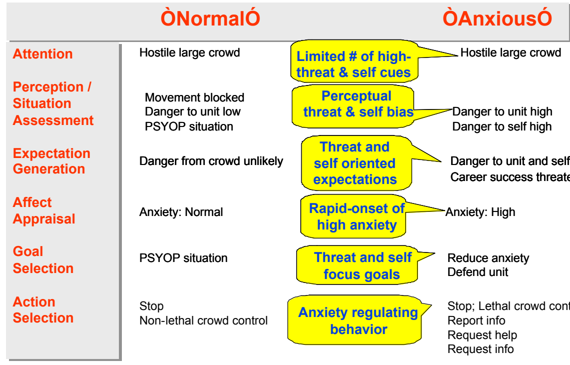

Figure 3: Contrasting Internal Model Processing for Normal and Anxious Commanders during 'Hostile Crowd' Encounter

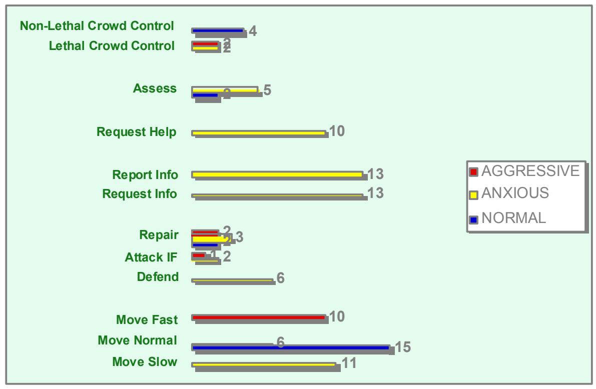

Figure 4: Summary of Behavior Generated by the MAMID Models of the 'Normal', 'Anxious', and 'Aggressive' Commanders

While much work remains to be done to fully evaluate and validate the MAMID modeling methodology and architecture, and a number of extensions to the architecture are possible, the initial evaluation demonstrates the feasibility of the overall approach to modeling individual differences in terms of parametric changes to the architecture processes, constructs and memory structures.

4.2 Modeling the Individual in Terms of a Profile within a Social Network

We now describe an alternative approach to modeling individual behavior, based on the use of profiles, embedded within social networks. This approach makes no attempt to emulate the human decision-making process, but rather aims to collect as much relevant information about the individual as possible in terms of a profile consisting of the critical behavior determinants, *and past behaviors*, as outlined earlier. A series of mappings among these determinants then enable the derivation of additional profile information, from existing data, as well as the prediction of likely behaviors.

Similarly to the cognitive architecture approach described above, the profile-based approach is able to represent a variety of individual differences that cause variations in individual behavior.

Below we describe a specific profile-based approach developed by Charles River Analytics and implemented within a prototype PSYOP (Psychological Operations) decision-aid. This approach originated with C2WARS and is now being extended under the IODA (Information Operations Decision Aid) program (Hudlicka et al. 2002; Hudlicka et al. 2004). We first describe the individual behavior determinant profile, discuss how its components are used to derive additional individual data and behavior predictions, and provide examples of rules deriving this information.

4.2.1 Individual Behavior Determinant Profile

Below we outline a catalog of behavior determinants we have identified as relevant to PSYOP decision aiding, but which also apply to other domains. These determinants include individual differences and behavior moderators, but go beyond these to include the individual's goals, characteristic beliefs and attitudes. The profile also include the psychosocial and information environment within which the individual operates, represented in terms of the variety of relationships of the individual to his/her social environment. These relationships then define the individual's *social network* and are a critical component of modeling the individual's organizational milieu. The primary categories of profile attributes are shown in Table 2. An example of a social network generated from the IODA profile information is shown in Figure 5.

Table 2: Categories of Behavior Determinants in Target Profiles

Demographic Info.	Training & Education
Individual History	Role
Intra / Inter personal Conflicts	Vulnerabilities, Pressure Points
Psychological Factors	Psychosocial Relationships
Attitudes / Beliefs	Situation Assessments
Goals / Goal Personnel	Goals Scripts
Info. Environment	Data Triggering Beliefs

4.2.2 Deriving Profile Values and Predicting Individual Behavior

The individual profile summarizes the knowledge about the individual, both static and dynamic. To derive additional information from the existing profile data, and to generate behavior predictions, the profile-based approach needs a means of manipulating this knowledge to derive the information of interest. This can be accomplished via a number of means. The approach adopted for the IODA decision-aid uses a combination of rules and belief nets, which map the individual profile attributes onto other attributes, eventually allowing the derivation of the likely predicted behavior for the individual.

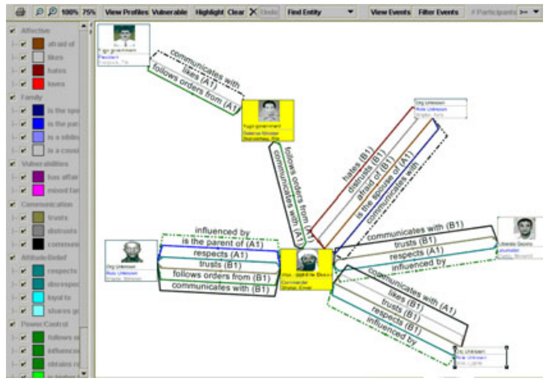

Figure 5: Example of a Social Network for a Set of Fictitious Individuals Modeled within the IODA Decision-Aid

A variety of mappings may be constructed and encoded in the rules and belief nets, relating different attributes within the profile (e.g., relating traits with attitudes and goals), and eventually resulting in the derivation of the likelihood of particular behaviors of interest (e.g., selection of a particular strategy to achieve a particular goal). These mappings are derived from a combination of knowledge from academic and applied psychological studies (e.g., correlations or particular trait configurations with specific attitudes, beliefs, values and goals), and practical field knowledge (e.g. correlations of particular characteristics with likely behavior).

An example of a belief net deriving the vulnerability 'Mixed Family Loyalties' is shown in figure 6. Examples of rules deriving profile attributes are shown in Table 3 below; examples of behavior prediction rules are shown in Table 4 below.

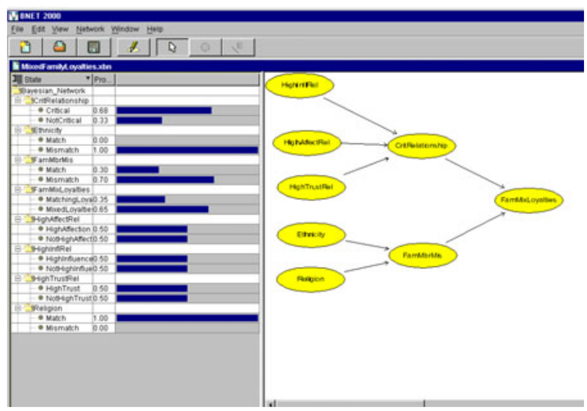

Figure 6: Example of a Belief Net Deriving a Particular Individual Vulnerability: 'Mixed Family Loyalties'

The profile-based approach described above was implemented in several prototypes, using fictitious but realis tic operational scenarios, and focusing on distinct objec-

Table 3: Examples of Rules Deriving Profile Attributes from Existing Data

High preference for face-to-face contact
IF (extraversion=high) AND (agreeableness = high) THEN
(preference for face-to-face contact = high)
(preference for team collaborative decision-making = high)
(diverse sources of information = high)
High need for collaborative decision making
IF (need for affiliation = high) And (Trust = high) AND (paranoia = low)
THEN (Need for consensus = high) (need for collaborative decision making = high)
(general relationship with subordinates = empowers)

Table 4: Examples of Behavior Prediction Rules

IF	Person Y's religious extremism = high Person Y's event history includes violence	THEN	Person Y's likelihood of violence = high
IF	Person Y's goals include "Peaceful co-existence" Person Y's religious extremism = low	THEN	Person Y's likelihood of violence = low
IF	Person Y's event history includes violence	THEN	Person Y's likelihood of violence = high

tives. The C2WARS prototype implemented a proof-of-concept demonstration, instantiating profiles of specific individuals within a Balkans-like PSYOP training scenario, deriving additional individual information from existing data, and focusing on the identification of specific vulnerabilities (e.g., 'Mixed Family Loyalties' shown in Figure 9). The IODA prototype implemented a different training scenario, involving civil-war context in a multi-ethnic environment, and focused on behavior prediction, expanding the profile and inferencing accordingly.

5 INTEGRATING INDIVIDUAL MODELS WITHIN ORGANIZATIONAL SIMULATIONS

We now briefly discuss how the two approaches described above would be integrated within organizational simulations, and what enhancements would be required. In each case, the primary objective is to capture the set of relationships between the individual and the organization, and the resulting interactions and mutual influences. Exactly what information about the organization is required, how this information is represented, and at what level of abstraction the organization is represented, depend on the objectives of the particular simulation.

5.1 Integrating Cognitive Architecture Models within Organizational Simulations

There are several ways in which a cognitive architecture can be integrated within an organizational simulation. A given *instance* of an architecture can represent an individual within the organization, so that multiple instances can represent multiple interacting individuals within the organization. Under some circumstances a given instance of an architecture can also represent a group of individuals, a component of the organization, or even the organization as a whole, depending on the level of modeling fidelity required by the simulation objectives.

When using this approach, we must first characterize the types of interactions that occur between the individual and the organization, and then augment the corresponding models accordingly, by adding schemas and knowledge that: (1) represent these interactions; (2) allow the perception and parsing of the 'messages' inherent in these interactions; (3) enable modeling of the effects of these 'messages' on the processing in both models; and (4) enable the generation of meaningful responses.

This type of augmentation will typically require additional content of the knowledge structures, both *knowledge and data in long-term memories*, and the *knowledge necessary to use and manipulate these* (e.g., rules, belief nets), as well as the generation of simulation-driven dynamic data that provide information about the organizational context. However, incorporating a cognitive architecture within an organizational simulation is not likely to require changes to the architecture itself; that is, the modules, their internal algorithms, and the mental constructs they manipulate.

The exact nature of the additional schemas required, and the dynamic data generated during a simulation, depend entirely on the nature and objectives of the associated organizational simulation, but are likely to include the following: (1) types of information provided by or about the organizational context (e.g., messages sent / received among members of the organization or other subgroups); (2) explicit representation of other relevant entities within the organization (e.g., individuals, departments, subgroups, the organization as whole, as well as specific resources); (3) Baseline knowledge about these entities and their roles within the organization (e.g., individual x is head of department y, department z has n units of resource r); and (4) relevant states and behavioral repertoire of the other active entities within the organization (individual, organizational subgroups, or the organization as a whole) (e.g., 'person x knows fact b', 'department y can perform procedure d', 'president x is pleased with outcome y', 'organization p is lacking resource r').

5.2 Integrating Profile-Based Social Network Models within Organizational Simulations

By explicitly representing the individual's social relationships and information environment, the behavior determinant profile is already well-suited for integration within an organizational simulation context. Depending on the nature and requirements of the overall organizational simulation, integrating an individual profile may only require adding the corresponding content to the existing profile structures; that is, the nature and type of relationships between the individual and his/her organization. Depending on the representational resolution of the organization, this may involve adding multiple relationships to other individuals comprising the organizations, or adding relationships to subgroups within the organization represented as a single model entity (e.g., a single 'node' in a social network may represent a group of individuals or a component of the organization, such as a department).

To support the additional inferencing required, the knowledge base associated with the profile must be augmented. For example, the rules or belief nets must be added to use the additional 'organizational' knowledge and derive from it the necessary data, such as an appropriate response to a particular 'message' arriving from a different component of the organization.

6 CONCLUSIONS

In order to optimize organizational structure to enhance individual creativity on the one hand, and limit the possibly adverse effects of individual behavior on the other, we must improve our understanding of the complex interactions between the individual within the organizational context. Such improved understanding requires computational modeling approaches, due to the complexity of the phenomenon, which precludes purely non-computational empirical studies. These computational approaches must be able to adequately model individual behavior, particularly the types of individual differences that give rise to idiosyncratic behavior, which can be both beneficial and detrimental to the organization as a whole. Understanding the effects of individual behavioral variations on the organization as a whole is also critical for any type of organizational behavior predictions.

Both of the approaches to modeling the individual described here are well-suited to modeling the individual within an organization. However, we have yet to develop adequate criteria to determine which approach is best suited for which application. Systematic evaluations of the various modeling approaches are necessary to identify their benefits and shortcomings, across various contexts. Additional research is necessary to explore these, and other, modeling approaches, in various contexts, to define these criteria, and to contribute to defining a concrete set of guidelines for developing organization simulations. Such guidelines would help determine which method to use when, what level of representational abstraction is most appropriate for a particular application or objective, and how distinct modeling approaches may be combined.

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