

**Toward Unified Organization Theory:  
Perspectives on the State of Computational Modeling**

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**Abstract**

Scholars engaged in the study of work group and organizational behavior are increasingly calling for the use of integrated methods in conducting research, including the wider adoption of computational models for generating and testing new theory. Our review of the state of modern computational modeling incorporating social structures reveals steady increases in the incorporation of dynamic, adaptive, and realistic behaviors of agents in network settings, yet exposes gaps that must be addressed in the next generation of organizational simulation systems. We compare 29 models according to more than two hundred evaluation criteria, ranging from simple representations of agent demographic and performance characteristics, to more richly defined instantiations of behavioral attributes, interaction with non-agent entities, model flexibility, communication channels, simulation types, knowledge, transactive memory, task complexity, and resource networks. Our survey assesses trends across the wide set of criteria, discusses practical applications, and proposes a research and development agenda that motivates advancement of computational science toward unification of organization theory.

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# **Toward Unified Organization Theory: Perspectives on the State of Computational Modeling**

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## **Introduction**

Work is central to every aspect of modern life. What we “do for a living” influences not only government policy, community norms, and economic status but also our individual self-esteem, social activities, and even seemingly unrelated decisions such as when to marry and if and when to have children (Hulin, 2002). The usual environment for work is some form of organization, ranging from companies, where people are linked as employees engaged in activities supporting profit or welfare maximizing motives, to an array of other organizational forms, such as families, communities, religious groups, and even nation states, where connections between people are based less on economic motives and more on genetics, social identity, or concern for promoting or defending the welfare of its members. However, despite the pervasiveness and critical importance of organizations to society and individuals, a unified theory of organizations remains elusive. Economists have a coherent body of theory underlying their understanding of the market transactions or contractual mechanisms that motivate organizations, but management scientists still struggle to provide an integrated theoretical rationale for the complex behavioral, cognitive, and attitudinal aspects of those same organizations (Simon, 1991). To understand why this is so, we must look to the core of the types of organizations considered in this study – human beings. Notwithstanding the existence of automata and avatars, organizations are principally comprised of *human* agents who contract tacitly or explicitly for an exchange of some degree of authority or autonomy for combinations of compensation, social identity, preservation, or other objectives of enlightened self-interest. Comprised thusly of human agents, organizations, from the simplest of partnerships to the most intricate of international corporations, reflect not only the richness, complexity, variation, chaos, and beauty of human behavior but also its seeming defiance of theoretical conformity. We should not be astonished then why predicting or even understanding organizational behavior is indeed daunting. Nor should we be astonished by the multitude of partial theories of group and organizational behavior, which, although insightful and stimulating, oftentimes fall well short of theoretical unity or even harmony.

It is precisely this state of affairs that motivates our review of computational organizational models. In the domain of computational modeling, ideally any number of theories can be fused and tested using the touchstone of simulation modeling, enabling the integration and generation of organizational theory that reflects both reality and emergence in human complexities (Masuch & LaPotin, 1989). Our primary aim is to examine the extent to which researchers are beginning to harness computational modeling’s power to integrate the many desultory theories of behavior of individuals, groups, organizations, and groups of organizations ultimately in a unified theory of organizational behavior. To review progress toward this end, we examine twenty-nine organizational simulation models developed over the past fifteen years. We first introduce a framework for organizational simulation modeling that will guide our analysis of the reviewed models. Then, based on our nomological construct, we discuss each class of models and their contributions to understanding organizations and their effectiveness. Finally, we suggest a research agenda for extending the application of computational modeling toward the goal of integrating and ultimately unifying theories of organizational behavior.

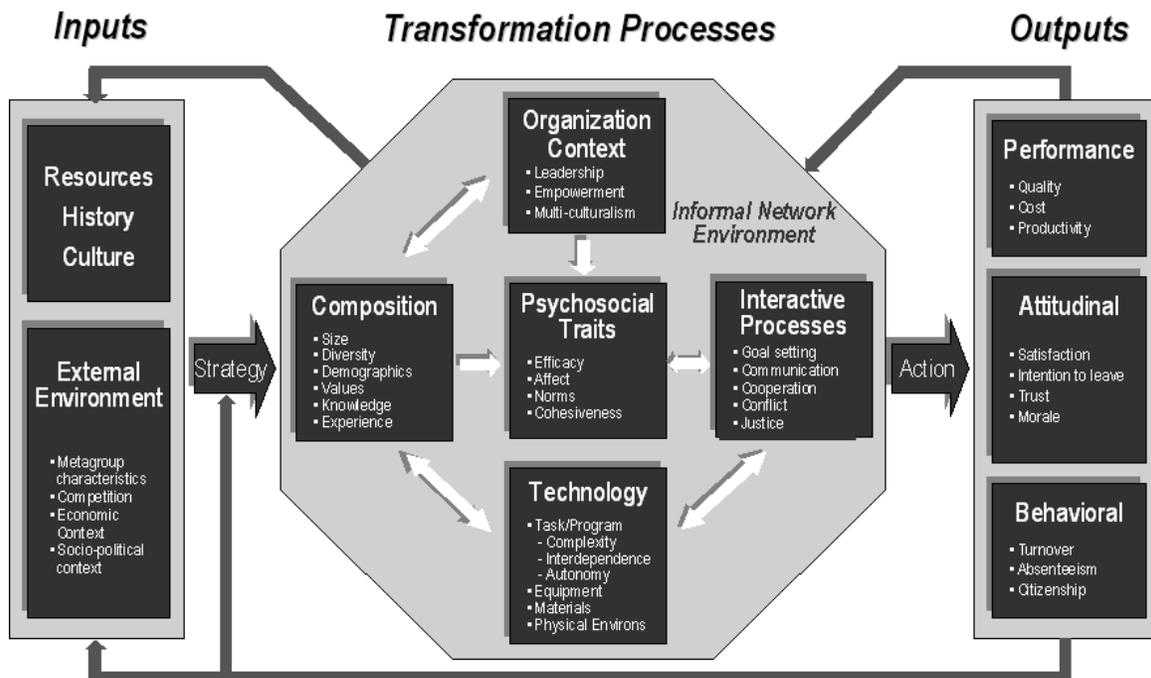
## **Model Selection Process**

Simulation models included in this review span the period from 1989 to 2003. To select models, we first searched general, business, psychology, interdisciplinary, social science, and dissertation abstract databases using the primary terms *simulation*, *model*, and *expert system*, in conjunction with numerous antecedent and secondary terms such as *computer*, *computational*, *system dynamics*, *agent-based*, and *multi-agent*. This initial sweep yielded several hundred abstracts, from which we ultimately chose models introduced in twenty-nine peer-reviewed journal articles. Our selection rules specifically required that models (1) focus on *human* organizations and networks (i.e., no robotic or avatar-based interactions except as part of overall human systems), (2) inculcate theory at a level at least as aggregate as individual behavior (i.e., no biological or chemical level models), and (3) enable investigation of multiple aspects of individual, group, and inter-group behavior (i.e., models that extend beyond single-purpose use for testing an existing theory, as in the case of Repenning’s (2002) exemplary application of system dynamics to the investigation of existing theory on innovation adoption). An additional condition we applied for inclusion is that the code for the models be publicly available or identifiable based on publicly available information. Despite our rigorous identification methodology, the twenty-nine models reviewed are not intended necessarily to be “exhaustive.” We nevertheless believe the selected models are widely representative of organizationally oriented simulation systems introduced over the past fifteen years and will thus form a sound basis for providing perspectives on the present and future states of computational modeling.

## Definitions

**Organizational Simulation Model.** We define an organizational simulation model as a type of Turing machine in which the discrete-state machine represents performance of a group of two or more individuals interacting to achieve a common goal. Inputs and outputs are combinations of physical, behavioral, and cognitive characteristics of the individuals and groups comprising the organization. State transitions are described by empirically based associations or mathematical relations founded on existing and proposed theory.

**Organizational Simulation Framework.** Rather than simply reporting on models and their capabilities, one of our aims is to understand the state of computational organization modeling in the context of theories of organization and organizational behavior. To do so, we require a *framework* for modeling organizational behavior against which we can measure the coverage of respective models reviewed in the study. We take this approach in recognition that the scientific standards applicable to a good mathematical model also apply to simulation. Such standards dictate that we (1) provide categories of assumptions so that insights and intuitions can be transferred from one context to another and cross-checked between different contexts, (2) allow insights and intuitions to be subjected to tests of logical consistency, and (3) establish the ability to trace back from observations to underlying assumptions to see which assumptions are really at the heart of particular models (Kreps, 1990). Thus, our review is organized around components of a heuristic model of organizational effectiveness that integrates and extends earlier effectiveness frameworks introduced by Hackman and Morris (1975), Nieva, Fleishman, and Rieck (1978), Nadler and Tushman (1980), Hackman (1983), McGrath (1984), Gladstein (1984), Goodman (1986), Sundstrom, DeMeuse, & Futrell (1990), Cohen and Bailey (1997), and Marks, Mathieu, and Zaccaro (2001).



**Figure 1. Organizational Simulation Framework.**

The framework has fourteen factors, categorized as “Inputs” (Resources, History, Culture, and External Environment), “Transformation Processes” (Composition, Organization Context, Psychosocial Traits, Technology, and Interactive Processes), outputs (Performance, Attitudinal, Behavioral), and linkages (Strategy and Action). The framework embeds individual characteristics, described by “Composition” attributes, within the group or organization-level transformation processes. Transformation processes represent the means by which strategy translates organizational inputs into meaningful action resulting in performance, attitudinal, and behavioral outputs. Results of both transformation processes and outputs have feedback impacts on inputs and the processes themselves. Performance outcomes range from *objective* measures – such as efficiency, cost, productivity, quality, safety, errors, or customer service – to *perceived* measures of those same dimensions. “Perceived” performance outcomes measure how organizations and organizational units appear to work together, including the perceived level of integration of social identity groups (by gender, age cohort, or role, for example) and the perception of overall team functioning. Examples of attitudinal outcomes are job satisfaction, worker morale, turnover intentions, change resistance, and commitment. Behavioral outcomes range from absenteeism and turnover to communication patterns,

innovation, and learning. We represent organizational design factors in a multi-dimensional construct encompassing technology, composition, and organizational context. We further break down each factor into specific sub-categories in order to surface more explicit distinguishing factors of organizations (Kozlowski & Bell, 2003). For example, we disaggregate technology design into variables representing task (complexity, interdependence, and autonomy) and non-task technology (equipment, materials, and physical environment). Composition variables are disaggregated into sub-categories that include individual characteristics such as personality, values, knowledge, experience, and tenure, and group and organization level characteristics such as size, demography, and diversity. Similarly, organizational context includes constructs for leadership, empowerment, and multi-cultural influences.

With respect to group and unit-level processes, we define categories of cooperation and communication variables in both internal and external contexts as well as separate group goal-setting and organizational justice variables. Cooperation encompasses processes such as conflict resolution, collaborative decision making, and reflexivity. Communication broadly includes processes that facilitate social and cognitive information sharing. Following Cohen and Bailey (1997), we differentiate psychosocial variables as group and unit-level constructs such as efficacy, affect, norms, cohesiveness, and cognition. Collective efficacy is an expression of a group's confidence in working together in general, while group affect is a measure of consistent or homogeneous affective reactions in a group (George, 1990). Norms are tacit understandings or implied agreements of how group members should behave under certain conditions, and cohesiveness reflects the level of shared identity in a group or the extent to which members of a group view themselves as a group. Group cognition encompasses group learning processes, shared mental models, and group transactive memory (Wegner, 1986). Finally, our framework incorporates environmental factors as a distinct category that broadly encompasses industry characteristics, competition, and economic context.

### Analysis of Models Surveyed

Our analysis approach consisted of first coding the capabilities of each of the twenty-nine models (see Figure 2) according to 290 capability evaluation factors representing the following categories: range of organization designs, actor characteristics, organizational performance measures, agent physical attributes, agent behavioral attributes, agent cognitive attributes, task characteristics, task assignment, technology, resources, knowledge, simulation type, network representation, and communication processes. Then, based on a mapping of each capability evaluation factor to one of the fourteen factors in the organization simulation framework, we calculated an index describing the models' coverage of theoretical constructs in the framework.

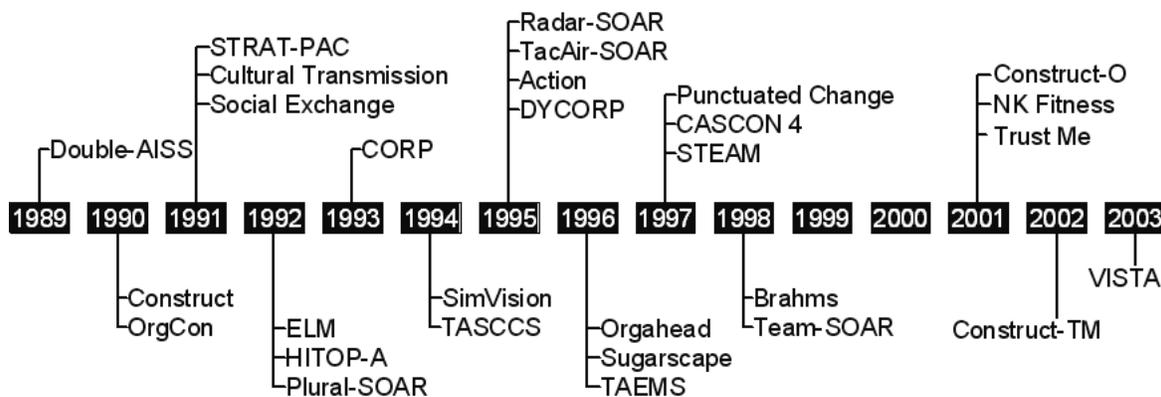


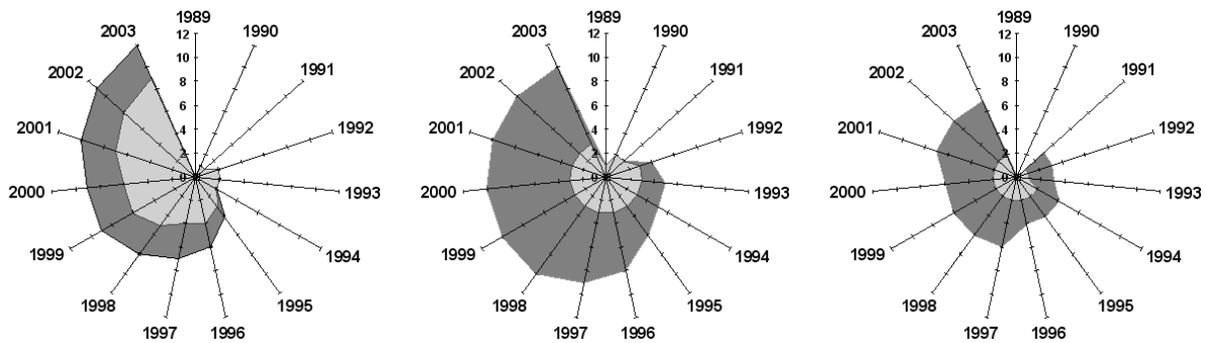
Figure 2. Simulation Models Included in Review.<sup>1</sup>

**General Findings.** Simulation models in our review are grouped into three broad categories according to simulation type: agent-based models, expert systems, and mathematical models. As shown in Figure 3, while there has been a similar pattern of growth between model types, agent-based models now outnumber other types and are growing at a faster rate; in addition, agent-based simulations have the greatest representation of network structures. Networks are used to characterize not only social relationships but also organizational roles, communication linkages, advice relationships, tasks, knowledge, and resources. Among the models surveyed, a wide range of organizational structures is represented, from hierarchies and bureaucracies to networks and nation-states. The most prevalent type of structure is team-based, with fairly even focus on both traditionally managed and autonomous teams.

Models are generally limited to focusing on one level of analysis. However, some models simulate two or more levels (e.g., ELM, TASCSS, DYCORP, STEAM), with linkages defined as one or more performance or

<sup>1</sup> Due to space restrictions, the conference version of this paper does not list references for the 29 models. A complete list of references for the models is available from the authors.

decision making outcomes communicated from one level to another. One model, OrgCon, theoretically permits investigation of the effects of an unlimited number of levels; however, the measure is incorporated, as are other measures in such rule-based systems, as a set of ranges reflecting varying levels of influence of complexity or hierarchy on other organizational design variables. Time is generally defined in the form of generic Markovian “time steps,” with linkages to normative or positive scientific interpretation completely dependent on the time frame of the inputs provided by the modeler. Thus, most models offer only a means of construing time on a relative basis between simulations in a given study, not an absolute basis for making time-based predictions.



3a. Multi-Agent Models.

3b. Expert Systems.

3c. Mathematical/System Dynamics.

**Figures 3a-c. Growth in Simulation Models by Type.**  
**Lightly-shaded region represents percentage that is network-based.**

While all models instantiate one or more bodies of theory as an analytical foundation, applications of models generally fall into two broad categories – theory-building and situational simulation. Theory-building models (e.g., Table 1) pose and test new theory based on results that emerge based on interactions of existing theory. Situational simulations (e.g., Table 2) apply existing theory to situations typically unsuited to empirical investigation to validate theory under those conditions. Both theory-building and situational simulations are useful for examining robustness of propositions under scenarios in which some or all key independent variables are changed.

Theory Domain	Representative Models
Organization Design	Double-AISS CORP SimVision Orgahead NK Fitness
Organization Change	Punctuated Change
Enculturation	Cultural Transmission SugarScape
Cooperation	Social Exchange
Gossip	Trust Me

**Table 1. Examples of Theory-building**

Situational Domain	Representative Models
Tailor Shop	Construct
Airlines	OrgCon
Manufacturing	ACTION
Warehouse Order Picking	Plural-SOAR
Petroleum Refining	SimVision
Radar Detection	Team-SOAR
Air Combat	TacAir-SOAR
Resource Allocation	STRAT-PAC
Hospital Scheduling	TAEMS
Border Hostility	CASCON 4
Urban Threats	VISTA

**Table 2. Examples of Situational Models.**

As shown in Table 3, the range of theory encompassed by the surveyed models is dominated by socio-technical systems theory (Emery & Trist, 1960), although the focus of such models is on simulating the *interaction* of people, task, and technology rather than on *optimization* of their social and technological outcomes. Not surprisingly, most of the socio-technical models also incorporate social network representations of actors. Closely aligned with socio-technical approaches are models incorporating contingency theory. These models are concerned less with agent specific behavior and more with aspects of design that are predicated on factors such as differing levels of formalization, centralization versus decentralization, and proactive versus reactive planning time horizons.

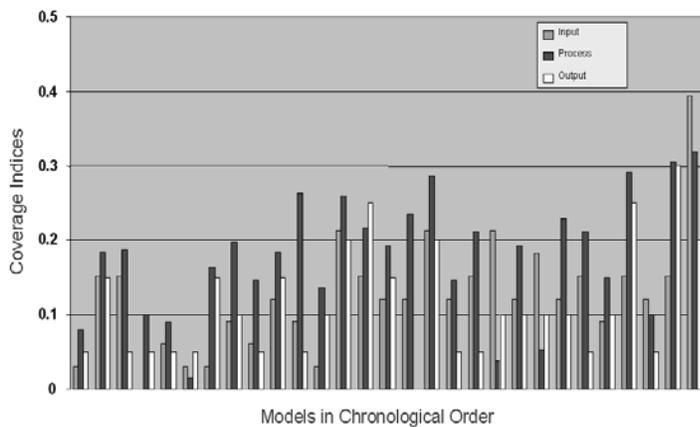
While models based on socio-technical systems approaches are cybernetic and constructivist in nature, seeking to balance technology and task in a context of socially shared meaning, models based on artificial intelligence (AI) theory presume that knowledge alone, rather than having a social dimension, is a commodity and that the application of such knowledge is in fact the true expression of intelligence (Minsky, 1967). Thus, models

such as TASCSS (Verhagen & Masuch, 1994) and STEAM (Tambe, 1997) instantiate agents with decision logic oriented around agents' respective skills, assigned tasks, memory, and mental models of other agents, enabling them to act and interact based on pre-programmed rules. The "task" of learning thus becomes a pre-programmed routine of reinforcing the agent's stock of knowledge based on responses the agent keeps in memory. AI models are particularly useful for exploring the actions of both human and technological agents engaged in highly standardized processes with protocols defined for as near to all conceivable situations as possible.

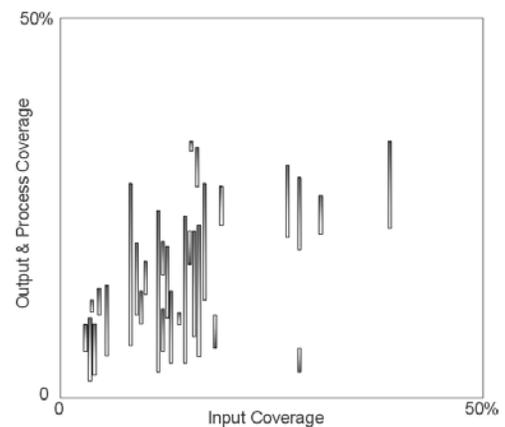
Underlying Theory	Representative Models	
Socio-Technical Systems Theory	Double-AISS Construct ELM Brahms HITOP-A	CORP ACTION Orgahead DYCORP VISTA
Artificial Intelligence Theory	Double-AISS Plural-SOAR TASCSS	Radar-SOAR STEAM Team-SOAR
Organizational Information Processing Theory	SimVision Trust Me Brahms	Orgahead Construct
Contingency Theory	OrgCon CASCON 4	NK Fitness
Evolutionary Theory/Population Ecology	Cultural Transmission Sugarscape	NK Fitness STRAT-PAC
Punctuated Organization Change	Punctuated Change	
Joint Intentions Theory	STEAM	
Dynamic Phase Conflict Model	CASCON 4	
Social Learning Theory	Social Exchange Model Trust Me	STEAM

**Table 3. Underlying Theories of Reviewed Models.**

Still other models are based on evolutionary designs and population ecology, enabling simple agents to explore complex organizational search spaces based on genetic algorithms or relatively simple sets of rules for death and regeneration. These models tend to be more intellectual in nature and are thus powerful for theory-building but less useful for situational emulation. Models incorporating more specific theories, such as joint intentions theory and social learning theory, tend to represent those premises in combination with broader theories such as contingency theory and general artificial intelligence. These models' unique additions extend the detail with which models can address goal and outcome interdependence as opposed to simple task interdependence.



**Figure 4. Coverage indices of models in chronological order, 1989-2003.**



**Figure 5. Input versus Process (dark) and Output (light spectrum).**

**Specific Findings on Coverage of Simulation Framework.** While we recognize that the idea of a unified theory of organizations is epistemological in nature, and that establishing the capability to simulate the behaviors of organizations in increasing detail may no more lead to such unification than the present panoply of partial theories, we nevertheless believe that such ideas and attempts to model those ideas are worthy goals (Hulin & Ilgen, 2000). Hence, our calculations of indices of coverage of the simulation framework (Figure 1) are intended less as absolute measures than as indicators of the richness and vastness of organizational behavior yet to be integrated. Based on these calculations, as Figure 4 indicates, there is a discernible if variable trend upward in the coverage of inputs, processes, and outputs in the framework. However, as Figure 5 depicts, the capabilities of most models cluster in the 5 to 15 percent coverage range, with a handful of models covering 25 to 30 percent of the framework. Finally, Figure 6 summarizes average coverage of the simulation framework across all models and provides a scorecard value for each factor in the framework. Given that the framework, despite its theoretical grounding, is arguably much less than 100 percent representative of organization theory, our coverage estimates are clearly biased on the high side. Thus, our analysis reveals there is much ground to cover in integrating existing theory.

### Discussion

As Figure 4 shows, the richness of simulation models has increased over the past fifteen years. Representation of processes tends to dominate input and output coverage, indicating that existing simulations focus primarily on transformation factors such as group composition, technology, communication, and cooperation. Somewhat surprisingly, output coverage is generally superseded by both input and process representation. Most models focus on some aspect of performance or productivity, with little or no attention to behavioral and attitudinal measures. Future research should increase the incorporation of attitudinal and behavioral outcomes in models, along with dynamic feedback of those outcomes to input and process variables.

While most models exhibit fairly low coverage of the simulation framework (see Figure 5), even models with richer feature sets tend to have similar underlying theories and cover many of the same types of factors in the simulation framework. Thus, if there is a road to “unification of theory,” it clearly not one of merely adding or integrating multiple models together. The range of underlying theory must expand beyond the fractional and mechanistic to the holistic and emergent. Just as understanding biological evolution requires less about what atoms themselves are made of and more about how they behave in chemical and physical networks, discovering unified laws of organizational behavior will only result from understanding how sundry partial theories of organization interplay at each level in complex networks of people, resources, tasks, knowledge, and technology. Future research should examine the appropriate range of theories further, refining the unified simulation framework ultimately with a level of dependent, independent, and control variables that fosters the study of both integrative and emergent organizational behavior irrespective of the specific goals of the simulation.

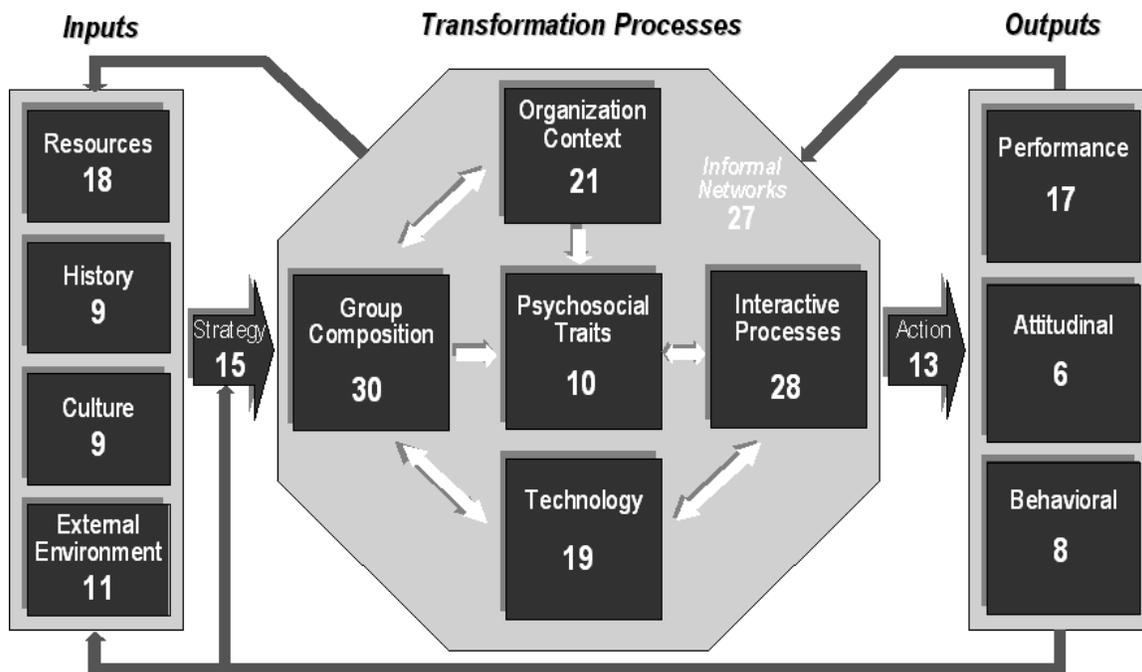


Figure 6. Simulation Framework Scorecard (0-100 scale).

## Conclusion

The current state of organizational simulation modeling largely continues to reflect the classical approach to empirical studies, limiting dependent variables to specific outcomes of interest and independent variables to those believed to be most associated with explaining variance. This approach, while enabling organization scientists an additional tool for corroborating and testing relationships between restrictive sets of variables, leads to the same partial theories that result from empirical and experimental methods. Although this result is not a poor one, it is certainly one that deprives researchers of the broader capability of computational modeling to integrate bodies of theory that would be impossible to combine otherwise, enabling exploration of unforeseen emergence and identification of new, more unified theory. The boundaries of simulation modeling must persist in widening beyond the present state of mirroring empirical limitations. Yet, to do this, simulation models themselves must adopt improved theories of computation and applications of existing computer science to enable them to take full advantage of their ability to process complex interactions of increasingly human-like agents. In addition, simulations must widen their boundaries with respect to organizational behavior by incorporating broader empirical grounding synthesized with computational approaches such as structural equation methods, system dynamics, and constraint satisfaction modeling. Consequently, as computer science and simulation methods alike continue to advance, computational organization science may very well have opportunities for unification of theory in view at last.

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