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# Evidence-Based Decision Making (EbDM):

*Techniques for Adding Rigor to Decision Support Processes in Complex Government and Industrial Organizations*


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Government and industry organizations today are under increased pressure to respond to rapidly changing conditions. Managers must make complex, expensive decisions, riddled with risk and uncertainty. Evidence-based decision making (EbDM) provides results where organizations need to make better-informed decisions, faster. Through the use of collaboration, mathematical, and organizational behavior tools, EbDM combines several technologies and disciplines that add rigor to the decision support process through an emphasis on refining the objective, finding evidence, analysis, visualization, and a taking action framework. From heuristics and optimization to simulation and predictive models, computer-based techniques provide traceable, repeatable methodologies that assist organizations in decision support. Our approach to decision-making support through EbDM provides empirical and parametric evidence, showing how modeling and simulation can provide faster, more accurate reporting, improved decision making, improved customer service, and reduced costs.

## The Art of Decision Making

"Decision making is a process of choosing among two or more alternative courses of action for the purpose of attaining one or more goals" (Turban et al., 2011, p. 41). In Mintzberg's (1980) foundational research on managerial work, decision making was one of the top 10 responsibilities of managers in the daily performance of their work. Making decisions is part of every phase of an operation, from organizing, planning, executing, and controlling, to closing or completing actions. According to Simon (1977), managerial decision making is synonymous with the entire management process. Once thought of as an art acquired through years of experience and using one's intuition, decision making in organizations today is far more complex, requiring institutional processes to be able to track, replicate, and defend the who, what, where, and why decisions were made to stakeholders and regulators alike.

Simon identified four phases of the decision-making process; intelligence, design, choice, and implementation (1977). Figure 1 (Turban et al., 2011, p. 46) provides a representation of those decision-making phases. The decision-making process begins with the intelligence phase. This phase examines the organizational objectives surrounding the decision, initiates problem identification, ownership, and classification. A clearly defined problem statement is an output of the intelligence phase. The design phase is characterized by formulating a model that captures elements of the problem and its relationship to attributes in the system from which it operates. The design phase concludes with potential alternatives that meet the criteria of solving the problem. The choice phase includes examining the alternatives through qualitative and quantitative analysis leading to a proposed solution. The final phase includes implementation of the solution. If implementation is successful, the organization moves forward on to other issues. If implementation is not successful, the decision-making process is returned to an earlier phase to repeat the process.

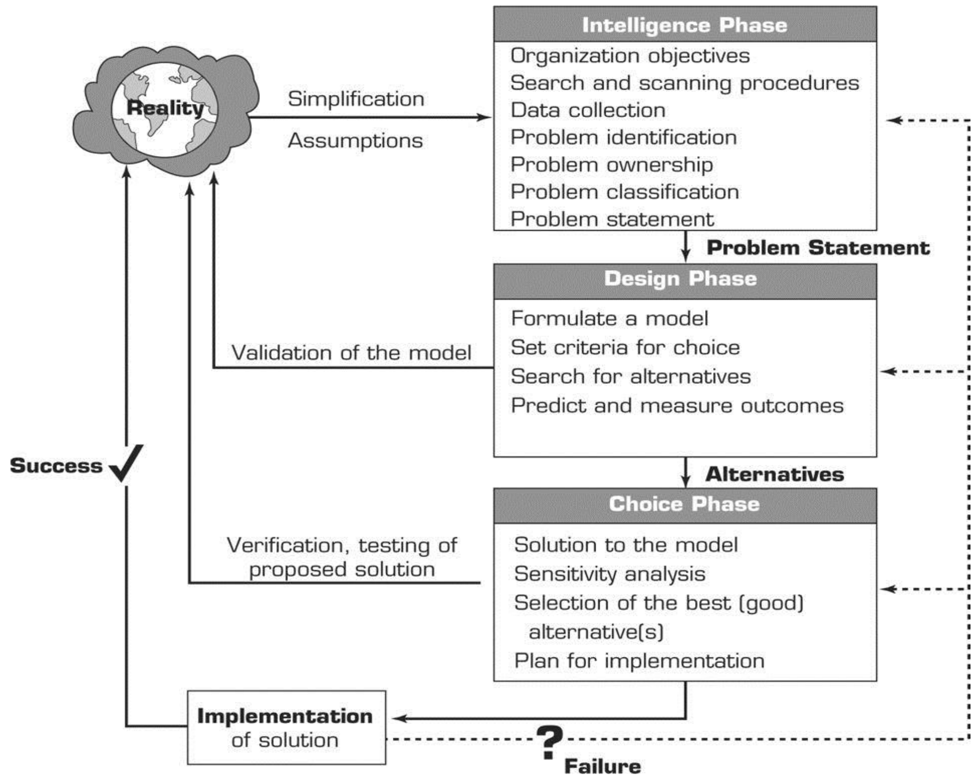


**Figure 1. Decision-making model.**

Turban (2011) identified three conditions under which decisions are made. These include decision making under conditions of certainty, uncertainty, and risk. "In decision making under certainty, it is assumed that complete knowledge is available so that the decision maker knows exactly what the outcome of each course of action will be (as in a deterministic environment)" (Turban et al., 2011, p. 148). In this environment, modeling and simulation have a limited role since the decision maker has all the information he or she needs. There are some conditions that are rule based and automated decision systems can be employed. The second environment in which decisions are made are under conditions of uncertainty. There are several outcomes for each choice, and there is usually insufficient information for the decision maker. Modeling and simulations are key tools that can be used to equip decision makers with the information they seek. Finally there, is decision making under risk, wherein "the decision maker must consider several possible outcomes for each alternative, each with a given probability of occurrence" (Turban et al., 2011, p. 149). This environment is also ripe for analytic tools that include modeling and simulations.

## Framework for Business Intelligence

The concept of business intelligence (BI) has gained acceptance as an information system that contains all of the data an executive needs. Indeed, BI is linked to decision making, but a BI system is not a decision system in and of itself. BI is relevant in decision support since it is viewed as an overarching term that includes architectures, tools, databases, applications, as well as methodologies (Turban et al., 2008). BI is based on the concept of transforming data into information from which decisions are made and actions taken. This is done through interactive access to data and real-time data manipulation. BI contains four major components as part of its architecture: a data warehouse, analytical tools, a performance management system for analyzing performance, and a user interface.

According to Thompson (2004), BI is most commonly seen being used in general reporting, sales and marketing analysis, planning and forecasting, financial consolidation, budgeting, profitability analysis, and statutory reporting.

The main benefits of BI are to provide accurate information when needed. Thompson (2004) reported four key benefits of BI systems:

- Faster, more accurate reporting
- Improved decision making
- Improved customer service
- Increased revenue

Traditional BI applications are, too often, large monolithic infrastructures that are inflexible and reliant on an information technology department. These systems often answer only predefined questions, denying the user the ability to satisfy their curiosity and to drill down or look across the data in order to answer questions. The focus is too often on data alone and not on how the data relates to the vision, mission, strategy, operational readiness requirements, and current decision processes. As processes evolve, these systems do not offer users insight to the data in a manner that supports their evolved responsibilities or the revised metrics. If the processes change, if the decisions being supported change, or if the answers suggest additional questions to the user, the business intelligence capability has typically not had the ability to quickly adapt. The inability of the analyst to explore and ask additional questions of the data leads to frustration and does not effectively support a dynamic decision-making process.

## Decision Support Systems

In assisting the decision maker, decision support systems (DSS) "were meant to be adjuncts . . . extending their (the decision-makers' capabilities but not replacing their judgment." (Turban et al., 2011, p. 75). Scott-Morton described the major concepts of a DSS in the early 1970s by describing them as "interactive computer-based systems, which help decision makers utilize data and models to solve unstructured problems" (Gorry and Scott-Morton, 1971, p.55). Yet others provided many other definitions of a DSS, leading to the conclusion that there is no universally accepted definition of a decision-support system (Alter, 1980; Bonczek et al., 1980; Keen, 1980; and Little, 1970). However, there is general consensus on key characteristics that can be found in a DSS, as shown in Figure 2 (Turban et al., 2011, p77). Power (2002) proposed six classification schemes for DSS that have since been adopted by the Association for Information Systems Special Interest Group for Decision Support, Knowledge and Data Management Systems (AIS SIGDSS):

- Communications driven

- Data driven
- Document driven
- Knowledge driven
- Model driven
- Compound system (integrates two or more DSS groups)

Figure 2 shows key characteristics that not only comprise DSS but BI systems as well. This intersection of DSS and BI systems lends itself to a set of tools and techniques that define business analytics. It is in this arena that computer modeling and simulation can yield the greatest benefits. These benefits include (Turban et al., 2011, p. 45):

- Manipulating a model (changing decision variables or the environment) is much easier than manipulating a real system. Experimentation is easier and does not interfere with the organization's daily operations.
- Models enable the compression of time. Years of operations can be simulated in minutes or seconds of computer time.
- The cost of modeling analysis is much lower than the cost of a similar experiment conducted on a real system.
- The cost of making mistakes during a trial-and-error experiment is much lower when models are used.
- The business environment involves considerable uncertainty. With modeling, a manager can estimate the risks resulting from specific actions.
- Mathematical models enable the analysis of a very large, sometimes infinite, number of possible solutions. Even in simple problems, managers often have a large number of alternatives from which to choose.
- Models enhance and reinforce learning and training.
- Models and solution methods are readily available on the Web.

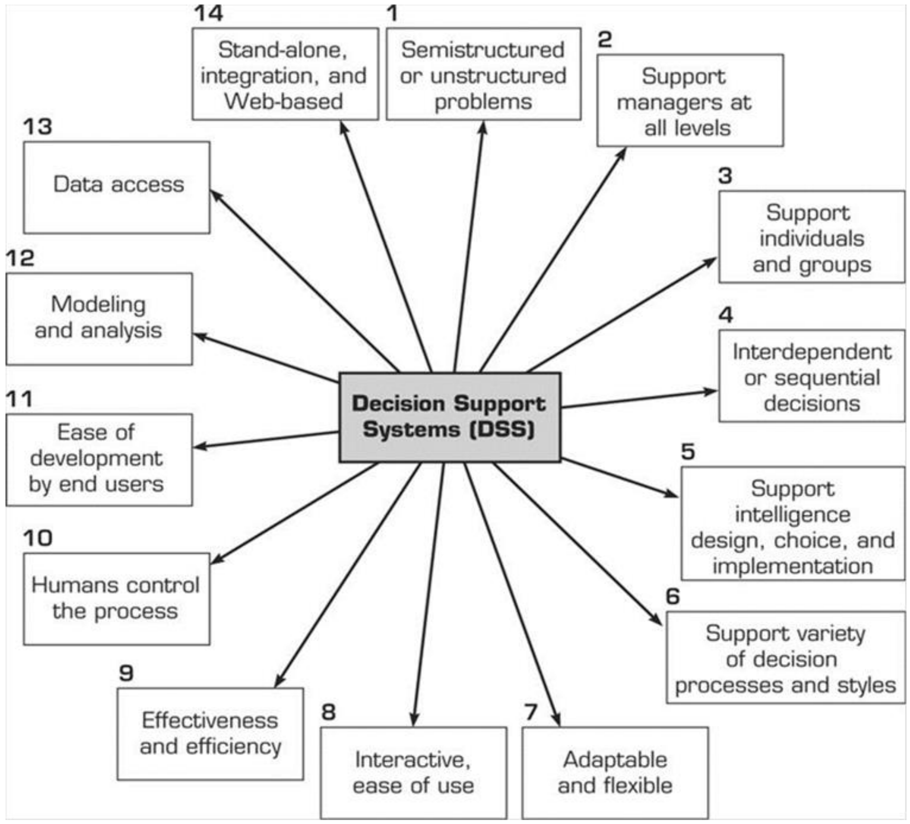


**Figure 2. Key characteristics of a decision support system.**

## Evidence-Based Decision Making

Today, leaders and key personnel need to be empowered to explore and discover insights from the data, solve problems, and ultimately make informed decisions in a dynamic environment. DSS and BI systems provide an excellent foundation for constructing a framework that is traceable, repeatable, and defendable, yet flexible enough to adapt to changing customer needs. Building on the methodologies and technologies of DSS and BI systems, we designed EbDM, a scientific-based approach and tool set designed to provide our customer's needs. There are five elements of EbDM that are supported by business discovery applications (see Figure 3) that are repeated through a series of sprints (see Figure 4) until decision makers are satisfied that their objectives have been met.

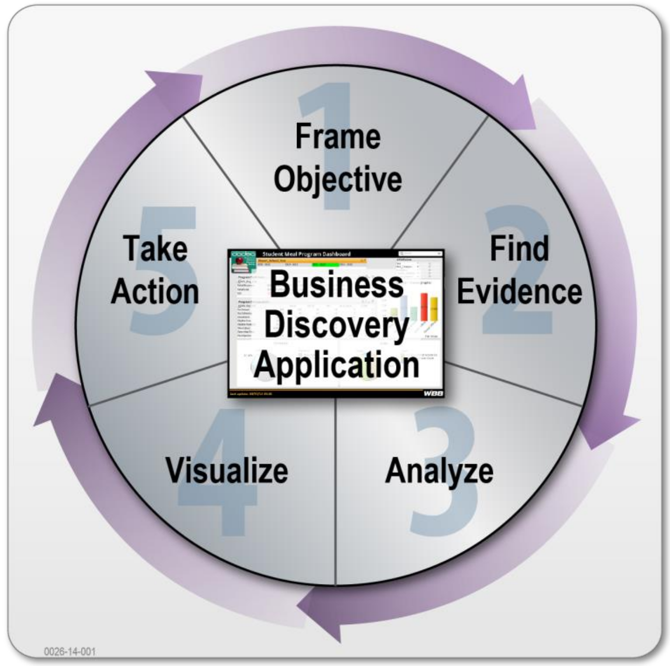


**Figure 3. Five elements of evidence-based decision making.**

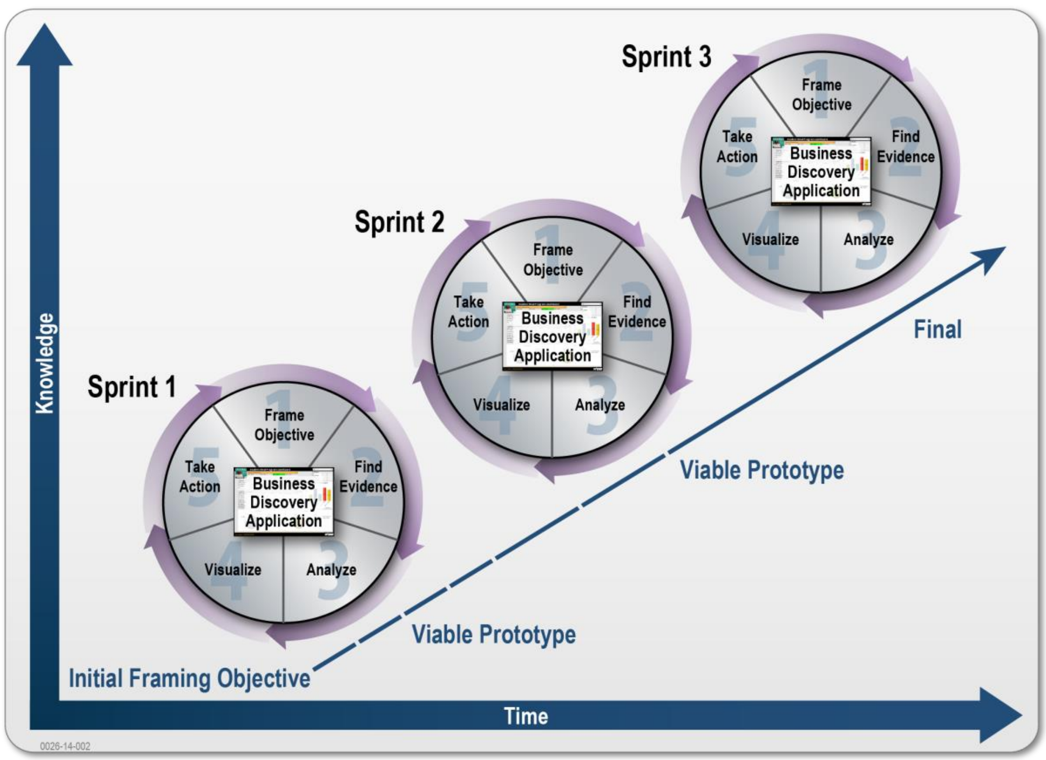


**Figure 4. Employing lean startup methodologies with EbDM.**

### EbDM Element 1: Refine Objective

The first element, refine the objective, begins with an understanding of the objectives of the decision-making process, the strategic context within how it fits in the organization, and the desired end result. It is essential to link organizational data to the most important drivers of value and performance. Decision makers must be able to describe the key questions to be resolved, from which key performance indicators (KPIs) are developed. This in turn informs the main hypothesis, relevant metrics, and the data collection plan.

### EbDM Element 2: Find Evidence

The second element in an EbDM approach considers finding the right evidence necessary to guide sound decision making. Selecting only the appropriate data critical to addressing key questions is pivotal to finding the right evidence. By understanding the KPIs, organizations can quickly sift through large amounts of data and focus only on relevant information. Collecting and integrating relevant evidence is not just limited to quantitative data (numerical data) but also qualitative data (judgment information that provides context). Evidence comes in multiple forms that provide context such as numbers, sounds, text, graphics, and pictures. Business discovery applications such as database management systems (DBMS), online analytical processing (OLAP) tools, performance management (BPM/CPM) systems, and group support systems (GSS) are often used here.

### EbDM Element 3: Analyze

The third element, analyze, focuses on transforming critical data into actionable knowledge. Many organizations are so focused on the collection and distribution of data that there is little effort placed on meaningful analysis. To overcome these shortfalls, a rigorous methodology that includes discovery, diagnoses, prescription, and prediction is needed.

*Discovery*. The analysis starts with developing a complete understanding of the descriptive nature of the data. This builds insights that identify statistical associations among events or observations and helps to confirm causal relationships. Looking at the data from different perspectives proves or disproves hypotheses generated during the framing and evidence gathering. The exploration allows for the identification of hidden trends and/or gaps in the data. Discovery is an iterative process of continuous profiling (what it is, who it belongs to, where it is used) and validating (identification and mitigation of flaws) the data.

*Diagnoses*. The key analytics questions and KPIs provide the foundation of the diagnostics analysis. Through the use of business discovery applications such as optimization models, mathematical programming, trend analysis, and forecasting, a higher degree of analytics can be achieved. This enables the team to quickly drill into root causes and identify/implement appropriate business rules, algorithms, and mathematical models.

*Prescription*. Reports and queries are performed against databases to address decision makers' questions and produce prescriptive recommendations. Given the growth of data and the shortened decision cycle time, KPIs are programmed into a business discovery dashboard. This enables the analysts and decision makers to rapidly identify the issues, refine their questions, and develop the necessary information.

*Prediction*. Data is transformed for use in predictive models and integrated into the business discovery platform. The predictive models are used in trend analysis to generate forecasts with well-characterized accuracies about the future or diagnoses. Such forecasts or diagnoses can be harnessed within procedures that generate recommendations to the analyst on how to react to what the data represents. The cycle of data-prediction-action provides a pervasive decision support capability engendering decision confidence.

The key to EbDM is the ability to rapidly provide a pervasive analytical delivery mechanism, enabling a whole new level of analysis, insight, and value to existing data stores with user interfaces that are clean, simple, and straightforward. Using a business discovery platform simplifies the analysis using a variety of user driven interactive and intuitive presentations. The dashboard becomes the "glue" to conducting descriptive, diagnostic, prescriptive, and predictive analysis.

### Element 4: Visualize

It is crucial when analyzing data to keep the target audiences and their specific needs in mind. EbDM is only fully effective when the right information is delivered to the right people at the right time. Business discovery tools include geographic information systems (GIS), informational portals, multidimensional presentations, and dashboards.

Throughout the previous steps, stakeholders, analysts, and decision makers are identified who interact with the data. The basis for the design of the interactive user interface comes from the decision process models and use cases. This provides context to what will follow and ensures that the charts, graphs, and tables are focused squarely on meeting a critical information need of the target audience. This avoids the trap of focusing on "interesting" rather than "valuable" information.

In traditional models that follow a linear path of analysis, presentation, and decision maker feedback, time is wasted between receiving decision maker feedback and cycling back through analysis and presentation to provide answers to the decision maker's previous questions. In a visualization model that uses adaptive dashboard techniques, the linear model is replaced with a circular model where the decision maker is part of the analysis visualization cycle. Instead of waiting for feedback from the decision maker, supporting analysts are more apt to move directly into the "take action" element of EbDM.

Sometimes decisions must be made under conditions of risk, when there are multiple outcomes each with its own probability distribution function. Or, sometimes there is just insufficient information to make a decision and the data does not exist that can help inform the decision maker. In situations like these, a different approach must be taken to assist the decision maker. One methodology designed for situations like these, called Lean Startup, was developed by Eric Ries (2011). Lean Startup was initially developed for technology-driven startup companies but has been adapted to general industry faced with the need to make decisions with less than ideal information. Lean Startup aims to shorten product development cycles by adopting a combination of business-hypothesis-driven experimentation, iterative product releases, and validated learning principles. Applying a Lean Startup methodology to EbDM produces a series of repeated cycles or sprints that each produce a viable prototype and build on lessons learned from earlier efforts (see

Figure 4). Users, stakeholders, and decision makers work closely to discover, validate, improve, and pivot, if necessary, throughout each iteration. This drives immediate value and gives stakeholders control over the outcome. The intent is to capture inputs early by starting small, incorporating user collaboration, and then building incremental capability. The process focuses on critical decisions, processes, required data, and KPIs.

### EbDM Element 5: Take Action

Adoption of EbDM enabled by a business discovery application provides widespread analytical capabilities across an organization, allowing it to exploit fleeting opportunities in a budget-constrained environment. However, streamlining decision processes often requires active change management that builds successful practices into the beliefs and culture of an organization, enabling faster and more effective reactions to external events. As described in the visualization element, effective use of dashboards depends on using the right business discovery tools and incorporating the correct KPIs and analytics to deliver the information decision makers need to develop a knowledge base sound enough to make a traceable, repeatable, defendable decision. Sometimes this can occur in one event. Alternatively, discovery is made and a different prototype of the model must be developed to address different questions and KPIs. Figure 4 captures this iterative process of building on discovery through the use of repetitive prototypes, each designed to provide decision makers with the knowledge base they require. Business discovery applications that commonly use this element include multi-criteria decision making with pairwise comparisons and analytic hierarchy process (AHP) techniques.

## Conclusion

EbDM enables government and industry leaders to rapidly achieve a cross-functional advanced analytic capability. This methodology is scientific and aligns data collection to strategic value drivers and collects the best available evidence. This evidence is then used to extract valuable knowledge and share analytics in a way that allows all users to act on those insights. In short, the approach

- Provides evidence-based business discovery that lets users ask questions of data, thus effectively gaining insight from relevant data.
- Installs rapid access to multiple federated data sources to monitor, measure, and manage operational performance, resources, requirements, and project status, as well as the relationships and dependencies among them.
- Provides the analytical tools that support analysts and decision makers, giving them the ability to quickly discover and assess shortfalls in required data, support tradeoff decisions, and assess risk in near real time.
- Collaborates quickly across the organization by sharing content and filtered data, annotating elements, sharing snapshots of their data set, or sharing their session and enabling guests to actively make selections.

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