MAKING SOUND DECISIONS: A FRAMEWORK FOR JUDGING THE WORTH OF YOUR DATA

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In our daily lives, we encounter decision points on a continuous basis. To maximize the likelihood of successful decisions, organizational members must draw on relevant, reliable, valid, and complete data. Sometimes copious data are available, but an overabundance can make it difficult to judge the worth of the data. This article presents a data evaluation framework that provides guidance for decision makers to evaluate and determine the potential effectiveness of the data they will use to inform their decisions.

IN OUR DAILY LIVES, we encounter decision points on an almost continuous basis: Should I do this, or should I do that? Should I go right or left? Should I take the highway or the back streets? Should I buy now or later? In an organizational setting, we are also continuously faced with decisions about what programs to sustain, which to change, and which to abandon, to name just a few dilemmas. How do organizational members go about making sound decisions? They use relevant, reliable, valid, and complete data, gathered through a sound evaluation process that is aligned with desired, long-term outcomes (Guerra-López, 2007).

Unfortunately, these data are not always readily available. If they are being collected elsewhere in the organization, decision makers may not be aware such data exist; or they may know but do not have access to them; or they do have access but do not know how to judge whether the data are relevant, reliable, valid, and complete. In essence, the appropriate set of data may not be considered in the decision-making process. In fact, Cronbach (1980) and others have argued that decisions often emerge rather than being logically and methodically made. Others, like Ackoff (2000), argue that it is not the lack of data that is the problem but rather the overabundance of data.

A critical role of organizational leaders is decision making. With this role comes pressure and risk, and the greater the consequences, the greater are the pressure and the higher the risk. Hence, decision makers may find themselves caught between analysis paralysis and a rush to judgment. Classical mathematical probability decision theories would have us analyze, assess, calculate, predict, and do all sorts of analytical, rational, deliberate machinations before making decisions. Alas, this ideal process can be quite impractical in a fast-paced, competitive business world. At the other extreme, decision makers may rely more on their opinions of their intelligence, power, and confidence than on the realities of the situation. And the outcomes of such overconfident, evidence-void, snap decisions can be disastrous (Anderson & Kilduff, 2009; Campbell, Goodie, & Foster, 2004;). Clearly, neither exhaustive analyses nor snap judgments are conducive to timely yet sound decision making.

As a number of studies have found, the credibility of the information is also critical to decision making (See, 2009; Stewart, Billings, & Stasser, 1998; Stewart & Stasser, 1995). Unfortunately, we rarely feel fully informed. Instead, we typically make decisions under some degree of uncertainty (See, 2009). Despite such realities, effective leaders are capable of making sound decisions based on sound data.

Evaluators can do much to influence the leadership decision-making process. Evaluation can provide a systematic framework that aligns stakeholders, evaluation purposes, desired outcomes, and all evaluation activities, such that the evaluation produces a responsive and clear recipe for improving performance. This in turn not only allows the decision-making process to be clearer and more straightforward, but also better enables effective leaders to make sound decisions based on sound data.

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This article presents a data evaluation framework that provides guidance for decision makers, evaluators, needs assessors, and other performance improvement professionals and their clients in determining the potential effectiveness of the data they will use to inform their decisions.

Desired results drive both the processes we employ and how we carry them out.

WHERE WE WANT TO GO: DESIRED OUTCOMES

The starting point of any organizational endeavor is identifying and verifying the ultimate ends the organization wishes to accomplish. These ends are about results, accomplishments, products, outputs, outcomes, or consequences (rather than the processes, activities, or resources to be implemented and used).

While ends are what the organization exists to accomplish and deliver, means are how it goes about doing that. Means include processes, programs, projects, activities, resources, and a host of others things that the organization uses and does to accomplish the desired ends. For example, increased sales might be one desired result, and one potential means to increasing sales might be introducing a new sales incentive plan for the sales force. Another might be a new quoting and sales process, and still another a new promotional program for customers.

A useful framework for portraying this means and ends distinction is the organizational elements model (OEM; Kaufman, 1992, 2006). The OEM consists of five overarching elements in two major categories:

1. Ends—strategic, tactical, and operational results
2. Means—processes and inputs

The OEM is a useful conceptual framework for beginning to think about the relationships among different levels of results and between these results and the means used to accomplish them. According to Kaufman, there are three levels of results:

1. *Strategic:* Long-term organizational results that ultimately benefit clients and society, often stated in terms of a consistent vision. Collins and Porras (1996) provide an excellent discussion of an organizational vision and define it as the organization's reason for being. They concur with Kaufman in that the vision is the foundation for strategic planning and execution. Their recommended time line for the achievement of strategic aims tends to be at least a decade. Using this time line as a reference is helpful in judging the relevance and completeness of performance measures.
2. *Tactical:* Shorter-term organizational results that help operationally define the vision, usually stated in terms of an organizational mission. The time line for the achievement of such accomplishments tends to be set on an annual or biannual basis. It is not so much that the types of results seek change, but rather that there are concrete annual targets to reach.
3. *Operational:* The building-block objectives—perhaps at the department, unit, team, or individual level—that contribute to the accomplishment of the organization's mission. In settings such as the military, operations describe not only the building-block results but also the processes to produce them.

All levels of results must be aligned and identified in the context of strategic planning. Desired results drive both the processes we employ and how we carry them out. Processes and inputs may be important to achieving results; however, performance goals and objectives exclusively concern results, not how they are achieved.

HOW WE NAVIGATE: PERFORMANCE INDICATORS

Performance indicators, also referred to as *measures* or *metrics*, are specific and concrete gauges of a result, process, or activity that allows us to make complex systems palpable and manageable. Neely, Adams, and Kennerley (2002) make a distinction between a performance measure, a parameter used to quantify a result, and a performance metric, the definition of the scope, content, and component parts of a broader performance measure. For simplicity, we make one simple distinction between performance results (the final end result) and performance indicator (a specific measure of that result). Much as the gauges on your car's dashboard offer a synopsis of its performance status, performance indicators provide organizations with essential information for making decisions. These indicators provide the basis for determining what data to track both now and into the future (in fact, continuously) and are used to make decisions regarding specific actions for improvement. A result can, and usually will, have multiple performance indicators. For example, sales completed—a result—can be measured through a number of performance indicators such as sales revenue, sales profits, and sales volume. Likewise, customer satisfaction can be measured through various

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performance indicators such as referrals, repeat business, account activity, returns, and customer opinion, to name a few possibilities.

Data are what we get when we measure a performance indicator. These data then become the basis for deriving information. A quantitative or qualitative value or set of values are data. However, once we attribute meaning to such data and use them as reference points for supporting a statement, the data become information. For example, say that the average sales revenue per quarter for this year (performance indicator) is found to be $1 million (data point). On its own, this data point is void of context and does not inform decisions. In contrast, this data point becomes information in the context of a statement such as, "Since we implemented the new incentive program last year, our sales revenue has doubled to an average of $1 million per quarter." This sort of transformation of data point to information is essential to making sound decisions.

GETTING THERE: THE EVALUATION PROCESS

For evaluation to be worth the resources it consumes, it must enable decision makers to make sound decisions based on relevant, reliable, and valid data that lead to improved performance. It is from here that all evaluation efforts stem. All components of the evaluation must be aligned with those objectives and expectations that the organization values and the decisions that will have to be made as a result of the evaluation findings. The key ingredient for successfully collecting relevant, reliable, valid, and complete data is *alignment*. The impact evaluation process (Guerra-López, 2007, 2008) provides a framework for such alignment (see Figure 1).

Guiding evaluation questions come from various perspectives and stakeholder groups. Each stakeholder group represents a unique point of view based on where in (or out of) the organization the group views the issues. It is important that the evaluator identify a comprehensive and representative list of questions. However, there is a

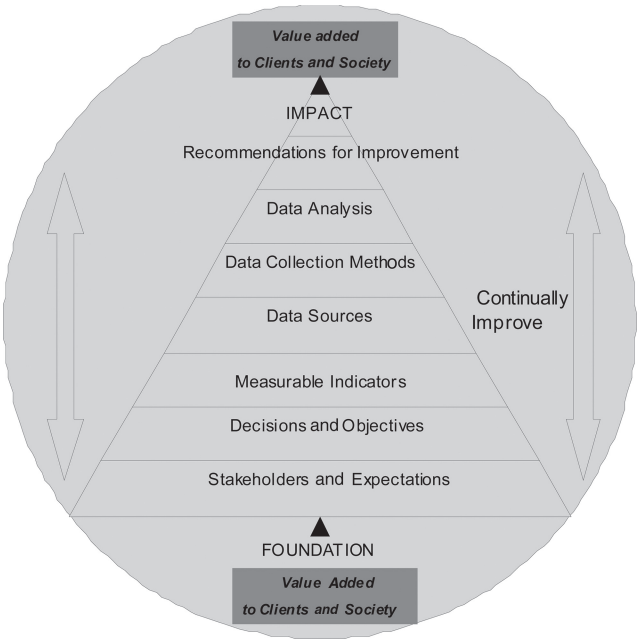

FIGURE 1. IMPACT EVALUATION PROCESS

chance that not all questions will be within the scope of this particular evaluation effort. To help narrow the list of questions, a discussion about important decisions has to be undertaken. The evaluator must determine the type of decisions that will be made with the evaluation findings. These decisions, and in turn evaluation questions, relate to specific organizational results and objectives. If you cannot confirm the types of decisions, and therefore the questions that must be asked and answered, then how will you know what relevant, reliable, valid, and complete data must be collected?

Ultimately all of the questions we ask are related to the results we want to achieve. One of the evaluator's functions is to help create the linkages among stakeholders' initial questions, the decisions they have to make, and the results to which they are inherently (and sometimes covertly) related. All organizations have an ultimate result that they want to reach, and to make that possible, numerous building-block results have to be accomplished along the way. Everything else that we do or use within the organization must contribute to those, or else we are wasting valuable and limited resources without any benefit.

This conceptual framework must be in place before any data of potential information value can be collected. Otherwise you are likely to end up with reams of data but little, if any, information for decision making. In addition, you would have wasted resources on data that may not be relevant, reliable, valid, and complete for the decisions at hand.

TABLE 1 DATA QUALITIES AND KEY QUESTIONS

	QUALITY	DESCRIPTORS	KEY QUESTIONS
First-level judgment: Performance indicator	*Relevant* Is what I have pertinent?	Relevant data are related to questions that must be answered to make a decision. Data about variables that you have designated as important to the decision and questions at hand. Data related to the time period of interest. Not all data that are available are automatically relevant.	Do the data relate to a question that must be answered to make the decision? Do the data relate to a performance indicator of interest? Do the data relate to a time period relevant to the questions that must be answered?
	Valid Is what I have meaningful?	Data point is a true measure of what it is supposed to measure. Data are accurate measurements of the indicator I claim to be measuring. Data point is well founded in the variables I have identified as important.	Do the data tell me something of value? Do the data accurately tell me something about an indicator of interest? Are the data representative of the indicator of interest?
Second-level judgment: Data	*Reliable* Can I trust what I have?	A particular data point is consistent across a variety of measures. Data come from credible sources. The data point is precise enough to render the same result each time I measure it. Data rendered for a specific indicator should be the same across various data collectors.	Do I have enough confidence in the data that I would put my job on the line? Are the sources of the data credible? Were the data generated in a credible way? Do various data points support or contradict each other?
	Complete Do I have all I want?	The data set includes related risks. The data set includes costs (financial or nonfinancial). The data set includes consequences (financial or nonfinancial; positive or negative; short, medium, and long term). All the data I have could be relevant, but perhaps not all relevant data are in your data set.	Do the data relate to a significant indicator of risk? Do the data relate to indicators of financial and nonfinancial costs? Do the data relate to indicators of financial and nonfinancial and positive or negative consequences, in the short, medium, and long terms? Do I have data for all performance indicators relevant to my questions? In other words, is what I have sufficient?

CROSSROADS: USING DATA QUALITIES TO GUIDE THE WAY

All too often you may find yourself in situations without the resources (time, money, expertise) to conduct a comprehensive evaluation from beginning to end. Perhaps a decision must be made relatively quickly, yet you still want to be diligent about using the best data available to help you make a decision. Few among us ever feel we have absolutely all of the information we want. Instead the reality is that decisions are made under varying conditions of uncertainly. But all is not lost.

You can indeed take steps to better ensure that the data you have are likely to enable sound decisions. These steps are summarized in Table 1, which also provides brief descriptors of each of the four data qualities and key questions to ask and answer to help you determine whether the data you have, or will collect, will render useful information that facilitates sound decisions.

Now that you have a sense of the data qualities and key questions (see Table 1), we examine how to put them into action. The flowchart in Figure 2 illustrates the data quality evaluation process. The process has two general rules. The first one is that order is important: begin with relevancy, next validity, then reliability, and end with completeness. Furthermore, proceed to the next quality only if you can answer "Yes" to each of that quality's key questions. Whereas, if you answer "No" to any of the key questions about a quality, then stop and exclude those data. Do not continue to the next quality until your data meet all the criteria for the previous quality.

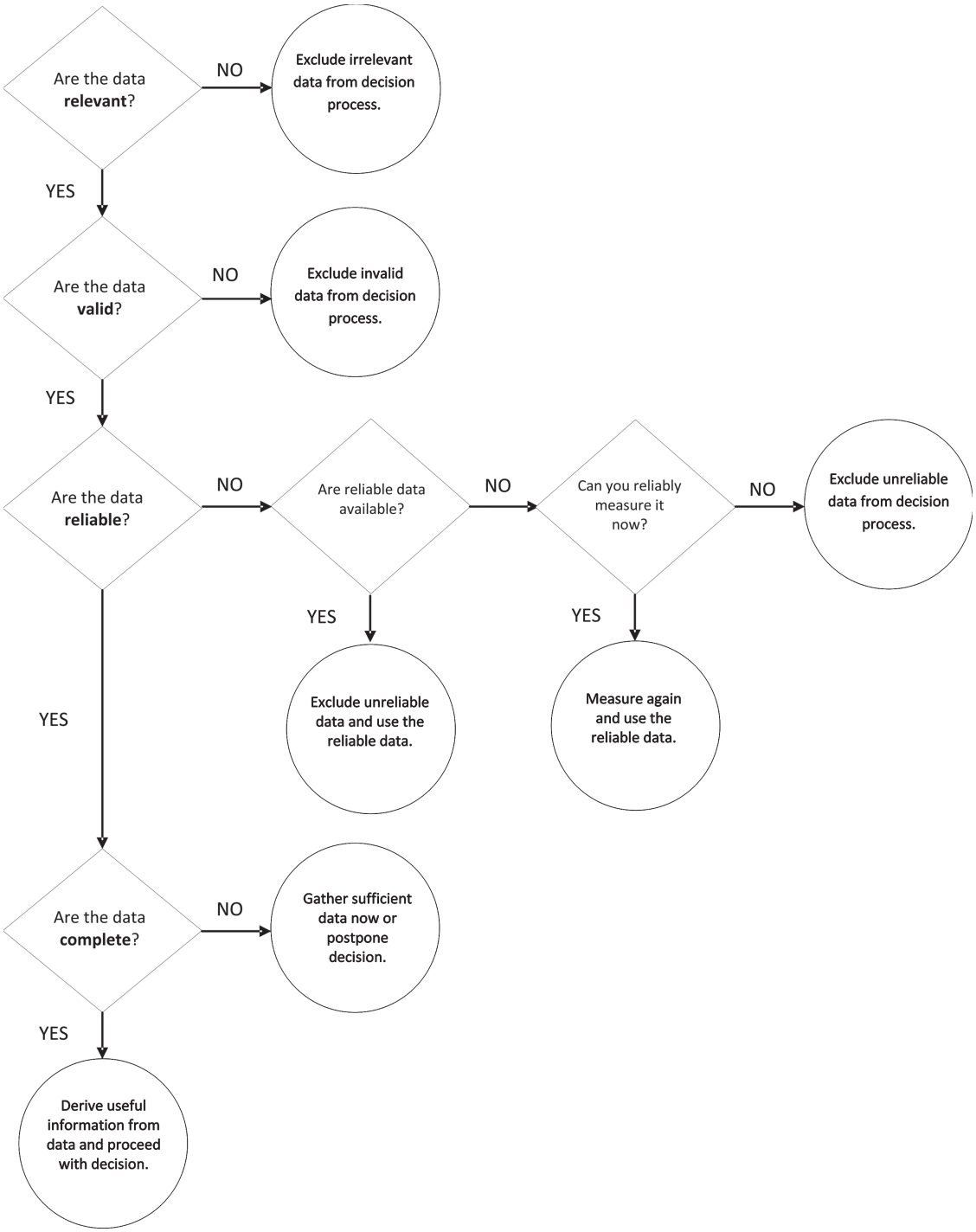

FIGURE 2. EVALUATION OF DATA QUALITIES FLOWCHART

The following descriptions describe the data qualities evaluation process in Figure 2:

1. *Relevant.* As shown in Figure 2, if you can answer yes to all of the key questions about relevance, then proceed to the valid quality. However, if you answer no to any of the key questions about relevancy, then stop and exclude all nonrelevant data. It does not make sense to continue with evaluating your data in terms of any of the other qualities if those data are irrelevant.
2. *Valid.* If you can answer yes to all of the key questions about validity, then continue to the next quality: reliability. Alternatively, if you answer no to any of the key questions about validity, then stop. Discard all invalid

data from further consideration, and do not bother with the reliability questions. The rationale here is that data that are not valid are by definition meaningless. Therefore, we do not care whether the data may or may not be reliable. But before giving up, take a look around; perhaps valid data for that indicator do exist. If so, then use those data. Now you are back in business and can proceed to consider the reliability of your data.

3. *Reliable.* If you answer no to any of the key questions about reliability, discard those data from consideration. Even if your data are relevant to an important performance indicator and the data are valid but inconsistent (unreliable), you cannot trust their accuracy. Again, however, you may not yet have reached a dead end. Consider whether you are able to reliably measure that indicator in order to generate reliable data or whether there are other reliable data for that indicator already available.
4. *Complete.* The completeness quality is not so much used to ask questions about each data point but rather about the data set as a whole. Answering no to any of the completeness questions does not necessarily mean you should eliminate your current data from consideration; rather "no" answers direct your attention to data you should have but do not. If you answer no to any of these questions, consider whether it is prudent to proceed to the decision-making stage without complete data.

PUTTING IT ALL TOGETHER

The ideal decision-making scenario is to begin with a clear definition of the long-term results that stakeholders want to accomplish. It is from this strategic perspective that mid- and short-term results and related questions should stem. These questions in turn clarify what performance indicators we should measure to generate the data required for sound decision making. In some instances, you will have the time and other resources to conduct a rigorous and practical evaluation that will help you collect the relevant, reliable, valid, and complete data you require. In other instances, you may not be able to conduct a comprehensive evaluation. Should you find yourself in the latter situation, then follow these steps to ensure that you are able to select the most useful data from what is already available, and remember to involve stakeholders in every step:

Step 1. Identify or confirm the stakeholders who can affect or be affected by the decision.

Data quality evaluation can have bountiful rewards.

Step 2. Specify long-term and strategic results that stakeholders desire.

Step 3. Specify relevant mid- and short-term required results with the help of stakeholders.

Step 4. Derive key questions to be answered to make sound and informed decisions.

Step 5. Determine appropriate performance indicators.

Step 6. Evaluate the soundness of the available data with regard to their relevancy, reliability, validity, and completeness.

Step 7. Determine whether you have sufficient data to make a sound and informed decision.

Keep in mind the possibility that available data may not be useful, and the data that are useful may not be sufficient to make sound decisions. Going through the exercise of evaluating data qualities may reveal critical insights that can help you build a case for putting off the decision at hand until you have the relevant, reliable, valid, and complete data required to make the best decisions possible. Beware of the rush-to-judgment trap. Making half-blind decisions imposes great risk of failure, jeopardizing potential gains or worse. Instead, take the time to evaluate the quality of your data before risking poor decisions. Data quality evaluation can have bountiful rewards. For example, it can lead you to realize the importance of having a performance measurement system that continually tracks key performance indicators and is consistently used for managing and improving performance (Guerra-López, 2010).

CONCLUSION

It has often been said that numbers speak for themselves. If this were true, then we could dispense with decision makers altogether. Data do not make decisions; people make decisions. Green and Hall (1984) remind us that "data analysis is an aid to thought, not a substitute" (p. 52). Gigerenzer and Hoffrage (1995) reinforce this important point that mathematically determined decisions such as "average" decision strategies do not hold up because individuals, not averages, make decisions.

People attribute meaning to data, and meaningful data then inform sound decisions. Of course, the attribution of meaning can be subjective and point different people to different decisions. Moreover, this attribution can be affected by our individual perceptions of purpose and what ought to be. For these reasons, it is critical to begin with a clear and agreed-on list of desired results. Our ultimate goals should be the basis for the questions that must be asked and answered before making a sound and informed decision, as well as the specific indicators we will have to measure. Only in this way do we generate relevant, reliable, valid, and complete data.

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