

# ON THE LIMITS TO VALUE OF DECISION SUPPORT SYSTEMS (DSS)

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## Introduction

IT value has been measured at various levels of analysis, including the economy, firm, business process and individual levels (Brynjolfsson and Yang 1996). However, understanding where *potential value* lies – and how best to measure the firm's *realized value* – remain important concerns. This research examines predictors of *value gaps* for IT investments that reflect losses in realized value relative to potential value. Its theoretical perspective treats a range of IT investments that involve human users who leverage systems to improve business process outcomes.

We draw on information economics (Demski, 1980), judgment analysis (Cooksey 1996) and the IT value literature. *Limits to value* of a decision system may be imposed by variations in bounded rationality (Simon 1960). They arise in business processes from individual human factors. At this level, potential for value creation exists, but value realized by the firm may be inefficient. We model revenue management decision making, using simulations that enable measurement of actual versus predicted revenue in reservation making. Revenue management is a tactical choice: value is measurable and experimental manipulation is feasible. Consequently, we can assess how DSS information value is degraded.

## Understanding Value

Three perspectives for understanding IT value bear on our investigation.

*The Economic Perspective on Information Value* provides a normative account of DSS value. Economics defines a decision problem in terms of selecting an appropriate action. The goal: *to maximize expected value given a set of possible states in the presence of a probability function specifying their likelihood, and a value function specifying values associated with action/state combinations*. Decisionmakers (**DMs**) are value-maximizers who make choices in a stochastic environment. Information offers insights on the probability distribution of states that may ensue, enabling the DM to improve upon unaided decisions. The information can be *perfect*, defining the ensuing state, or *imperfect*, yielding probabilistic estimates of the state. Information has value when it changes the value-maximizing action that a rational DM selects,

improving performance. This yields a change in expected value of the DM's value function.

DMs are boundedly rational: they conduct less-than-exhaustive information searches, and have incomplete knowledge of stochastic environments. DSSs can reduce impacts of the DM's bounded rationality on decision performance. However, bounded rationality limits a DM's ability to understand embedded DSS knowledge and evaluate outcomes from using it. Thus, where a DSS aids, but does not "decide," the DM's bounded rationality may have unintended consequences: potential value may go unrealized.

*The Judgment Analysis Perspective on Information Use* offers a descriptive account. Realizing potential DSS value requires users to appropriately weight DSS outputs in decisionmaking. Researchers have studied human judgment and information use in *probabilistic environments* (Cooksey, 1996). Several findings have been established:

- simple models capturing relevant information often outperform human judgment (Camerer and Johnson 1991);
- simple outcome feedback is not very useful in improving performance (Remus et al. 1996);
- people do not deal well with stochasticity, and misperceive random patterns as having structure (Gilovich et al. 1985).

Thus, DMs will have difficulty learning how useful DSS information is, particularly in stochastic environments. So potential DSS value may go unrealized.

*The Business Process Perspective on IT Value* is useful for working out the mechanics of IT value measurement. The *locus of value* (Kauffman and Weill 1989) of DSSs – where potential value is realized – is usually in a business process. Here, organizational production occurs, and system characteristics make or lose money (e.g., suggesting how hotel rooms may be packaged, priced and sold in the market). System and process design choices can overcome limits to value imposed by the DM's bounded rationality (Davamanirajan et al. 1997).

## Theory

*Value Measurement Theory.* Measuring DSS value, even *ex post*, is complicated: it is hard to determine the value of actions that are *not* taken. However, in revenue management this complication almost disappears. Revenue management involves forecasting micro-market demand and optimizing pricing and product availability to maximize revenue (Cross 1997). Its basic tenets are market segmentation, multiple rate pricing and using price to handle demand fluctuations. Because *ex post* it is possible to estimate what demand was, we can determine the revenue that would have been produced by pricing schemes *not* chosen. The hotel industry commonly measures a revenue manager's performance this way.

Perfect performance,  $R_p$ , is the revenue obtained with optimal pricing, given materialized

demand – perfect information revenue. Baseline performance,  $R_0$ , is the revenue when no revenue management practices are used (first-come first-served reservation making).  $E[R_p - R_0]$  is the value of perfect information. To understand the value loss due to human cognitive limits, we model steps on a continuum between *perfect information* and *no information* conditions (our baseline), for perfect and imperfect users of information. (Table 1)

\*\*\*\* TABLE 1 GOES ABOUT HERE \*\*\*\*

The idea of a “perfect” user is important. A perfect user’s rationality is unbounded; she does not exhibit typical flaws that the judgment analysis literature predicts will be present. More realistically, revenue managers are “imperfect” users. They may misinterpret the capabilities of a revenue management model and mistakenly override DSS recommendations.

In contrast to the expected value in Case 1 (Perfect Information/Perfect User),  $E(V_p) = E[R_p - R_0]$ , Case 2 relaxes the requirement of perfect information (Imperfect, Best *Ex Ante* Information) but assumes a perfect user. The expected value is  $E(V_{ib}) = E[R_{ib} - R_0] = E[f(R_{ib}, R_0)] = E[f(g(R_p, N), R_0)]$ , and  $E(V_p) > E(V_{ib})$ . In this expression and those that follow,  $f[\cdot]$  and  $g[\cdot]$  are continuous and differentiable functions, and  $N$  measures noise in the environment.

The impact of user imperfections in decision making occur in Case 3 (Imperfect, Best *Ex Ante* Information/Imperfect User). Expected value is given by  $E(V_{ib}') = E[f(g(R_p, N, h(N, I)), R_0)]$ .  $I$  measures user imperfection in decision making, and  $E(V_p) > E(V_{ib}) > E(V_{ib}')$ . In this expression,  $h[\cdot]$  indicates the extent to which a typically imperfect DM – varying in her biases – is affected by noise. We expect cumulative losses to potential value.

When Imperfect, Less Than Best *Ex Ante* Information is involved (Cases 4 and 5), a perfect DM’s expected value outcomes are likely to dominate those of a boundedly rational DM:  $E(V_{il}) > E(V_{il}')$ , with  $E(V_{il}) = E[R_{il} - R_0] = E[f(R_{ib}, R_0)] = E[f(g(R_p, N), R_0)]$ , and  $E(V_{il}) = E[f(g(R_p, N, h(N, I)), R_0)]$ . With imperfect users, however, the expected value of Imperfect, Best *Ex Ante* Information diminishes. It should dominate that of Imperfect, Less Than *Best Ex Ante* information,  $E(V_{ib}') > E(V_{il}')$ . For such dominance to occur,  $h[\cdot]$  must be sufficiently independent of the quality of the information provided to the user. However, research shows people tend to evaluate information inconsistently. They prefer deterministic over probabilistic information about the future, and overreact to extreme information (Yates et al. 1996). Whether such biases in information evaluation are perverse enough to break the dominance of Best *Ex Ante* information is an empirical question we are addressing.

**Hypotheses.** These observations lead us to specify three hypotheses:

**H1:** As noise increases, Imperfect Best *Ex Ante* information becomes less valuable relative to Perfect Information for a perfect user.

- H2:** As noise increases, user imperfections lead to greater value losses for a given level of information quality.
- H3:** For imperfect users, value outcomes with Imperfect Best *Ex Ante* information will dominate those with Imperfect Less Than Best *Ex Ante* information.

### **Experimental Design**

**Simulator.** A hotel revenue management simulation game was developed and used to test the hypotheses. The simulator provided current and historical information (e.g., reservations on book, cancellations, etc.). A DSS provided recommendations on expected demand, and appropriate pricing and overbooking. Subjects were instructed to maximize revenue, and could choose how much they followed DSS recommendations. To evaluate the DSS, subjects were given outcome feedback for their own performance (“U” in Sample Screenshot, Figure 1) and the system (“S”).

\*\*\* FIGURE 1 GOES ABOUT HERE \*\*\*

**Subjects/Method.** 104 graduate and executive education students were given 30-minute overviews of revenue management principles and simulator operation. They made 60 demand forecasts, and pricing and overbooking decisions over a series of reservation nights. 15 initial training decisions were followed by a re-initialized game with 45 experimental decisions.

**Design.** A 2x2 factorial design was employed. Half the subjects received Best *Ex Ante* demand forecast information via the DSS; the other half received Less Than Best *Ex Ante* information. Noise was set high (to 25%) for half and low (to 10%) for the rest. The computer tracked actual demand, and subjects’ and DSS forecasts. We computed revenue achieved in the six cases by applying a perfect *ex-post* pricing algorithm to the appropriate demand number. (Table 2.) This yielded raw data for hypothesis testing.

### **Ongoing Work**

Preliminary results suggest potential value losses occur with user imperfections. DMs given Best *Ex Ante* information often chose not to use the DSS – they overrode its recommendations. This behavior remained robust even after DMs had opportunities to learn about DSS forecast value. Override behavior appears to asymptote to non-zero values in frequency and amount. (Figure 2 and Table 3).

\*\*\* FIGURE 2 AND TABLE 3 GO ABOUT HERE \*\*\*

Our current efforts involve modeling the value losses associated with the DMs’ override behavior. We are also exploring interventions to minimize impacts of user imperfections on override behavior and reduce consequent value losses that we observe in real world revenue management.

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**Table 1. Value and Revenue Outcomes for Six Information / User Conditions**

Case	Information Conditions	User	Value of Information	Revenue
1	Perfect Information	Perfect	$V_p$	$R_p$
2	Imperfect, Best <i>Ex Ante</i>	Perfect	$V_{ib}$	$R_{ib}$
3	Imperfect, Best <i>Ex Ante</i>	Imperfect	$V_{ib}'$	$R_{ib}'$
4	Imperfect, Less Than Best	Perfect	$V_{il}$	$R_{il}$
5	Imperfect, Less Than Best	Imperfect	$V_{il}'$	$R_{il}'$
6	No Information	No User	$0$	$R_0$

*Note:* The subscripts  $p$ ,  $i$ ,  $b$  and  $l$  on the Value and Revenue variables are intended to indicate perfect, imperfect, best *ex ante* and less than best information, respectively. The prime mark (') indicates an imperfect user.

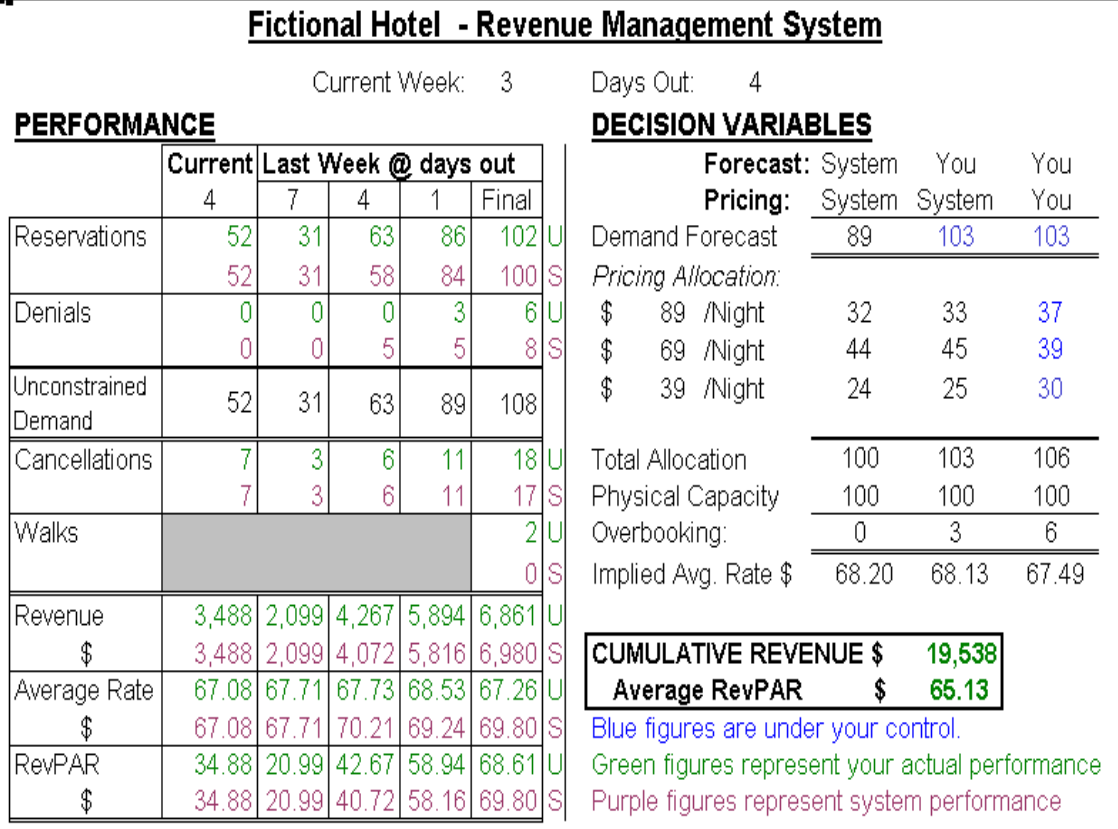
**Imperfect, Best *Ex Ante* Information** is the best historically-based information. The difference between **Imperfect, Best *Ex Ante* Information** and **Perfect Information** is limited by how representative history is of the future (i.e., how much signal versus noise exists in historical data). In a noiseless environment **Imperfect, Best *Ex Ante* Information** is perfect.

**Table 2. Demand Figure Used for Revenue Calculations for Each Case**

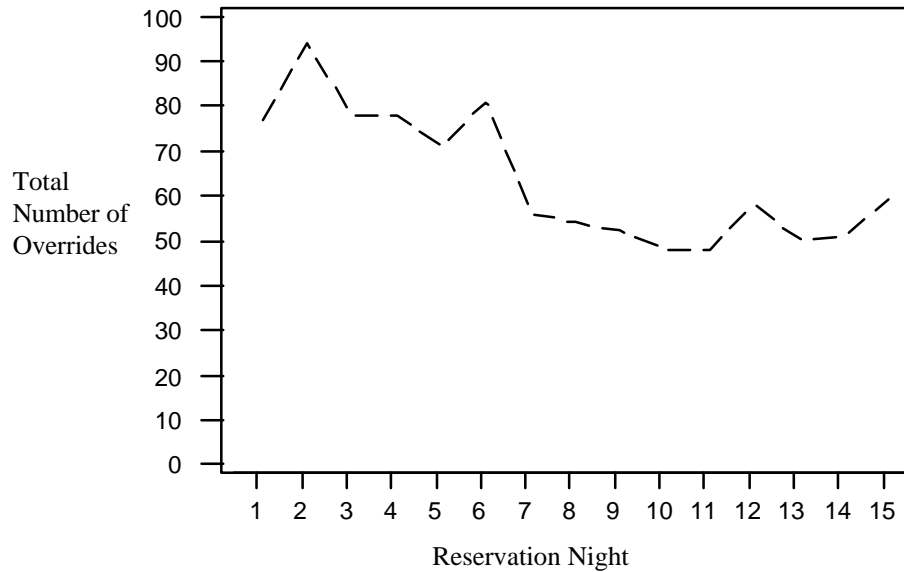
Case	Information	User	Demand Used for Revenue Calculation
1	Perfect Information	Perfect	<i>Actual Demand</i>
2	Imperfect, Best <i>Ex Ante</i>	Perfect	<i>DSS Forecast</i>
3	Imperfect, Best <i>Ex Ante</i>	Imperfect	<i>Subject Forecast</i>
4	Imperfect, Less Than Best	Perfect	<i>DSS Forecast</i>
5	Imperfect, Less Than Best	Imperfect	<i>Subject Forecast</i>
6	No Information	No User	<i>No Forecast (first-come first-served pricing)</i>

*Note:* The practice of revenue yield management involves several steps. A demand forecast is made. Then pricing decisions are made based on the demand forecast. The revenue numbers for our analysis are calculated on the basis of Actual Demand, DSS Forecast and Subject Forecast, depending on the case, assuming a value-maximizing set of choices for room prices.

**Figure 1. The Revenue Management Game Screenshot**



**Figure 2. Total Number of Overrides by Reservation Night (for Subjects with Imperfect, Best *Ex Ante* Information)**



*Note:* Subjects made demand forecasts at 3 different points in time leading up to a given reservation night. Thus the theoretical maximum number of overrides for a given night is 156 (52 subjects x 3 forecasts).

**Table 3. – *t* -Tests of Override Behavior During the Final Three Nights**

Variable	Mean	Standard Deviation	<i>t</i>	<i>P</i>
Number of Overrides	2.96	3.205	6.66	0.0000
Mean Absolute Override	9.02	15.64	4.16	0.0001

*Note:* Results are for 52 subjects provided with Imperfect, Best *Ex Ante* Information. Subjects made demand forecasts at 3 points in time periods leading up to a given reservation night. The theoretical maximum Number of Overrides is 9 (3 forecasts x 3 nights). The capacity of the hotel was 100 rooms, so a Mean Absolute Override of 9.02 translates to adjusting the DSS forecast by 9% of the hotel capacity.