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Task Complexity: Definition of the Construct

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A general theoretical model of tasks is presented in which the three essential components of all tasks are products, (required) acts, and information cues. These components are defined and are then used to derive three analytical dimensions of task complexity: component complexity, coordinative complexity, and dynamic complexity. Various indexes which can be used in the quantification of these constructs are also presented. Two examples which illustrate the calculation of some of the indexes for a relatively simple task and a relatively complex task are presented and the relationship between task complexity and task performance is briefly discussed. © 1986 Academic Press, Inc.

INTRODUCTION

Despite the centrality of the task concept to the study of human behavior in organizations, no adequate theoretical model has emerged for describing tasks and how they differ from one another (Ferguson, 1956; Hackman, 1969; Weick, 1965). This state of affairs has been a major stumbling block to the aggregation of data on task effects and has meant that tasks have represented a major source of uncontrolled variation in behavioral studies (Weick, 1965). It is the aim of this paper to present the constructs that can be used to describe one important characteristic of tasks, complexity. This requires that we outline some building blocks for a general theory of tasks from which we can derive the analytical dimensions to describe task complexity. To commence, we discuss some of the approaches that have been taken to the study of tasks and justify our choice of approach.

Approaches to the Study of Tasks

The most prevalent approach to the analysis of tasks has been "an empirical approach" in which task characteristics are derived from individuals' perceptions of a sample of tasks, using factor analyses or some other multivariate technique. This approach has been employed in group task analysis (Shaw, 1963), job analysis (McCormick, 1976; N. G. Pe-

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terson & Bowners, 1982), and task redesign (Hackman & Lawler, 1971; Hackman & Oldman, 1980). Theoretical frameworks are sometimes used to organize data collection in these studies; however, the task characteristics described are inductively derived and are not based on a formal definition of tasks. Several problems arise with this empirical approach to task analysis.

First, the task characteristics identified frequently confound task and nontask elements, particularly interactions between task attributes and individual attributes. For example, the six dimensions of group tasks identified by Shaw (1963) appear to differ in type, including one dimension which refers to formal task structure (solution multiplicity), one dimension which refers to individual skill requirements (intellectual/manipulative requirements), three dimensions which refer to person–task interactions (difficulty, population familiarity, and intrinsic interest), and one dimension which refers to group organization requirements (cooperation requirements). This confounding of task and nontask characteristics is a major threat to construct validity in studies of tasks and their effects.

Further construct validity problems are evident when one considers the instability of the characteristics identified in these empirical analyses. This instability is illustrated in Dunham, Aldag, and Briefs' (1977) summarization of the job characteristics identified in 20 different samples using measures from the Hackman and Oldman (1980) job design model. They concluded that the number of separate characteristics identified by the measures varied from sample to sample. Similarly, studies using the Position Analysis Questionnaire (PAQ), developed by McCormick and his colleagues, have not been able to reliably produce a stable set of task characteristics across different samples of tasks, despite very large samples (McCormick, 1976; N. G. Peterson & Bowners, 1982). In summary, the empirical approach to the study of tasks has failed to provide definitions of task characteristics with sufficient construct validity to either reliably describe how tasks differ from one another or validly predict the effects that are due to variances in tasks. This presents major problems for the classification and design of tasks used in research.

An alternative approach to task analysis is a "theoretical approach" in which task characteristics are specified a priori and then measured and tested empirically. Hackman (1969), building on the work of McGrath and Altman (1966), has identified four distinct theoretical frameworks used in the study of tasks.

1. Task qua task. Tasks are defined as a pattern of stimuli impinging on the individual. Task characteristics are "real world" dimensions which relate to the physical nature of either the stimuli (e.g., stimulus input rate) or the stimulus material (e.g., clarity of instructions).

2. *Task as behavior requirements.* Tasks are defined in terms of the behavioral responses a person should emit in order to achieve some specified level of performance. This approach has included definitions which focus on critical behaviors, i.e., those necessary for adequate performance (e.g., Roby & Lanzetta, 1958) and definitions which focus on general behavior requirements (Gagne, 1964; Miller, 1962).

3. *Task as behavior description.* Tasks are described and grouped in terms of the kinds of behaviors that people exhibit when actually performing the task. This approach attempts to describe tasks in terms of the typical task behavior by identifying the mean or modal behavioral responses of individuals who have performed the task (e.g., Marquardt & McCormick, 1974; McCormick, 1976).

4. *Task as ability requirements.* Tasks are differentiated on the basis of the different skills that are required to perform them. In practice this usually becomes tasks as ability descriptions because the identification of skills and abilities is based on measures of individuals who actually perform the task (e.g., Fleishman & Hogan, 1978).

Selecting an Approach

It would be possible to develop a definition of task complexity within any one of these four frameworks. However, comparisons show that they differ in their potential for construct validity, prediction of task effects, and feasibility of operationalization. We agree with Hackman (1969, pp. 110–111) that the "task as behavior description" and "task as ability requirements" frameworks are both unsuitable because they involve the substitution of a dependent variable for the independent variable of interest and, therefore, lack construct validity.

If we wish to separate individual and task effects, then we should logically expect to describe tasks independently of individuals who perform the task. The "task qua task" framework, in which the task is described as a class of phenomena that is totally independent of individual phenomena, clearly satisfies this requirement. However, the "task qua task" approach leaves the researcher with the difficult problem of identifying appropriate stimuli and analytical dimensions for the description of task characteristics. The task stimuli in many work settings consist of highly dynamic flows of information and resources from varied media and in different forms. The number of stimuli confronting an individual in any given situation is very large, as is the number of characteristics that could be derived to describe these stimuli. Many task stimuli are not amenable to definition, in quantitative or qualitative terms. In the absence of a general theory of situations there is no theoretical basis for choosing stimuli or analytical dimensions to guide the measurement or manipulation of tasks. Therefore, while the "task qua task" approach would clearly separate effects due to task characteristics from individual effects, the operational definition of objective task characteristics is a very difficult problem. The degree of difficulty in operationalization, however, will depend upon the type of task analysed.

One area in which task analysis has involved operationalization of objective task characteristics has been the study of information processing in human judgment (e.g., Slovic & Lichenstein, 1971). In that research, the description of task stimuli has been limited to the characteristics of information cues that are utilized in judgment and inference tasks. However, these descriptions of information cues are not easily applied to tasks which involve high levels of physical and motor activities relative to the levels of cognitive activity. Physical and motor activities are often performed in a highly automatic manner which does not include the conscious processing of any information cues. For this reason, it would be practically impossible to identify and describe the information cues that a person utilizes in the performance of motor activities for many tasks. The "behavioral requirements" framework appears more adaptable to the description of such task inputs.

Because behavior requirements differ from one task to the next and are a relatively stable property of a given task, they can be described independently of the characteristics of task performers. If we specify a task product, such as dollar sales or units produced, then we can usually also specify the behaviors required to produce that product. Also, the product and required behaviors for a task are variables that can be assessed with greater degrees of precision than the environmental stimuli associated with a task. From these points we conclude that a valid operationalization of the task construct is feasible within the "behavior requirements" framework. Of course, the use of required behaviors as a basis for describing tasks is not the same as using the properties of the task stimuli. However, it is not subject to the same problems as task classifications which are based on the behavioral responses of individuals to tasks. As with the "task qua task" framework, the description of tasks in the "behavioral requirements" framework is from the viewpoint of a detached, omniscient observer. The definition of a task by an individual who performs it, which may not correspond with the formal definition, is an individual characteristic, not a task characteristic.

To summarize our argument, the "behavior description" and "ability requirements" frameworks are both rejected on the grounds of inadequate construct validity. Of the remaining two frameworks discussed by Hackman (1969), the "behavior requirements" framework is expected to provide a more feasible operationalization of tasks which involve physical and motor activities than the "task qua task" framework, without a significant loss of construct validity. For judgment and inference type tasks which require the conscious attention to and processing of information cues, the "task qua task" framework has proven to be applicable to the description of the cues utilized in these tasks. Therefore, a combination of the "behavior as requirements" and "task qua task" frameworks appears to have the greatest potential for the general theoretical analyses of tasks and the development of the task complexity construct.

A THEORETICAL MODEL OF TASKS

Employing a combined "tasks as behavior requirements" and "task qua task" framework leads to the postulate that all tasks contain three essential components; products, (required) acts, and information cues. These constructs are the building blocks for the definition of task complexity, but also represent the foundations of a general theory of tasks and could be used to define other task characteristics. In defining these constructs we will draw on the work of Naylor, Pritchard, and Ilgen (1980), hereafter referred to as NPI.

Products

Products are entities created or produced by behaviors which can be observed and described independently of the behaviors or acts that produce them. In NPI terms, products are the measurable results of acts. Tasks are identified and differentiated from one another by the products associated with them. A product is an abstract quality of a task which, once defined, is independent of the goals and expectations of individuals who perform or evaluate tasks.

The task product must be specified before required acts and information cues can be identified as task inputs. A product is a set of attributes assembled in some identifiable form. Product descriptions will include an object (e.g., a trial balance, a report, a cupboard) or event (e.g., serve a customer, counsel a worker), plus some defining attributes, such as quantity, quality, timeliness, and cost. The multiattributed nature of products is often masked by the use of commonly understood descriptions or generic product names which refer only to the object or event. However, in our theory of tasks, when the set of product attributes changes so that a different set of behavioral requirements is generated, then we are talking of a new task. For example, producing a quality product is often a very different task, i.e., involves a very different set of behavioral requirements, than the production of a cost efficient product.

Acts

The required acts for the creation of a defined product can be described at any one of several levels of abstraction, varying from a very specific activity (e.g., clasping fingers) to a more complex pattern of behavior with an identifiable purpose (e.g., lifting). It is the latter, i.e., the pattern of behaviors with some identifiable purpose or direction, which we define as acts and treat as the basic unit of behavioral requirements. The direction of an act is typically implicit in the verb used when referring to the act (e.g., reading, walking, identifying) and provides a focus to the lower level mental and physical activities that make up the act. It is this directional aspect which separates one act from another.

It must be emphasised that the "required" act is a task component and *not a property of an individual* or his or her behavior. By comparison, NPI use the act construct to describe actual behavior in terms of amplitude and direction (1980, p.285). In the NPI model, amplitude refers specifically to "the amount of the individual's resources allocated to the act" (1980, p. 5). Amplitude cannot be treated as a property of a required act because the time and effort required to complete an act will depend upon the knowledge and skills of the person who performs the act and the resources (e.g., equipment, support staff) available to that person. Because of this, amplitude cannot be specified independently of individuals or task contexts, and it is excluded from our definition of acts.

The direction of an act, i.e., the specific kind of activity or process carried out when an act is performed, can be described independently of any individual who actually performs the act and any context in which the act is performed, and is the fundamental attribute of acts in our model. As previously mentioned, judgment and inferential acts frequently require that certain information cues be consciously attended to and processed during the performance of a task. These information cues are the third component of tasks.

Information Cues

Information cues are pieces of information about the attributes of stimulus objects upon which an individual can base the judgments he or she is required to make during the performance of a task. As such, they are descriptions of certain properties of the stimulus complex for a task and not the raw unprocessed data of the stimuli. Not all task stimuli act as cues and not all cues are information cues. Stimuli that are used to make discriminations during the performance of a task are cues, and when these cues are presented in the form of facts that can be processed to make conscious discriminations, i.e., judgments, then they are what we refer to as information cues.

Summary

The two types of input components (i.e., acts and information cues) and products can be used to describe any task and, therefore, represent the basis for developing a general theory of tasks. Task description requires that the product of interest first be identified and then the inputs required for that product be described at increasing levels of specificity until the components being identified represent specific acts and the information cues that must be attended to and processed in the performance of these acts. The only requirements for fitting a task to the form of the model are (a) that the task involve at least one behavioral act, and (b) that there be a product which can be identified as not being the same as simply performing the act(s) that produced it. The total number of acts and information cues will vary from one task to the next, as will the relationships between task inputs and products. Many analytical constructs may be needed to characterize these differences in task inputs in a systematic manner. One of these constructs, task complexity, is developed in detail in the next section.

TASK COMPLEXITY

The required acts and information cues in a task are important task inputs because they set upper limits on the knowledge, skills, and resources individuals need for successful task performance. Therefore, task complexity, which describes the relationships between task inputs, will be an important determinant of human performance through the demands it places on the knowledge, skills, and resources of individual task performers. Task complexity is often used as an explanatory variable in discussions of task performance without definition or reference to one of the existing definitions of task complexity. These include definitions which focus on judgment tasks (Naylor & Dickinson, 1969), small group tasks (Oeser & O'Brien, 1967), and intergroup tasks (Thompson, 1967). In our model, which is primarily focused on individual task performance, we build on the work of these earlier theorists to provide a definition of task complexity which is both more complete and more general in its application than earlier definitions of the construct. Three types of task complexity are defined: component, coordinative, and dynamic.

Component Complexity

Component complexity of a task is a direct function of the number of distinct acts that need to be executed in the performance of the task and the number of distinct information cues that must be processed in the performance of those acts. As the number of acts increases the knowledge and skill requirements for a task also increase, simply because there are more activities and events that an individual needs to be aware of and able to perform. In this sense, building a house is more complex (i.e., involves more distinct acts) than sawing a log. The concept label, component complexity, is drawn from the work of Naylor and his colleagues (Naylor, 1962; Naylor & Briggs, 1963; Naylor & Dickinson, 1969) who use the term to refer to the "information processing and/or memory-storage demand requirements" (Naylor & Dickinson, 1969, p. 167).

The knowledge and skill requirements that result from component complexity are reduced by the level of another task characteristic, "component redundancy," which refers to the degree of overlap among the demands imposed by different task inputs (Naylor & Dickinson, 1969). When the knowledge or skill requirements for the performance of one act generalize to another act then the total knowledge or skill required for performance of a task is reduced. The extreme case of total redundancy would be where a task performance requires multiple executions of the same act.

A simple and general index for component complexity is the unit weighted summation of distinct task acts, where an act is considered distinct if it is nonredundant with other acts. For example, in a game of chess, knowledge about how to move different pieces is nonredundant while knowledge about how to move a particular type of piece (e.g., a pawn or a knight) generalizes across all movements of that pieces and, therefore, is fully redundant. As a result, using only the movements of the pieces as the acts in the task, the component complexity for a game of chess would be the summation of *different* pieces used in the game (i.e., 6) and not the sum of the total number of pieces (i.e., 16).

An objection may arise to the use of a *unit* weighting of different acts on the grounds that different acts require different amounts of information processing during their performance. For judgment tasks in which an individual utilizes configurations of cues to draw inferences the level of component complexity will depend upon the number of distinct information cues in the configuration being utilized. A judgment task in which an individual must utilize a single cue is less complex than a judgment task in which he or she must utilize two or more cues. As the number of cues that an individual must attend to and integrate when making a judgment increase, perceptual and information processing requirements for performance of that act of judgment also increase. An index of component complexity should reflect differences in the number of information cues that need to be processed when performing acts.

Another level of component complexity arises when a task involves the completion of several other tasks, as inputs to the task product. For example, assembling a carburetor is a task with a product (the assembled carburetor) which becomes an input or subtask of the larger task of assembling an engine. Component complexity of a task, therefore, can require measures at the subtask, act, and information cue levels of a task. A general formula which captures the aggregated effects of component complexity at each of these levels is as follows:

$$TC_1 = \sum_{j=0}^{j=p} \sum_{i=1}^{i=n} W_{ij} \tag{1}$$

where n = number of distinct acts in subtask j, W_{ij} = number of information cues to be processed in the performance of the i^{th} act of the j^{th} subtask, p = number of subtasks in the task, and TC_1 = component complexity.

The formula in Eq. (1) can be used to compute a component complexity index for a wide variety of different types of tasks. For example, in cognitive tasks of the type studied within the "probability learning" paradigm (e.g., Dudycha & Naylor, 1966; Naylor & Carroll, 1969; Naylor & Schenck, 1968), acts refer to the judgments made and the TC_1 index will include the effects of acts and information cues by summing the numbers of information cues to be utilized for each distinct judgment.

Assessment of component complexity at the level of information cues will not always be possible or necessarily appropriate. This is particularly true for physical and motor acts which are performed automatically, without any conscious processing of information. For tasks which involve high levels of physical and motor acts relative to cognitive acts the TC_1 index, therefore, will be calculated by simply summing the distinct acts (i.e., $W = 1$).

The concept of redundancy also applies equally well to tasks that are either predominantly cognitive or predominantly motor–physical type tasks. The earlier example of redundancy for the game of chess illustrated how knowledge about the required motor activities can be fully redundant from one act to the next. Naylor and Schenck (1968) used the same approach when they examined the effects of cue redundancy in cognitive inference tasks. In the Naylor and Schenck study, cue redundancy was indexed by the degree of correlation between two information cues. Therefore, the idea of covariance between knowledge and skills requirements, i.e., redundancy, can be applied to both descriptions of acts, when referring to either physical, motor, or cognitive activities, and to descriptions of information cues for a task.

Coordinative Complexity

Coordinative complexity refers to the nature of relationships between task inputs and task products. The form and strength of the relationships between information cues, acts, and products, as well as the sequencing of inputs, are all aspects of coordinative complexity. At a more specific level this will include timing, frequency, intensity, and location requirements for performances of required acts. As an example of variance in coordinative complexity, we might compare the simple linear combination of behavioral acts that are needed to paint a wall (although, even there, sequencing requirements can have a pronounced effect on the task outcome) with the more complex programming of acts needed for an individual to assemble a radio. In the case of the radio assembly, the acts performed in one part of the task are contingent upon acts performed at other stages and several acts may need to be performed simultaneously. These required interactions in sequencing and timing are conceptually equivalent to nonlinearity in the structural form of a task. The more complex the timing, frequency, intensity, and location requirements, the greater the knowledge and skill an individual must have to be able to perform the task.

The appropriate index for coordinative complexity of a task will depend upon the specific aspects of the relationships between task inputs that are being considered. One aspect of coordinative complexity which is illustrated by the radio assembly example is the timing or sequencing of acts that is required in the task performance. As the number of precedence relationships between acts increases, the knowledge and skill required for the coordination of acts will also increase because individuals who perform the task will have to learn and perform longer sequences of acts. A formula which captures this complexity of precedence relations, from Oeser and O'Brien (1967),[1] is

$$TC_2 = \sum_{i=1}^{i=n} r_i \tag{2}$$

where n = number of acts in the task, r_i = number of precedence relations between the i^{th} act and all other acts in the task, and TC_2 = coordinative complexity.

Another way of appraising coordinative complexity could be to examine the form of the relationship between the task inputs and the task product. With this approach, coordinative complexity would be low when the task product is a simple linear function of task inputs. The earlier example of sawing a log, where the intensity or frequency of the act of sawing is linearly related to the level of task outcome, would fit in this category. Tasks which require interactions of the type mentioned in the radio assembly example will have higher levels of coordinative complexity. NPI provide several examples of the various forms that the act-to-product relationships for tasks can take (1980, p. 174).

When confronted with nonlinear relationships between information

[1] Oeser and O'Brien refer to the intertask coordination index (C_{tt}) as a measure of the coordination requirements between different tasks (1967, pp. 91–92). We have adapted the formula to refer to coordination between acts, for a given task.

cues or acts and products an individual will require knowledge about the turning points in the function in order to regulate his or her performance of the task. Therefore, an index for the coordinative complexity of tasks is the number of turning points in the function that describes the relationship between inputs and products. This value is given by the absolute power of the first derivative of the function.[2]

The use of derivatives as indexes of coordinative complexity is also applicable to a wide variety of tasks. For example, Naylor and Carroll (1969) used the first and second derivatives of parabolic functions as cues for a cognitive inference task in which subjects had to predict correct numerical responses for points on the abscissas of parabolas. Naylor and Carroll also discuss some studies in which velocity and acceleration of objects were task inputs for perceptual–motor type tasks in which subjects were required to track and control the movement of an object, such as a cursor on a screen (e.g., Fuchs, 1962). As Naylor and Carroll point out, velocity and acceleration are the first and second derivatives of the function which describes the position of the object being controlled.

Therefore, it appears that the first- and second-order derivatives for relationships between task inputs and products can be used as indexes of coordinative complexity for a wide variety of types of tasks. Judgment tasks of the type used in the Naylor and Carroll (1969) study are almost exclusively made up of cognitive acts while the system control tasks of the type used in the Fuchs (1962) study primarily involve perceptual–motor activities. However, in both types of tasks the relationships between task inputs and products could be indexed through the use of derivatives. In general, the higher the value of the derivative being considered the more coordinatively complex is the task being analyzed. Of course, a second-order derivative measures a higher level of coordinative complexity than a first-order derivative, and, therefore, comparisons between tasks in which both indexes of coordinative complexity are used may require the construction of a single combined index.

When there is a stochastic relationship between the inputs and product of a task, the magnitude of random effects in the process will represent another important aspect of coordinative complexity. For nondeterministic relationships, the frequency of a particular task input being associated with a product, i.e., the strength of the relationship, will influence task performance. In the information processing research, the strength of the relationship between an information cue and the objective criterion is indexed by the correlation between the cue and the criterion (Dudycha & Naylor, 1966; Slovic & Lichtenstein, 1971). This is possible in the

[2] This argument assumes a continuous relationship between acts and product, i.e., a function that can be differentiated. For discontinous functions the number of break points could provide an equivalent index of coordinative complexity.

experimental tasks that are characteristic of that research because the values for both the cue and the criterion are generated according to theoretical distributions which determine the levels of cue validity (e.g., Wherry, Naylor, Wherry, & Falls, 1965). However, for many task inputs, particularly acts which involve complex motor activities, there is no measurable metric value that can be associated with the act, and the true joint distribution of the task input and product is not known. Under these circumstances, an ordinal level index which simply discriminates between stochastic and deterministic relationships may be the only feasible measure of the strength of association between a task input and a product.

Dynamic Complexity

In addition to the static complexity of the acts and information cues needed to perform a task, individuals must frequently adapt to changes in the cause–effect chain or means–ends hierarchy for a task during performance of the task. This third dimension of task complexity, which we call dynamic complexity, is due to changes in the states of the world which have an effect on the relationships between task inputs and products. In dynamically complex tasks the parameter values for the relationships between task inputs and products are nonstationary. Changes in either the set of required acts and information cues or the relationships between inputs and products can create shifts in the knowledge or skills required for a task.

Performance of a dynamically complex task requires knowledge about changes in the component and coordinative complexities of a task over time. A simple index for dynamic complexity would, therefore, be the sum of differences across specified time periods for any or all of the indices for these two dimensions of (static) complexity. A formula for calculating these differences for the TC_1 and TC_2 indexes is given in Eq. (3).

$$TC_3 = \sum_{f=1}^{f=m} |TC_{1(f+1)} - TC_{1(f)}| + |TC_{2(f+1)} - TC_{2(f)}| \tag{3}$$

where TC_1 = component complexity measured in standardized units, TC_2 = coordinative complexity measured in standardized units, f = the number of time periods over which the task is measured, and TC_3 = dynamic complexity.

Examples of some specific applications of the differencing index proposed for dynamic complexity can be found in research on probability learning mentioned previously and dynamic decision making (e.g., Ebert, 1972; Rapoport, 1966). In probability learning experiments dynamic complexity has been manipulated by varying stimulus probabilities (e.g.

Friedman *et al.*, 1964) and objective weights of cues (e.g., C. R. Peterson, Hammond, & Summers, 1965) across trials in experiments. In the Friedman *et al.* and C. R. Peterson *et al.* studies the dynamic complexity of the task performed by subjects was due to shifts in the relationships between information cues and the product, i.e., a shift in coordinative complexity which would have shown up in the $TC_{2(f+1)} - TC_{2(f)}$ term in Eq. (3). Similarly, in their research on multistage decision making, Rapoport (1966) and Ebert (1972) employed tasks which changed in coordinative complexity over trials as a function of the inputs and outcomes on a previous trial plus some random process.

These examples all involved cognitive tasks in which the magnitude of dynamic complexity was the result of variations in the relationship between the values of information cues and the (objective) products of judgments and decisions. However, variations in either the required behavioral acts or the required programming of acts for a task could be captured equally well in the $TC_{1(f+1)} - TC_{1(f)}$ and $TC_{2(f+1)} - TC_{2(f)}$ terms, respectively. If the values of the static complexities (i.e., component and coordinative) can be calculated for a task, then the magnitude of the dynamic complexity for the task can be determined using the differencing formula for TC_3.

One aspect of dynamic complexity which is not captured in the differencing formula for TC_3 is the pattern of intertemporal changes, as distinct from the magnitude of changes, in TC_1 and TC_2. Changes in the indexes used to calculate TC_1 and TC_2 can occur in several different ways. First, dynamic complexity may result from a sudden change in either TC_1 or TC_2 which occurs within a single time period. In this type of change the nonstationarity is limited to a defined time period during which the static complexity of a task (i.e., TC_1 or TC_2) shifts from one stationary equilibrium to another. When dynamic complexity is due to a single, sudden discontinuity in the relationships between task inputs and product, the effects will depend upon the magnitude of the change, and we would expect them to diminish as a function of the time elapsed since the change.

A second type of change that leads to increases in dynamic complexity is the situation where there are continuous shifts in the level of static complexity for a task. This continuous change may, in turn, be either predictable or unpredictable in nature. When change is highly predictable the required knowledge about the task's dynamic complexity, which will control knowledge and skill requirements for the task's static complexity, will be stable over time. When changes in (static) complexity are less orderly the knowledge and skill requirements for dynamic complexity will be constantly evolving, requiring extensive, and sometimes intense, information processing during the performance of a task.

In order to reflect this effect, the formula for the dynamic complexity index given in Eq. (3) should include a set of terms for the predictability of changes in TC_1 and TC_2. One such set of terms are the autocorrelation coefficients for the static complexity indexes. The weaker the intertemporal correlations for the parameters used to calculate TC_1 and TC_2, the less predictable will be the changes in those terms and the greater the dynamic complexity of the task. Therefore, dynamic complexity will vary as a negative function of the autocorrelations for TC_1 and TC_2, and the general formula for the dynamic complexity index can be rewritten, as follows, to include the effect of predictability of change.

$$TC_3 = |TC_{1(f+1)} - TC_{1(f)}| (1 - \rho_{TC_1}) + | TC_{2(f+1)} - TC_{2(f)} | (1 - \rho_{TC_2}) \quad (4)$$

where TC_1 = component complexity measured in standardized units, TC_2 = coordinative complexity measured in standardized units, f = the number of time periods over which the task is measured, ρ_{TC} = autocorrelations for TC_1 and TC_2 indexes, and TC_3 = dynamic complexity.

In general, we would expect dynamic complexity to be a function of factors that are related to stability of the inputs—products relationships for tasks. Therefore, for example, tasks which are performed over longer time horizons will generally be more dynamically complex, as will tasks that are relatively unique (Simon, 1965). In the literature on organization tasks, variations in task environment factors such as resource availability or social support have been shown to lead to intertemporal changes in the nature of tasks performed by organizations (Emery & Trist, 1965; Galbraith, 1973; Thompson, 1967).

Total Task Complexity

In order to calculate total task complexity, we must specify the form of the relationship between the types of complexity and the total. From the preceding discussion, it could be inferred that the three types of complexity form a Guttman-type scale (% Thompson, 1967, p. 55).

However, the Guttman scaling model is inappropriate for assessment of total task complexity in two ways. First, tasks can be dynamically complex without being coordinatively complex. Dynamic complexity can result from changes in component complexity without any implication for coordination of task inputs. Second, although they are not totally independent, the level of each complexity can vary quite considerably without affecting the levels of the other two complexities. This means, for example, that high levels of component complexity may make a task more complex in an overall sense than low to moderate levels of coordinative complexity, or, that moderate to high levels of coordinative complexity may result in greater overall task complexity than low levels of dynamic complexity.

At this point, we cannot specify the exact form of the relationship between the different types of complexity and total task complexity. We can state, however, that total task complexity is a function of the component, coordinative, and dynamic complexities of the task and that, if TC_1, TC_2, and TC_3 are expressed in standardized units, the relative contributions to overall complexity should be weighted such that a unit of TC_3 contributes more than a unit of TC_2 which, in turn, contributes more than a unit of TC_1. Therefore, if we make the simplifying assumption that total task complexity (TC_t) is a linear combination of the three types of complexity, TC_t can be represented as follows:[3]

$$TC_t = \alpha TC_1 + \beta TC_2 + \gamma TC_3 \tag{5}$$

where $\alpha > \beta > \gamma$. TC_1, TC_2 and TC_3 are expressed in standardized units.

One benefit of the indexes discussed is that they represent a basis for the assignment of complexity values to different tasks and, therefore, should bring some standardization to the measurement and manipulation of the task complexity construct. The indexes also provide relatively standardized ways of thinking about task complexity for a wide range of tasks. Throughout our discussion, we have attempted to give examples which illustrate how each of the indexes apply to different types of tasks (i.e., cognitive, perceptual–motor, physical, etc.).

DISCUSSION

Validation of the task complexity constructs will require tests of their ability to both discriminate between tasks of differing complexity and to predict outcomes of interest, such as performance levels, individual attitudes, and behavioral responses. Such evidence is not yet available. We present, instead, two examples which illustrate the calculation of some

[3] Equation (5) ignores that TC_2 is a function of TC_1 and that TC_3 is a function of both TC_1 and TC_2. The more complete form of the function is

$$TC_t = TC_t[TC_1, TC_2(TC_1), TC_3(TC_1, TC_2(TC_1))]$$

Therefore

$$\frac{dTC_t}{dTC_1} = \frac{\partial TC_t}{\partial TC_1} + \frac{\partial TC_t}{\partial TC_2}\frac{dTC_2}{dTC_1} + \frac{\partial TC_t}{\partial TC_3}\left\{\frac{\partial TC_3}{\partial TC_1} + \frac{\partial TC_3}{\partial TC_2}\frac{dTC_2}{dTC_1}\right\}$$

and, to satisfy the relative contribution requirement,

$$\frac{\partial TC_t}{\partial TC_3} > \frac{\partial TC_t}{\partial TC_2} > \frac{\partial TC_t}{\partial TC_1}.$$

complexity indexes and provide some indication of how task complexity can influence individual performance. One example is the simple clerical task of "stock labeling" and the other the relatively complex air traffic controller task of "directing planes to land safely." In both examples the identification of required acts and information cues was done by a task description approach outlined by Gagne (1964) in which tasks are treated as sets of self-contained behavioral acts, with behavior referring to the processing of stimuli, such as information cues, into responses. This approach was chosen because it is consistent with the combined "behavioral requirements" and "task qua task" framework for task analysis.[4]

Example 1

The first example, taken from Gagne (1964) and Weick (1965), is the task of "labeling the prices of stock (product)." This task can be described as follows: "from printed lists giving prices of different sizes of vegetable cans (information cue 1), codes (behavioral act 1) a variety of sizes of cans (objects acted upon) to correspond with prices (indication of completedness)" (Gagne, 1964, p. 12; Weick, 1965, p. 23).

The relevant values for the calculation of TC_1, using the formula in Eq. (1), are as follows: $n = 1, p = 0, W_{10} = 1$. From Eq. (1), $TC_1 = 1$. The required act of coding is identified by the one action verb in the task description (therefore $n = 1$). It is the verb which identifies the specific kind of activity or process carried out when an act is performed, i.e., the direction of an act. In performing the task the person must attend to only one information cue, the price of the can size given on the list of prices (therefore $W = 1$). Because there is only one product or output in the performance of the task there is no need to aggregate acts and information cues across subtasks (therefore $p = 0$). In this one-act task, TC_2 would be equal to 0 because there are no sequencing requirements, and there is a simple deterministic relationship between the act of coding and the task product. Also, unless there were changes in the task over time, TC_3 would be set equal to 0.

Changes in TC_1 and TC_2 can be illustrated by changing the task description as follows: "from printed lists giving prices of different sizes of vegetable cans (information cue 1), date of purchase (information cue 2),

[4] This approach to the identification stage in the measurement of tasks is, of course, subject to some of the validity threats identified in our earlier discussion of the empirical approach to the study of tasks. However, our approach differs in two significant ways. First, the analytical constructs are specified a priori, with the theory determining the measurement method and not the reverse, as has been the case in earlier studies using job analysis or task description. Second, the identification process in the Gagne approach is focused specifically on behaviors and stimuli and does not include individual skills and contextual confounds as has been the case in job design and group task models.

and inflation of 1% per month (information cue 3), calculate (behavioral act 1) a new list of prices (product for subtask 1) and code (behavioral act 2) a variety of sizes of cans to correspond with new list of prices (indication of completion for total task)." For this expanded, two-act task, $TC_1 = 4$, with the following substitutions in Eq. (1): $n = 1, p = 1$, $W_{10} = 1$, $W_{20} = 0$, $W_{11} = 0$, $W_{21} = 3$. Because the calculation act must be performed before the coding act in this version of the task, a precedence relationship exists between the two required acts. Therefore, $TC_2 = 1$, if the following values are inserted in Eq. (2): $n = 2$; $r_1 = 1$, $r_2 = 0$. TC_3 would still be 0 if the required acts and information cues remained static over time. If we assume the relative weights for TC_1, TC_2, and TC_3 to be 1, 2, and 3, respectively, then $TC_t = 6$ for the two-act task of labeling stock, 6 based on the substitution of the following values in Eq. (5): $\alpha = 1$, $\beta = 2$, $\gamma = 3$, $TC_1 = 4$, $TC_2 = 1$, and $TC_3 = 0$. For the one-act task, $TC_t = 1$. Therefore, for relatively simple clerical tasks, it appears that the proposed indexes do reflect variations in the component and coordinative complexities of different tasks.

Example 2

The air traffic controller task of "landing planes safely," a task which is generally recognized as being complex, is a useful example to illustrate the calculation of complexity scores for relatively high levels of component, coordinative, and dynamic complexity. A summary of the required acts and related information cues for the task is shown in Fig. 1.

Component complexity (TC_1) of this task can be obtained by substituting the following values in Eq. (1): $n = 6$, $p = 0$, $W_{10} = 5$, $W_{20} = 2$, $W_{30} = 7$, $W_{40} = 6$, $W_{50} = 4$, and $W_{60} = 4$. This gives a value of $TC_1 = 28$. After adjusting for redundancy among the cues used in different acts, $TC_1 = 17$, which means that the air traffic controller's task may require the monitoring of 17 cues and the performance of six distinct acts in order to land a plane safely. The attention, memory, and information processing demands that can result from this high level of component complexity are a critical characteristic of the air traffic controller's task.

Coordinative complexity (TC_2) for the air traffic controller's task can be assessed along several dimensions, including the form of the relationship between information cues and acts plus the sequencing and timing of acts. In our earlier discussion it was suggested that TC_2 could be indexed by either the first derivative of the inputs–product relationship or the identifiable break points in that relationship. Values of the first derivative cannot be obtained for the task of landing planes safely because we cannot specify many of the relationships between information cues, acts, and the task product in a differentiable form. However, we can

Required acts	Information cues
1. Choice of hold pattern	1. Wind rate 2. Wind direction 3. Weather 4. Visibility at holding levels 5. Expected incoming planes
2. Order of landing	1. Position in hold pattern 2. Fuel availability
3. Instructions to (re)locate in holding pattern	1. Weather 2. Visibility at holding levels 3. Wind rate 4. Wind direction 5. Fuel available 6. Number in hold pattern 7. Actual incoming planes
4. Choice of runway	1. Wind rate 2. Wind direction 3. Ground conditions 4. Size of plane 5. Available runways 6. Position in hold pattern
5. Landing instructions to pilot	1. Weather 2. Visibility on ground 3. Ground conditions 4. Quality of approach
6. Taxiing instructions to pilot	1. Planes on ground 2. Ground conditions 3. Visibility on ground 4. Terminal position

FIG. 1. Required acts and information cues for landing planes.

identify the break points in relationships between the values of information cues and acts through an analysis of operational rules.

For example, in the relationship between ground level visibility (information cue) and landing instructions (behavioral act) there may be three break points that air traffic controllers need to be aware of and these will be embodied in operational rules such as the following: (1) visibility in excess of 300 feet—break off landing instructions at 500 feet; (2) visibility in the 50–300-f range—instruct to ground; (3) visibility less than 50 feet—divert to nearest open airport. These three rules establish break points in the relationship between the values of an information cue (ground level visibility) and a required act (landing instructions) and could be treated as three units of TC_2. Similiar sets of rules could be derived for each cue–act relationship in Fig. 1. Added to this would be the rules for interactions of cues. For example, ice on the ground (information cue 1) plus a cross wind (information cue 2) may require diverting an aircraft to another airport (act) while, individually, neither cue would warrant such action. Therefore, TC_2, using break points in relationships as the index, will equal the total number of operational rules which define both the simple and interactive relationships between information cues and acts for the task of landing planes safely.

The level of coordinative complexity can also be indexed as a function of the timing requirements for performance of the task. Landing a plane every 90 s requires much higher levels of coordination between acts and more frequent monitoring of cues than landing a plane every 60 min. In this sense, "landing a plane safely at O'Hare airport, Chicago" is a different task than "landing a plane safely at Champaign–Urbana airport." The required "sequencing of acts" for landing planes is another form of coordinative complexity which can be indexed. On a clear day with light, steady winds, the sequencing of acts for landing planes could be as shown in Fig. 2a, and, from Eq. (2), $TC_2 = 5$.

However, this required sequencing of activities could be altered by variations in the input cues, such as changes in the rate or directions of winds, resulting in dynamic complexity (TC_3). Other sources of TC_3 are exogenous events (e.g., mechanical failure, plane wanders into controlled air space, medical emergency) and self-generated crises (e.g., locating two planes too close to one another in the hold pattern, giving a plane the wrong relocation coordinates). Under conditions of dynamic complexity, acts later in the sequence may cause the air traffic controller to focus on an information cue which indicates the need for a revision of an earlier judgment or act. For example, variable winds may necessitate changes in the runway used and order of landing which then requires a change in the holding pattern for waiting planes. If the feedback loops in

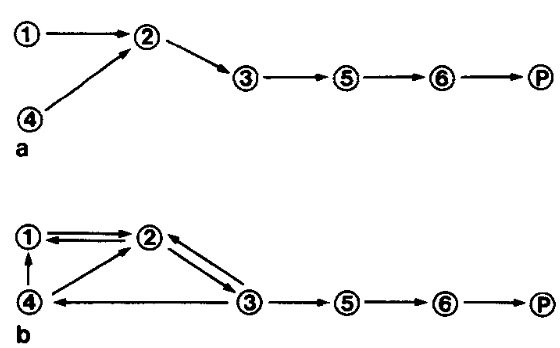

FIG. 2. Sequencing of acts in landing planes. The numbering of acts in both (a) and (b) corresponds to the numbering of required acts in the left-hand column of Fig. 1.

this sequence, shown in Fig. 2b, are treated as additional precedence relationships between acts, then, according to Eq. (2), TC_2 changes from 5 to 9. By substituting these TC_2 values Eq. (3), we could calculate a value for TC_3.

To calculate the full value of TC_3 for this task we would need to set f equal to the number of planes landed in a given work period, calculate TC_1 and TC_2 for each landing, and then substitute the obtained values in Eq. (3). Furthermore, to adjust for the predictability of the changes in TC_1 and TC_2, we would need to calculate ρ_{TC_1} and ρ_{TC_2} and substitute the obtained values in Eq. (4). Advance notice of changes in values for most of the input cues (visability, weather, ground conditions, winds, etc.) means that their effects on TC_1 and TC_2 are more predictable (i.e., $\rho_{TC} \geqq 1$, in Eq. (4) than the effects of either exogenous events or self-generated crises, both of which tend to have low predictability (i.e., $\rho \geqq 0$, in Eq. (4).

From this analysis, we can see that the coordinative complexity due to the "sequencing of acts," although greater than TC_2 for the stock labeling task in Example 1, is not a major source of complexity in the landing of planes. In fact, the level of TC_2 due to sequencing requirements is greater in most assembly tasks (e.g., assemblying one type of child's bicycle has a required sequencing of 15 distinct acts, resulting in a $TC_2 = 14$). The major sources of complexity in the landing of planes are the high level of TC_1, TC_2 due to timing requirements and the complex forms of cue–act relationships, and TC_3 due to unpredictable events.

Task Complexity and Task Performance

The two examples discussed suggest several points about the relationship between task complexity and performance. The first point deals with how task complexity influences task performance. Variations in task complexity appear to produce changes in the knowledge, skills, and effort requirements for successful task performance and these requirements, or task demands, depend upon the combinations of TC_1, TC_2, and TC_3 which make up TC_T. Both examples illustrate how attention demands can vary with TC_1. The second example also illustrates how demands for speedy motor activity, memory, and information processing can each vary with different aspects of TC_2, as well as with combinations of TC_2 and TC_3. Therefore, hypotheses for the complexity–performance relationship will need to consider the nature of the demands placed on individuals by the type of complexity being considered.

It is possible that the relationships between the different types of complexity and performance will have a basic curvilinear form. Increasing levels of complexity may initially lead to higher levels of challenge and activation (Scott, 1966) and have a positive affect on performance (e.g., Locke, Shaw, Saari, & Latham, 1981). However, at high levels of complexity, the resulting demands on individuals may begin to exceed their capacities to respond, creating a condition of "overload" which leads to lowered performance. Of course, the point at which this overload occurs will be a function of individual capacities as well as the level of task demands for the type of complexity being studied.

Evidence of lowered performance at high levels of complexity is available in descriptions of the air traffic controller's task of landing planes. Accounts of "near misses" and other violations of the air traffic controller's code frequently point to overloads in the types of task demands we have attributed to high levels of TC_1, TC_2, and TC_3 as causes of the lowered performance. By way of contrast, the demands for the stock labeling task would probably never produce an overload condition unless, perhaps, the time for completion of the task was set at an unrealistically low level.

A point to be drawn from this discussion is that studies of the complexity–performance relationship will need to sample a wide range of tasks to obtain the variance needed in the levels and types of complexity. Also, because possible turning points in the complexity–performance relationship may vary as a function of individual capacities, the attributes (e.g., knowledge, skills, strength) of samples will need to be taken into account in the study of complexity and performance. For example, graphs of the relationship between complexity and performance for experienced and highly skilled samples will probably have steeper slopes and higher turning points than graphs for less experienced and less skilled samples.

Finally, the possibility of a curvilinear relationship between complexity and performance has important implications for the design of tasks. If the aim in task design is to maximize outcomes such as performance and job satisfaction, tasks should be designed which include optimal levels of complexity for particular groups of individuals.

CONCLUSION

As was stated in the introduction, the purpose of this paper was to begin the development of a theory of tasks. To this end we have developed a theory of task complexity in which tasks were defined as consisting of a product and two types of task inputs: required acts and information cues. This definition, which represented a partial combining of the "task qua task" and "task as behavioral requirements" approaches outlined by Hackman (1969), was used to describe three types of task complexity. The three types of task complexity discussed were component, coordinative, and dynamic and various indexes for quantification of these constructs were presented.

Together, these three types of complexity determine the total complexity of a task and the resulting knowledge and skills required of individuals for performance of the task. In static–comparative analyses of tasks, TC_1 and TC_2 will determine the knowledge and skills required for the performance of different tasks. In longitudinal analyses of tasks, changes in TC_1 and TC_2, i.e., TC_3, will require individuals to evoke new knowledge about components and their coordination and may require the use of additional skills during the performance of the task. The different task demands that result from different types and levels of complexity will provide the explanatory link in arguments about the effects of task complexity on individual attitudes and task performance.

For some of the proposed indexes, calculation may lay beyond our present capability to describe tasks, particularly in field settings. However, the rigorous development of the analyical task constructs needed for task quantification is an important developmental activity in the study of task performance. A comprehensive analytical framework for tasks will greatly enhance our ability to integrate evidence of task effects from different studies by different researchers. This, in turn, will enable stronger empirical generalization and provide greater insight about individual–task interactions in the study of task effects.

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