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THE APPLICATION OF CLUSTER ANALYSIS IN STRATEGIC MANAGEMENT RESEARCH: AN ANALYSIS AND CRITIQUE

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Cluster analysis is a statistical technique that sorts observations into similar sets or groups. The use of cluster analysis presents a complex challenge because it requires several methodological choices that determine the quality of a cluster solution. This paper chronicles the application of cluster analysis in strategic management research, where the technique has been used since the late 1970s to investigate issues of central importance. Analysis of 45 published strategy studies reveals that the implementation of cluster analysis has been often less than ideal, perhaps detracting from the ability of studies to generate knowledge. Given these findings, suggestions are offered for improving the application of cluster analysis in future inquiry.

Strategic management research focuses on the relationships among strategy, environment, leadership/organization, and performance (Summer *et al.*, 1990). Each of these four constructs is multidimensional. Strategy, for example, can be viewed as composed of process and content concerns (Ansoff, 1965), scope and resource deployments (Hofer and Schendel, 1978), or corporate, business, and functional-level issues (Andrews, 1971). Similarly, environment may be divided into task and general elements (Thompson, 1967). Leadership/organization encapsulates a variety of firm characteristics, including structure and culture (Summer *et al.*, 1990). Performance consists of at least three categories: financial, operational, and overall effectiveness (Venkatraman and Ramanujam, 1986). The multidimensionality of these constructs creates a conceptual challenge in that a vast array of specific combinations could be developed along these dimensions to describe organizations.

One popular response to this challenge has been to identify 'organizational configurations': sets of firms that share a common profile along conceptually distinct variables (Meyer, Tsui, and Hinings, 1993; Miller and Mintzberg, 1983). For example, Mintzberg (1989) identified configurations whose members were similar in size, age, formality, and centralization. One is an 'entrepreneurial' configuration that consists of firms that are simultaneously small, young, informal, and have centralized decision making. In contrast, 'professional bureaucracies' are large, old, formalized, and rely on decentralized decision making. Examination of organizational configurations have been conducted under many labels, including strategic groups (e.g., Hatten and Schendel, 1977), organizational typologies (e.g., Miles and Snow, 1978), taxonomies (e.g., Galbraith and Schendel, 1983) and archetypes (e.g., Miller and Friesen, 1978). Thus, in essence, organizational configurations (or, more simply, configurations) as used here and elsewhere (e.g., Dess, Newport, and Rasheed, 1993; Ketchen, Thomas, and Snow, 1993) is a cover term that encapsulates a variety of research streams. Regardless of the specific label, the underlying assumption is that configurations represent a way to meaningfully capture the complexity of organizational reality.

Due to strategic management's emphasis on

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identifying groups of similar organizations, cluster analysis has been a popular methodology following its introduction into the field in a stream of research often referred to as the Purdue brewing studies (i.e., Hatten, 1974; Hatten and Schendel, 1977; Hatten, Schendel, and Cooper, 1978). Prior to these efforts, the search for configurations had been centered in the industrial/organization economics literature, where groups were defined across narrow sets of variables, often only one or two (e.g., Hunt, 1972; Porter, 1973). Such analyses allowed mapping of the structure of samples, but were too coarse-grained to capture the multidimensionality of the constructs of interest in strategy research (Hatten and Hatten, 1987). Cluster analysis, which takes a sample of elements (e.g., organizations) and groups them such that the statistical variance among elements grouped together is minimized while between-group variance is maximized, addresses this limitation. Specifically, cluster analysis permits the inclusion of multiple variables as sources of configuration definition. For example, Hatten *et al.* (1978) drew on 16 variables representative of manufacturing, financial, and market strategies as well as environmental characteristics. Thus, cluster analysis can provide very rich descriptions of configurations without overspecifying the model.

However, the use of cluster analysis in strategic management research has come under frequent attack (e.g., Barney and Hoskisson, 1990; Meyer, 1991; Thomas and Venkatraman, 1988). One cause for concern is the extensive reliance on researcher judgment that is inherent in cluster analysis. This is an issue throughout the process of using the technique, but perhaps most troubling is the fact that, unlike techniques such as regression and analysis of variance, cluster analysis does not offer a test statistic (such as an F-statistic) that provides a clear answer regarding the support or lack of support of a set of results for a hypothesis of interest. Instead, to a large extent, it is the researchers who are the arbiters of the meaning of results acquired through cluster analysis.

A second major issue for critics is their perception that most applications of cluster analysis in strategy have lacked an underlying theoretical rationale. Often clustering dimensions seem to be selected haphazardly (Reger and Huff, 1993). Without a theoretical foundation, however, the clusters that are identified may not reflect any real conditions but instead may simply be statistical artifacts that capitalize on random numerical variation across organizations (Thomas and Venkatraman, 1988). Further, cluster analysis' sorting ability is powerful enough that it will provide clusters even if no meaningful groups are embedded in a sample (Barney and Hoskisson, 1990). Thus, cluster analysis has the potential not only to offer inaccurate depictions of the groupings in a sample but also to impose groupings where none exist.

These concerns and others have led some observers to suggest that the frequent use of cluster analysis is an embarrassment to strategic management. For example, when Meyer (1991) asked prominent researchers to assess the field, cluster analysis was singled out as a source of 'methodological stigma'. Further, one claimed that 'the empiricism inherent in this method has been forever branded upon our collective backside' (Meyer, 1991: 826). Fueling this contempt are the equivocal results that cluster analysis often provides. The best illustration is strategic groups research, which has been unable to consistently find a group membership–performance link (Barney and Hoskisson, 1990). Thus, at the moment, the value of cluster analysis to strategy research is in doubt.

Despite the controversy surrounding cluster analysis, to date there has been no comprehensive assessment of the efficacy of its use. Thus, the purpose of this paper is to examine the application of cluster analysis in the field of strategic management. Our aim is not only to evaluate the past use of cluster analysis but also to lay out an agenda to guide future research toward making the best possible use of the technique. We begin by describing the issues identified in methodological research as critical when using cluster analysis as well as the appropriate ways for strategy research to address them. Next, we document all of the strategy articles published in the *Academy of Management Journal, Journal of International Business Studies, Journal of Management, Management Science*, and *Strategic Management Journal* from 1977 to 1993 that use the technique. Based on a comparison of existing practices with the guidelines developed through our review of methodological research, we then offer recommendations designed to maximize the value of cluster analysis to strategic management.

CRITICAL ISSUES IN THE USE OF CLUSTER ANALYSIS

This section describes the key issues involved when using cluster analysis. It is important to note that there is considerable variation in how unified methodological experts are regarding these issues. Specifically, experts tend to agree on *what* the important issues are, but often disagree about *how* to address them. As described below, there are some limited areas of agreement regarding appropriate 'remedies' for clustering issues. There is a larger body of issues, however, for which no consensus has emerged. Here we describe the disagreements and discuss how the issue should be dealt with in strategic management research to satisfy its own, often unique, requirements. Thus, in sum, one aspect of this section is the collection and synthesis of the wisdom offered by methodological experts. A perhaps more important element is the identification of the strengths, weaknesses, and trade-offs involved with each issue as it relates to the needs of the strategic management literature.

To avoid overlap with material that is available elsewhere, we do not provide detailed explanations of the mechanics of specific aspects of cluster analysis. Such information is offered by a number of prior efforts (e.g., Aldenderfer and Blashfield, 1984; Everitt, 1980; Hair *et al.*, 1992; Lorr, 1983; Punj and Stewart, 1983); the interested reader is referred to these sources.

Clustering variables

Choosing the variables along which to group observations is the most fundamental step in the application of cluster analysis, and thus, perhaps the most important. This process involves three critical issues: (1) how to select variables; (2) whether or not to standardize variables; and (3) how to address multicollinearity among variables.

Selection of variables

There are three basic approaches to identifying appropriate clustering variables: inductive; deductive; and cognitive (Ketchen *et al.*, 1993). The *inductive* approach focuses on exploratory classification of observations. In other words, neither the clustering variables nor the number and nature of the resultant groups are tightly linked to deductive theory. Instead, the inductive approach seems to follow McKelvey's (1975, 1978) suggestion to consider as many variables as possible because one cannot know in advance which variables differentiate among observations. Thus, the use of many clustering variables is expected to maximize the likelihood of discovering meaningful differences. One example of an inductive study is Hambrick (1983), where the author used 10 environmental variables to develop a taxonomy of mature industries with no *a priori* expectations about the likely nature of the resultant types.

When following a *deductive* approach, the number and suitability of clustering variables, as well as the expected number and nature of groups in a cluster solution, are strongly tied to theory (Ketchen *et al.*, 1993). Methodological research suggests that using deductive theory to guide variable choice is often wise. Cluster analysis derives the most internally consistent groups across all variables, thus irrelevant variables can cause a deterioration of a solution's validity (Punj and Stewart, 1983). An implication is that, when possible, studies should focus on variables with solid theoretical foundations. One example of a deductive study is Lawless and Finch (1989), where theory-based predictions of the relative performance of different configurations are tested within each type of environment identified by Hrebiniak and Joyce (1985).

The *cognitive* approach can be viewed as a 'conceptual cousin' of the inductive approach because both avoid making theory-based predictions. While inductive configurations are defined along dimensions that researchers view as important, the cognitive approach relies on the perceptions of expert informants such as industry executives (e.g., Mascarenhas and Aaker, 1989a, 1989b; Reger and Huff, 1993) to define clustering variables. This latter approach has its roots in research on interpretation in organizations, which posits that it is the meaning that top managers attach to phenomena, not 'objective' characteristics, which directs subsequent organizational action (Dutton, Fahey, and Narayanan, 1983) and performance (Thomas, Clark, and Gioia, 1993). One implication is that configurations based on the perceptions of top managers may be crucial to understanding any given setting (Porac and Thomas, 1990).

We suggest that the approach to selecting variables should match a study's purpose. When attempting to explain or predict relationships, a theoretical foundation is advisable, if not required

(Bacharach, 1989). Hence, studies designed to discern the nature and extent of links between key constructs (e.g., organizational configurations and performance) should rely on a deductive approach (Ketchen *et al.*, 1993). However, strategy research is often exploratory, with a focus on theory building rather than testing. Here variables should be chosen in a way that fosters rich description of a sample's characteristics (Meyer *et al.*, 1993). Both the inductive and cognitive approaches fit this requirement. The latter may often be preferred, however, because its use of experts (often top managers) enhances confidence that the variables are important in a particular data set.

Standardization of variables

Because cluster analysis groups elements (e.g., firms) such that the distance between groups along all clustering variables is maximized, variables with large ranges (i.e., where elements are separated by large distances) are given more weight in defining a cluster solution than those with small ranges (Hair *et al.*, 1992). As a result, a subset of variables can dominate the definition of clusters. The 'remedy' is standardization, which transforms the distribution of elements along variables so that each has a mean of zero and a standard deviation of one. This process allows variables to contribute equally to the definition of clusters but may also eliminate meaningful differences among elements (Edelbrock, 1979). This illustrates a dilemma of using cluster analysis: for any remedy, there is almost always an associated cost.[1]

Given this trade-off, whether to standardize clustering variables is an equivocal issue. Some experts (Hair *et al.*, 1992; Harrigan, 1985) recommend standardization, perceiving a need to eliminate the potential effects of scale differences among variables. Others offer evidence that standardization has no significant effects (Edelbrock, 1979; Milligan, 1980). Aldenderfer and Blashfield (1984) advise that because standardization may have adverse effects, it should be addressed on a case-by-case basis. However, they do not offer specific guidance about how to approach a particular case.

Because results may differ solely based on standardization, we suggest that analyses be done both using and not using standardization. If clusters are inconsistent across the two solutions, the validity of each should be assessed; the solution exhibiting the highest validity might then be adopted.

Multicollinearity among variables

High correlation among clustering variables can be problematic because it may overweight one or more underlying constructs. Thus, researchers may want to correct multicollinearity, especially if it is desirable that constructs be equally weighted. Hair *et al.* (1992) suggest using the Mahalanobis distance measure, which both standardizes variables and adjusts for high correlations. As noted above, however, standardization is controversial. Another problem is that statistical programs such as SAS and SPSS do not offer this measure.

Multicollinearity can also be addressed through subjecting variables to factor analysis (specifically, principal components analysis with orthogonal rotation) and using the resultant uncorrelated factor scores for each observation as the basis for clustering (Punj and Stewart, 1983). However, this technique is controversial because researchers often drop all factors with low eigenvalues (a statistic representing the amount of variance explained by a factor). The excluded factors may represent unique, important information (Dillon, Mulani, and Frederick, 1989), meaning that a less-than-optimal set of clusters may result. Thus, as with standardization, any remedy for multicollinearity has a cost.

Because both methods of correcting multicollinearity have potential pitfalls, researchers should attempt to assess the impact of their chosen technique. We suggest that the ideal approach is to perform a cluster analysis multiple times changing only the method of addressing multicollinearity. Consistent group assignments despite different methods would be evidence of stability whereas inconsistent assignments would suggest a tenuous cluster solution.

Clustering algorithms

The selection of appropriate clustering algorithms (i.e., the rules or procedures followed to sort observations) is critical to the effective use of cluster analysis (Punj and Stewart, 1983). There are two basic types of algorithms: hierarchical and nonhierarchical.

Hierarchical algorithms progress through a series of steps that build a tree-like structure by either

[1] We wish to thank an anonymous reviewer for this insight.

adding individual elements to (i.e., agglomerative) or deleting them from (i.e., divisive) clusters. The five most popular agglomerative algorithms are single linkage, complete linkage, average linkage, centroid method, and Ward's method (Hair *et al.*, 1992). The differences among them lie in the mathematical procedures used to calculate the distance between clusters. Each has different systematic tendencies (or biases) in the way it groups observations. For example, the centroid method has a bias toward producing irregularly shaped clusters. Further, it can only be used with interval or ratio data (Hair *et al.*, 1992). Ward's method tends to produce clusters with roughly the same number of observations (SAS Institute, 1990) and the solutions it provides tend to be heavily distorted by outliers (i.e., observations with extreme values—Milligan, 1980). Given such tendencies, there should be a match between the algorithm selected and the underlying structure of focal data (i.e., sample size, distribution of observations, and what types of variables are included—nominal, ordinal, ratio, or interval). Thus, for example, the centroid method should only be used when (a) data are measured with interval or ratio scales and (b) clusters are expected to be very dissimilar from each other. Likewise, Ward's method is best suited for studies where (a) the number of observations in each cluster are expected to be approximately equal and (b) there are no outliers.

The use of divisive methods in the social sciences has been limited to the field of archaeology (e.g., Whallon, 1972). As a result, divisive methods are not well known in strategic management. There are two types of divisive techniques: monothetic and polythetic (Everitt, 1980). The monothetic techniques are used with binary (i.e., dichotomous) variables. A sample is divided into groups based on each observation's possession (or lack) of an attribute. Groups are then broken into smaller groups based on the presence or absence of individual attributes. Because this procedure groups observations through *successive* rather than *simultaneous* application of variables, it would not be useful for configurational research as it has traditionally been conducted in strategic management.

Polythetic divisive methods, in essence, are the logical opposite or 'mirror image' of agglomerative methods. Agglomerative methods initially view each observation as a separate cluster and then compile them into successively smaller numbers of groups, eventually putting all observations into one group. It is the task of the researcher to decide at what point the number of groups is appropriate. Polythetic divisive methods follow the opposite approach: all observations are in one group initially, then observations are divided into smaller groups until eventually each observation becomes a separate cluster. Again, the researcher must decide what level of division is appropriate. Although the methods start at opposite ends of the clustering process, the number of groups identified should be the same regardless of which one is used. Thus, the distinction between the two methods is of little practical consequence. Should one wish to use divisive methods, however, a procedure using matrix algebra is described in Everitt (1980).

All hierarchical algorithms suffer from several problems. First, researchers often do not know the underlying structure of a sample in advance, making it difficult to select the 'correct' algorithm. Second, these algorithms make only one pass through a data set, thus poor cluster assignments cannot be modified.[2] Finally, solutions are often unstable when cases are dropped, especially when a sample is small (Jardine and Sibson, 1971). This is troublesome for strategy research, where sample sizes are often small (e.g., 19 in Dess and Davis, 1984; 16 in Lewis and Thomas, 1990). Because of these problems, confidence in the validity of a solution obtained using only hierarchical methods is limited.

Nonhierarchical algorithms (also referred to as K-means or iterative methods) partition a data set into a prespecified number of clusters. Specific nonhierarchical methods vary slightly, but function in essentially the same manner (Hair *et al.*, 1992).

[2] Only one pass is made through the data because of the hierarchical methods treatment of the observations. Focusing on the agglomerative algorithms for a moment, each observation starts as its own individual cluster. On each successive step, the two closest clusters are joined into a new aggregate cluster, thus reducing the number of clusters by one in each step. Eventually, all clusters are joined into one cluster. Multiple passes can not be made because the algorithm would treat the observations as individual clusters in the first step of the next pass. Thus, the same clusters would emerge from clustering the observations again. Given that the divisive methods follow the same process in reverse, the same arguments apply: multiple passes would produce the same results.

However, multiple passes with hierarchical algorithms might be helpful if the initial pass is used as a tool to identify outliers. One could then remove the outliers from the data set (assuming that this would be consistent with the purpose of the study) and run the analysis again. This might be particularly valuable if one has selected an algorithm that is particularly sensitive to outliers (e.g., Ward's method).

After initial cluster centroids (the 'center points' of clusters along input variables) are selected, each observation is assigned to the group with the nearest centroid. As each new observation is allocated, the cluster centroids are recomputed. Multiple passes are made through a data set to allow observations to change cluster membership based on their distance from the recomputed centroids. To arrive at an optimal solution, passes through a data set continue until no observations change clusters (Anderberg, 1973).

Nonhierarchical methods have two potential advantages over hierarchical methods. First, by allowing observations to switch cluster membership, nonhierarchical methods are less impacted by outlier elements. Although outliers can initially distort clusters, this is often corrected in subsequent passes as the observations switch cluster membership (Aldenderfer and Blashfield, 1984; Hair *et al.*, 1992). Second, by making the multiple passes through the data, the final solution optimizes within-cluster homogeneity and between-cluster heterogeneity. Obtaining this improvement, however, requires that the number of clusters be specified *a priori* (Milligan, 1980). In many fields (including strategic management), this is problematic because cluster analyses are often exploratory.

A solution advocated by many experts is to use a two-stage procedure where a hierarchical algorithm is used to define the number of clusters and cluster centroids; these results then serve as the starting points for subsequent nonhierarchical clustering (Hair *et al.*, 1992; Milligan, 1980; Punj and Stewart, 1983). Research has shown that this procedure increases validity of solutions (Milligan, 1980; Punj and Stewart, 1983). The only cost is the extra time and effort required on the researchers' part; a cost we contend is worth bearing. Thus, in summary, the best solutions may be those obtained by using hierarchical and nonhierarchical methods in tandem.

Determining the number of clusters

A variety of techniques are available to determine the number of clusters in a data set. When using hierarchical methods, the most basic procedure is to visually inspect a dendogram, a graph of the order that observations join clusters and the similarity of observations joined. Dendograms resemble decision trees with short 'limbs' representing the joining of observations. A researcher looks for natural clusters of the data that are indicated by relatively dense 'branches'. This method's reliance on interpretation requires that it be used cautiously (Aldenderfer and Blashfield, 1984).

The agglomeration coefficient (i.e., a numerical value at which various cases merge to form a cluster) is the basis for two related techniques. The first method involves graphing the coefficient on a y-axis and the number of clusters on an x-axis. A marked flattening of the graph suggests that the clusters being combined are very dissimilar, thus the appropriate number of clusters is found at the 'elbow' of the graph. Interpreting a graph, however, may be difficult; for example, the elbow may not be pronounced, indicating that there may not be any natural groups in the data (Hambrick and Schecter, 1983). Alternatively, the graph may have more than one elbow, indicating that more than one natural set of clusters fit the data (Aldenderfer and Blashfield, 1984). The second procedure involves examining the incremental changes in the coefficient. A large increase implies that dissimilar clusters have been merged; thus, the number of clusters prior to the merger is most appropriate. A major limitation with this approach is that there may be no large jumps in the coefficient, indicating that there may not be any natural groups in the data. In some cases, there may be several large jumps; this would be evidence for more than one natural set of clusters.

The cubic clustering criterion (CCC) is a measure of within-cluster homogeneity relative to between-cluster heterogeneity. The 'appropriate' number of clusters is indicated by the peaking of the CCC; however, Milligan and Cooper (1985) found that this test may suggest too many clusters. Strategy researchers need to be aware of this potential because several use the CCC (e.g., Fombrun and Zajac, 1987; Mascarenhas, 1989), but many oft-cited methodological works predate Milligan and Cooper's finding (e.g., Aldenderfer and Blashfield, 1984) or ignore the CCC (e.g., Hair *et al.*, 1992).

Finally, *a priori* theory can serve as a nonstatistical tool for determining the number of clusters (Hair *et al.*, 1992). Although *a priori* theory is, by definition, not central to exploratory research, it does provide a benchmark for assessing the results of theory-testing inquiry. For example, comparison of emergent clusters with a theory-based typology can provide evidence regarding the typology's descriptive validity (e.g., Ketchen *et al.*, 1993).

In summary, using a single method to determine the number of clusters is questionable because each method has limitations (Everitt, 1980). Thus, we advocate the use of multiple techniques that can *overcome* each others' shortcomings. For example, as noted above, the CCC may indicate too many clusters. If the CCC is part of an array of techniques and other techniques point to fewer clusters than does the CCC, it might be wise to discount the CCC. Thus, confidence in the number of clusters identified may be greater when determined through the convergence of multiple methods.

Validating clusters

The goals of validation are to ensure that a cluster solution has external validity (i.e., is representative of the general population of interest—Cook and Campbell, 1979) and criterion-related validity (i.e., is useful for the prediction of important outcomes—Kerlinger, 1986). Extreme care in validation is warranted because, despite the rigor used in previous steps, without validation one is not assured of having arrived at a meaningful and useful set of clusters (Punj and Stewart, 1983).

Reliability (i.e., consistency) is a necessary but not sufficient condition of validity (Kerlinger, 1986). Therefore, the reliability of a cluster solution must be established before validity is tested. There are two primary ways to evaluate reliability. First, as advocated above, researchers may perform a cluster analysis multiple times, changing algorithms and methods for addressing multicollinearity. The degree of consistency in solutions indicates reliability (Hair *et al.*, 1992). Second, researchers may split a sample and analyze the two halves independently (Hambrick, 1983). A modified version of this latter procedure is to obtain cluster centroids from half of a sample and use them to define clusters in the other half. In either case, consistency across sample halves indicates reliability (Hair *et al.*, 1992). However, there is no standard for assessing a satisfactory level of consistency, leaving this determination largely to researcher judgment. Also, in some strategy studies, sample sizes may be too small for meaningful clusters to be derived from sample halves. For example, splitting their sample of 18 companies probably would not have been helpful to Reger and Huff's (1993) efforts to establish the reliability of the three strategic groups they found.

If reliability has been demonstrated, attention can turn to external validity. This may be done by cluster analyzing both the sample of interest and a second, similar sample and then assessing the similarity of the results (Hair *et al.*, 1992; Hambrick, 1983). In many strategy studies, however, a 'hold-out' sample is not available. In other instances, the use of a second sample may not even be appropriate. For example, strategic groups are often viewed as industry specific (Thomas and Venkatraman, 1988), and thereby cannot be generalized to another setting. Thus, validation using multiple samples should be used only if consistent with the assumptions underlying a study.

Criterion-related validity can be assessed through significance tests (often multivariate analysis of variance) with external variables (Aldenderfer and Blashfield, 1984; Anderberg, 1973). Such variables should be theoretically related to the clusters, but not used in defining clusters. Given the field's emphasis on defining the strategy–performance relationship (Summer *et al.*, 1990), the external variables in strategy research are often performance measures (e.g., Miller, 1988; Robinson and Pearce, 1988). Significance tests with external variables offer a powerful tool to establish validity of a cluster solution because the technique uses a test static (often an *F*-statistic), thereby avoiding having the researcher provide the meaning of results. External variables are expensive to obtain in many fields (Bailey, 1994), but, in strategy research, the availability of archival data often solves this problem. Thus, we strongly advocate the use of this technique whenever possible.

In sum, techniques are available to help establish reliability and external validity, but the value of these techniques is limited because they use cluster analysis and thus are subject to its inherent problems, most notably the reliance on researcher judgment. More promising is the use of significance tests with external variables to establish criterion-related validity. Overall, we suggest that reliability and validity will be questionable whenever a research design uses clustering techniques in isolation. Only when cluster analysis is augmented with additional techniques—especially ones that are less subject to researchers' biases—can confidence in the results obtained be strong.

Summary

As described above, strategy researchers using cluster analysis face an array of challenges. Nonetheless, the technique has been widely used over the last 15 years. Much of this research (e.g., the strategic groups literature) has seemingly produced equivocal results, perhaps in part because of the role played by researcher judgment throughout the clustering process. Given the controversy surrounding cluster analysis, we examined the extent to which the technique has been used appropriately. A description of this effort and the related results are presented below.

METHOD

To identify important strategy studies that have used cluster analysis, we examined the 16 journals comprising the 'forum for strategy research' (MacMillan, 1991). Of these journals, five with a non-empirical orientation were eliminated,[3] leaving 11 journals as sources of empirical strategy research, including the *Academy of Management Journal (AMJ), Administrative Science Quarterly, Decision Science, Journal of General Management, Journal of International Business Studies (JIBS), Journal of Management (JOM), Journal of Management Studies, Management Science (MS), Omega, Rand Journal of Economics*, and *Strategic Management Journal (SMJ)*. These remaining journals were searched for strategy studies using cluster analysis for the period from 1977 (the year of the first published strategy research using cluster analysis—Hatten and Schendel, 1977) through 1993. Strategy studies were defined as empirical research efforts examining relationships among strategy, environment, leadership/organization, and performance (Summer *et al.*, 1990).

A total of 45 studies (see Appendix) were located.[4] The use of cluster analysis has increased over time: seven studies were found in the period's first half (1977–85) whereas 38 were found in the second half (1986–93). Most studies ($n=28$, 62%) were found in *SMJ*. Eight studies (18%) were found in *AMJ*, five (11%) in *JIBS*, three (7%) in *JOM*, and one (2%) in *MS*. The distribution of studies across these journals is not surprising, as *SMJ* publishes only strategy-related inquiry, while *AMJ* and *JOM* contain studies representative of the entire management discipline and *JIBS and MS* include research from a wider spectrum of business disciplines. It is interesting to note, however, that the other six empirical journals contained no studies using cluster analysis.

Coding procedure

The critical issues described above served as the basis for our coding scheme. Specifically, each study was coded according to issues involving clustering variables, clustering algorithms, determining the number of clusters, and validating clusters.

Clustering variables

Several issues related to the selection of clustering variables were coded. The justification of variables was coded as inductive, deductive, or cognitive. Studies focused on exploratory classification of observations (i.e., the clustering variables were not tightly linked to deductive theory) were coded as inductive. Studies that tightly linked clustering variables to theory were coded as deductive. Studies where clustering variables were based on experts' opinions were coded as cognitive. We also coded whether or not variables were standardized and if the Mahalanobis distance measure or factor analysis were used to address multicollinearity.

Clustering algorithms

Studies' clustering algorithms were coded as hierarchical, nonhierarchical, hierarchical and nonhierarchical used in tandem, or not specified. Where appropriate, the specific hierarchical clustering algorithms were coded as well.

Determining the number of clusters

The methods used to determine the appropriate number of clusters were coded. The methods included: dendogram observation, change in agglomeration coefficient, cubic clustering criterion, *a priori* theory, and other methods specified by authors.

Validating clusters

Similarly, the methods used for validating solutions were coded, including: multiple clustering

[3] These non-empirical journals include *Academy of Management Executive, Academy of Management Review, California Management Review, Harvard Business Review*, and *Sloan Management Review*.

[4] One study (Lawless and Finch, 1989) contained two independent applications of cluster analysis (one of environment types and the other of strategy types); each application was counted as one 'study'.

algorithms, split sample, hold-out sample, statistical tests on nonclustering variables, and other methods specified by authors.

Coding reliability

All studies were coded independently by the two authors. To ensure consistency, a random sample of nine studies was coded. The resultant interrater reliability, as measured by percentage of agreement, was 87 percent. A meeting was held to discuss the discrepancies. The remaining 36 studies were then coded with a 93 percent interrater reliability, which compares favorably to the 83 percent interrater reliability obtained in a similar study by Ford, MacCallum, and Tait (1986). All discrepancies were resolved by the authors reviewing the study and coming to a joint decision; relevant items were recoded accordingly.

RESULTS

Clustering variables

Most studies ($n = 35$, 78% of the total studies located) used an inductive approach to select clustering variables. Four studies (9%) took a deductive approach; in six studies (13%), a cognitive approach was evident. In 12 of the 45 studies (27%), variables were standardized; 14 studies (32%) used factor scores as the basis for clustering while none used the Mahalanobis distance measure. The results for these and other coded items are presented in Table 1.

Clustering algorithms

Only six studies (13%) used the preferred approach of hierarchical and nonhierarchical algorithms in tandem. In combination with nonhierarchical clustering, Ward's method was cited three times, and the centroid method, complete linkage, and average linkage were each used in one study. Hierarchical algorithms alone were cited in 24 studies (35%). Ward's method was used in 16 of these studies, the centroid method in four, complete linkage in two, and average linkage and CONCOR[5] each in one study. Nonhierarchical algorithms alone were used in eight studies (18%). Finally, in seven studies (16%), there was no mention of the algorithm(s) used.

Determining the number of clusters

Confidence in the number of clusters is greater when multiple methods converge; however, only 18 studies (40%) used this type of approach. In 21 studies (47%), one method was used; techniques used were not identified in six studies (13%).

Individual methods were also tallied; change in the agglomeration coefficient ($n = 19$, 42%) and observing breaks in the dendogram ($n = 16$, 36%) were the most widely cited. The CCC was used in five studies (11%), while *a priori* theory guided cluster definition in four studies (9%). In 13 studies (29%), other methods not grounded in the methodological literature were indicated, including, for example, ensuring equal-size groups and 'interpretability'.

Validating clusters

Validation may be the most neglected issue in cluster analysis. Ideally, reliability and both external and criterion-related validity should be assessed, but none of the 45 studies examined all three. Further, no validation techniques were cited in 17 studies (38%).

Reliability was addressed in 13 studies (29%); all of these efforts used multiple clustering algorithms and four (9%) also analyzed split samples. External validity was tested by analyzing hold-out samples in two studies (4%). While such efforts can be valuable in establishing validity, this value is sharply limited because each technique shares the fundamental concern inherent in cluster analysis: the heavy reliance on researcher judgment. In 10 studies (22%), statistical tests on nonclustering variables were done to assess criterion-related validity.[6] These latter studies are noteworthy because they validated results using a technique (i.e., ANOVA or MANOVA) where researcher judgment is limited to the choice of criterion variables.

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[5] CONCOR is an algorithm introduced by Breiger, Boorman, and Arabie (1975) for clustering relational data in social network analysis.

[6] We did not include in this count several studies that examined differences between clusters along non-clustering variables as part of their hypothesis testing but did not mention that such efforts also provide evidence regarding validity. Our reasoning was that many readers would not be aware of this relation to validity unless alerted to it and thus could not use this information to make informed judgments about the results.

Table 1. Summary of decisions made by strategy researchers when using cluster analysis

	Number of studies	Percent of total
Clustering variables		
Justification of input variables		
Inductive	35	78
Deductive	4	9
Cognitive	6	13
Factor analysis used	14	32
Variables standardized	12	27
Clustering algorithms		
Hierarchical		
Ward's method	16	36
Centroid method	4	9
Complete linkage	2	4
Average linkage	1	2
CONCOR	1	2
Nonhierarchical	8	18
Combination		
Ward's method and *K*-means	3	7
Centroid method and *K*-means	1	2
Complete linkage and *K*-means	1	2
Average linkage and *K*-means	1	2
Not specified	7	16
Determining the numbers of clusters		
Multiple methods	18	40
Single method	21	47
Not specified/none	6	13
Specific methods		
Change in agglomeration coefficient	19	42
Dendogram observation	16	36
Cubic clustering criterion	5	11
A-priori theory	4	9
Other techniques	13	29
Validating clusters		
Reliability		
Multiple algorithms	13	29
Split-half samples	4	9
External validity		
Hold-out samples	2	4
Criterion-related validity		
Statistical tests on non-clustering variables	10	22
Other		
Statistical tests on clustering variables	11	24
Expert opinion	3	7
Not specified/none	17	38

Two techniques not advocated in the methodological literature were found. Eleven studies (24%) used MANOVA to demonstrate that the means of the clustering variables differ across clusters and took this as evidence that the cluster solution reflects the underlying structure of a data set (e.g., Kim and Lim, 1988). Such tests, however, should always be significant because cluster analysis, by design, creates groups that have minimal overlap along the clustering variables (Aldenderfer and Blashfield, 1984). Hence, this technique does little to establish the validity of a solution. A final technique—expert opinions of clusters' validity—is not widely discussed by methodologists but was used in three studies (7%).

In total, our findings indicate that the 'norm' for strategy research using cluster analysis is to (1) select variables inductively, (2) use a hierarchical or nonhierarchical algorithm by itself, and (3) pay limited attention to determining the number of and validating clusters.

DISCUSSION

The search for organizational configurations has long been a focus of the field of strategic management. Cluster analysis has played a key role in this research because it allows for the inclusion of multiple variables as sources of configuration definition, thus enabling the creation of potentially rich descriptions. Despite this strength, the use of cluster analysis has been widely criticized (e.g., Barney and Hoskisson, 1990; Meyer, 1991). As with any technique, however, the results provided by cluster analysis are only as good as its implementation and, more generally, the overall design of a study. With this in mind, below we assess the current state of cluster analysis research. Our efforts here are both general and specific. We discuss overall trends but also examine specific methodological decisions that authors made (i.e., what they did 'right' and 'wrong'), assess the likely empirical consequences of poor choices, and note how such consequences might have been prevented or at least minimized. We then look to the future and offer suggestions to maximize the value of cluster analysis to strategy inquiry. Underlying these suggestions is our assertion that the ill-effects of the weaknesses of cluster analysis can be controlled through *triangulation*; bringing to bear multiple, disparate methods (Denzin, 1978; Jick, 1979). Specifically, for cluster analysis to be a helpful tool in the effort to create knowledge about organizations, the technique needs to be embedded in research designs that include other methods that are far less subject to researcher judgment.

The state of cluster analysis research

Our results suggest that the ability of research using cluster analysis to generate knowledge has been hindered by the technique's implementation. This is perhaps not surprising given the state of the relevant methodological research. Methodological texts generally agree that the critical issues when using cluster analysis are: selecting clustering variables; whether or not to standardize variables; addressing multicollinearity among variables; selecting appropriate clustering algorithms; determining the number of clusters; and validating clusters. These texts often disagree, however, about *how* to address the issues. This may help to explain why many studies suffer from shortcomings: because the available guidance is often unclear or even contradictory, rigor is an elusive achievement.

In analyzing extant research, we found problems at each step in the clustering process. First, far more authors have used an inductive approach to the selection of clustering variables than have conducted deductive or cognitive inquiry. In 1993, for example, two-thirds of the studies derived configurations based on an inductive approach. Although such exploratory efforts were recommended in earlier guidance (Hambrick, 1984; Harrigan, 1985), they are less desirable now given the advancing state of theory development about strategy and the emergence of the cognitive approach. Indeed, the relatively slow rate of knowledge accumulation in studies using cluster analysis (most notably in the strategic groups literature—Ketchen *et al.*, 1993) may be attributable in part to the imbalance of the past. Thus, we believe that the divergent contributions to knowledge promised by each approach require that scholars pursue a more balanced research agenda (cf. Montgomery, Wernerfelt and Balakrishnan, 1989). Specifically, there is a need to 'reconfigure' configurational research toward a substantial increase in the attention paid to deduction and cognition.

The standardization of clustering variables has advocates and detractors among methodologists. When no clear guidance is available, as is the case here, researchers need to make choices guided by the goals of their study and the nature of their data (McGrath, Martin, and Kulka, 1982). We suggest that researchers take a very conservative path: specifically, that they perform analyses both using and not using standardization and compare the results. No strategy studies to date have taken this approach; most did not standardize. Careful attention to this issue is needed, however, because strategy studies often include both large- and small-scale variables. For example, in Ketchen *et al.* (1993), clustering variables included both *number* *of hospital beds* (a relatively large-scale measure, with a mean of approximately 250) and hospitals' *current ratio* (a relatively small-scale measure, with a mean of approximately 2.3). This disparity led the authors to (appropriately) standardize their variables, but confidence in the results would have been heightened if (a) they had done their analysis with nonstandardized variables as well and (b) the two sets of results were consistent.

Addressing multicollinearity presents a similar dilemma; clear guidance is lacking, so researchers must use their best judgment, given the specifics of each study. Some pieces have seemingly fallen short here. We found some instances, for example, where high correlations among clustering variables (i.e., 0.50 or higher) were evident but no corrective action was reported nor was justification offered for not acting (e.g., Hitt and Tyler, 1991; Ketchen *et al.*, 1993; Roth, 1992). Many other authors did not report the correlations among clustering variables (e.g., Dess and Davis, 1984; Hambrick, 1983; Manu, 1992; Miles, Snow, and Sharfman, 1993). Authors may feel that reporting such correlations is unnecessary because the linear, continuous relationships among variables are not central to configurational research. Without correlations, however, the reader is unable to make an informed judgment about whether or not multicollinearity was a concern. This is illustrative of a more general problem: articles often do not describe how crucial issues were addressed. In *any* study, the rationale underlying methodological decisions should be presented in sufficient detail to allow readers to make informed judgments about the findings (Daft, 1985). This is vital for studies using cluster analysis, however, because of the role played by researcher judgment.

The selection of clustering algorithms is an issue for which there is consensus among methodologists. Unfortunately, however, strategy research has rarely followed the guidance that is offered. The two-stage procedure we advocate (hierarchical and non-hierarchical methods used in tandem) has been recommended by many (Aldenderfer and Blashfield, 1984; Hartigan, 1975; Hair *et al.*, 1992; Milligan, 1980; Punj and Stewart, 1983) because both methods have weaknesses when used alone, hence the 'true' structure of data sets may not be reflected in the solutions that either provides. Most strategy researchers have ignored or are unaware of this guidance, however, only six studies used the dual technique. To illustrate the problems created when using a single method, we consider the use of Ward's method, the most often used hierarchical algorithm in strategy research. As noted earlier, Ward's method is greatly impacted by outliers. Although we can not be conclusive (due to the lack of detail presented in many studies), at least some researchers may not have paid sufficient attention to the role of outliers. In most cases, all observations in the sample were represented in the cluster solution (e.g., Birley and Westhead, 1990; Lewis and Thomas, 1990; Manu, 1992; Zahra and Covin, 1993), indicating either there were no outliers or the outliers were ignored. In each of these studies, using an iterative method to refine the solution derived using Ward's method would have enhanced validity because the iterative methods do not share the biases of Ward's. Thus, while the varied, often contradictory guidance offered by methodologists can be frustrating, strategy researchers need to pay careful attention to those instances where methodologists agree on the correct tack.

Turning to the issue of determining the number of clusters in a solution, each of the available techniques has biases, leading us to echo Everitt's (1980) call for the use of multiple techniques. Unfortunately, the majority of strategy studies did not employ multiple methods; in these studies, clusters may have been shaped by the biases of a solitary method. Given this potential, it is disconcerting that two influential articles (i.e., Dess and Davis, 1984; Hambrick, 1983) are in this group. Also troublesome are the studies that did not specify how clusters were identified (e.g., Dominguez and Sequeira, 1993; Hitt and Tyler, 1991; Miller, 1988). At this and other steps of the clustering process, the burden of proof lies with the authors. Absent relevant 'evidence', the reader is unable to render any verdict regarding the clusters identified.

A final concern raised by our findings is the scant attention often paid to validating cluster solutions. Reliability was ignored in over two-thirds of prior studies. A particularly effective method for assessing reliability was noted, however: two authors independently derived clusters using different algorithms and then assessed the convergence between their solutions (Reger and Huff, 1993). Researchers should be encouraged to devise other innovative methodologies. External validity (generalizability) was tested only twice (i.e., Hambrick, 1983; Mascarenhas, 1989). Unless generalizability is assessed, however, there can be no confidence that results are relevant beyond the sample at hand. Likewise, criterion-related validity often was not assessed; as a result, the predictive utility of solutions frequently remains unknown. Ironically, the number of studies that tested criterion-related validity through significance tests on external (i.e., non-clustering) variables was very close to the number that inappropriately cited significance tests on clustering variables as evidence of validity. Thus, in sum, researchers need to be wary of errors of omission *and* commission.

The future of cluster analysis research

Despite the problems associated with its past use, we believe that cluster analysis can be valuable to future strategy research because of the technique's unparalleled ability to classify a large number of observations along multiple variables. At the same time, the long-running interest in identifying groups of similar organizations continues to grow, as shown by the explosion of studies using cluster analysis since the late 1980s and the publication of an issue on 'configurational approaches to organizational analysis' in the *Academy of Management Journal* in 1993.

For cluster analysis to be of maximum value, however, researchers must take steps to overcome its weaknesses. The main problem is that cluster analysis' reliance on researcher judgment makes the validity of results subject to serious doubts. We believe that the key to surmounting this problem is the vigorous pursuit of triangulation; i.e., the application of multiple techniques to a single research problem. All research methods have both strengths and weaknesses but, importantly, different methods have different strengths and weaknesses. Thus, in many instances, the strengths of one method may complement the strengths of another while neutralizing the latter's weaknesses (Denzin, 1978; Jick, 1979). Applying multiple techniques helps to ensure that results are not methodological artifacts; specifically, agreement between two or more methods provides evidence that results are not a product of the biases of one method.

In considering triangulation, it is important to note that there are two types. *Within-method* triangulation occurs when a research issue has been examined using multiple approaches, but these approaches share a common weakness which prevents high levels of confidence in the results obtained (Denzin, 1978). For example, within-method triangulation is apparent in studies that use multiple clustering techniques in an effort to establish validity (e.g., Hawes and Crittenden, 1984; Smith and Grimm, 1987). While preferable to the use of a single clustering approach, the results are still vulnerable to methodological critique because all clustering techniques share the reliance on researcher judgment. *Between-methods* triangulation can occur when multiple techniques that do not share a common weakness are applied. If these methods arrive at the same set of results or support the same conclusions, confidence can be high that results are valid and not driven by one's method (Denzin, 1978). Given that cluster analysis' 'Achilles heel' is its reliance on researcher judgment, the logical implication is that studies using cluster analysis should include other techniques that do not rely heavily on such interpretations. When such techniques support the conclusions of cluster analysis, there is assurance that findings are not driven by researcher judgment.

Some methodological research on cluster analysis advocates triangulation in efforts to establish validity (though usually without using the term). Authors' suggestions are generally limited to the pursuit of within-method triangulation. For example, recommendations offered include the use of multiple clustering techniques (Aldenderfer and Blashfield, 1984), clustering of hold-out samples (Hair *et al.*, 1992), and supplementing cluster solutions with other judgment-laden techniques, such as multidimensional scaling (Arabie, Carroll and DeSarbo, 1987). Perhaps not surprisingly, most triangulation in strategy research using cluster analysis has been of the within-method type.

While the guidance offered by methodologists is helpful, strategy researchers should be vigilant for opportunities to develop within-method triangulation in order to help meet the specific needs of strategy research. We believe that the inclusion of monothetic clustering techniques in studies offers one such opportunity. Specifically, this might help to address a key limitation of most cluster analysis techniques (agglomerative hierarchical as well as nonhierarchical). Regardless of the algorithm selected, cluster analysis treats all variables as equally important to defining clusters. As a result, none of the strategy studies to date have purposefully weighted variables.[7] This has not been prob-

[7] Unintentional weighting of clustering variables may occur if, as noted above, there are scale differences between variables or if multicollinearity is present.

lematic because the literature has been dominated by exploratory (i.e., inductive) inquiry, where no *a priori* rationale for differential weights is available. As strategy research moves toward an emphasis on theory testing (i.e., deductive studies), however, the relative weights of strategic concepts in our theories must be represented empirically. Similarly, when using top managers' cognitions as the source of clustering variables (i.e., cognitive studies), managers may suggest that variables are not equally important; such differences must be reflected in empirical efforts. By splitting samples on the most important variable first, then along the second, and so on, monothetic techniques offer a means for weighting variables such that their relative importance in clustering is better aligned with their importance in the perspective underlying the derivation of clusters. Thus, the inclusion of monothetic techniques as part of an array of clustering methods might often be helpful in efforts to develop valid cluster solutions. It is important to caution, however, that monothetic techniques' need for dichotomous variables would usually require the manipulation of data because many variables of interest are continuous.

The stiffer challenge to researchers is the need to develop between-methods triangulation, where methodological guidance has been sparse. One exception is the advocation of significance testing on external variables through ANOVA or MANOVA (Anderberg, 1973; Aldenderfer and Blashfield, 1984). In the remainder of this section, we expand upon this initial foray into building between-methods triangulation by suggesting how researchers can use techniques that do not share cluster analysis' strong reliance on researcher judgment to develop confidence in empirical results, and more broadly, well-founded knowledge about organizations.

We look first to extant strategy research. A promising validation tool for inductive and deductive studies that is not discussed in methodological works but has been used by a few strategy authors is experts' opinions of clusters' validity. Like cluster analysis itself, the use of expert opinions relies heavily on perceptions. If the experts used are other researchers, this technique may only help build within-method triangulation. If the experts are practitioners, however, between-methods triangulation is possible because the perspectives and assumptions of researchers and managers are generally quite different. Indeed, Reger and Huff (1993) offer evidence that while managers perceive groups of firms, these groups are often based on different variables than those used by researchers. Expert opinions also can establish the practical value of a study. This is a central concern in strategic management because of its aim to be an applied field (e.g., Rumelt, Schendel, and Teece, 1994). When the experts are relevant practitioners like executives in a focal industry, their views can establish the 'real world' value of a set of results. In sum, experts' opinions can help maximize validity and establish practical value; thus, they should be sought whenever possible.

Another tack with multiple benefits is to use cluster analysis in conjunction with other statistical tools. This not only helps establish validity (to the extent that the tools are objectively based) but also can enable the testing of powerful and sophisticated theoretical models. The intent behind past applications of cluster analysis has been to capture the complexity of organizational reality. Yet the models examined have been relatively simple; research generally depicts clusters as stand-alone entities or as a means of explaining outcome variables. These approaches have provided insights, but are limited in the ability to capture complexity. Thus, we believe that the advancement of knowledge will be hastened by viewing cluster analysis as one possible piece of any methodological puzzle. Some research has begun to follow this path. One example is the use of strategic groups as a context within which to examine the link between firm-specific characteristics and performance (Cool and Schendel, 1988; Lawless, Bergh, and Wilsted, 1989). To take a more comprehensive view, studies might include strategic group membership as one of several factors in a structural equation or path analysis model designed to predict performance. Interestingly, the earliest research using cluster analysis emphasized the use of the technique alongside others (e.g., Hatten and Schendel, 1977; Hatten *et al.*, 1978) as did early methodological guidance (Anderberg, 1973). We assert that such designs are now a necessity.

To examine specifically how such designs might take shape, we consider the possible value of time series analysis to studies that include clustering. The dominant thrust of research using cluster analysis has been the attempt to explain the performance of organizations through their membership in a configuration. Studies of the link between organizational configurations and performance across multiple time periods generally use repeated cross-sectional tests (e.g., Fiegenbaum and Thomas, 1990). Such a design can uncover patterns within years (e.g., finding differentially performing groups in a particular year) and across years (e.g., the number of years that configurations are and are not linked to performance) but is limited in its ability to address other interesting questions. Specifically, time series analysis could be used to address the cumulative effect of configuration membership on performance over time and the extent to which the passage of time impacts the configurations–performance relationship (Bergh, 1993). Time series analysis also can be used to explore different lag times between the derivation of configurations and the measurement of performance; an important but unexamined issue (cf. Ketchen *et al.*, 1993). In terms of methodological concerns, time series analysis offers a heightened level of protection from potential statistical problems, most notably the chance of committing Type I errors (Bergh, 1993). Given that the use of cluster analysis introduces significant methodological difficulty into a study's design, such protection is highly desirable. Thus, we advocate the incorporation of time series analysis into research on the organizational configurations–performance relationship and, more generally, to any study of multiple time periods that uses cluster analysis.

CONCLUSION

Cluster analysis has been an important tool for examining the relationships among strategy, environment, leadership/organization, and performance; links which define the field of strategic management (Summer *et al.*, 1990). In the field's infancy, knowledge about these relationships was obtained primarily through in-depth case studies focusing on small numbers of firms (e.g., Chandler, 1962). However, strategic management's dominant epistemology changed as the field matured. Indeed, cluster analysis' introduction in the late 1970s and frequent use in the 1980s paralleled an increased emphasis on developing knowledge through sophisticated statistical tests of large data bases. We believe that cluster analysis can have a place in strategic management's methodological tool box in the 1990s and beyond, but the technique must be applied prudently in order to ensure the validity of insights that it provides. Further, to maximize the development of knowledge, cluster analysis should be used in combination with other methods to test sophisticated theoretical models.

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REFERENCES

Aldenderfer, M. S. and R. K. Blashfield (1984). *Cluster Analysis*. Sage, Newbury Park, CA.

Anderberg, M. R. (1973). *Cluster Analysis for Applications*. Academic Press, New York.

Andrews, K. R. (1971). *The Concept of Corporate Strategy*. Irwin, Homewood, IL.

Ansoff, H. I. (1965). *Corporate Strategy*. McGraw-Hill, New York.

Arabie, P., J. D. Carroll and W. S. DeSarbo (1987). *Three-way Scaling and Clustering*. Sage, Newbury Park, CA.

Bacharach, S. B. (1989). 'Organizational theories: Some criticism for evaluation', *Academy of Management Review*, **14**, pp. 496–515.

Bailey, K. D. (1994). *Typologies and Taxonomies: An Introduction to Classification Techniques*. Sage, Newbury Park, CA.

Barney, J. B. and R. E. Hoskisson (1990). 'Strategic groups: Untested assertions and research proposals', *Managerial and Decision Economics*, **11**, pp. 187–198.

Bergh, D. D. (1993). 'Watch the time carefully: The use and misuse of time effects in management research', *Journal of Management*, **19**, pp. 683–705.

Birley, S. and P. Westhead (1990). 'Growth and performance contrasts between "types" of small firms', *Strategic Management Journal*, **11**(7), pp. 535–557.

Breiger, R. L., S. A. Boorman and P. Arabie (1975). 'An algorithm for clustering relational data with applications to social network analysis and comparison with multidimensional scaling', *Journal of Mathematical Psychology*, **12**, pp. 328–383.

Chandler, A. D. (1962). *Strategy and Structure*. MIT Press, Cambridge, MA.

Cook, T. D. and D. T. Campbell (1979). *Quasi-experimentation: Design and Analysis Issues for Field Settings*. Houghton-Mifflin, Boston, MA.

Cool, K. and I. Dierickx (1993). 'Rivalry, strategic groups and firm profitability', *Strategic Management Journal*, **14**(1), pp. 47–59.

Cool, K. and D. Schendel (1987). 'Strategic group formation and performance: The case of the U.S. pharmaceutical industry, 1963–1982', *Management Science*, **33**, pp. 1102–1124.

Cool, K. and D. Schendel (1988). 'Performance differences among strategic group members', *Strategic Management Journal*, **9**(3), pp. 207–223.

Daft, R. L. (1985). 'Why I recommend that your manuscript be rejected and what you can do about it'. In L. L. Cummings and P. J. Frost (eds.), *Publishing in the Organizational Sciences*. Irwin, Homewood, IL, pp. 193–209.

Denzin, N. K. (1978). *The Research Act*. McGraw-Hill, New York.

Dess, G. and P. Davis (1984). 'Porter's (1980) generic strategies as determinants of strategic group membership and organizational performance', *Academy of Management Journal*, **27**, pp. 467–488.

Dess, G., S. Newport and A. M. A. Rasheed (1993). 'Configuration research in strategic management: Key issues and suggestions', *Journal of Management*, **19**, pp. 775–795.

Dillon, W. R., N. Mulani and D. G. Frederick (1989). 'On the use of component scores in the presence of group structure', *Journal of Consumer Research*, **16**, pp. 106–112.

Dominguez, L. V. and C. G. Sequeira (1993). 'Determinants of LDC exporters' performance: A cross-national study', *Journal of International Business Studies*, **24**, pp. 19–40.

Douglas, S. P. and D. K. Rhee (1989). 'Examining generic competitive strategy types in U.S. and European markets', *Journal of International Business Studies*, **20**, pp. 437–463.

Dutton, J. E., L. Fahey and V. K. Narayanan (1983). 'Toward understanding strategic issue diagnosis', *Strategic Management Journal*, **4**(4), pp. 307–323.

Edelbrock, C. (1979). 'Comparing the accuracy of hierarchical clustering algorithms: The problem of classifying everybody', *Multivariate Behavioral Research*, **14**, pp. 367–384.

Everitt, B. (1980). *Cluster Analysis* (2nd ed.). Heineman Educational Books, London.

Fiegenbaum, A. and H. Thomas (1990). 'Strategic groups and performance: The U.S. insurance industry, 1970–1984', *Strategic Management Journal*, **11**(3), pp. 197–215.

Fombrun, C. J. and E. J. Zajac (1987). 'Structural and perceptual influences on intraindustry stratification', *Academy of Management Journal*, **30**, pp. 33–50.

Ford, J. K., R. C. MacCallum and M. Tait (1986). 'The application of exploratory factor analysis in applied psychology: A critical review and analysis', *Personnel Psychology*, **39**, pp. 291–314.

Galbraith, C. and D. Schendel (1983). 'An empirical analysis of strategy types', *Strategic Management Journal*, **4**(2), pp. 153–173.

Hair, J. F., R. E. Anderson, R. L. Tatham and W. C. Black (1992). *Multivariate Data Analysis* (3rd ed.). Macmillan, New York.

Hambrick, D. C. (1983). 'An empirical typology of mature industrial-product environments', *Academy of Management Journal*, **26**, pp. 213–230.

Hambrick, D. C. (1984). 'Taxonomic approaches to studying strategy: Some conceptual and methodological issues', *Journal of Management*, **10**, pp. 27–41.

Hambrick, D. C. and S. M. Schecter (1983). 'Turnaround strategies for mature industrial-product business units', *Academy of Management Journal*, **26**, pp. 231–248.

Harrigan, K. R. (1985). 'An application of clustering for strategic group analysis', *Strategic Management Journal*, **6**(1), pp. 55–73.

Hartigan, J. A. (1975). *Clustering Algorithms*. Wiley, New York.

Hatten, K. J. (1974). 'Strategic models in the brewing industry', unpublished doctoral dissertation, Purdue University.

Hatten, K. J. and M. L. Hatten (1987). 'Strategic groups, asymmetrical mobility barriers and contestability', *Strategic Management Journal*, **8**(4), pp. 329–342.

Hatten, K. J. and D. E. Schendel (1977). 'Heterogeneity within an industry: Firm conduct in the U.S. brewing industry', *Journal of Industrial Economics*, **26**, pp. 97–113.

Hatten, K. J., D. E. Schendel and A. C. Cooper (1978). 'A strategic model of the U.S. brewing industry: 1952–1971', *Academy of Management Journal*, **21**, pp. 592–610.

Hawes, J. and W. Crittenden (1984). 'A taxonomy of competitive retailing strategies', *Strategic Management Journal*, **5**(3), pp. 275–287.

Hitt, M. A. and B. B. Tyler (1991). 'Strategic decision making models: Integrating different perspectives', *Strategic Management Journal*, **12**(5), pp. 327–351.

Hofer, C. W. and D. Schendel (1978). *Strategy Formulation: Analytical Concepts*. West Publishing, St. Paul, MN.

Hoskisson, R., M. Hitt, R. Johnson and D. Moesel (1993). 'Construct validity of an objective (entropy) measure of diversification strategy', *Strategic Management Journal*, **14**(3), pp. 215–235.

Hrebiniak, L. G. and W. F. Joyce (1985). 'Organizational adaptation: Strategic choice and environmental determinism', *Administrative Science Quarterly*, **30**, pp. 336–349.

Hunt, M. S. (1972). 'Competition in the major home appliance industry 1960–1970', unpublished doctoral dissertation, Harvard University.

Jardine, N. and R. Sibson (1971). *Mathematical Taxonomy*, Wiley, New York.

Jick, T. D. (1979). 'Mixing qualitative and quantitative methods: Triangulation in action', *Administrative Science Quarterly*, **24**, pp. 602–611.

Kerlinger, F. N. (1986). *Foundations of Behavioral Research*. Holt, Rinehart & Winston, Fort Worth, TX.

Ketchen, D. J., J. B. Thomas and C. C. Snow (1993). 'Organizational configurations and performance: A comparison of theoretical approaches', *Academy of Management Journal*, **36**, pp. 1278–1313.

Kim, L. and Y. Lim (1988). 'Environment, generic strategies, and performance in a rapidly developing country: A taxonomic approach', *Academy of Management Journal*, **31**, pp. 802–827.

Kim, W., P. Hwang and W. Burgers (1993). 'Multinationals' diversification and the risk-return trade-off', *Strategic Management Journal*, **14**(4), pp. 275–286.

Lafuente, A., and V. Salas (1989). 'Types of entrepreneurs and firms: The case of new Spanish firms', *Strategic Management Journal*, **10**(1), pp. 17–30.

Lawless, M. and L. Finch (1989). 'Choice and determinism: A test of Hrebiniak and Joyce's framework on strategy–environment fit', *Strategic Management Journal*, **10**(4), pp. 351–365.

Lawless, M., D. D. Bergh and W. Wilsted (1989). 'Performance variations among strategic group members: An examination of individual firm capability', *Journal of Management*, **15**, pp. 649–661.

Lewis, P. and H. Thomas (1990). The linkage between strategy, strategic groups and performance in the U.K. retail grocery industry', *Strategic Management Journal*, **11**(5), pp. 385–397.

Lorr, M. (1983). *Cluster Analysis for the Social Sciences*. Jossey-Bass, San Francisco, CA.

Macmillan, I. C. (1991). 'The emerging forum for business policy scholars', *Strategic Management Journal*, **12**(2), pp. 161–165.

Manu, F. A. (1992). 'Innovation orientation, environment and performance: A comparison of U.S. and European markets', *Journal of International Business Studies*, **23**, pp. 333–359.

Mascarenhas, B. (1986). 'International strategies of non-dominant firms', *Journal of International Business Studies*, **17**, pp. 1–25.

Mascarenhas, B. (1989). 'Strategic group dynamics', *Academy of Management Journal*, **32**, pp. 333–352.

Mascarenhas, B. and D. Aaker (1989a). 'Strategy over the business cycle', *Strategic Management Journal*, **10**(3), pp. 199–210.

Mascarenhas, B. and D. Aaker (1989b). 'Mobility barriers and strategic groups', *Strategic Management Journal*, **10**(5), pp. 475–485.

McDougall, P. and R. Robinson (1990). 'New venture strategies: An empirical identification of eight "archetypes" of competitive strategies for entry', *Strategic Management Journal*, **11**(6), pp. 447–467.

McGrath, J. E., J. Martin and R. A. Kulka (1982). *Judgment Calls in Research*. Sage, Beverly Hills, CA.

McKelvey, B. (1975). 'Guidelines for empirical classification of organizations', *Administrative Science Quarterly*, **20**, pp. 509–525.

McKelvey, B. (1978). 'Organizational systematics: Taxonomic lessons from biology', *Management Science*, **24**, pp. 1428–1440.

Meyer, A. D. (1991). 'What is strategy's distinctive competence?', *Journal of Management*, **17**, pp. 821–833.

Meyer, A. D., A. S. Tsui and C. R. Hinings (1993). 'Configurational approaches to organizational analysis, *Academy of Management Journal*, **36**, pp. 1175–1195.

Miles, G., C. C. Snow and M. P. Sharfman (1993). 'Industry variety and performance', *Strategic Management Journal*, **14**(3), pp. 163–177.

Miles, R. E. and C. C. Snow (1978). *Organizational Strategy, Structure, and Process*. McGraw-Hill, New York.

Miller, A. (1988). 'A taxonomy of technological settings, with related strategies and performance levels', *Strategic Management Journal*, **9**(3), pp. 239–254.

Miller, D. and P. Friesen (1978). 'Archetypes of strategy formulation', *Management Science*, **24**, pp. 921–933.

Miller, D. and H. Mintzberg (1983). 'The case for configuration'. In G. Morgan (ed.), *Beyond Method*. Sage, Beverly Hills, CA, pp. 57–73.

Milligan, G. W. (1980). 'An examination of the effect of six types of error perturbation on fifteen clustering algorithms', *Psychometrika*, **45**, pp. 325–342.

Milligan, G. W. and M. C. Cooper (1985). 'An examination of procedures for determining the number of clusters in a data set', *Psychometrika*, **50**, pp. 159–179.

Mintzberg, H. (1989). *Mintzberg on Management*. Free Press, New York.

Montgomery, C. A., B. Wernerfelt and S. Balakrishnan (1989). 'Strategy content and the research process: A critique and commentary', *Strategic Management Journal*, **10**(2), pp. 189–197.

Morrison, A. and K. Roth (1992). 'A taxonomy of business-level strategies in global industries', *Strategic Management Journal*, **13**(6), pp. 399–418.

Morrison, A. and K. Roth (1993). 'Relating Porter's configuration/coordination framework to competitive strategy and structural mechanisms: Analysis and implications', *Journal of Management*, **19**, pp. 797–818.

Nohria, N. and C. Garcia-Pont (1991). 'Global strategic linkages and industry structure', *Strategic Management Journal*, Summer Special Issue, **12**, pp. 105–124.

Porac, J. F. and H. Thomas (1990). 'Taxonomic mental models in competitor definition', *Academy of Management Review*, **15**, pp. 224–240.

Porter, M. E. (1973). 'Consumer behavior, retailer power, and manufacturer strategy in consumer goods industries', unpublished doctoral dissertation, Harvard University.

Punj, G. and D. W. Stewart (1983). 'Cluster analysis in marketing research: Review and suggestions for application', *Journal of Marketing Research*, **20**, pp. 134–148.

Rajagopalan, N. and S. Finkelstein (1992). 'Effects of strategic orientation and environmental change on senior management reward systems', *Strategic Management Journal*, Summer Special Issue, **13**, pp. 127–142.

Reger, R. K. and A. S. Huff (1993). 'Strategic groups: A cognitive perspective', *Strategic Management Journal*, **14**(2), pp. 103–124.

Robinson, R. and J. Pearce (1988). 'Planned patterns of strategic behavior and their relationship to business-unit performance', *Strategic Management Journal*, **9**(1), pp. 43–60.

Roth, K. (1992). 'International configuration and coordination archetypes for medium-sized firms in global industries', *Journal of International Business Studies*, **23**, pp. 533–549.

Rumelt, R. P., D. E. Schendel and D. J. Teece (1994). *Fundamental Issues in Strategy: A Research Agenda*. Harvard Business School Press, Boston, MA.

SAS Institute, Inc. (1990). *SAS Users Guide: Statistics*, Version 6. SAS Institute, Cary, NC.

Smith, K. and C. Grimm (1987). 'Environmental variation, strategic change and firm performance: A study of railroad deregulation', *Strategic Management Journal*, **8**(4), pp. 363–376.

Summer, C. E., R. A. Bettis, I. H. Duhaime, J. H. Grant, D. C. Hambrick, C. C. Snow and C. P. Zeithaml (1990). 'Doctoral education in the field of business policy and strategy', *Journal of Management*, **16**, pp. 361–398.

Thomas, H. and N. Venkatraman (1988). 'Research on strategic groups: Progress and prognosis', *Journal of Management Studies*, **25**, pp. 537–555.

Thomas, J. B., S. M. Clark and D. A. Gioia (1993). 'Strategic sensemaking and organizational performance: Linkages among scanning, interpretation, action, and outcomes', *Academy of Management Journal*, **36**, pp. 239–270.

Thompson, J. D. (1967). *Organizations in Action*. McGraw-Hill, New York.

Venkatraman, N. and J. E. Prescott (1990). 'Environment–strategy coalignment: An empirical test of its performance implications', *Strategic Management Journal*, **11**(1), pp. 1–23.

Venkatraman, N. and V. Ramanujam (1986). 'Measurement of business performance in strategy research', *Academy of Management Review*, **11**, pp. 801–814.

Waddock, S. and L. Isabella (1989). 'Strategy, beliefs about the environment and performance in a banking simulation', *Journal of Management*, **15**, pp. 617–632.

Walter, G. and J. Barney (1990). 'Management objectives in mergers and acquisitions', *Strategic Management Journal*, **11**(1), pp. 79–86.

Whallon, R. W. (1972). 'A new approach to pottery typlogy', *American Antiquity*, **37**, pp. 13–33.

Woo, C. Y. Y. and A. C. Cooper (1981). 'Strategies of effective low share businesses', *Strategic Management Journal*, **2**(3), pp. 301–318.

Zahra, S. and J. Covin (1993). 'Business strategy, technology policy, and firm performance', *Strategic Management Journal*, **14**(6), pp. 451–478.

APPENDIX: Strategy Articles That Use Cluster Analysis

Academy of Management Journal

Hatten, Schendel, and Cooper (1978)
Hambrick (1983)
Hambrick and Schecter (1983)
Dess and Davis (1984)
Fombrun and Zajac (1987)
Kim and Lim (1988)
Mascarenhas (1989)
Ketchen, Thomas and Snow (1993)

Journal of International Business Studies

Mascarenhas (1986)
Douglas and Rhee (1989)
Manu (1992)
Roth (1992)
Dominguez and Sequeira (1993)

Journal of Management

Lawless, Bergh, and Wilsted (1989)
Waddock and Isabella (1989)
Morrison and Roth (1993)

Management Science

Cool and Schendel (1987)

Strategic Management Journal

Woo and Cooper (1981)
Galbraith and Schendel (1983)
Hawes and Crittenden (1984)
Smith and Grimm (1987)
Cool and Schendel (1988)
Miller (1988)
Robinson and Pearce (1988)
Lafuente and Salas (1989)
Lawless and Finch (1989)
Mascarenhas and Aaker (1989a)
Mascarenhas and Aaker (1989b)
Birley and Westhead (1990)
Fiegenbaum and Thomas (1990)
Lewis and Thomas (1990)
McDougall and Robinson (1990)
Venkatraman and Prescott (1990)
Walter and Barney (1990)
Hitt and Tyler (1991)
Nohria and Garcia-Pont (1991)
Morrison and Roth (1992)
Rajagopalan and Finkelstein (1992)
Cool and Dierickx (1993)
Hoskisson, Hitt, Johnson and Moesel (1993)
Kim, Hwang, and Burgers (1993)
Miles, Snow, and Sharfman (1993)
Reger and Huff (1993)
Zahra and Covin (1993)