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The Validity of Computational Models in Organization Science: From Model Realism to Purpose of the Model

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Abstract

"...even though the assumptions of a model may not literally be exact and complete representation of reality, if they are realistic enough for the purposes of our analysis, we may be able to draw conclusions which can be shown to apply to the world."

Kalman J. Cohen and Richard M. Cyert (1965)

Computational models are widely applied to address fundamental and practical issues in organization science. Yet, computational modeling in organization science continues to raise questions of validity. In this paper, we argue that computational validity is a balance of three elements: the question or purpose, the experimental design, and the computational model. Simple models which address the question are preferred. Non-simple, imbalanced computational models are not only inefficient but can lead to poor answers. The validity approach is compared with well-known validity criteria in social science. Finally we apply the approach to a number of computational modeling studies in organization science, beginning with Cyert's. They were pioneering and are examples of well designed computational models.

1. Introduction

Can we learn about organizations with computational modeling? Can computational models be applied in organization science to test a hypothesis, train a manager, understand organization decisionmaking or aid in the design of an organization? The early contributions of

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Cyert and his colleagues provide a resounding affirmative response. Their computational model studies help us understand organization decisionmaking, train managers and design organizations. They addressed the validity of computational models—a question which remains today.

In this paper, we argue that there are three elements which should be kept in balance: the question or purpose, the experimental design and the computational model. These three form a triangular icon as a reminder that imbalanced design will likely create difficulties in various ways: outcomes are difficult to analyze, the purpose is not met, the computational model is overly complex. A valid computational model is one that is effectively appropriate to the end goal.

In the next section, Cyert's pioneering computational models are described; they focused on the validity question in terms of relevancy; realism was a central issue. Validity in social science studies grew out of concerns for what we can learn from field studies and laboratory studies. Those validity constructs provide a base reference, but are not as directly applicable to computational studies; nonetheless, the fundamental concerns are the same. We then argue that the three elements: purpose, computational model and experimental design, should be in balance; a simple model which meets the purpose is preferred. That purpose can be to test a hypothesis, train a manager, understand decisionmaking or design an organization. Finally, we examine a number of computational studies in terms of these criteria, beginning with Cyert's computational studies which are balanced and do effectively and appropriately meet their purpose.

2. Cyert's Contributions to Computational Modeling in Organization Science

Cyert pioneered the application of computational modeling to organization science. His contributions were not only extensive, but varied in application and approach. Cohen and Cyert's (1965) handbook chapter on simulation of organizational behavior is a detailed summary which also includes other contributions of the Carnegie School. They define (p. 305) a model as "a set of assumptions from which a conclusion or a set of conclusions is logically deduced"; computer models are a special case. Cohen and Cyert focus on the reality of the model:

> *It is important to realize that in interesting and useful scientific theories, the assumptions need not be* exact representations *of reality, but they may instead be* reasonable abstractions . . . *we mean that only certain aspects of reality are contained in the assumptions, namely, those aspects to be relevant.*

The reality of the model is a central issue. But just how close must a model be to "reality" to be relevant. What is a reasonable abstraction? Clearly, totally unrealistic models become abstract fictions. But the question remains; how close is close enough? We suggest that one should look to the purpose, or question being asked, for guidance. They suggest reality itself is an illusive goal, but more importantly, inappropriate by itself. Relevancy for the intended purpose must be the focus.

Cohen and Cyert (p. 308) then provide a four category taxonomy of computational models in organization behavior:

> *The four major classes into which we divide simulations of organizational behavior are differentiated according to the purposes for which the models were formulated. First, there are descriptive simulation studies of existing organizations. The purposes of these types of computer models are to formulate theories which explain why existing organizations have behaved in particular ways, to test these theories by comparing the observed past behavior with the simulated behavior generated by the model, and to predict how these organizations will behave in the future. Second, there are illustrative (or "intellective') simulation studies of quasi-realistic organizations. The purposes of these types of simulation models are to explore the implications of reasonable assumptions about organizational behavior, in order to determine what the world is like when these assumptions are true. Third, there are normative simulation studies for designing organizations. The purposes that models of this type serve are to allow us to determine which of several possible forms of organizations are in fact best suited to particular goals we want these organizations to fulfill. Finally, there are man-machine simulations, which are intended to train people to function better in organizational settings.*

"Closeness" to reality is the important concern in the first two categories: description and illustrative computational models. Normative models implicitly must be realistic to some degree to be relevant. Finally, man-machine simulations for training people require a level of reality. In this categorization, closeness to reality is a primary concern. However, relevancy can be obtained with computational models which are not necessarily "close" to reality. The normative studies for designing organizations can be less "realistic" than the descriptive studies, and yet, be quite relevant for the design purpose. Cohen and Cyert provide illustrations of their four categories.

2.1. Descriptive Computational Studies

Cyert, March and Moore (Cyert & March, 1963, p. 128–148) developed a computational model to describe a store buyer's behavior which decides the amount of stock to order and the price to charge. The validation test is to compare the model results with the actual decisions, i.e., a valid model is one which mimics reality. Their model is very close to the actual decisions. In their test, they were very demanding: "unless the predicted price matched the actual to the exact penny, the prediction was classified as incorrect," (p. 311). They had 95.4% correct predictions which is very accurate. Nonetheless, generalizability remains an issue, i.e., what do we learn from the study which can be generalized to other situations.

2.2. Quasi-Realistic Studies

Cohen, Cyert, March and Soelberg (Cyert & March, 1963, p. 149–182) simulated the general behavior of price and output determination in oligopoly firms. The model firm is representative—not a specific firm. The purpose is to illustrate in a quantitative form general hypotheses about oligopoly behavior and derive implications. Price and output determination are the focus decision variables. The firm can be thought of as segmented into three subdivisions—pricing, production and sales. Each operated rather independently, subject to cross department pressures.

The model and its decision making behavior are consistent with the behavioral theory of the firm. The multiple goals are attended to more less independently and search routines are adjusted to feedback from experience.

2.3. Normative Computational Studies for Designing Organizations

Two studies are summarized to illustrate normative computational studies. Bonini (1963) devised a model of the firm made up of three areas: manufacturing, sales and an executive committee. The purpose was to study and manipulate information flows and decision processes to determine effects on firm performance, and hence to suggest changes in the firm's design.

Forrester's (1961) industrial dynamics focusses on how to change policies, organization structure, decision processes and time delays to effect growth and stability. The industrial dynamics model is formulated as an information-feedback system.

Both approaches are clearly normative. The tests of validity are less clear. Realism is important: even so, greater realism may not lead to better recommendations for a change. This difficult question is unresolved.

2.4. Man-Machine Computational Studies for Training

The Carnegie Tech Management Game (Cohen, Cyert, Dill, Kuehn, Miller, Van Wormer and Winters, 1960) was created to train individuals to become more effective managers. Managers, or students, were asked to submit decisions on price, output, etc. for one month. The computer model represented a three firm packaged detergent industry which incorporated parameters and relations for the industry and each company's infrastructure. The computer model determined what happened in this "real world," and presented feedback to participants for another month. It was "developed to mirror more realistically than earlier business games the problems of running a company." Realism is a primary goal for developing the computational model, and implicitly, a more realistic model is a better model, or a more valid model.

Cyert's contributions in computational modeling are very important to the development of the field. First, his studies were very early, and in many cases the first of their kind. The store buyer behavior model was an early descriptive study. The Carnegie Tech management game was one of the first, if not the first, computer based manager training computational. Second, the studies span a broad area of application: explaining behavior of store buyers to training managers to understanding duopoly decisionmaking strategies. Third, Cyert began with the phenomenon itself and let the purpose drive the model, e.g., understanding duopoly strategies—not a model for its own sake. A principle which should drive any computational modeling.

Yet, realism was also a major concern. The validity of the computational models is tied closely to the realism of the model; however, the relevancy of the model to its purpose is the more encompassing test.

3. Validity: Criteria to Keep in Balance

Realism in computational modeling is clearly germane;but, balance is a more demanding criterion. Without some degree of realism, computation modeling becomes a logical and/or numerical exercise. At the other extreme, total realism may create an imbalance with all the experimental and analytical issues that any real world field experiment has. The purpose may be lost in the quest for realism. Even management training games yield such a mass of data from a complex model that it is difficult to sort out cause-and-effect relations, or, even devise appropriate statistical tests and controls to test hypotheses. Simpler laboratory experiments have been more successful here. Yet, some realism is mandatory; too much may make it difficult to sort out these cause-and-effect relations and know what we learned and what we did not. E.g., Cyert's duopoly computational model may provide more insight on decisionmaking than a two firm management game. As a single criterion, there is no way to optimize the degree of realism. Balance suggests realism is important, but only within the context of the purpose. We must turn to multi-criteria considerations of validity.

The classic work on the validity issue in social science is Campbell and Stanley (1963). Cook and Campbell (1976) later developed four concepts of validity: internal validity, statistical conclusion validity, external validity and construct validity. Feldman and Arnold (1983) define validity in terms of content, construct, and criterion-related validity. They need answers to the questions: does it make sense to a group of experts, is it measuring the underlying characteristics, and is it related to the real world intent? Baligh et al. (1994) develop these validity issues for a knowledge-base organizational design program.

As a single criterion, realism is most closely related to construct validity: is (the model) measuring the underlying characteristics (Feldman and Arnold, 1983) or, external validity and the generalizability (Cook and Campbell, 1976). There are other trade-offs to consider in order to obtain balance. Burton and Obel (1984, p. 44-62) compared field experiments, laboratory experiments and computational experiments with respect to internal validity, statistical conclusion validity, external validity and construct validity. They argue that the computational models score well on all four dimensions when compared with field experiments and laboratory experiments, except for a subcategory of correspondence of the model where field experiments are better. This is the concern for realism and why realism must be addressed in computational modeling.

Referring to Feldman and Arnold (1983), content, construct and criterion-related validity provide a first level reference for testing the validity of a computational model. See Figure 1. Each criterion is an issue, or question and it is difficult, perhaps inappropriate to offer a general response. The content validity: does it make sense to a group of experts, depends upon the model, and the group of experts. The question requires that we must be able to argue persuasively to a relevant group of colleagues that the model captures some important aspects of the phenomenon, and, we hope to learn something about the phenomenon from the model.

Social Science Validity Criteria	Computational Modeling
Content: does it make sense? to a group of experts?	realism
	↑
	Do the variables, parameters and relations capture the phenomenon of study?
	↓
Construct: is it measuring the underlying characteristics:	relevancy
Criteron-related: is it related to the real world intent?	purpose, intent, questions of interest

Figure 1. Computer simulation validity.

Similarly, construct validity, is it measuring the underlying characteristics, requires that the model and the computation contain parameters, variables and relations which yield outcomes with correspondence to the real world. Finally, criterion-related, is it related to the real world intent, focusses on the intent and how the model and its results are to be used. Computational models can be used for many purposes. Cyert's computational models ranged from describing reality to training managers.

All of these criteria relate to an underlying issue of generalizability: can we say something beyond the model itself. Generalizability is related to intent. A model may be generalizable for one purpose and not another. The Carnegie Tech Game (Cohen, et al., 1960) generalizes for training managers. It may be less good as a description of managerial decisionmaking.

These social science validity criteria were originally devised from field experiments and have been applied to other settings. They are general, but not always easily operationalized for computational models. Nonetheless, some issues seem clear. Validity is a multi-criteria issue. There are trade-offs among the criteria, i.e., a model and/or experiment will not meet all criteria perfectly (McGrath, et al., 1982). A good model and experiment is one which meets its purpose, and we need to understand the purpose of the computational model.

4. Validity in Computational Models: In Praise of Simplicity and Balance

The validity of the computational models requires multiple considerations and trade-offs among the various criteria. We shall argue that balance and simplicity should be overriding concerns in devising a computational model. Occam's razor applies to computational models and we seek parsimonious explanations.

In developing a computational model, we propose a balance among the following considerations:

- purpose,
- model and computation, and,
- experimental design and data analysis.

In Figure 2, these considerations are placed in a triangle to suggest that a balance of all three is required.[1]

The purpose of the computational model provides the anchor. Usually, we are trying to answer some question. Before the model is devised and results analyzed, we should be able to say that whatever results are obtained, we will have answered, at least in part, the question and met the purpose. Criterion-related validity is a similar concern. Cyert's computational models were clear in purpose: describe the organization and its decision making processes, or to train managers. Each purpose suggested a different computational model.

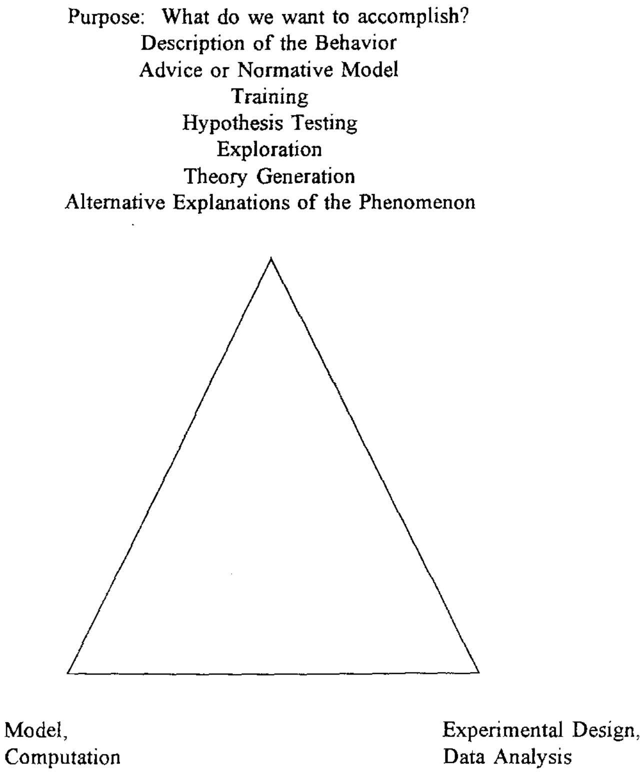

Figure 2. Computation model design—balance and simplicity.

We can also add that computational models can be devised to: test hypothesis, explore organizational processes, generate theoretical issues, and eliminate alternative explanations. This list is representative, not complete.

The model, i.e., the statement of the parameters, variables and relations, can now be stated to meet the purpose. Cyert's descriptive model of buyer behavior included decision making variables on price and stock levels and associated parameters and relations to create the computational model. The model contained nothing on the buyer's happiness—it was not the purpose to explain happiness. The computational model is an explicit set of instructions on how to operate the model, i.e., run or update the model. In a computational model, a program, or set of instructions, is required. The Cyert models were discrete time models, each required an algorithm to update the program from one period to the next period. The Carnegie Tech Game was updated by the computer program which incorporated the participants' decisions. The model statement of variables, parameters and relations and the computational process must fit together and can be thought of as the computational model. The experimental design and data analysis are closely linked. The experimental design question is: how is one going to manipulate the computational model or change parameter values so that the model outcomes permit us to meet the purpose, or help answer the question. Usually, the data analysis is analysis of comparisons for different parameter values to test a hypothesis. The comparison in the Cyert buyer model was to compare the computational model results with the real world buyer behavior—which is perfectly matched for a descriptive purpose. Here, the parameters were adjusted to meet the descriptive purpose. Again, the experimental design and data analysis are closely linked so that the data analysis can be as simple as possible to meet the purpose. In the extreme, it is easy to create manipulations which yield data which are impossible to analyze. However, such an approach could meet an exploratory purpose.

Plott (1982, P. 1520) in his defense of experimental economics, notes that laboratory markets are "real" markets in that basic economics principles must apply—general theories should apply to special cases. Computational models are special cases by their very nature; indeed, we want special cases which are relevant, but always less than "real." The trick is to create a simplicity which meets the purpose and addresses the question being posed; and there is an advantage in simplicity.

The argument for simplicity and balance is partly one of economy. We want to devise a computational model and experimental design which meets the purpose. All three of these issues can be dealt with simultaneously in the beginning. With a clear statement of purpose, the computational model and experimental design can be devised to meet the purpose.

However, the argument for simplicity goes beyond economy. Complex models are not only more expensive to devise, but may require statistical data analysis problems which limit our ability to address the question. E.g., a descriptive purpose requires a realistic model, where testing a hypothesis does not necessarily require a realistic model. The more complex model may introduce complexities which may be difficult to sort out in the data analysis. Thus, the purpose or question may be missed. The computational model and experimental design must be sufficiently complex to meet the purpose, but greater complexity can be detrimental (Burton and Obel, 1984).

This greater complexity is a threat to construct validity (Cook and Campbell, 1976). High construct validity requires that the potential causes and effects are carefully defined so that results can be sorted out. E.g., if the experiment involves a factorial design then only a few factors can be manipulated and maybe only with discrete variation. However, the nonmeasured and noncontrollable factors may be the underlying determinations of the result (Burton and Obel, 1984, p. 54). Of course, these issues can be controlled statistically, if we can know a priori the potentially explanatory variable. We are arguing that it is preferable to eliminate these complexities in the design of the computational model itself, and not be forced to rely on sophisticated statistical analyses. There is a lesser risk of these false inferences from simple models and experiments than complicated ones. Simplicity and economy are the basic.

In maintaining a balance, accumulated knowledge can be developed in variations. For a given computational model, a different purpose may be served by devising a new experimental design and analysis. E.g., a different set of experimental variants can be devised for a new research question; this is one way to build upon accumulated knowledge. At the same time, care must be taken that the purpose is being served and the model itself is not driving the purpose. More fundamentally, a different purpose may well require a new computational model and a new experimental design. The purpose remains the anchor.

5. Balance and Simplicity in Organizational Computational Models

Computational models in organizational science come in a wide variety of forms: large and small, realistic and less so, computer only, computer aided, normative and descriptive, experimental and exploratory, etc. None are necessarily valid, nor invalid. We have argued that simplicity and balance of purpose, computational model and experimental design provide a validity focus.

Computational modeling in organizational science is rich in its diversity of application and approach. Nonetheless, they can be analyzed within these validity frameworks. We review a number of organizational science simulation studies and applications. We begin with Cyert, Feigenbaum and March's behavioral theory of the firm duopoly model.

5.1. A Behavioral Theory of the Firm Duopoly Model

Cyert, Feigenbaum and March's (1959) purpose was to gain a better understanding of the decision-making processes in the duopoly firm. The decision variables of interest were how much to produce and what price to charge. Unlike analytical equilibrium duopoly models, the computational model focussed on the complexities in decision-making and understanding of organizational processes. The organizational decision-making characteristics depend upon "...information, estimates and expectations that ordinarily differ appreciably from reality... organizations consider only a limited number of alternatives... conflict and potential conflict of interests is a feature of most organizations..." (p. 82). With this purpose, goal and general characteristics of the firm, the model and the computation captured this level of complexity and incorporated decision-making processes.

The nine step decision-making process outlines how the computation is to be run. The model is a specific duopoly model. The computational procedure and the duopoly model are closely tied and comprise the computational model. It follows from and matches well the purpose of gaining a better understanding of the decision-making process.

The experimental design was explicit in stating beginning conditions and following a large number of variables over time; aspiration levels, outputs, prices and profits. The data analysis compared the computational model results with the actual data from American and Continental Can companies from 1913 through 1926. The results suggest that the computational model yielded results of the same level and directionally similar to the real data. The purpose of the computational model was to understand better the decision-making processes. In observing that the model major business decisions are close to the actual decisions, it can be inferred that the complex nine step decision-making process and its characteristics capture essentials of the actual decisionmaking process. However, it does not eliminate alternative explanations. The authors (p. 94) close with "we need a great deal of work in actual organizations identifying the decision procedures used in such things as output decisions," and a call for human decision-making in the laboratory under conditions found in business organizations.

In terms of the purpose, computational model and experimental design-analysis, this study is clear and balanced. The purpose is to gain a better understanding of duopoly behavior; the computational model spells out the variables, parameters and relations, and how the computation will be run; the experimental design and data analysis are designed to test the behavioral theory of the firm propositions. The balance is appropriate. The model itself is a representative model and it is relevant, but is not a real world replicate. Would more have been gained with greater realism; it is questionable. The clarity of the cause and effect relations may have suffered. Could a simpler model have been devised? The purpose was to understand the decision-making processes—not just the decision results. Simpler models may eliminate the decision-making process and may not meet this purpose. This duopoly model illustrates the balance and simplicity of computation models.

5.2. *The Carnegie Tech Management Game*

Cohen, et al. (1960) developed the Carnegie Tech Game to help future managers become better managers in an environment of complexity and realism.

The model was based on the packaged detergent industry. It was a national market with a few firms with differentiated products. The model included production, marketing and finance variables. The computation was a two step process. First, management teams analyzed the data about the market environment and the internal production situation, and then, made decisions on prices, production, etc. Second, the computer model replicated the firms' environment and created outcomes including firm profits.

The experimental design tested how well the future managers forecasted and planned in this complex situation, and how well the management teams worked together. The outcomes analysis is largely qualitative.

The Carnegie Tech Game was a great step forward to create more realistic management games for future managers and remains the base model for sophisticated management games. Realism is an important concern to meet the purpose here, the purpose of training managers.

5.3. The Garbage Can Model of Organizational Choice

Cohen, March and Olsen (1972) devised a computational model of organizational anarchy where decision-making processes do not proceed in the usually presumed rational manner. In the garbage can, there are choices looking for problems, feelings looking for venues to be aired, solutions looking for problems and decision-makers looking for work. It is a complex situation which proceeds according to a "new" rationality; is this possible?

The purpose is to offer a plausible explanation for the existence and viability of the garbage can and explain how reasonable decisions can be made in such disorder. The model contains four basic variables: stream of choices, stream of problems, flow of solutions and streams of energy of participants. The relations include energy allocation and problem allocation assumptions.

The experimental design required the manipulation of the organizational structure to affect the organizational outcomes on decision style, problem activity, problem latency and decision- making activity and decision difficulty. The analysis generated a number of implications. They provide answers to the questions whether the garbage can is possible, and insights on how it is possible. The analysis yielded these implications:

- resolution of problems as a style is not the most common style,
- the process is sensitive to variations in load,
- a tendency of decision makers and problems to track each other through choices,
- important interactions among problem activity, problem latency and decision time,
- the process is frequently sharply interactive,
- important problems are more likely to be solved than unimportant ones,
- important choices are made by oversight and flight; unimportant by resolution, and
- choice failures appear among the most and least important choice.

The garbage can studies are well-balanced. The purpose is clear to understand the organized anarchy. The model includes the variables, parameters and relations to meet the purpose. The experimental design and data analysis yielded results which provide answers about the organized anarchy.

5.4. Designing Efficient Organizations

Burton and Obel (1984) developed a hierarchical decision-making model for assessing the effect of various organizational decisions on the firm's performance. It is a multi-agent model which incorporates individual actions and flow of information. The general model could be modified to incorporate a M-form or U-form organization, tightly or loosely linked technology and price or budget resource allocation schemes under various levels of uncertainty. The computational process mimicked the up-down-up interactive planning processes in hierarchical organizations. Each specific computational model, e.g., M-form with loosely linked technology, must fit the computational procedure, e.g., the budgeting of resources.

The experimental designs were classical 2-way complete factorial designs where the dimensions were the contingencies of interest. The data analysis utilized non-parametric statistical tests to test hypothesis on organizational forms, technology and resource allocation schemes. One particular computation tested the effect of a M-form vs. U-form and loosely linked technology vs. tightly linked technology, holding the price directed resource allocation scheme constant. Four specific models and computational procedures were developed to realize the required experimental variations, or manipulations. The 2 × 2 complete factorial experimentation design yielded four outcome cells. Hypotheses on organizational form and technology linkage were tested using nonparametric statistical tests on the data. In brief, the M-form performed better for the U-form organizational, but particularly so for loosely linked technology. Loosely linked technology is easier to coordinate than tightly linked technology in a hierarchical organization.

A related laboratory experiment (Burton and Obel, 1988) was developed on the same general model. Within the hierarchical organization, one division was played by an individual; the other divisions and headquarters were run on the computer. The research question was to test the opportunism proposition: would individuals understand a situation to be opportunistic, could they figure how to take advantage of the situation and would they take advantage (Williamson, 1975)? Yes, individuals readily understand an opportunistic situation, almost all knew how to be opportunistic, and many took advantage, but some were altruistic in their behavior.

Laboratory experiments and computational modeling are very close, especially when the computational models contain well defined individual or organizational unit roles.

These computational models were devised to test hypotheses concerning alternatives in the design of the firm. The model is a small hierarchical model where the variables, parameters and relations, which together mimic the hierarchical decision process. The experimental design and data analysis were chosen to permit the simplest of statistical tests for the hypotheses. The purpose, computational model and experimental design are balanced to provide the simplest model and simplest statistical test to meet the purpose of testing organizational design hypotheses.

5.5. Agent Honesty, Cooperation and Benevolence

Carley, Park and Prietula (1993) extend the SOAR model to investigate the effect of three variables: agent honesty, cooperation and benevolence, on form outcome variables: cognitive effort, physical effort, communication effort and wait time. SOAR is a multi-agent artificial organization which incorporates individual cognitive capabilities, e.g., problem-solving and memory and here, individual characteristics in an organization with various information flows. Each agent searches through a problem space to satisfy goals. The computational model is a computer model which is run through time to replicate the organizational process of problem solving.

The experimental design is a 2 × 2 × 2 complete factorial design; varying the organizational size from 1 to 5. The observed outcomes for the four variables; cognitive effort, physical effort, communication effort and waiting time are analyzed for general patterns. The U-shaped total cognitive effort vs. organizational size is demonstrated as well as the orthogonality of physical and social effort.

The purpose, computational model and experimental design are well balanced—each is devised in light of the other requirement. There is no excess baggage, but only those essential elements of reality in the SOAR to meet the purpose.

5.6. The Virtual Design Team

Having observed that engineering project design relies on adaptation of past organization structures, Levitt, et al. (1994) employ ideas from AI (artificial intelligence) for modeling the behavior of full-scale organizations. The purpose is to predict task duration for engineering design teams in carrying out routine designs.

The model is an information processing model of an organization: tasks, actors, communications, tools and structure. The actors are boundedly rational. Each player operates in an "in-tray, out-tray" environment supported by communication tools.

The computer processes the set of tasks for a project network—a three-year petroleum refinery design project. The experimental design is a 2×2 design; one dimension is centralized, decentralized organization, the other dimension, voice mail, without voice mail. The null hypotheses are that the organization structure and the voice mail do not affect the work-hours required to complete the project design. They found that a decentralized organization required lower total work-hours, and voice mail reduced the total effort required.

These studies have a broader purpose of modeling the design process as well as the specific purpose of predicting task duration and testing related hypotheses. The refinery design project model is more than sufficient for the specific purpose; but the more complex, more realistic design project is required for the more general purpose. However, the greater complexity can create data analysis issues in testing the specific hypotheses unless careful Monte Carlo techniques are utilized. Not infrequently complex models create data analysis problems; the appropriate experimental design and manipulation guide this relation.

6. Summary

Cyert's pioneering studies began with a consideration of validity, i.e., is it relevant to the purpose. Realism then became a derived issue to make the studies in description and training, in particular, relevant. Validity in the field and laboratory studies in social science grew from a different, but related, set of concerns. However, the social science validity concerns can be operationalized for computational model studies in organization science. Validity must be defined in terms of the purpose of the computational model.

Computational models provide more flexibility in their construct. We argue that the computational model can be devised with simultaneous consideration to: the purpose, the computational model and the experimental design. The triangular icon represents three criteria to keep in balance, and this balance is realized by creating simple computational models and simple experimental designs which meet the purpose or intent of the study. In the last quarter century, there have been numerous computational studies; some of which we review in terms of our three criteria. Cyert's early studies provide an approach to computational models in organization science which illustrate the fundamental concerns of validity and how to address them, although model realism was a concern, the underlying purpose of the model was paramount.

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Note

1. The triangle of purpose, model and computation, and experimental design and data analysis is an icon. There are five elements and a pentagon is an alternative icon. Each pair: the model and computation, and the experimental design and data analysis, are so closely tied we chose the triangle.

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