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AUTHOR	Hackman, Judith Dozier
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ABSTRACT

Seven potentially useful maxims from the field of human information processing are proposed that may help institutional researchers prepare and present information for higher education decision-makers. The maxims, which are based on research and theory about how people cognitively process information, are as follows: (1) more may not be better; (2) augment humans with models; (3) chunk data wisely; (4) know decision makers; (5) heuristics are not always helpful; (6) arrange tables by patterns; and (7) negative evidence and new hypotheses are okay. Cognitive findings underlying each maxim are given, with concrete examples of how institutional researchers can apply the maxims to improve the collection, analysis, and especially the presentation of information for academic decision-makers. In regard to maxim 1, it is suggested that researchers should remember that people have difficulty combining more than six or seven bits of information at a time, without some kind of decision aid. The use of computer models for a limited range of structurable and semi-structurable academic decisions is probably the major application of maxim 2 currently found in universities. Three of the most frequently used heuristics are examined: availability, representativeness, and anchoring and adjustment. Four guidelines for arranging tables are as follows: round to four significant digits, use row and column averages or totals, present the main pattern of data in columns, and order the rows and columns by some measure of their size. It is suggested that when decision-makers remain open to alternative solutions and disconfirming evidence, their decisions may be more effective. (SW)

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Seven Maxims for Institutional Researchers: Applying Cognitive Theory and Research

Judith Dozier Hackman
Associate Director
Office of Institutional Research
451 College Street
Yale University
New Haven, Connecticut 06520
203-436-4705

THE ASSOCIATION FOR INSTITUTIONAL RESEARCH

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D. R. Coleman, Chairman
Forum Publication
Advisory Committee

Abstract

The paper presents seven institutional research maxims that are based on research and theory about how people cognitively process information: (I) More may not be better. (II) Augment humans with models. (III) Chunk your data wisely. (IV) Know your decision makers. (V) Heuristics are not always helpful. (VI) Arrange tables by patterns. (VII) Negative evidence and new hypotheses are okay. Cognitive findings underlying each maxim are given, with concrete examples of how institutional researchers can apply the maxims to improve the collection, analysis, and especially the presentation of information for decision makers.

Introduction and Perspective

How can we as institutional researchers, who collect, analyze, and prepare information for university decision makers, increase the effectiveness of what we do? One possibility is to look to the findings of scholars in other areas to learn whether their basic theories and research can inform our own work. A field that holds great promise for such learning is cognitive information processing as almost everything that institutional researchers do centers around the processing of information or the preparation of information for others. This paper draws on cognitive theory and research to identify useful applications. In accord with findings that the span of immediate human memory is limited to seven bits of information--give or take a few, <u>seven maxims for institutional researchers</u> are proposed:

I. More may not be better.

II. Augment humans with models.

III. Chunk your data wisely.

IV. Know your decision makers.

V. Heuristics are not always helpful.

VI. Arrange tables by patterns.

VII. Negative evidence and new hypotheses are okay.

For each maxim, first some of the major underlying theory and research will be reviewed, and then one or two practical institutional research applications will be described. One caveat: The goal of this paper is <u>not</u> to distill the thousands of articles and books on behavioral decision making into seven summary rules. Rather, in a more limited way, the purpose is to propose seven potentially useful maxims from the field of human information processing that may help institutional researchers prepare and present information for academic decision makers.

The Seven Maxims

I. More may not be better.

"If a little information improves a decision, then more information will make it even better." This is what most decision makers (and many institutional researchers) believe, but numerous cognitive psychology experiments prove otherwise. The amount of information that people can receive, process, and remember is severely constrained by cognitive limitations, particularly by a limited short-term memory and by the slowness of storage and retrieval in long-term memory (Slovic, 1981).

Simon (1957, p. 198) explains this phenomenon with the concept of "bounded rationality":

> The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior.

Both neurophysiological and linguistic limitations affect our ability to make decisions with "perfect" rationality.

Even experienced decision makers use much less information than they believe they use. Research with such varied "experts" as stockbrokers, physicians, court judges, racing touts, and livestock judges has yielded the following conclusions which can inform the preparation and presentation of information for academic decision makers:

1. Experts believe they can make use of large pools of information, but in reality they rely primarily on a few items. Given a list of "cues" (pieces of information), expert decision makers routinely use less than 10 of the items--ranging from 2 or 3 cues in studies of judges setting bail (Ebbesen & Konecni, 1975) to 6 or 7 in studies of stockbrokers (Slovic, 1969).

2. The judgment of experts and non-experts does not improve when the pool of information is increased, indeed it sometimes is less consistent (Einhorn, 1971). As information amount grew from four to six to eight items, for example, Anderson found no increase in multiple correlations between the items and quality of outcome (1977).
3. Expert decision makers apparently use more information in simulated situations than in real ones (Ebbeson & Konecni, 1975; Phelps & Shanteau, 1978).

Institutional research application.

What are the implications of this maxim for institutional research? First, we should stop deluding ourselves that more information in a "raw" form is better, and not continue to multiply unwisely the amount of data for making decisions. Second, where there is valid information from multiple sources, we can follow Maxim II and combine data with models, or we can "chunk" data as described in Maxim III. Maxim I has important implications for institutional researchers, both for how we go about preparing and extracting information and for how we then present the information to university decision makers. We should continually keep in mind that people have great difficulty combining more than six or seven bits of information at a time, without some kind of decision aid.

Two related reminders: Remember that decision makers typically will be adding in numerous pieces of information from sources other than institutional research as they work on a particular decision! Second, because people frequently think that they do better with more information, institutional researchers often may need to produce the reams of data anyway, although it may be possible to "educate" decision makers about the maxims described here.

If, for example, the Academic Vice President requests "everything that you can get" for a particular decision, try to find out which "things" she believes are most essential. Together, try to extract priorities for the items of information, and begin work on the top ones. If information low on the list cannot be found or prepared in time, relax in the knowledge that this may be fortunate.

II. Augment humans with models.

When multiple pieces of relatively valid and independent information are available, decisions often can be improved by the construction of models which may be used separately or in combination with human judgment. Obviously, institutional researchers will not want to say to their provosts or vice presidents: "I recommend that we replace you with a model!" And, in fact, this would be impossible. However, studies have shown that where structurable and repetitive decisions must be made, models can increase consistency and efficiency, and in some cases reduce the misweighting of data.

Libby (1981) reviews research on two major types of formal models--"expert measurement and mechanical combination" and "environmental regression" models. In his discussion of the first type of model, Libby concludes that experienced decision makers are much better at selecting and coding information than at combining and integrating. Although experts often must make the final, intuitive choices, for many decisions it is useful to augment humans by inserting a model someplace in the decision process, ranging from a simple pencil-and-paper computation to a highly sophisticated computer simulation. Such modelling techniques are a major part of the developing decision aid technologies. The new area of "decision support systems" (Keen & Scott Morton, 1978; Hackman & Libby, 1981) takes advantage of this growing technology to fit the needs of decision makers to the appropriate computer hardware and software and to other, non-computer aids.

The second type of formal modelling--environmental regression--requires outcome or criterion values to describe "true" environmental relationships. When feasible, this method can improve consistency, increase efficiency, and also more accurately weight data.

Models usually refer to the combination of numbers, however, we also could classify as models some techniques of combining qualitative data. Examples would include the development of opinion consensus through the Delphi technique and the method known as "nominal group judgment" (Hammond & Adelman, 1976). Even these more qualitative methods incorporate some quantified methods.

Institutional research application. The use of computer models for a limited range of structurable and semistructurable academic decisions is probably the major application of Maxim II currently found in universities. Examples include such modelling tools as EFPM (Educom Financial Planning Model), MAPSS (Management Analysis and Planning Suport System) and VISICALC. These packages can help explore the implications of alternative decisions on such topics as faculty flow, enrollment projections, and budget surpluses (or deficits) with modest cost in time and effort.

Models also can be used to fill in one segment of a larger decision. For example, algorithms can be developed from admissions committee selection procedures which will create indices that accurately reflect a large proportion of the admissions process. Such indices can be used reliably and validly as cut-off measures for the first stage of admissions. How often admissions professionals will agree that "a machine" can do part of their work is another question, although universities and colleges do incorporate such aids.

At a more routine operational level, it is commonplace in many academic institutions to replace much of the tedious accounting and budget monitoring computation with management information systems. Monthly budget-to-actual statements are an important "model-segment" of administrative decision making in universities and colleges.

III. Chunk your data wisely.

The advice in this maxim is based on two related cognitive research findings: first, that the span of human short-term memory is quite limited, and second; that people fail to account properly for intercorrelations among pieces of information. Limitations in short-term memory frequently cause decision makers to focus on a small subset of the information available for a decision, and improper accounting for correlated information often leads them to emphasize redundant data in their decisions. Not only may resulting decisions be less accurate, but also the consistency among correlated cues tends to give decision makers a false sense of security which breeds overconfidence. We may have greater confidence in less accurate decisions.

Miller, in his classic article "The Magical Number Seven, Plus or Minus Two," summarizes much of the early research about short-term memory and the differences between "chunks of information" and "bits of information"(1967). Although "the magical number seven" relates to both concepts, the span of people's absolute judgment among different points on a single dimension (i.e., among bits of information) differs from their span of memory for items of information (i.e., for chunks of information). The span of immediate memory seems to be almost independent of how many bits there are in a chunk. Take, for example, the immediate memory of a list of numbers along the number dimension 1-to-100. If the numbers are random and without apparent pattern, we may be lucky to remember seven or eight of them (e.g., 90, 7, 72, 83, 43, 88, 15).

However, if we can see a pattern, we need remember only one chunk (e.g., a pattern of numbers in even sequence, "by 2's", would make it easy to remember 2, 4, 6, 8, ...100). Similarly, we could remember about seven different chunk-patterns at once, (e.g., first by 2's, then by 9's, then by 6's, then by 4's, then by 8's, then by 5's, then by 9's). And, if the chunks could be "chunked," (e.g., by 1's, by 2's, by 3's....by 100's), we could remember an almost infinite series of numbers. The capacity of the human mind to organize bits of information into chunks is an essential part of unstructurable and semistructurable decision making.

The second aspect of this maxim, the "wisely" part, is that although pieces of redundant data add little new information, intercorrelated data often give decision makers an unwarranted security about their decisions and may lead to overconfident judgments (Slovic & Lichtenstein), 1971.

Institutional research application. For example, if SAT-Verbal scores are highly correlated with Achievement Tests in English; and if these two test scores correlate in equal amounts with freshman grades, then the second test adds little to freshman grade prediction. However, the decision maker may feel intuitively that two test scores are better than one. In a way, SAT-Verbal and English Achievement here are both bits on one dimension of student ability. If SAT-Math scores (which we will pretend for sake of argument are independent of SAT-Verbal) also predict grades in freshman year, then a combination of SAT-Math and SAT-Verbal would tell us much more than would SAT-Verbal and English Achievement.

Now, if we expand the number of tests to a list of 15 scores per applicant to a college, cognitive limitations come into play. Even if there were independently useful information in each of the 15 tests (which is unlikely), the decision maker will not be able to take advantage of this information in a "raw" list. In various ways, institutional researchers can prepare and present information so that the "chunking process" is made easier. In the above admissions process example, we might by analysis of past students discover that there are really two "chunks" of useful information in the 15 test scores--a mathematical ability chunk and a verbal ability chunk. From statistical knowledge, we also would know that combining the various mathematical-related scores into one index would give a more reliable measure of math ability than a random score from the set.

At least three applications of this maxim might be tried. First, the admissions committee might know (or we might "educate them") that the 15 scores really measure two kinds of ability, and they might on their own look through the "raw" data list for an idea of a student's level on the two chunks. Second, we might give them all 15 scores, but visually group the scores according to the two abilities. Or, third, the admissions staff and institutional research office might agree that it would be preferable to compute two indices from the 15 scores, and only present these chunks.

IV. Know your decisions makers.

An awareness and understanding of the decision styles of those for whom information is prepared can lead to more effective communication by institutional researchers. There is some debate about how much we should tailor information for individual members of large organizations, such as colleges and universities. The argument against such tailoring is twofold. First, as Libby (1981) argues, research on information processing demonstrates that the best way of presenting information will be best for everyone, regardless of personal style. Second, even if there were some best format for a particular decision maker, large organizations often require that several people with different styles use the same information or the person holding a particular position may change over time. The wisest path may be to follow what is known about the optimal, general way of presenting information. Nevertheless, it clearly is beneficial to know how our most frequent colleagues and our immediate superiors typically process information. It is to our advantage (and for their convenience) to understand the preferences of these key figures and then either to organize information with these preferences in mind, or to explain why we are presenting information in different ways, given what we know about information processing.

V. <u>Heuristics are not always helpful.</u>

Many higher education decisions are based on beliefs about the likelihood of uncertain events: how good a student an applicant will be, how good a worker an employer will be, what amount of higher education dollars the state legislature will appropriate, what future job market incoming graduate students will face, how many students will enroll in a new program, whether a grant proposal will be funded.

In making predictions of uncertainty, humans naturally rely on a limited number of heuristic principles. Because of cognitive limitations and because most decisions have some element of uncertainty, people employ these simplifying strategies to reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In general, these heuristics are quite useful, but sometimes they lead to severe and systematic errors (Tversky & Kahneman, 1974).

Three of the most frequently used heuristics are (p. 1131):

1. Availability--"the availability of instances or scenarios, which is often employed when people are asked to assess the frequency of a class or the plausibility of a particular development."
2. Representativeness--"is usually employed when people are asked to judge the probability that an object or event belongs to a class or process."
3. Anchoring & Adjustment--"adjustment from an anchor, which is usually employed in a numerical prediction when a relevant value is available."

A thorough discussion of what is known about the several systematic and predictable biases that frequently result from applying the three heuristics would fill a paper (or a book) and indeed the work described by Tversky and Kahneman in 1974 has been followed by considerable additional research. The present paper will list only the biases that Tversky and Kahneman show are associated with the three simplifying strategies and then give an example of a single bias that may frequently occur in higher education decisions.

<u>Availability</u> <u>Biases</u>:

--Biases due to the retrievability of instances.

--Biases due to the effectiveness of a search set.

--Biases of imaginability.

--Illusory correlation.

Representativeness Biases:

--Insensitivity to prior probability of outcomes.

--Insensitivity to sample size.

--Misconceptions of chance.

--Insensitivity of predictability.

--The illusion of validity.

--Misconceptions of regression.

Adjustment and Anchoring Biases:

--Insufficient adjustments.

--Biases in the evaluation of conjunctive and disjunctive events.

--Anchoring in the assessment of subjective probability distributions.

Institutional research example of an availability bias. People often assess the frequency of a class or the probability of an event by how easily they can remember instances or occurrences. For example, an academic vice president might need to make decisions about implementing a more effective early retirement system in order to open up more tenure positions. The vice president needs to know what the present rate of early retirement is as one ingredient in predicting future retirements, and availability is a heuristic he surely will call on. Availability can be an extremely useful clue for assessing the frequency or probability of uncertain events as instances of large classes usually are recalled better and more swiftly than instances of less frequent happenings.

However, in the example given here, the vice president may stumble on the bias due to retrievability of instances. The vice president may be a chemist who has several friends in the natural science departments. If natural scientists at the university are much more likely to retire early than faculty in other departments, then the vice president's judgment about future early retirements will probably be too large. If the vice president or his institutional researchers are knowledgable about this bias, then his estimation will be tested by a more systematic look at the total university. Unfortunately, people usually are not aware of the biases inherent in such estimates. The past five students reviewed by an admissions committee, the most recent department chairman visited by a dean, the more retrievable instances are likely to carry the most weight in judgments of uncertainty.

Institutional research example of a representativeness bias. Just as is the case with availability, the probabilistic estimates of future events depend on more than representativeness. Although this heuristic usually is very effective in simplifying information and predicting future events, severe errors can occur. Insensitivity to prior probabilities, that is to base-rate frequencies of outcomes, is one such bias. When no evidence of representativeness is given, people use knowledge of base rates properly. However, when some evidence of representativeness is known--even highly unreliable or worthless evidence, then the base-rate knowledge is ignored.

Let us consider an academic example of two such situations. A dean knows that the Space Science Agency ("SSA") has a track record over the past five years of approving one out of ten grant applications. If asked the general question, "What is the likelihood of getting an SSA grant?", she will answer "One in ten."

In contrast, suppose the Dean needs to make a decision about whether to support the Planetary Research Project in the Astronomy Department from the General Fund contingency budget. The Project's Director has asked for six months of support as an emergency measure until he hears about his recently submitted SSA proposal. The Dean knows nothing about the worth of the grant proposal; she doesn't even know what specific areas of research are officially listed as high priority by the SSA. The Planetary Research Project previously has been funded by the Astronomical Division of the Weather Service, which has dropped this division because of "irrelevance." The Dean also is unaware of this. The Project Director gives her an abstract of the highly technical and obscure proposal together with the proposed budget. He says they have been working very hard on preparing the application and that it is very well written. He is very friendly and interpersonally competent. What probability does she assume for an estimate of the grant's acceptance? Surely not one in ten--in fact, the Dean (unless she is highly unusual) will ignore her knowledge of the base rate of grant acceptances, and will decide whether the university's project is likely to be successful based on her mostly irrelevant conversation.

Academic example of an anchoring and adjustment bias. In many decision situations, people make estimates of uncertainty by starting from an initial value and then adjusting to yield the final answer. People usually make insufficient adjustments because of the original anchor. Higher education examples include incremental budgeting, building estimates both for cost and time required, departmental distribution of faculty slots. In each of these instances, there is an anchor from past years or from an initial estimate. Adjusting estimates for present decisions based on past anchors usually is an effective heuristic, which avoids the impossible task of, for example, annually starting budgetary allocations from scratch. The difficulties in implementing zero-based budgeting attest to this near impossibility.

However, if a decision must be made about a greatly changed department's budget, the past budget amount will inexorably affect the new allocation. Assume that the Mathematics Department's "ideal" budget would be $300,000. If last year's budget was $200,000, the new budget will be lower than if last year's allocation was $400,000, regardless of the same objective needs for the upcoming year.

VI. Arrange tables by patterns.

When the probable patterns of numerical results are known beforehand, tabular presentations can be more effectively arranged by making patterns and exceptions obvious. There surely are a number of ways to implement this maxim. One "particularly insightful article" (Ehrenberg, 1977, described by Libby, 1981) gives four basic guidelines for tabular presentation of data. The following guidelines can help a reader identify patterns and exceptions in comparison with a probable known pattern.

1. Round to four significant digits. Ehrenberg says that this is helpful for mental arithmetic. The reader usually does not require detailed numbers, and the cognitive limitations of short-term memory do not need to be "clogged" with the extra digits.
2. Use row and column averages or totals. Averages and totals help the reader keep important relationships in mind, such as above and below the average or relative totals among departments. Also, in comparing the table with patterns known beforehand (such as "expert chunks" from previous years or inflation expectations), the average and total figures can be scanned for gross patterns and deviations.

3. Present the main pattern of data in columns. This allows the reader to compare individual digits by running the eye up and down a column. For example, a person may want to look for similarities and differences at the ten-thousands level. It is easier to scan up and down the fifth-digit column than to hop across the row from left to right.

4. Order the rows and columns by some measure of their size. This makes it easier to interpret a particular number by the general pattern of surrounding figures.

Institutional research application. Much of the information that institutional researchers prepare for decision makers is in the form of statistical or financial tables. There may be instances where custom or other requirements prohibit the adoption of the four guidelines, but it usually will be possible to use all or most of them. Let us look at an example:

Assume that the institutional research office has been asked to assist in preparing information for a decision of whether or not to add a new faculty position in the Cognitive Psychology program. The Psychology Department argues that in recent years the program has fallen below its traditional pattern (and excellence), and they want a new position and the dollars to support it. Obviously, a variety of quantitative and qualitative considerations will come into play here, but one request from the Academic Vice President is "the financial facts" for instructional costs in the Psychology Department in past years. She wants to know what the total salary figures have been by program for each year since 1976-77. We could present the figures in at least two ways:

Insert Tables 1 & 2 about here.

Table 1

The Old Way:

As Organized in the Psychology Department's Annual Report

Program Areas	1976-77	1977-78	1978-79	1979-80	1980-81	1981-82
Clinical	400,813	410,032	422,326	455,677	482,299	510,888
Social	300,083	301,187	306,987	323,562	336,389	350,187
Experimental	240,023	144,401	148,287	259,786	169,483	180,287
Cognitive	340,432	355,924	366,563	367,982	350,000	351,982
Developmental	350,013	361,111	372,199	401,683	425,000	450,483
TOTAL	1,631,364	1,572,655	1,616,362	1,808,690	1,763,171	1,843,827

Table 2

The New Way:

As Organized by Ehrenberg's Guidelines

Years	TOTAL	Clinical	Develmntl	Cognitive	Social	Experimntl
1976-77	1,630,000	400,000	350,000	340,000	300,000	240,000
1977-78	1,570,000	410,000	361,000	360,000	300,000	140,000
1978-79	1,620,000	420,000	370,000	370,000	310,000	150,000
1979-80	1,810,000	460,000	400,000	370,000	320,000	260,000
1980-81	1,760,000	480,000	430,000	350,000	340,000	170,000
1981-82	1,840,000	510,000	450,000	350,000	350,000	180,000
AVERAGE	1,700,000	450,000	390,000	360,000	320,000	190,000

It is very difficult to discern a pattern in "The Old Way" (Table 1) but "The New Way" (Table 2) employs all four tabular guidelines to make the data much more interpretable. Guidelines 1 and 3 can help the reader scan down columns in Table 2 to identify the Cognitive Psychology "exception." During the past three years, Cognitive salaries have fallen while salary totals for the other four areas have all increased. Guideline 4 places the programs in dereasing order of expenditure size, and makes it easier to compare Cognitive Psychology with its "neighbors." Guideline 2 provides averages and totals which are helpful in this process. Looking to the left of Cognitive, we discover that in 1976-77 the program was $10,000 behind Developmental salaries; in 1981-82 the difference has grown to $100,000. To the right, the overall six-year average of Cognitive is still greater than that of Social, but for the years 1980-81 and 1981-82, Social is nearly the same. Compared with their six-year averages, all the programs but Cognitive have grown far beyond the mean by 1981-82. The Cognitive program is <u>below</u> its six-year salary average.

Similarly, this maxim can apply to a host of other institutional research responsibilities. When analyzing and preparing information, institutional researchers should remember their <u>own</u> limitations, and take advantage of grouping, indices, and other "chunking" techniques. Particularly in the presentation of numerical data, this maxim can greatly ease the decision maker's understanding and use of complex information.

VII. <u>Negative evidence and new hypotheses are okay</u>.

On first reading, this final maxim may appear to contradict the advice of Maxim I, that "More may not be better." But Maxim VII does not call indiscriminately for more data. Rather, the advice is to remain open to two frequently ignored types of information--to new hypotheses and to negative evidence.

When decision makers remain open to alternative solutions and disconfirming evidence, their decisions may be more effective. Studies about problem solving suggest that experts begin work on a decision by retrieving a small set of hypotheses from their long-term memory, starting with available information about the situation. These hypotheses are based on knowledge about patterns of occurrences, stored in long-term memory as "chunks." The next step is to seek out information consistent with each of the initial hypotheses, evaluating in a simplified fashion whether it is confirming, disconfirming, or noncontributory.

Much of the research examines the decisions of physicians who first generate potential diagnoses from an initial medical work-up, retrieving prototypical symptom patterns from their memory. They then test for the symptoms associated with each hypothesis. Sometimes disconfirming evidence may cause the doctor to return to the hypothesis generation stage. But researchers Elstein, Shulman, and Sprafka (1978) in comprehensive investigations found that physician choices among the competing hypotheses may underweigh or even ignore disconfirming evidence, particularly toward the end of the process.

Libby notes that all three of Tversky and Kahneman's heuristics (Maxim V) come into play at different decision stages (1981). He reviews some decision aids that can help people identify correct hypotheses and also reject incorrect ones. Fault trees, standard work-ups, and lists of confirming and disconfirming evidence are recommended.

Social psychologists have come to similar conclusions about group decision making. Janis (1972) suggests ways that groups can avoid "groupthink." For example, they can appoint a "group critic" role alternating among group members at different sessions, or they can invite visitors to participate in meetings. Hackman and Oldham (1979) recommend that groups begin their work by actively discussing group strategies so that alternative ways of approaching the problem are not as likely to be missed.

Institutional research application. Academic adinistrators repeatedly are faced with decisions that are complex. One kind of "standard work-up" that a decision maker or his institutional research advisors could use to help cover the range of information and hypotheses and evidence is a systems analysis. Another aid is to prepare lists of confirming and disconfirming evidence for decision alternatives to help avoid the problem of overlooking disconfirmation.

Conclusion

The long-range goal of this paper is to discover ways that human information processing research and theory can contribute to better decisions in colleges and universities. The work of cognitive researchers can improve how institutional researchers collect and prepare information, and how they present it to campus decision makers. Seven maxims for institutional researchers have been formulated and discussed, with illustrative applications of each one to higher education. These maxims are not meant to summarize the complex and far-reaching work on human information processing, but rather to explore the usefulness of such an approach to our field.

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