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STRATEGIES FOR THEORIZING FROM PROCESS DATA

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In this article I describe and compare a number of alternative generic strategies for the analysis of process data, looking at the consequences of these strategies for emerging theories. I evaluate the strengths and weaknesses of the strategies in terms of their capacity to generate theory that is accurate, parsimonious, general, and useful and suggest that method and theory are inextricably intertwined, that multiple strategies are often advisable, and that no analysis strategy will produce theory without an uncodifiable creative leap, however small. Finally, I argue that there is room in the organizational research literature for more openness within the academic community toward a variety of forms of coupling between theory and data.

As change sweeps through industries, organizations, and workgroups, we are seeing a surge of interest among organizational researchers in process theory and dynamic phenomena, such as organizational learning (Cohen & Sproull, 1991), competitive interaction (Illnitch, D'Aveni, & Lewin, 1996), innovation and change (Van de Ven & Huber, 1990), and strategic evolution (Barnett & Burgelman, 1996). One group of researchers has chosen to address these dynamics by formulating a priori process theories and testing them using coarse-grained longitudinal time series and event-history methods. Another camp has chosen rather to plunge itself deeply into the processes themselves, collecting fine-grained qualitative data—often, but not always, in real time—and attempting to extract theory from the ground up (Bower, 1997; Pettigrew, 1992; Van de Ven, 1992). The philosophy of this camp is that to truly understand how and why events play out over time, we must examine them directly (Mintzberg, 1979).

I identify myself as a member of the second camp, but in no way think the task we have set ourselves is easy. Process data are messy. Making sense of them is a constant challenge. In this article I examine a number of different strategies for approaching this task. My objective is not to advocate one strategy or another, or even to propose radically new strategies (although I do draw on my own research with colleagues in delineating some of them), but, rather, to consider the strengths and weaknesses of different modes of analysis of process data in terms of their capacity to generate theory that is accurate, parsimonious, general, and useful (Weick, 1979). I further draw attention to the mutual dependence between methods and theories.

I begin by clarifying what I mean by process theory and process data and how I conceive of the theory-building task. After presenting the different analysis strategies, I discuss their various qualities, place them within an overall framework, and argue for more openness within the academic community toward a variety of forms of coupling between theory and data.

PROCESS DATA AND PROCESS THEORIZATION: THE CHALLENGE

Process data collected in real organizational contexts have several characteristics that make

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them difficult to analyze and manipulate.[1] First, they deal mainly with sequences of "events": conceptual entities that researchers are less familiar with. Second, they often involve multiple levels and units of analysis whose boundaries are ambiguous. Third, their temporal embeddedness often varies in terms of precision, duration, and relevance. Finally, despite the primary focus on events, process data tend to be eclectic, drawing in phenomena such as changing relationships, thoughts, feelings, and interpretations. I elaborate briefly on these four characteristics below.

Data Composed of Events

Process research is concerned with understanding how things evolve over time and why they evolve in this way (see Van de Ven & Huber, 1990), and process data therefore consist largely of stories about what happened and who did what when—that is, events, activities, and choices ordered over time. In his classic work on organization theory, Mohr (1982) makes a clear distinction between what he calls "variance theory" and "process theory." Figure 1 illustrates this distinction applied to the problem of explaining strategic change.

Whereas variance theories provide explanations for phenomena in terms of relationships among dependent and independent *variables* (e.g., more of X and more of Y produce more of Z), process theories provide explanations in terms of the sequence of *events* leading to an outcome (e.g., do A and then B to get C). Temporal ordering and probabilistic interaction between entities are important here (Mohr, 1982). Understanding patterns in *events* is thus key to developing "process" theory.

"Events," however, are quite different entities from the "variables" that dominate methodology seminars and that most of us are more used to manipulating. The analysis of process data, therefore, requires a means of conceptualizing events and of detecting patterns among them. As suggested by Van de Ven and Poole (1995), these patterns may take a variety of different forms, but the most common pattern found in the literature is the linear sequence of "phases" that occur over time to produce a given result (e.g., Burgelman, 1983; Rogers, 1983). However, the passage from raw data to synthetic models, whether expressed in terms of phases or otherwise, is far from simple. Abbott (1990) and Van de Ven (1992) have presented a number of techniques for analyzing event sequences when events are sharply defined in terms of the units of analysis they refer to and their location in time. These provide one strategy for analysis that I will discuss later. However, raw process data usually do not come quite so neatly sliced and packaged.

Data on Multiple Units and Levels of Analysis with Ambiguous Boundaries

Any researcher who has collected qualitative process data in organizations has seen how difficult it is to isolate units of analysis in an unambiguous way. For example, what should or should not be included in the definition of a decision-making process? Can researchers always distinguish (as Eisenhardt, 1989a, did in her research) between the decision to make a strategic change and the decision about what strategy should be adopted?

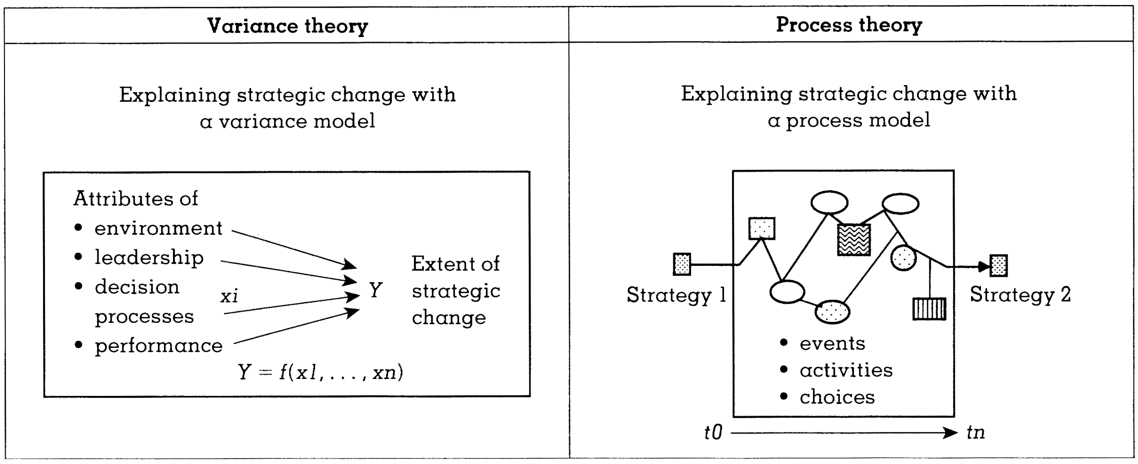
More complex phenomena, such as strategy formation or learning, are even harder to isolate. Process phenomena have a fluid character that spreads out over both space and time (Pettigrew, 1992). In addition, one of the main reasons for taking a qualitative process approach is precisely to take into account the context (Pettigrew, 1992; Yin, 1994). This leads, inevitably, to the consideration of multiple levels of analysis that are sometimes difficult to separate from one another—made up of a continuum, rather than a hierarchy or a clear classification. This further complicates the sensemaking process.

Data of Variable Temporal Embeddedness

When collecting process data, the researcher attempts to document as completely as possible the sequence of events pertinent to the processes studied. However, unless the process is highly circumscribed, certain phenomena will tend to be absent from a systematic list of or-

[1] Note that the *collection* of process data and the *design* of process studies also pose a number of challenges. However, these are not the main focus of this article. While recognizing that, to some extent, data collection and design issues constrain future options, my concern here is how to deal with the data, once collected. For more on design and data collection issues, see Eisenhardt (1989b), Leonard-Barton (1990), Pettigrew (1990), and Yin (1994).

FIGURE 1
Two Approaches to Explaining Strategic Change[a]



[a] After Mohr (1982).

dered incidents. For example, there are often gradual background trends that modulate the progress of specific events. Also, part of what interests us may be going on in people's heads and leave no concrete trace of the exact moment of its passing.

Despite the apparent temporal precision indicated by the word "event," there are also clearly different levels of events: an event may include a bad year, a merger, a decision, a meeting, a conversation, or a handshake. Finally, particularly in macrolevel studies of such processes as strategy making, innovation, and decision making, the researcher is often obliged to combine historical data collected through the analysis of documents and retrospective interviews with current data collected in real time. While the first type of data is sparse and synthetic, focusing on memorable moments and broad trends, the second is richer and finer grained. And, while the first type misses certain useful nuances and details, the second type may require a certain distancing before it is possible to separate out what is really significant from what will be treated as merely noise (Leonard-Barton, 1990). These phenomena are often unavoidable, but they all render analysis and interpretation more difficult.

Data That Are Eclectic

In his work Mohr (1982) insists strongly on the necessity of keeping variance and process theories separate. This requirement is extremely difficult to satisfy. Perhaps for aesthetic reasons, Mohr (1982) seems to want to artificially separate variables and events, although, in practice, phenomena of different kinds are intertwined. I would argue that the insistence on exclusion of variables from process research unnecessarily limits the variety of theories constructed. It may be important to understand the effect of events on the state of an entity (a variable) or to identify the effect of a contextual variable on the evolution of events. Process research may also deal with the evolution of relationships between people or with the cognitions and emotions of individuals as they interpret and react to events (Isabella, 1990; Peterson, 1998). Thus, although temporal phenomena remain one of their distinguishing features, process data are not composed only of descriptions of discrete events. They also incorporate a variety of other types of qualitative and quantitative information. Again, this makes analysis and interpretation more complex.

A process database, thus, poses considerable challenges. The sheer volume of words to be organized and understood can create a sense of drowning in a shapeless mass of information (Pettigrew's, 1990, much-quoted "death by data asphyxiation"). The complexity and ambiguity of the data make it difficult to know where to start. Also, although offering greater potential for new discovery, the open-ended inductive approach that most researchers use in process research tends to lead to postponement of the moment of decision between what is relevant and what is not, sometimes aggravating these difficulties (Miles & Huberman, 1994).

The complexity of process data is, of course, a reflection of the complexity of the organizational phenomena we are attempting to understand. More and more researchers have been questioning simple process models that assume neat linear progressions of well-defined phases leading to well-defined outcomes (Schwenk, 1985; Van de Ven, 1992). Although the linear phase model still has attractions, process representations now often show divergences from the main route, recycling between phases and parallel tracks (Mintzberg, Raisinghani, & Théorêt, 1976; Nutt, 1984; Schroeder, Van de Ven, Scudder, & Polley, 1989). Researchers are also increasingly recognizing that the presence of multilayered and changing contexts, multidirectional causalities, and feedback loops often disturb steady progression toward equilibrium. Several scholars have, in fact, argued that chaos theory or complexity theory may offer the potential for better understanding organizational processes (e.g., Stacey, 1995; Thiétart & Forgues, 1995).

Thus, it is clear that we need better ways to model process phenomena. However, research that concludes simply that "everything is complex" or that "simple normative models do not work" is limited in its appeal. As Van de Ven (1992) notes, process theorization needs to go beyond surface description to penetrate the logic behind observed temporal progressions—whether simple or complex. I find it difficult to share the enthusiasm of some writers for the application of complexity theory to organizational phenomena, precisely because the specific explanatory mechanisms behind its application are often not specified. The general but banal insight that organizational processes involve opposing forces, nonlinear relationships, and feedback loops needs fleshing out. One interesting point raised by these theorists, however, is that the interaction of a relatively small number of simple deterministic elements may generate complexity, if they take into account such phenomena. With this, there is hope that relatively parsimonious theoretical formulations may be able to make sense of the complexity observed in process data.

And this is where the central challenge lies: moving from a shapeless data spaghetti toward some kind of theoretical understanding that does not betray the richness, dynamism, and complexity of the data but that is understandable and potentially useful to others. Throughout the remainder of this article, I examine seven generic strategies for achieving this. Following Weick (1979), I term these *sensemaking* strategies. The word "sensemaking" is used for two reasons. First, it implies the possibility that a variety of "senses" or theoretical understandings may legitimately emerge from the same data. In fact, I argue that different strategies tend to produce different forms of theory that are neither intrinsically better nor worse but may have different strengths and weaknesses. Second, it implies that the closing of the gap between data and theory can begin at either or both ends (data or theory) and may often iterate between them (Orton, 1997). Rigid adherence to purely deductive or purely inductive strategies seems unnecessarily stultifying. Indeed, Tsoukas (1989) goes further, arguing that while the data themselves can yield empirical regularities, abstract conceptualization is required to imagine the "generative mechanisms" that are driving them. For him, understanding comes from a combination of the two.

STRATEGIES FOR SENSEMAKING

The seven strategies for sensemaking described in this section were derived from an in-depth reading of the organization studies and methods literature and from my own research experience. I see the strategies as generic approaches, rather than step-by-step recipes or techniques. They are not necessarily exhaustive, and they can be used in combination. Each approach tends to overcome the overwhelming nature of boundaryless, dynamic, and multilevel process data by fixing attention on some anchor point that helps in structuring the material but that also determines which elements will receive less attention. It is because of this that the strategy used can have an important impact on the nature of the emerging theory.

Thorngate's (1976) and Weick's (1979) categories of *accuracy, generality*, and *simplicity* are used here to consider the theoretical forms likely to be developed using different strategies. Some strategies tend to stick closely to the original data, whereas others permit greater abstraction. Close data fitting reflects what Weick

(1979) calls "accuracy." However, accuracy may act against generality—another desirable quality related to the potential range of situations to which the theory may be applicable. Finally, simplicity concerns the number of elements and/or relationships in a theory. It affects the theory's aesthetic qualities. Simple theories with good explanatory power may actually be preferred to complex ones that explain a little more; as Daft (1983) suggests, good research is more like a poem than a novel.

In describing each strategy, I draw on exemplars in the organizational literature that appear to represent the best of what can be achieved with each approach. In my analysis I also look at the relative data needs of each approach both in terms of depth (process detail) and breadth (number of cases), as well as the extent to which each strategy deals with each of the process data characteristics mentioned above. Finally, I show how each strategy tends to favor different types of process understanding ("senses"). Some strategies seem best adapted to the detection of *patterns* in processes, whereas others penetrate their driving *mechanisms*. Some are more oriented toward the *meaning* of process for the people involved, whereas some are more concerned with *prediction*. The discussion is summarized in Table 1.

Narrative Strategy

This strategy involves construction of a detailed story from the raw data. In the area of strategic management, the classic example of this style is Chandler's (1964) history of the evolution of American enterprise. The same style also dominates the work of strategy researchers who adopt a "contextualist" perspective, notably Andrew Pettigrew and members of the Centre for Corporate Strategy and Change (Pettigrew, 1985, 1990; Pettigrew & Whipp, 1991), but also others working in this tradition (Dawson, 1994; Johnson, 1987). Descriptive narratives (or "realistic tales") are also the traditional tool of ethnographers (Van Maanen, 1988), and they frequently play a key role in studies of cultural change (Bartunek, 1984).

In fact, almost all process research involves recourse to this strategy at some point. However, the narrative can serve different purposes, depending on the objectives of the researcher. For many it is merely a preliminary step aimed at preparing a chronology for subsequent analysis—essentially, a data organization device that can also serve as a validation tool (e.g., Eisenhardt, 1989b). For "contextualists" it plays a more substantial role, incorporating an analytical element:

> Our analytical chronologies reach towards theory presentation but are prepared to get on top of the data, to clarify sequences across levels of analysis, suggest causal linkages between levels, and establish early analytical themes (Pettigrew, 1990: 280).

Finally, for others who adopt a constructivist or naturalistic perspective (Dyer & Wilkins, 1991; Guba & Lincoln, 1994), the narrative can be the main product of the research. The aim is to achieve understanding of organizational phenomena—not through formal propositions but by providing "vicarious experience" of a real setting in all its richness and complexity (Lincoln & Guba, 1985: 359). For the proponents of this approach, it is the contextual detail in the narrative ("thick description") that will allow the reader to judge the transferability of the ideas to other situations. Indeed, good research of this type will often produce a sense of "déjà vu" among experienced readers. The theorist who adopts this philosophy tries to avoid excessive data reduction and to present as completely as possible the different viewpoints on the process studied.

This strategy avoids commitment to any specific anchor point, although because of the structure of narrative, time tends to play an important role. Also, because of its focus on contextual detail, this approach works best for one or a few cases. Ideally, the variety and richness of the incidents described and of the linkages between them should convey a high degree of authenticity that cannot be achieved economically with large samples (Golden-Biddle & Locke, 1993). In the hands of an accomplished writer, this sensemaking strategy has the great advantage of reproducing in all its subtlety the ambiguity that exists in the situations observed. It avoids the necessity of clear definitions when boundaries are not clear, and it easily accommodates variable temporal embeddedness and eclectic data. The philosophy behind this type of analysis is well expressed by Van Maanen: "To be determinate, we must be indeterminate" (1995: 139).

In Weick's (1979) terms, *accuracy* is therefore expected to be high. However, those who adopt

TABLE 1
Seven Strategies for Sensemaking[a]

Strategy	Key Anchor Point(s)	Exemplars	Fit with Process Data Complexity	Specific Data Needs	"Good Theory" Dimensions (Weick)	Form of Sensemaking
Narrative strategy	Time	Chandler (1964) Bartunek (1984) Pettigrew (1985)	Fits with ambiguous boundaries, variable temporal embeddedness, and eclecticism.	One or few rich cases. Can be helped by comparison.	High on *accuracy*. Lower on *simplicity* and *generality*.	Stories, meanings, mechanisms
Quantification strategy	Events, outcomes	Garud & Van de Ven (1992) Van de Ven & Polley (1992)	Focuses on "events" and their characteristics. Eschews ambiguity.	Needs many similar events for statistical analysis: one or few dense cases is best.	High *simplicity*, potentially high *generality*, modest *accuracy* (abstraction from original data).	Patterns, mechanisms
Alternate templates strategy	Theories	Allison (1971) Markus (1983) Pinfield (1986) Collis (1991)	Adaptable to various kinds of complexity. Different templates capture different elements.	One case is enough. Degrees of freedom come from multiple templates.	Each theory can be *simple* and *general*. Together, they offer *accuracy*, but *simplicity* and *generality* disappear with theory integration.	Mechanisms
Grounded theory strategy	Incidents (units of text) Categories	Sutton (1987) Isabella (1990) Gioia, Thomas, Clark, & Chittipeddi (1994)	Adapts well to eclectic data and ambiguity. May miss broad high-level patterns.	Needs detail on many similar incidences. Could be different processes or individual-level analysis of one case.	High on *accuracy*, moderate *simplicity*. May be difficult to go from substantive theory to more *general* level.	Meanings, patterns
Visual mapping strategy	Events, orderings	Meyer (1984, 1991) Nutt (1984, 1993) Langley & Truax (1994)	Deals well with time, relationships, etc. Less good for emotions and interpretations.	Needs several cases in moderate level of detail to begin generating patterns (5–10 or more).	Moderate levels of *accuracy*, *simplicity*, and *generality*. Not necessarily good at detecting mechanisms.	Patterns
Temporal bracketing strategy	Phases	Barley (1986) Denis, Langley, & Cazale (1996) Doz (1996)	Can deal with eclectic data, but needs clear temporal breakpoints to define phases.	One or two detailed cases is sufficient if processes have several phases used for replication.	*Accuracy* depends on adequacy of temporal decomposition. Moderate *simplicity* and *generality*.	Mechanisms
Synthetic strategy	Processes (e.g., decisions, change efforts, new products)	Eisenhardt (1989a; with Bourgeois, 1988) Meyer & Goes (1988)	Needs clear process boundaries to create measures. Compresses events into typical sequences.	Needs enough cases (5+) to generate convincing relationships. Moderate level of detail needed for internal validity.	Modest *accuracy* (but much better than questionnaire research). Can produce *simple* and moderately *general* theories.	Prediction

[a] Note that the entries in this table are indicative only. There is obviously considerable variation amongst the research following each strategy.

a more traditional research perspective may be dissatisfied because this approach does not, on its own, lead to either *simple* or *general* theory. Without denying the usefulness of the narrative approach for communicating the richness of the context to readers, most of us expect research to offer more explicit theoretical interpretations. When relying on this strategy alone, one may too easily end up with an idiosyncratic story of marginal interest to those who were not involved and a rather thin conceptual contribution. Appealing process research needs to push beyond authenticity to make readers feel that they learned something of wider value (Golden-Biddle & Locke, 1993).

The instrinsic interest of the phenomenon studied can sometimes offer this value—for example, narratives that dig under the surface of dramatic events can be very effective, as in Vaughan's (1996) analysis of the Challenger disaster. But, beyond this, the most interesting and compelling narratives (including Vaughan's) are not so purely descriptive. They know where they are going. Like Chandler's (1964) stories of the invention of the M-form organization, they have embedded "plots" and "themes" that serve as sensemaking devices (Woiceshyn, 1997) and that ultimately become more explicit theories (e.g., "structure follows strategy"). However, simultaneously telling the complete story while setting the plot is a tall order. Other strategies can help out here.

Quantification Strategy

At the opposite end of the spectrum from the narrative strategy is a form of process analysis that has been most effectively promoted by Andrew Van de Ven and colleagues of the Minnesota Innovation Research Project (Van de Ven & Poole, 1990). In this approach researchers start with in-depth process data and then systematically list and code qualitative incidents according to predetermined characteristics, gradually reducing the complex mass of information to a set of quantitative time series that can be analyzed using statistical methods.

For example, in their innovation project, Van de Ven's team first collected detailed real-time data and then identified five characteristics or tracks that could be used to analyze each identifiable incident (people, ideas, transactions, context, and results). The incidents and their corresponding tracks were transformed into a series of binary codes associated with a specific date, forming a 0-1 matrix that the authors call a "bit-map." Each incident corresponded to a line in the matrix. One column was reserved to indicate positive outcomes (0 or 1) associated with an incident and another was reserved for negative outcomes. A third column was used to indicate whether or not there was a change in the people involved in the innovation, and so on (Van de Ven & Poole, 1990). Once the coding was complete, the researchers worked with the binary data matrix and used statistical methods to search for patterns and test theoretical explanations. For example, Garud and Van de Ven (1992) and Van de Ven and Polley (1992) tested a dynamic theory of learning during innovation. The same data were used to examine whether the sequences reflected random, chaotic, or periodic processes as the innovation evolved (Cheng & Van de Ven, 1996).

Similar approaches have been used by Smith, Grimm, and Gannon (1992) to analyze competitive interactions among airlines and by Romanelli and Tushman (1994) to examine patterns of change in the microcomputer industry. Unlike Van de Ven's team, however, these researchers began with mainly documentary databases consisting of newspaper articles, 10K reports, and the like.

The advantage of the quantification approach lies in the systematization of process analysis. Assuming that the original data are complete and that the coding of incidents is reliable, descriptive patterns in the sequence of events can be verified systematically and explicit process theories can be tested rigorously. Note, however, that despite the conversion of the data to quantitative form, the types of statistical analysis appropriate to process theorizing are somewhat different from those used in most variance research.

For example, many process theories are founded on the idea that there are fundamental similarities in the patterns of event sequences across cases. However, traditional techniques (regression, ANOVA, and so forth) are designed to explain *differences* (variance)—not to show *similarities*. The sequence methods proposed by Abbott (1990) include the use of multidimensional scaling, to identify "typical sequences" across different cases, and of optimal matching algorithms (like those used in DNA testing), to estimate the proximity between sequences and to develop event-sequence typologies. Sabherwal and Robey (1993) adopted this method, for example, to develop a taxonomy of information-system implementation processes based on the detailed coding of 53 event chronologies.

More commonly, however, quantitative researchers examining process phenomena have used techniques such as event-history analysis, lagged regression, log-linear models, and dynamic simulation. Rather than testing for the similarity of whole sequence patterns *across* cases, these methods are appropriate for examining the dynamic relationships between events *within* a single case or a population. Monge (1990) provides a detailed overview of the theoretical forms that can be considered in this way and the appropriate statistical techniques for each. The approach seems particularly useful for the verification of dynamic theories that include causal feedback loops. All this supposes, however, that comparable incidents within the same case or across similar cases are sufficiently large in number to create enough degrees of freedom for the statistical analysis. For this, "incidents" must be defined to be very generic in form, with little contextual richness and variability remaining attached to them.

In contrast with the narrative approach, this strategy leads more easily to parsimonious theoretical conceptualizations (i.e., *simplicity*). Because of the generic character of coded events and the mathematical formulation of the models tested—often supported by deductive reasoning—the theorization is also likely to have greater potential *generality* (although replication is needed to verify this). Yet, to achieve this result, the approach drastically simplifies the original data, setting aside certain dimensions and replacing the ambiguous, rich, and specific context by precise, thin, and general indicators. There is little room for variable temporal embeddedness or ill-defined boundaries in the emerging models. *Accuracy*, thus, is not necessarily the strong suit of such theories, even though the gap between the data and the emerging model may appear to be more defensible than in certain other strategies, because it can be assessed and justified rationally by reasonable interrater reliabilities (that take us from the data to its coded representation) and good R-squareds (that get us from the coded representation to the final model).

In fact, although I have taken part in similar exercises myself and know why we do these things, there is a certain irony in the idea that researchers who give themselves the trouble of collecting rich qualitative data in real organizations are so uncomfortable with this richness that they immediately rush to transform it, through another extremely demanding process, into a much thinner data set that can be managed in traditional ways. The quantification strategy will be much more convincing if it is used in combination with other approaches that allow contextualization of the abstract data, adding nuances of interpretation and confirming the mechanics of the mathematical model with direct evidence. The articles by Garud and Van de Ven (1992) and Van de Ven and Polley (1992) on learning during innovation are interesting from this viewpoint. However, those who rely solely on the quantification strategy may lose critical elements of process understanding in abstractions so general that the results obtained may be clear but fairly banal.

The two strategies just described lie at the two ends of a continuum that opposes empirical accuracy and theoretical parsimony. I now present some more middle-of-the-road approaches.

Alternate Templates Strategy

In this sensemaking strategy the analyst proposes several alternative interpretations of the same events based on different but internally coherent sets of a priori theoretical premises. He or she then assesses the extent to which each theoretical template contributes to a satisfactory explanation.

The strategy was popularized by Allison (1971), in his classic study of the decisions made during the Cuban Missile Crisis. The three explanatory templates used by Allison were a "rational actor model," in which the United States and the Soviet Union were viewed as unified rational actors selecting alternatives to achieve national objectives; an "organizational process model," in which decision making was seen as driven by organizational routines (Cyert & March, 1963); and a "political model," in which individuals involved in the crisis were viewed as pursuing their own personal interests within a distributed power structure. Allison (1971) produced three retellings of the story, each drawing on a different model. He concluded that the last two seemed superior to the first, allowing the explanation of certain events that otherwise appeared mysterious.

This strategy has been used often since then for the study of decision processes (e.g., Pinfield, 1986; Steinbruner, 1974), perhaps partly because of Allison's example, but also perhaps because of the difficulty of developing a unique model of decision making that simultaneously captures all of its dimensions (Langley, Mintzberg, Pitcher, Posada, & Saint-Macary, 1995). The strategy also has attracted adherents among information systems researchers concerned with implementation processes (e.g., Lee, 1989; Markus, 1983). In strategic management the work of Collis (1991) on globalization also reflects this approach.

Because this strategy draws theory from outside the data, it is essentially deductive. In some applications predictions of the competing theories are formally "tested" in a hypothetico-deductive fashion, with specific predictions being refuted to reject weaker theories (e.g., Markus, 1983). This is similar to Yin's (1994) idea of "pattern-matching." Often, though, the different interpretations are less like true "tests" of theory and more like alternate complementary readings that focus on different variables and levels of analysis and reveal different types of dynamics. Many broad process theories, such as political models (Allison, 1971), organizing theory (Weick, 1979), or structuration theory (Giddens, 1984), are alternative modes of sensemaking that are not easily refutable because their constructs seem adaptable (e.g., in political models it is usually possible to find personal goals that make observed action rational). However, a confrontation among different interpretations can reveal the contributions and gaps in each.

Although some researchers have counseled against using single case studies in process research because of the lack of material for replication and comparison (Eisenhardt, 1989b; Pettigrew, 1990), this strategy provides a powerful means of deriving insight from a single rich case because the different theoretical interpretations provide the base for comparison needed (Lee, 1989; Yin, 1994). Each interpretation strategy may also force the researcher to collect different types of data, with the more finely grained theories actually becoming very demanding, further revealing the relative contribution of each perspective (Allison, 1971).

Overall, this strategy combines both richness and theoretical parsimony (*simplicity*) by decomposing the problem. Qualitative nuances are represented through the alternative explanations, and theoretical clarity is maintained by keeping the different theoretical lenses separate (at least in most applications of this approach). Between them, then, different theoretical perspectives provide overall *accuracy*, although each one is inaccurate on its own. *Generality* in this approach comes from the use of deductive theories that have broad application.

However, despite its advantages, the use of this strategy often leaves the researcher and the reader puzzled as to how the various theoretical perspectives can be combined. Almost inevitably, each explanation taken alone is relevant but insufficient. Yet, any theory that attempted to integrate the different perspectives would tend to become unwieldy and aesthetically unsatisfying. As Allison indicates at the end of his book:

> The developed sciences have little hesitation about partial models. . . . The aspiring sciences tend to demand general theory. In satisfying this demand, they often force generalization at the expense of understanding. Refining partial paradigms, and specifying the classes of actions for which they are relevant, may be a more fruitful path to limited theory and propositions than the route of instant generalization (171: 275).

Grounded Theory Strategy

As noted by several meta-analysts of qualitative research (Larson & Löwendahl, 1995; Locke, 1996), Glaser and Strauss's (1967) *The Discovery of Grounded Theory* is one of the most-cited methods texts in qualitative research articles. And, yet, there is sometimes limited evidence in these articles of the systematic theory-building methods proposed by the authors and subsequently refined by Glaser (1978) and Strauss and Corbin (1990; see Locke, 1996). For many, "grounded theory" is basically a generic synonym for any kind of inductive theorizing. This is perhaps not surprising, for the language itself expresses this idea. However, in this article I use grounded theory strategy to refer to the more specific methods described by the original authors.

When followed "by the book," the grounded theory approach as described most recently by Strauss and Corbin (1990) incorporates a series of highly structured steps. It involves the systematic comparison of small units of data (incidents) and the gradual construction of a system of "categories" that describe the phenomena being observed. The categories may have several "subcategories," and associated "dimensions" and "properties," which are gradually elaborated and refined as specific incidents are examined, systematically coded, and compared. As the categories are developed, the researcher deliberately seeks out data that will enable verification of the properties of emerging category systems. The analysis should eventually result in the identification of a small number of "core categories," which serve to tightly integrate all the theoretical concepts into a coherent whole firmly rooted ("grounded") in the original evidence.

At first sight, process data offer many opportunities for grounded theorizing. Indeed, Glaser (1978) and Strauss and Corbin (1990) insist on the necessity of incorporating processes into any grounded theory study. They note that processes are categories that have two or more identifiable "stages" (Glaser, 1978) and that the most useful core categories are often expressed as gerunds (i.e., in process terms). Several grounded theory process studies in the literature are faithful to this portrait (e.g., Sutton's, 1987, model of organizational death as "disbanding" and "reconnecting" and Gioia & Chittipeddi's, 1991, representation of the initiation of strategic change as "sensemaking" and "sensegiving").

However, I would argue that the strategy "makes more sense" for some types of process data than for others. Generally, it demands a fairly large number of comparable incidents that are all richly described. Thus, while one setting may be sufficient, there should at least be several distinct processes that can be compared in depth (e.g., as in Burgelman's, 1983, internal venturing study). Alternatively, the level of analysis can be dropped away from the overall site to a more microlevel to explore the interpretations and emotions of different individuals or groups living through the same processes (e.g., Isabella, 1990; Sutton, 1987). It is here that the strategy often appears at its most powerful. However, when the objective is to understand more macroscopic processes that occur one at a time over long periods (like strategic change in a large organization), the processes' broad sweep seems to fit less well with the microanalysis of the textbook grounded theory approach. The data themselves may not have the density required to support it, and the microfocus risks losing the broad pattern of the forest for the descriptive detail of the trees.

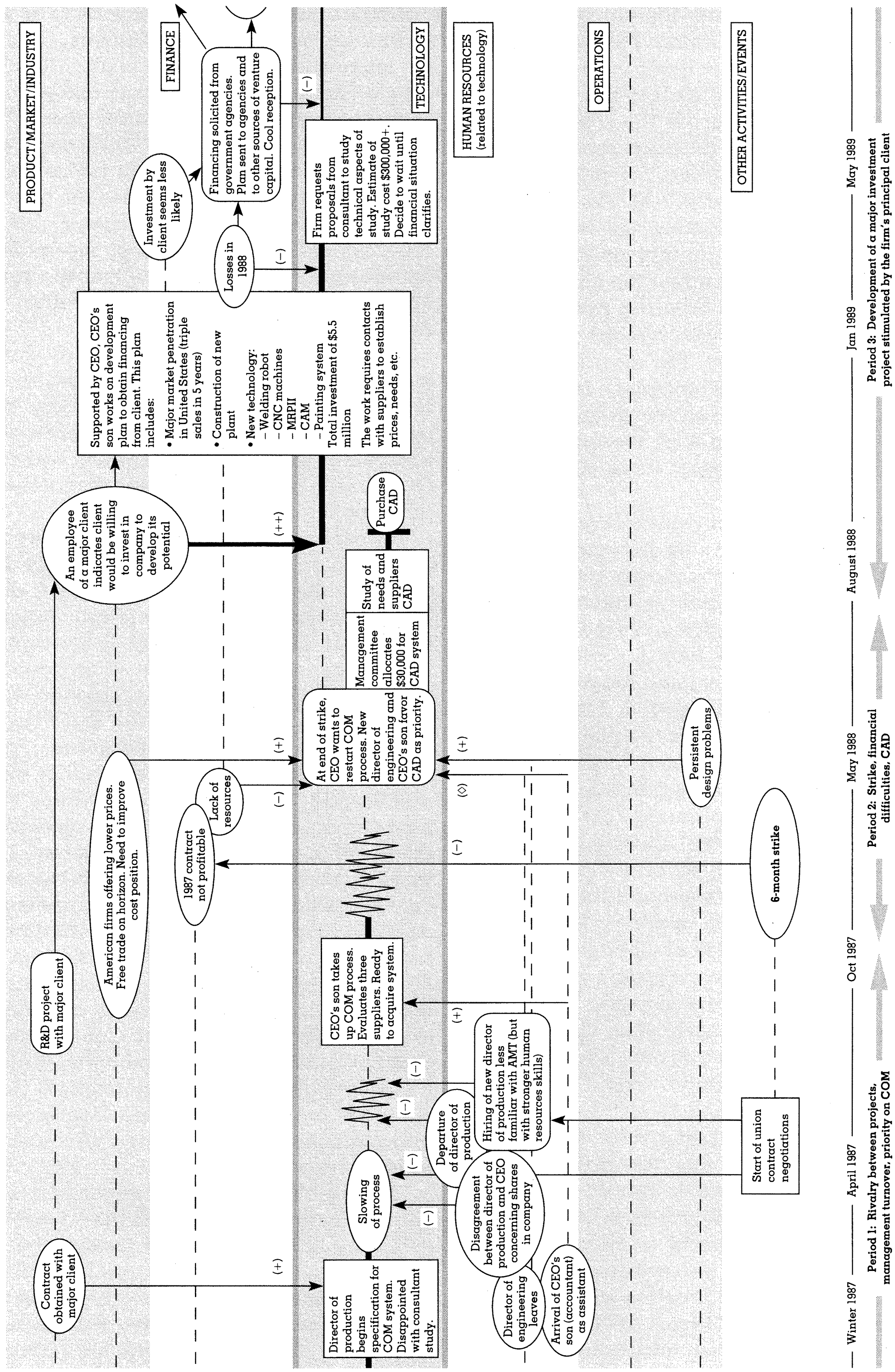
In summary, used alone, this is a strategy that tends to stay very close to the original data and is therefore high in *accuracy*. It starts with empirical details expressed in interview transcripts and field notes and attempts to build a theoretical structure "bottom up" from this base. Yet, because of the specialized language, the logic of the method, and the deliberately hierarchical structure of category systems, theories developed in this way are at the same time very dense (low to moderate in *simplicity*) but often seem to have a similar flavor and general structure (compare, for example, the exemplary grounded theory studies of very different phenomena by Gioia, Thomas, Clark, & Chittipeddi, 1994, and Browning, Beyer, & Shetler, 1995). As its proponents note, firm grounding in the raw data can also sometimes make it difficult to move from a "substantive" theory of a specific phenomenon to more *general* formal theory (Glaser & Strauss, 1967).

Visual Mapping Strategy

Process data analysis may involve the manipulation of words (e.g., narrative strategies or grounded theory), of numbers (quantification), or of matrix and graphical forms (Miles & Huberman, 1994). Such forms have several advantages over narrative approaches, according to Miles and Huberman (1994). They allow the presentation of large quantities of information in relatively little space, and they can be useful tools for the development and verification of theoretical ideas. Visual graphical representations are particularly attractive for the analysis of process data because they allow the simultaneous representation of a large number of dimensions, and they can easily be used to show precedence, parallel processes, and the passage of time.

For example, Figure 2 is taken from a study of the process of adoption of new technology in small manufacturing firms (Langley & Truax, 1994). The drawing presents an event chronology coded in multiple ways. The form of the boxes indicates whether the event described represents a decision (round-cornered rectangles), an activity (sharp-cornered rectangles), or an event outside the control of the firm (ovals). The location of each box in one of the six horizontal

FIGURE 2
Extract from a Process Flowchart[a]



[a] From Langley and Truax (1994).

bands indicates the issue domain with which the event is associated. Certain boxes cross several bands, indicating the integrative character of that event. The arrows leading from each box to the central band indicate the effect of this event on the technology adoption process (positive effect [+], negative effect [−], precipitating effect [++], reorienting effect [◊]). The thickness of the horizontal lines linking the boxes indicates the degree of continuity among linked events. Finally, the horizontal time scale allows representation of event ordering and parallel tracks over time and provides a rough indication of their temporal duration. The drawing is obviously a summary of what took place in the case, but the link between it and the qualitative database is maintained through the use of short descriptions of each element in its corresponding box.

This type of drawing obviously is not a "theory" but an intermediary step between the raw data and a more abstract conceptualization. To move toward a more general understanding, one might, in further analysis, compare several such representations to look for common sequences of events and common progressions in sources of influence (Langley & Truax, 1994). One could also proceed to developing more abstract coding to generate local "causal maps" that would constitute the beginnings of a middle-range theoretical explanation (as described by Miles & Huberman, 1994). Finally, one might compare and integrate several such causal maps to elaborate a more general theory. Lyles and Reger (1993) apply an approach like this in their study of the evolution of managerial influence in a joint venture over a period of 30 years.

Different forms of process mapping have long been used by organizations to plan, understand, and correct their own work processes (in systems analysis, quality improvement, business process reengineering, and so forth). Organizational researchers could perhaps learn from this example. Meyer (1991) notes how flowcharts of capital budgeting processes proved useful in making sense of disparate accounts and in communicating with informants to collect further data. These charts also became the raw material for the development of both a more comprehensive process model (Meyer, 1984) and a variance model of innovation adoption (Meyer & Goes, 1988).

Process mapping also has been a favored technique for decision researchers, constituting the foundation of Mintzberg et al.'s (1976) classic article and of Nutt's (1984) work on decision process typologies. In his advocacy of a "grammatical" approach to process analysis, Pentland (1995) also implicitly suggests the usefulness of process mapping. He discusses the need to detect the underlying rules (grammar) driving the ordering of different types of moves (specific operations) or syntactic elements (groups of moves serving similar functions) within a repetitive process.

Approaches like those described require many observations of similar processes. This indicates that the mapping strategy may be most fruitful as a theory development tool for the analysis of multiple holistic or embedded cases. Of course, as a simple presentational method, it has broader application.

Process mapping allows the preservation of some dimensions of data ambiguity but excludes others. For example, Figure 2 does not force artificial clarity on the identification of the main unit of analysis, and it conceptualizes technology adoption as an evolutionary phenomenon that interacts in a dynamic way with other issues important to the firm (Langley & Truax, 1994). Yet this representation gives no room to such factors as power, conflict, and emotion. In part, the range of possibilities for mapping depends on the researcher's objectives and creativity (e.g., see Newman & Robey, 1992, for ways of representing encounters between actors on process diagrams). However, graphical forms may be biased toward the representation of certain types of information and against others. Relations of temporal precedence, authority, and influence between objects or individuals are quite easily represented. Continuous traces could even be used to represent the levels of key variables (e.g., financial performance). However, emotions and cognitions are less easy to express in this way, being more difficult to temporally pin down.

The graphical strategy, thus, offers a means of data reduction and synthesis that is less radical and more flexible than that used in the quantification strategy (moderate *accuracy*). However, unless supported by other methods, the conclusions derived from it can have a rather mechanical quality, dealing more with the surface structure of activity sequences than with the underlying forces driving them. For this reason its conceptualizations will tend to be of moderate *generality*. The approach can produce useful typologies of process components, but attempts to reach beyond this to deeper generalizations are often less parsimonious because of the large number of variations possible and the difficulty of predicting which ones will occur and why (moderate *simplicity*).

Temporal Bracketing Strategy

The time scale along the bottom of Figure 2 is decomposed into three successive "periods." These periods do not have any particular theoretical significance. They are not "phases" in the sense of a predictable sequential process but, simply, a way of structuring the description of events. If those labels were chosen, it was because there is a certain continuity in the activities within each period and there are certain discontinuities at its frontiers (Langley & Truax, 1994). Many temporal processes can be decomposed in this way, at least partly, without presuming any progressive developmental logic. However, beyond its descriptive utility, this type of temporal decomposition also offers interesting opportunities for structuring process analysis and sensemaking. Specifically, it permits the constitution of comparative units of analysis for the exploration and replication of theoretical ideas. This can be especially useful if there is some likelihood that feedback mechanisms, mutual shaping, or multidirectional causality will be incorporated into the theorization. We see this strategy at work in the contributions of several process researchers (e.g., Barley, 1986; Denis, Langley, & Cazale, 1996; Doz, 1996; Dutton & Dukerich, 1991).

We call this strategy "bracketing" in reference to Gidden's (1984) structuration theory—a classic example of a perspective involving mutual shaping. At the heart of structuration theory is the idea that the actions of individuals are constrained by structures (including formal and informal rules and norms) but that these actions may also serve to reconstitute those structures over time. Because mutual influences are difficult to capture simultaneously, it is easier to analyze the two processes in a sequential fashion by temporarily "bracketing" one of them (Giddens, 1984). The decomposition of data into successive adjacent periods enables the explicit examination of how actions of one period lead to changes in the context that will affect action in subsequent periods.

In his study of structuring in two radiology departments following the acquisition of CT scanners, Bailey (1986) consciously adopts this approach. He observed how the initial institutional context of the departments studied affected the pattern of interactions between radiologists and technicians and then how these patterns evolved and led to changes in the institutional context. This, in turn, became the point of departure for another phase of structuring. His detailed process data were analyzed and compared across successive periods separated by discontinuities in the institutional context, producing a compelling account of the role of technology in the evolution of structure.

In their study of strategic change under ambiguous authority, Denis et al. (1996) also adopted this strategy in order to better understand the mutual linkages between the tactics used by the members of a management team and the evolution of leadership roles within it. These were traced over five periods, separated by discontinuities in team membership. Denis et al. (1996) observed that certain types of tactics favor the creation of a unified team with the power to successfully promote change. However, once the team is created, the temptation and the possibility of using more coercive tactics lead to the fragmentation of the team, even as the change is solidified. Alternating dynamics, thus, are observed in successive periods. Again, the "periods" become units of analysis for replicating the emerging theory. Doz (1996) used a similar approach to trace patterns in the cycles of learning and reevaluation associated with strategic alliance development.

With this strategy, a shapeless mass of process data is transformed into a series of more discrete but connected blocks. Within phases, the data are used to describe the processes as fairly stable or linearly evolving patterns. Evidence is also drawn together to examine how the context affects these processes, and what the consequences of these processes are on the future context and other relevant variables of interest. Discontinuities lead to replication of the analysis in a new phase.

This sensemaking strategy fits well with a nonlinear dynamic perspective on organizational processes, and it can quite easily handle eclectic data that include events, variables, interpretations, interactions, feelings, and so on. Because of its internal replication possibilities, one or a few cases may be sufficient to produce useful insights (all studies cited in this section are based on one or two cases only). However, temporal decomposition can create certain distortions. For example, there is no a priori guarantee that discontinuities will naturally synchronize themselves to produce unequivocal periods. Overall, then, *accuracy* is likely to be moderate to high, depending on the appropriateness of the temporal decomposition and the robustness of the analysis to different periodizations. Conceptualizations emerging from the process are unlikely to be very *simple*, although they stand a better chance of dealing with fundamental process drivers than those produced by certain other strategies. Assuming that they have been derived inductively, they will also have moderate *generality*, until tested on more data.

Synthetic Strategy

One recurring criticism of process theorizing is that despite its capacity to produce enriched understanding and explanation, it often lacks predictive power (Rumelt, 1997; Van de Ven, 1992). With the sensemaking strategy that we have termed *synthetic*, the researcher takes the process as a whole as a unit of analysis and attempts to construct global measures from the detailed event data to describe it. The researcher then uses these measures to compare different processes and to identify regularities that will form the basis of a predictive theory relating holistic process characteristics to other variables (e.g., outcomes and contexts). The work of Eisenhardt and colleagues (1989a,b; Eisenhardt & Bourgeois, 1988) on decision making in high-velocity environments is the obvious exemplar for this strategy. Others include Meyer and Goes' (1988) work on technology adoption and Bryson and Bromiley's (1993) work on new product planning and implementation.

When this strategy is used, the original process data are transformed from stories composed of "events" to "variables" that synthesize their critical components. The emerging models, thus, are "variance theories"—not "process theories"—in Mohr's (1982) words. For example, Eisenhardt (1989a) compared eight cases of decision making and developed a causal model to explain decision speed as a function of five process constructs: (1) the type of information used, (2) the pattern of alternatives examined, (3) the advice process adopted, (4) the conflict-resolution approach used, and (5) the degree of integration of decisions. In this case the constructs were developed through inductive exploration and coding of case narratives, as well as certain quantitative indicators. Their linkages to the dependent variable (speed) were verified through tabular displays and investigation of the mechanisms by which the effects were obtained, drawing on both the data and existing theory.

One interesting aspect of these process variables is that they are not necessarily the standard process variables (e.g., use of planning and rationality) that might have been chosen had the researcher simply developed a questionnaire-based study (e.g., cf. Dean & Sharfman, 1996). Rather, they incorporate more subtle nuances, including aspects of timing (e.g., simultaneity of alternatives, deadline versus leader-driven conflict resolution, and real-time versus delayed information), that could only be detected as important through close contact with real processes. In this way detailed process data can lead to more meaningful and potentially more powerful explanatory variables for nomothetic research (see also Nutt, 1993, for another example).

However, this is not process theory; the complexities of the probabilistic interaction of events, parallel and alternate tracks, patterns of mutual shaping over time, and evolving performance have been compressed into positions on a small number of scales that can now be related to a single overall "success" assessment. In fact, it is clear that despite major investments in the collection of process data, synthetic variance models exert an inexorable attraction. As soon as researchers become interested in understanding the reasons for different outcomes, they tend to be drawn into formulating the problem in terms of explanatory variables (see, for example, even the major longitudinal studies on strategic change processes by Hinings & Greenwood, 1988, and by Pettigrew & Whipp, 1991). Such an approach can generate important conclusions—often richer and more credible ones than could be obtained from thinner cross-sectional data, because the causal links are more explicitly traceable. Nevertheless, as with the quantification strategy, care must be taken not to ditch the detailed temporal understanding obtained for its shadow. This means drawing (as the researchers cited do) on the entire qualitative database to show *how* and *why* the variables identified lead to the consequences predicted.

In terms of data requirements, the synthetic strategy requires a clear definition of the boundaries of the processes studied and a level of abstraction high enough to permit the comparison of several cases (*accuracy* will therefore be moderate at best). It also requires sufficient cases to allow satisfactory comparison and conclusion drawing (e.g., Eisenhardt, 1989a, used 8 cases and Nutt, 1984, included 78 cases). This tends to correspond to a thinner level of detail in process tracing for each case than for other strategies. When the number of cases is moderate, this adds to the need to show strong grounding of the explanatory mechanisms within the data itself and to connect these to other literature, in order to make the relationships identified credible and to enhance external validity (Eisenhardt, 1989b). Like the quantification strategy, this strategy has the advantage of producing relatively *simple* theoretical formulations that are also moderately *general* because they have been conceived to make sense of data from a number of cases.

Qualitative/Quantitative Data versus Process/ Variance Analysis: Other Approaches

The description of seven sensemaking strategies for process data is now complete. In my analysis I assumed that the problem was to construct theory from *qualitative* "process data" collected in close contact with real contexts. Thus, I emphasized the large area of overlap between qualitative data and process theorizing. However, it is important to note that qualitative data do not necessarily demand process analysis and that process theory can be built from quantitative data.

The first point should be obvious. Qualitative data can be used for many purposes that have little to do with how events are sequenced over time. For example, they can be used to develop rich descriptions of meanings, behaviors, and feelings evoked by workplace issues at one point in time (e.g., Pratt & Rafaeli, 1997, on organizational dress). They can be used to understand individuals' mental maps of the elements in their world (Huff, 1990) and so on. Some but not all of the seven sensemaking strategies I have described can be used in these non-process situations (e.g., grounded theory in the first example and visual mapping in the second), but my discussion does not pretend to deal with these rather different applications.

The second issue is whether process theory can be derived from purely quantitative data, such as archival time series or panel questionnaires. It can, of course, using similar statistical techniques to those mentioned under the quantification strategy, but this is not a perspective that I have explored or favored here. Quantitative time series constitute rather coarse-grained outcroppings of events and variables over time: they skim the surface of processes rather than plunge into them directly. Nevertheless, such methods are rapidly penetrating the strategy field and contributing significantly to a more dynamic understanding of strategic evolution (e.g., Barnett & Burgelman, 1996). As such, they are complementary to the approaches discussed here. Indeed, as Ven de Ven and colleagues' work has shown, there is much to be gained from collecting both quantitative time series *and* qualitative stories in the same process research effort (Brewer & Hunter, 1989).

It is also worth mentioning another quantitative approach to developing process theory that, at first sight, appears to be even more distant from real processes because its "data" are entirely artificial. This is computer simulation, of which the most influential examples are Cyert and March's (1963) behavioral theory of the firm and Cohen, March, and Olsen's (1972) "garbage can" model of organizational choice (but see also Sastry's, 1997, formalization of the punctuated equilibrium model of change and Lant & Mezias's, 1992, work on organizational learning). As Weick (1979) himself noted, these models are high in *simplicity* and *generality* but generally weak in terms of *accuracy*. Real data may have been collected at some time and may have inspired the ideas behind the model. But, in most cases, the model is not linked to specific empirical observations.[2]

Yet, such models have several advantages. First, provided their basic assumptions are intu-

[2] Note, however, that empirical calibration can be attempted and may add to the credibility of such models. See, for example, Hall's (1976) study of the decline and failure of the *Saturday Evening Post*.

itively reasonable, the models can be used as sites for risk-free experimentation. Second, because they are not constrained by real measurements, they can deal with constructs that would be unobservable in reality (e.g., managerial energy in the garbage can model). Third, they may allow the detection and correction of inconsistencies in existing theoretical frameworks (e.g., Sastry, 1997). But, above all, these models are powerful when they show how a few simple and plausible mechanisms can generate complex behavior patterns that we all recognize. Paradoxically, just like the narrative strategy, which is, on the contrary, very deeply rooted in real-life processes, the strength of a simulation comes from its capacity to create a feeling of "déjà vu," making sense of previously impenetrable experience. (It is surely no accident that the garbage can model has been popular among academics!)

DISCUSSION AND CONCLUSION

There are constant calls in the scholarly literature for more in-depth process research that will enable us to understand organizational phenomena at more than a superficial level. And yet, when we actually go out and get the data required to achieve this, we find that the deep understanding we sought does not magically leap out at us. Process data are notoriously challenging. In this article I have examined seven generic strategies for making sense of them (see Table 1). In the following discussion I review the strategies from a number of different angles. First, I compare their positioning according to Weick's (1979) criteria. Second, I situate them within a more general framework and examine the ways in which they can be combined. Third, I consider the roles of induction, deduction, and inspiration in the theory development process.

Accuracy, Simplicity, and Generality

All seven strategies have unique strengths. But all have weaknesses. As Thorngate (1976) and Weick (1979) indicate, any research strategy demands tradeoffs among accuracy, generality, and simplicity. In particular, accuracy tends to conflict with both simplicity and generality, while, at least in my analysis, simplicity and generality tend to be more compatible (see Table 1). The approximate positioning of each strategy with respect to the dimensions is illustrated in Table 2. For the sake of contrast, I have also included the computer simulation approach in this diagram.

This portrait of the different strategies does not provide an answer to the question "Which strategy is best?" However, it maps the terrain and shows that "good" process research can take a variety of routes. Some strategies favor accuracy, remaining more deeply rooted in the raw data (narrative strategy and grounded theory). Others are more reductionist, although they allow the development and testing of parsimonious theoretical generalizations (quantification, synthetic strategy, and simulation).

Overall (see Figure 2), the different strategies tend to run the length of an "efficient frontier" that represents the range of tradeoffs between accuracy and simplicity. From a pragmatic standpoint, the two extremes (simulation and narrative) are riskier because of the sacrifices they require on key dimensions. In addition, the alternate templates approach is a special case not positioned within the table. While each individual template provides simplicity but limited accuracy, between them multiple templates can increase overall accuracy while maintaining simplicity and generality, as long as the temptation to integrate divergent perspectives is avoided. The idea that multiple templates can produce better understandings may also be generalized to the use of multiple strategies, again provided the combinations are complementary and provided simplicity is not compromised in the attempt to achieve integration.

TABLE 2
Sensemaking Strategies and Accuracy, Simplicity, and Generality[a]

Strategy	Accuracy	Simplicity	Generality
	High	Low	Low
Narrative	↑	↓	↓
Grounded theory			
Temporal bracketing			
Visual mapping			
Synthetic strategy			
Quantification			
Computer simulation			
	Low	High	High

[a] The orderings in this table are approximate; there are variations among specific applications. In particular, while accuracy and simplicity are almost always in opposition to one another, the generality of emerging theories will depend on other factors, such as the degree and scope of replication and the source of the conceptual ideas.

Variations, Permutations, and Combinations

One way to explore the potential for combinations of sensemaking strategies and to organize them within a common framework is to consider them as falling into three sequentially linked groups that I term *grounding strategies*, *organizing strategies*, and *replicating strategies*.

The grounded theory and alternate templates strategies can be considered as grounding strategies because they suggest two different sources for concepts that can be used within the context of other strategies. Grounded theory involves *data*-driven categories, whereas the alternate templates strategy involves *theory*-driven constructs. The two strategies, thus, represent the purist forms of inductive and deductive reasoning, respectively. Both forms of grounding can contribute to the construction of narratives and visual maps, and both strategies can be used as tools in the comparative analysis of cases (the synthetic strategy) or the comparative analysis of phases (temporal bracketing). Alternate templates also can be used to test quantitative process models.

The narrative and visual mapping strategies can be viewed as organizing strategies because, as described earlier, they are ways of descriptively representing process data in a systematic organized form. As such, they often, although not always, constitute the initial rather than final steps in the sensemaking process. Both narratives and visual maps can serve as intermediary databases for the identification of phases (temporal bracketing), events (quantification), and constructs (synthetic strategy) and for the formulation of hypotheses and propositions. Since narratives are closer to the raw data than visual maps, they may also precede their development.

Finally, the remaining three strategies (temporal bracketing, quantification, and synthesis) can be considered replicating strategies since they represent different ways of decomposing the data for the replication of theoretical propositions (by phase, by event, and by case). These strategies can draw on almost any or all of the others. Quantified event data may also be aggregated for use in synthetic case comparisons (Eisenhardt, 1989b) or for comparative analysis of phases (e.g., see Barley, 1986). Conversely, phase-by-phase information (Garud & Van de Ven, 1992) or case-by-case information (Cheng & Van de Ven, 1996) may be incorporated into quantitative models.

This categorization imposes some order on what may so far have seemed a rather eclectic typology of sensemaking approaches—but not, I hope, too much order. The last thing I wish to advocate is a homogenous recipe for theorizing from process data that leaves no room for loose ends or creativity. The choice of strategies is more than just a case of desired levels of accuracy, simplicity, and generality and more than just a case of picking logically linked combinations; it is also a question of taste, of research objectives, of the kind of data available, and of imagination. Moreover, variety contributes to richness. The seven sensemaking strategies produce seven different senses. Method and theory are closely intertwined. As I have noted, some strategies tend to focus on the *meaning* of processes for individuals—that is, the way they are experienced (grounded theory and narrative strategy). Others are better equipped for tracing overall temporal *patterns* (visual mapping, quantification, and grounded theory). Some more easily reveal driving process motors or *mechanisms* (alternate templates, temporal bracketing, and quantification), and some are more useful for *prediction* (synthetic strategy). There are also undoubtedly other strategies with which I am less familiar (e.g., literary or critical approaches) that could make different kinds of sense again.

Induction, Deduction, and Inspiration

Beyond the individual strategies and their biases, my reading of the literature and my own experience reinforce the belief that there is a step in the connecting of data and theory that escapes any deliberate sensemaking strategy a researcher might decide to apply. As Mintzberg (1989) insists, analysis does not produce synthesis. Theory development is a synthetic process. Whatever strategy is used, there will always be an uncodifiable step that relies on the insight and imagination of the researcher (Weick, 1989). Wolcott (1994) distinguishes clearly between the two processes of analysis and interpretation. Interpretation corresponds to this creative element. Clearly, this does not absolve the researcher from the need to test his or her interpretations systematically. Analysis, thus, is important to stimulate and verify theoretical ideas. But, unfortunately for those who seek the magic bullet, it cannot produce them alone.

This also means that persistent calls for codification of qualitative methods (Larson & Löwendahl, 1995; Orton, 1997) can reach a point of diminishing returns, because we just do not know and cannot tell where that critical insight came from. Nobody asks quantitative researchers to explain how they thought up their conceptual frameworks (although Sutton, 1997, suggests that many may have been inspired by "closet" qualitative research!).

Another way to think about this is that theory building involves three processes: (1) induction (data-driven generalization), (2) deduction (theory-driven hypothesis testing), and (3) inspiration (driven by creativity and insight). "Inspiration" may be stimulated by empirical research, by reading, by thought experiments, and by mental exercises (Weick, 1979, 1989), but its roots are often untraceable. It draws indiscriminately on formal data, experience, a priori theory, and common sense. It works when it succeeds in creating new and plausible connections between all of these that can be made explicit as theoretical products, exposed to the scrutiny of others, and verified.

In closing, this brings me to the question of the nature of the linkage between data and theory in process research. In theorizing from process data, we should not have to be shy about mobilizing both inductive (data-driven) approaches and deductive (theory-driven) approaches iteratively or simultaneously as inspiration guides us. There is room not only for building on existing constructs to develop new relationships (Eisenhardt, 1989b) but for designing process research that selectively takes concepts from different theoretical traditions and adapts them to the data at hand, or takes ideas from the data and attaches them to theoretical perspectives, enriching those theories as it goes along. There is also room for developing new strategies for understanding processes that mix and match those I have presented here or that take a new tack entirely. Sensemaking is the objective. Let us make sense whatever way we can.

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