Why Managers Don't Use Good Decision Models and What We Can Do About It

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Potential for OR Models in Marketing….

- The Global 1,000 companies spend about $1 trillion on Marketing. (Source: Accenture).
- 68% of the participants indicate they have problems even articulating, much less measuring, the ROI of marketing (Source: Accenture).
- Systematic marketing decision making can improve marketing productivity by 5 – 10% with minimal additional costs (i.e., it has very high ROI)….many sources.

➔High potential for OR models/DSS's???

And yet…

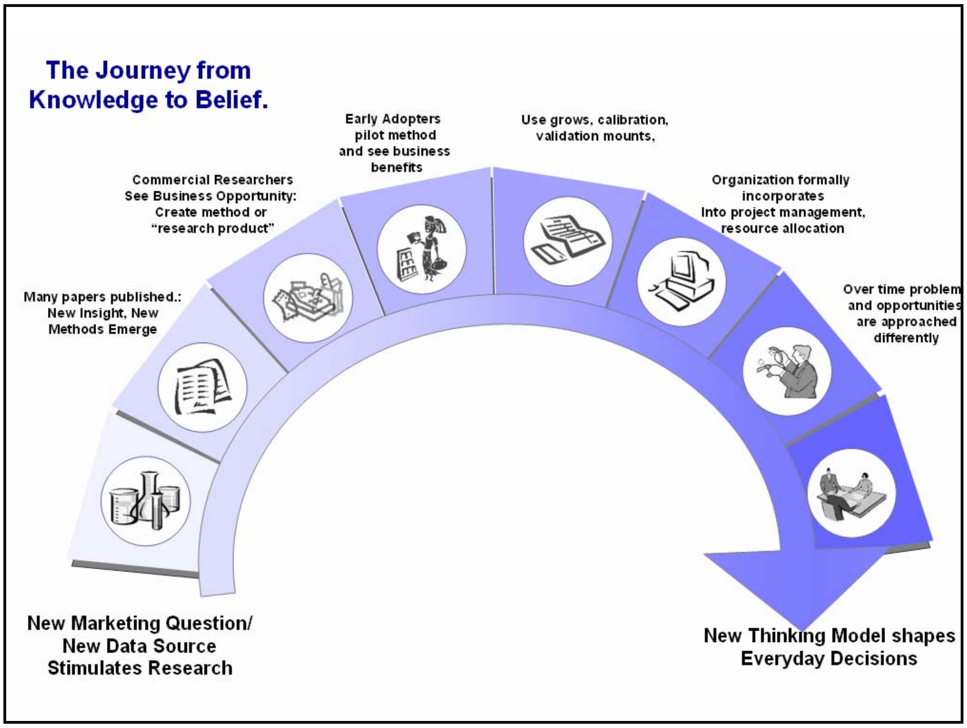
- "….it is highly unlikely that decision makers will consistently outperform a good quality model-based decision support system and they are better off relying on even a simple, but systematic model…" (Hoch and Schkade 1996, p. 63).
- Retail pricing DSSs that include price-optimization models dramatically outperform retail managers (Reda 2003, Montgomery 2005)
- Only 5 to 6% of retailers use such DSSs even after their organizations have purchased them, with most managers preferring to use gut-feel for making pricing decisions (Sullivan 2005)
- Research shows managers' disinclination to use DSSs even when the models embedded in the systems are known to improve decision quality and performance (Ashton 1991, Singh and Singh 1997, Yates, Veinott, and Patalano 2003, Sieck and Arkes 2005).

An Industry Perspective

"Adoption of Marketing Science"

What Success Looks Like for One Marketing Organization (P&G)

Delaine Hampton
Director, Consumer and Market Knowledge
Procter & Gamble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New Insight, New
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Over time problem
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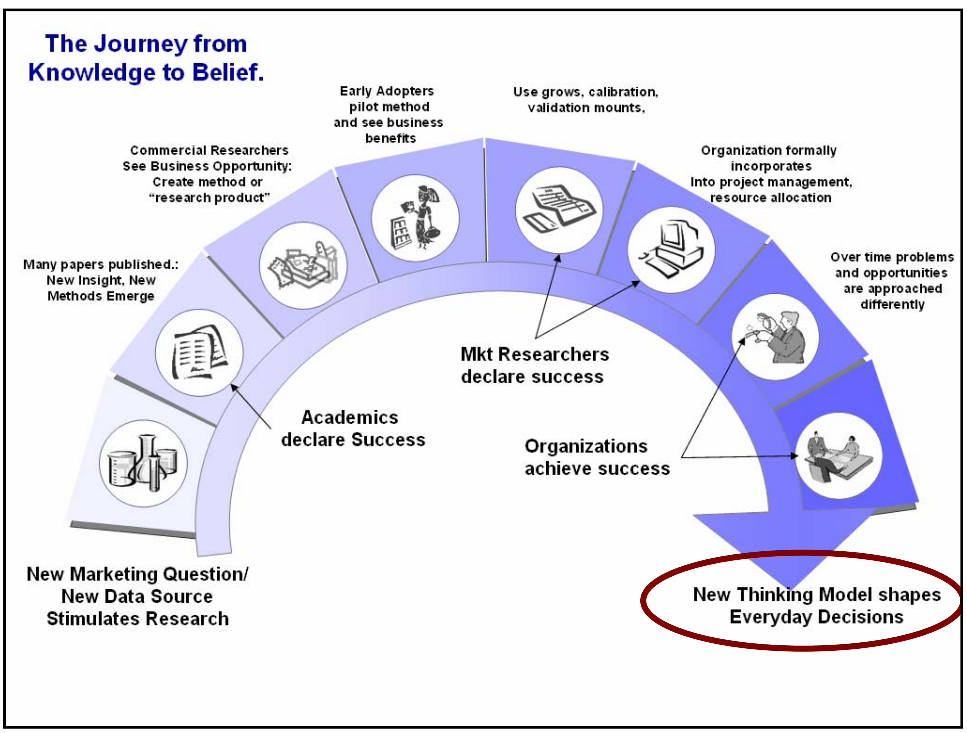
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New Insight, New
Methods Emerge
Over time problems
and opportunities
are approached
differently
Mkt Researchers
declare success
Academics
declare Success
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How Successful are Our Most Visible Marketing Models?

(Van Bruggen and Wierenga,,European Management Journal 2001)

Table 2 Marketing Management Support Systems in the Sample

Type of MMSS	Systems in the sample
Marketing Models	MEDIAC (Little and Lodish, 1969) SPRINTER (Urban, 1970) GEOLINE (Hess and Samuels, 1971) CALLPLAN (Lodish, 1971) DETAILER (Montgomery *et al.*, 1971) ADMOD (Aaker, 1975) MODEL FOR ALLOCATING RETAIL OUTLET BUILDING RESOURCES (Lilien and Rao, 1976) STRATPORT (Larréché and Srinivasan, 1981) PRICESTRAT (Simon, 1982) DEFENDER (Hauser and Shugan, 1983) SALES TERRITORY ALIGNMENT MODEL (Zoltners and Sinha, 1983) SH.A.R.P. (Bultez and Naert, 1988) SIMOPT (Green and Krieger, 1989)
Marketing Expert Systems	INNOVATOR (Ram and Ram, 1988) NEGOTEX (Rangaswamy *et al.*, 1989) ADCAD (Burke *et al.*, 1990) DEALMAKER (McCann and Gallagher, 1990) PROMOTION DETECTIVE (McCann and Gallagher, 1990) TEXTBOOK PROMOTION ADVISOR (McCann and Gallagher, 1990) ESWA (Neibecker, 1990) SHANEX (Alpar, 1991)
Marketing Decision Support Systems	ADBUDG (Little, 1970) THE SYSTEM OF PROMOTIONAL MODELS (Rao and Lilien, 1972) NEWPROD (Assmuss, 1975) BRANDAID (Little, 1975) THE A/S RESPONSE MODEL (Rao and Miller, 1975) PERCEPTOR (Urban, 1975) MAPLAMOD (Bloom and Stewart, 1977) TRACKER (Blattberg and Golanty, 1978) ADVISOR2 (Lilien, 1979) ASSESSOR (Silk and Urban, 1978) NEWS (Pringle *et al.*, 1982) SCANPRO (Wittink *et al.*, 1988)
Marketing Knowledge-Based Systems	PROMOTOR (Abraham and Lodish, 1987) CAAS (Kroeber-Riel, 1990) DATASERVER PARTNERS/COVERSTORY (Schmitz *et al.*, 1990)
Marketing Case-Based Reasoning Systems	ADDUCE (Burke, 1991) CASE-BASED REASONING SYSTEM FOR FORECASTING PROMOTIONAL SALES (McIntyre *et al.*, 1993)

How Successful are our Most Visible Marketing Models?

Table 6 The Perceived Impact of the Marketing Management Support Systems

Impact measures	Mean (st. dev.)
Number of companies that implemented the MMSS	46.3 (79.3) (Range: 0–333)
Percentage of companies that still use the MMSS	44.3 (42.2) (Range: 0–100)
Impact of MMSS on actual decisions[a] (small – large)	5.40 (1.33)
Success of implementation of MMSS[a] (not successful – very successful)	5.43 (1.19)
Satisfaction of users[a] (not satisfied – very satisfied)	5.47 (1.07)
Impact Scale (Cronbach $\alpha = 0.80$)	

[a]For these indicators 7-point scale items were applied

Our Most Successful Models???

Many Ways to Fail---Few to Succeed?

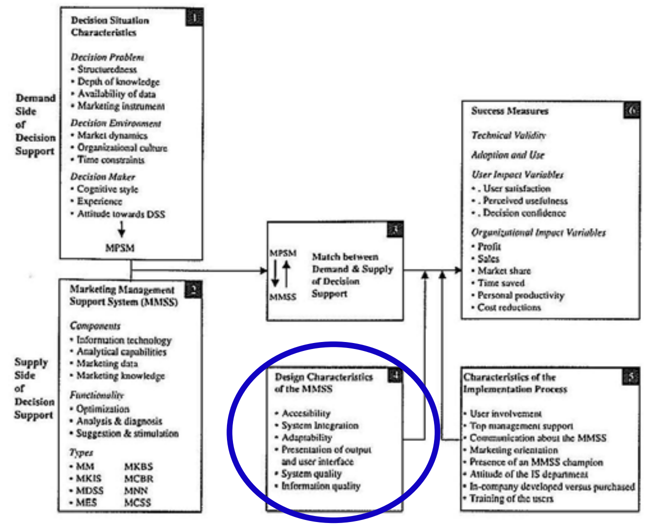

Figure 9.1 An Integrating Framework of Factors That Determine the Success of Marketing Management Support Systems (*Source:* adapted from Wierenga, Van Bruggen, and Staelin 1999)

#1: DSS Effectiveness in Marketing Resource Allocation Decisions: Reality vs. Perceptions (ISR 2004)

How do OR models influence managerial decisions?

- ❑ **Objective Outcomes:**
  - ❑ **Profit realized (as computed by model; compared to reality)**
  - ❑ **Decision quality as judged by experts**
  - ❑ **Perceptual measures of performance (e.g., satisfaction)**
- ❑ **Subjective Outcomes**
  - ❑ **Decision Satisfaction**
  - ❑ **Learning**
  - ❑ **DSS Usefulness**

How…

- Experimental study
  - Two real business cases (ABB, Syntex; Winners of Edelman prize)
  - 56 pairs of students in eight experimental conditions
    - Subjective measures at individual level
    - Objective measures for team performance
  - All subjects had access to spreadsheet; those in the treatment conditions had additional built-in modeling capabilities
  - Clearly specified anchor points (status quo) in both cases

Method

Experiment with both within- and between-subject measurements

Experimental Design

	ABB Case	Syntex Case
Condition 1	No DSS	No DSS
Condition 2	No DSS	DSS
Condition 3	DSS	No DSS
Condition 4	DSS	DSS

Note: Order of cases were also randomized.

Decision Models Selected for Study

- **ABB:** Select 20 customers to focus incremental marketing effort (model helps users to move toward segmentation based on switchability, but does not provide specific directive suggestions)
- **Syntex:** Determine level of sales effort, and allocation of effort across products (Model allows users to optimize contribution under various user-imposed constraints, and provides specific directive suggestions)
  - Both cases are based on real decision situations where we know the actual outcomes and were Edelman Prize winners.
  - Both cases are part of the Marketing Engineering suite of software programs -- we can control the kind of decision aids given to subjects

Syntex Model

(Lodish et al.)

Product Model

Unit Cost of Salesperson $ 63

Segment	Base Selling Effort	Recom-mended Sales Force	Recom-mended Sales Level ($)	Unit Margins (0 - 1)	Shadow Price ($000)	Constra Low	High	Base Estimates None	1/2-	1/2+	Sat.	Current Response Estimates None	1/2-	1/2+	Sat.
Naprosyn	96.8	96.8	214,400	0.700				0.47	0.68	1.26	1.52	0.47	0.68	1.26	1.52
Anaprox	142.4	142.4	36,500	0.550				0.15	0.48	1.20	1.35	0.15	0.48	1.20	1.35
Nor135	52.7	52.7	21,200	0.720				0.31	0.63	1.15	1.25	0.31	0.63	1.15	1.25
Nor150	24.1	24.1	37,200	0.720				0.45	0.70	1.05	1.10	0.45	0.70	1.05	1.10
Lidex	27.3	27.3	38,000	0.530				0.56	0.80	1.11	1.20	0.56	0.80	1.11	1.20
Synalar	29.7	29.7	14,600	0.530				0.59	0.76	1.07	1.11	0.59	0.76	1.07	1.11
Nasalide	56.8	56.8	11,200	0.520				0.15	0.61	1.46	1.76	0.15	0.61	1.46	1.76
Total	429.8	429.8	373,100												

Net Profit = ($000) $218,827 $218,827

Help

Note:
1. Only unit margins and the cost of a saleperson can be changed by the user.
2. Shadow Price -- the economic value of relaxing the constraint by one unit.

ABB Choice Model

(Gensch et al.)

10		Ann. Purchase		Firm	Estimated Purchase Probabilities			
11	Customer	Volume ($ K)	District	Chosen	A(ABB)	Firm B	Firm C	Firm D
12	1	$761	1	B	15.3%	82.3%	2.4%	0.0%
13	2	$627	1	D	0.0%	0.0%	2.6%	97.4%
14	3	$643	2	A	74.7%	25.3%	0.0%	0.0%
15	4	$562	3	D	48.8%	39.7%	0.0%	11.5%
16	5	$469	3	C	2.0%	0.0%	98.0%	0.0%
17	6	$233	1	B	0.0%	96.8%	3.1%	0.0%
18	7	$664	3	D	40.5%	7.7%	0.1%	51.8%
19	8	$767	3	D	0.0%	56.4%	0.0%	43.6%
20	9	$467	1	D	0.3%	0.0%	1.3%	98.4%
21	10	$844	1	B	6.0%	94.0%	0.0%	0.0%
22	11	$1,722	3	A	22.2%	5.0%	72.7%	0.0%
23	12	$928	1	D	0.0%	0.0%	0.6%	99.4%
24	13	$466	2	A	63.8%	0.0%	36.2%	0.0%
25	14	$211	1	C	0.0%	0.1%	99.9%	0.0%
26	15	$696	2	B	1.1%	98.9%	0.0%	0.0%
27	16	$894	3	B	55.6%	16.7%	20.3%	7.3%
28	17	$1,364	3	B	21.3%	13.1%	7.7%	57.9%
29	18	$408	3	C	0.5%	0.0%	99.5%	0.0%
30	19	$733	1	B	0.3%	99.7%	0.0%	0.0%
31	20	$1,009	2	B	0.0%	99.6%	0.4%	0.0%
32	21	$749	3	A	87.8%	11.5%	0.0%	0.6%

Experimental Procedure

1. **Pre-Experimental Questionnaire**
2. **Case 1**
   - ❑ **Case Description**
   - ❑ **Model Tutorial**
   - ❑ **Recommendation forms**
3. **Post-Experimental Questionnaire 1**
4. **Case 2**
   - ❑ **Case Description**
   - ❑ **Model Tutorial**
   - ❑ **Recommendation forms**
5. **Post-Experimental Questionnaire 2**

ABB Case:
Gains from Resource Allocation

	Incremental Profit ($)	Sales volume of selected firms
Unaided Groups (n=28)	3,249 (1,979)	44,933 (14,697)
Model-Aided Groups (n=28)	4,770 (2,089)	30,860 (13,511)
	F(1,55)= 7.82 p=.007	F(1,55) = 13.91 p=.000

Objective Improvement

Note: Incremental profit based on scoring rule calibrated from actual sales.

Syntex Case: Profit Outcomes

	Net Profit
Unaided Groups (n=27[1])	252,918 (16,477)
Model-Aided Groups (n=28)	267,553 (13,535)
	F(1,54) = 13.0 p=.00

Objective Improvement

Numbers in parentheses are standard deviations.
[1]: One outlier was dropped from the analysis

Expert Rater's Evaluations (ABB Model Recommendations)

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	53.09	7.65		6.94	0.00
Order	-2.30	3.04	-0.09	-0.76	0.45
Word Count	0.09	0.02	0.54	4.60	0.00
ABB Model	0.81	3.39	0.03	0.24	0.81
De-Anchoring	0.00	0.00	0.10	0.77	0.45

Raters Saw No Improvement

$R^2 = 0.32$

Dependent variable: Overall rating of case analysis by experts

Expert Rater's Evaluations (Syntex Model Recommendations)

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	24.54	6.65		3.69	0.00
Word count	0.17	0.03	0.66	6.41	0.00
Order	1.10	3.52	0.03	0.31	0.76
Syntex model	5.00	3.71	0.14	1.35	0.18
De-Anchoring	0.02	0.02	0.16	1.53	0.13

Raters Saw Almost No Improvement

$R^2 = 0.48$

Dependent variable: Overall rating of case analysis by experts

Results

- The availability of models (either ABB or Syntex) objectively improved resource allocation performance—good models➔ good decisions
  - And can change the basis of allocation decisions (e.g., shift focus to growing products, profitable products, switchable customers, etc.)
- Model users made decisions that shifted them farther away from anchor points (e.g., larger sales force size in Syntex, less focus on larger customers in ABB).
- However-- Expert judges (managers?) could not identify objectively better decisions. They reacted positively to the supporting argument (Word Count)

Observations

- (Good) DSS use improves performance,
- Users often don't perceive this improvement
- Expert raters (e.g., top management???) are not able to judge quality of decisions
- DSS's can help in de-anchoring from prior beliefs

➔ ???? What's needed???

#2: One Take on the Problem…Feedback??

[Under 2nd round review, ISR]

One Take on the Problem

Decision Support Systems

Ample evidence that decision models improve the objective quality of decision making

(McIntyre 1982, Lodish et al. 1988, Hoch & Schade 1996, Lilien et al. 2004)

↓

High objective evaluations

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High objective evaluations

Decision makers

(users)

Ample evidence that users have difficulty recognizing the value of decision models, resulting in reduced usage (McIntyre 1982, Davis 1989, Van Bruggen et al. 1996)

Low subjective evaluations

One Take on the Problem

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Low subjective evaluations

What is the source of this inconsistency?
What can be done to resolve this inconsistency?

Source

- A DSS recommends customers to be selected for a direct marketing campaign
- Customers are described on Recency/Frequency/Monetary Value (RFM).
- Model underlying DSS:

Attractiveness = w_1*R + w_2*F + w_3*M,

where,

w_1= .4

w_2= .5

w_3= .1

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where,

w_1= .4

w_2= .5

w_3= .1

- A direct marketing manager with extensive experience has strong beliefs of weights
- Manager's mental model is sticky
- Manager's Mental Model:

Attractiveness = w_1*R + w_2*F + w_3*M,

where,

w_1= .1

w_2= .2

w_3= .7

Source

DSS model weights

w1= .4

w2= .5

w3= .1

Recommends customers

Manager's mental model

w_1= .1

w_2= .2

w_3= .7

"Knows" best customers

Source

DSS model weights

w1= .4

w2= .5

w3= .1

Recommends customers

GAP

Manager's mental model

w_1= .1

w_2= .2

w_3= .7

"Knows" best customers

Source

DSS model weights

w1= .4

w2= .5

w3= .1

Recommends customers

Manager's mental model

w_1= .1

w_2= .2

w_3= .7

"Knows" best customers

GAP

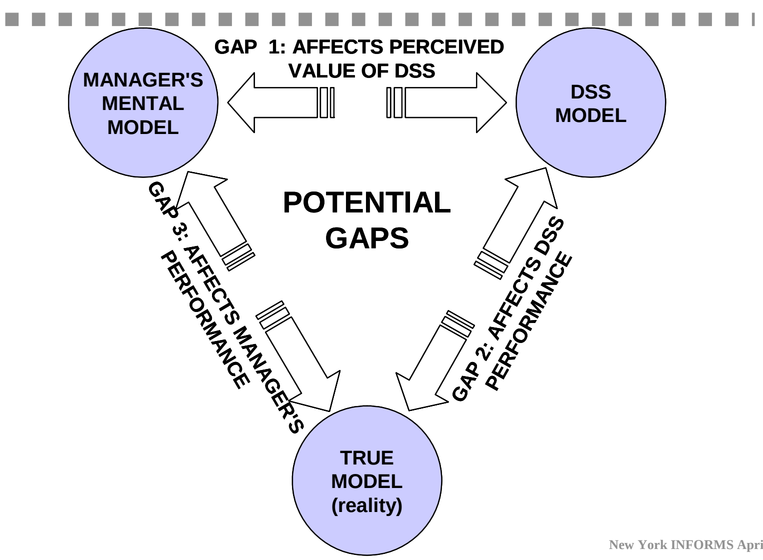
? ?

Gap leads to uncertainty (Einhorn & Hogarth 1980)

Discounting of preference

Lower likelihood of usage and adoption

3-GAP MODEL



Connecting DSS Evaluation to Mental Model Changes

- Therefore, for a DSS to be **successful** (**i.e., adopted and used**), it has to help users update their mental models (reduce Gap 1)

- **So, how can a DSS be designed to change users' mental models?**

A change in a mental model can be of two types:

- A real change: Internalization of new model
  - Deep learning: A change in a mental model that endures over time and/or changes in conditions – a relatively permanent acquisition of knowledge. **per Delaine Hampton/P&G**

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- A real change: Internalization of new model
  - Deep learning: A change in a mental model that endures over time and/or changes in conditions – a relatively permanent acquisition of knowledge— **per Delaine Hampton/P&G**
- A transient change: No internalization of new model
  - Mechanistic Learning: A change in a mental model that occurs only in the presence of external feedback, but disappears over time or when supporting conditions are eliminated.

Connecting Mental Model Changes to Feedback

To obtain deep learning, individuals must:

1. Exert effort, but they should know why – need an incentive
   - **Upside potential feedback**

Connecting Mental Model Changes to Feedback

To obtain deep learning, individuals must:

1. Exert effort, but they should know <u>why</u> – need an incentive
   - **Upside potential feedback**

AND

2. Know <u>how</u> to change their mental model – need guidance on where they are going wrong and what

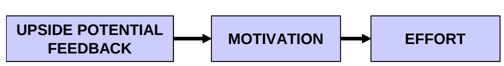
   action to take to improve.
   - **Corrective feedback**

Effect of Upside Potential Feedback on Learning

<u>Positives</u>

Increases motivation & effort

Economic agency theory (Eisenhardt 1989), goal-setting theory (Locke et al. 1981), self-efficacy theory (Bandura 1986)



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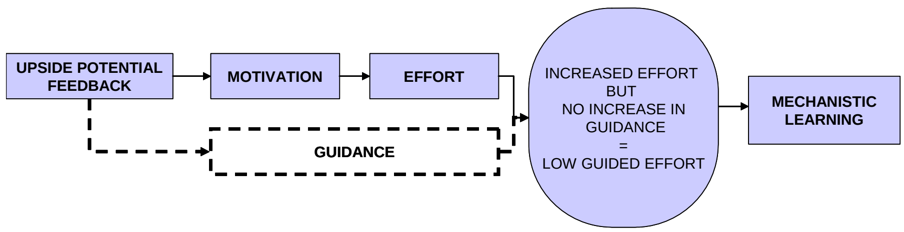
Increases motivation & effort

Economic agency theory (Eisenhardt 1989), goal-setting theory (Locke et al. 1981), self-efficacy theory (Bandura 1986)

Negatives

Focus on self, not task-learning processes

(Wood et al. 1990, Hogarth et al. 1991, Kluger and Denisi 1996)

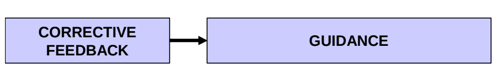


Effect of Corrective Feedback on Learning

Positives

Focuses attention on task-learning processes

(Kluger and Denisi 1996)



Effect of Corrective Feedback on Learning

Positives

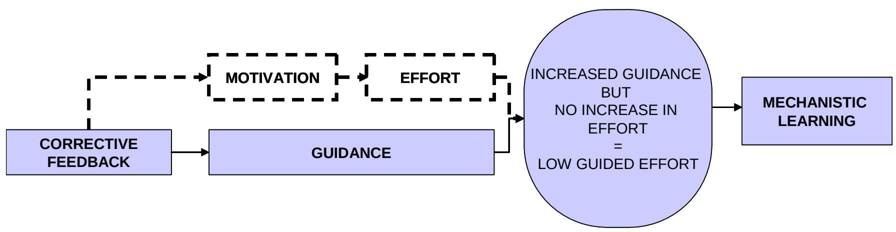
Focuses attention on task-learning processes

(Kluger and Denisi 1996)

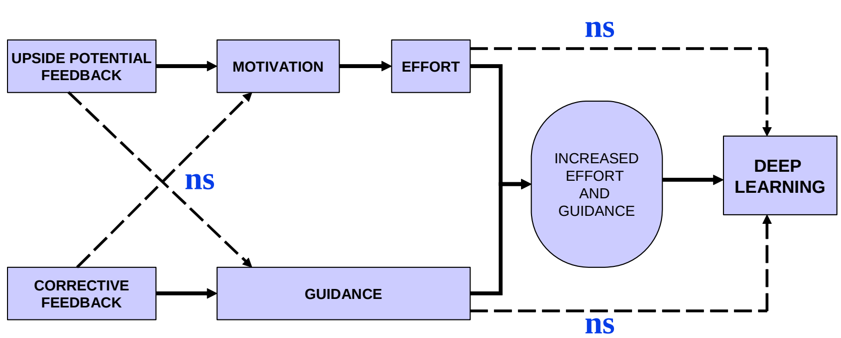
Negatives

Effort-minimizing behavior results in mechanistic learning

(Wood & Goodman 2005, Goodman 1998, Balzer et al. 1989)



Combining Upside Potential and Corrective Feedback



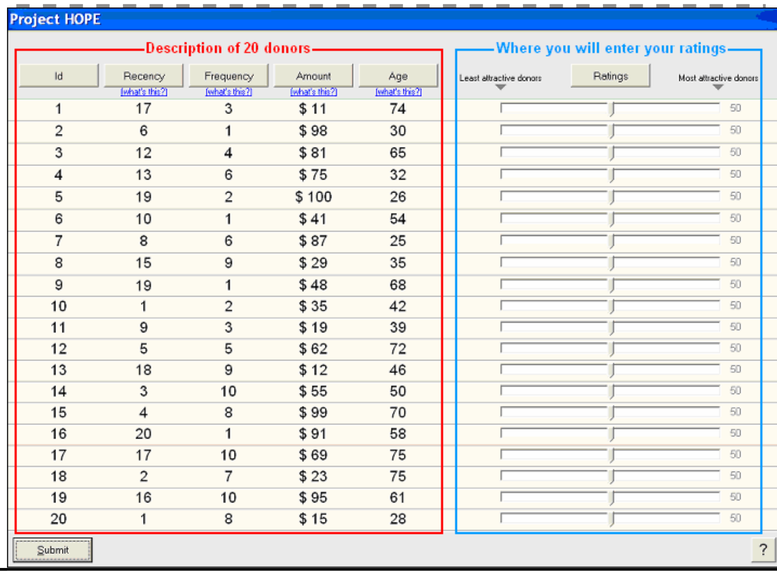
Criteria for Study Design

- Realistic
- Complex
- A good DSS, with ability to manipulate feedback
- Allows measurement of:
  - Mental models
  - Changes in mental models
  - Process variables

Context

- Solicitation of donors for a direct-mail campaign of a non-profit
  - Requires assessment of donor attractiveness
  - Requires managers to have mental model of what drives donor behavior
  - Managers use DSSs to assist in donor selection
- Main task: Identify most attractive donors for solicitation

Context – Main Task



Id	Recency	Frequency	Amount	Age	Ratings
1	17	3	$ 11	74	50
2	6	1	$ 98	30	50
3	12	4	$ 81	65	50
4	13	6	$ 75	32	50
5	19	2	$ 100	26	50
6	10	1	$ 41	54	50
7	8	6	$ 87	25	50
8	15	9	$ 29	35	50
9	19	1	$ 48	68	50
10	1	2	$ 35	42	50
11	9	3	$ 19	39	50
12	5	5	$ 62	72	50
13	18	9	$ 12	46	50
14	3	10	$ 55	50	50
15	4	8	$ 99	70	50
16	20	1	$ 91	58	50
17	17	10	$ 69	75	50
18	2	7	$ 23	75	50
19	16	10	$ 95	61	50
20	1	8	$ 15	28	50

Context - Decision Environment

- Database of 200,000 hypothetical donors described on recency, frequency, donation amount, and age
- Probability of donation:

  where,

$$p = 1/\left(1 + exp(5 - (X/20))\right)$$

- True parameters were:

$$X = \beta_0 + (\beta_1 \times recency) + (\beta_2 \times frequency) + (\beta_3 \times amount) + (\beta_4 \times age)$$

$$\beta = \{20, -20, 40, 10, 30\}$$

Context - Decision Environment

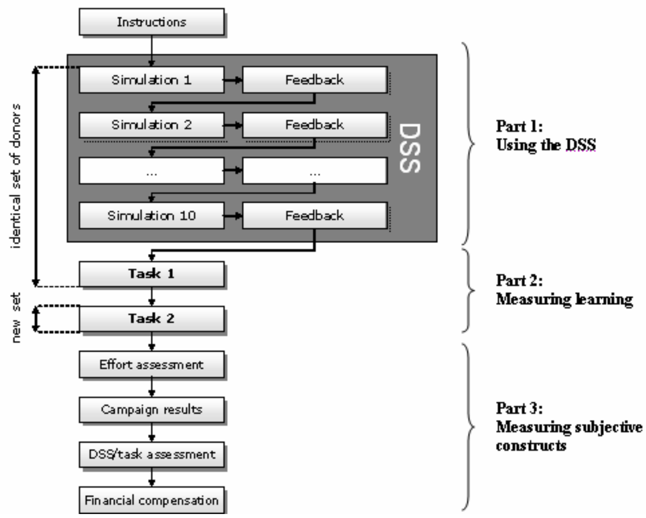
- Donor's true attractiveness ranged from 0-100, with average of 50.
- Probability of donation ranged from .67% to 50% with average of 7.6%
- Data generating model = Decision Model + error

Context - Calibrating Mental Models

- To estimate mental model, we require:
  - Sufficient variation in description of donors on each factor
  - Minimal multicollinearity across factors
- Applied mental model to database
- If probability of donation>10%, then solicit
  - Campaign sought $20, cost of solicitation = $2.
- Actual donation is a random process.

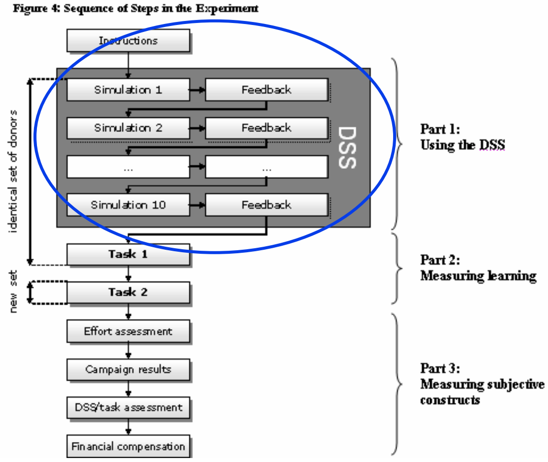
Experiment Design

Figure 4: Sequence of Steps in the Experiment



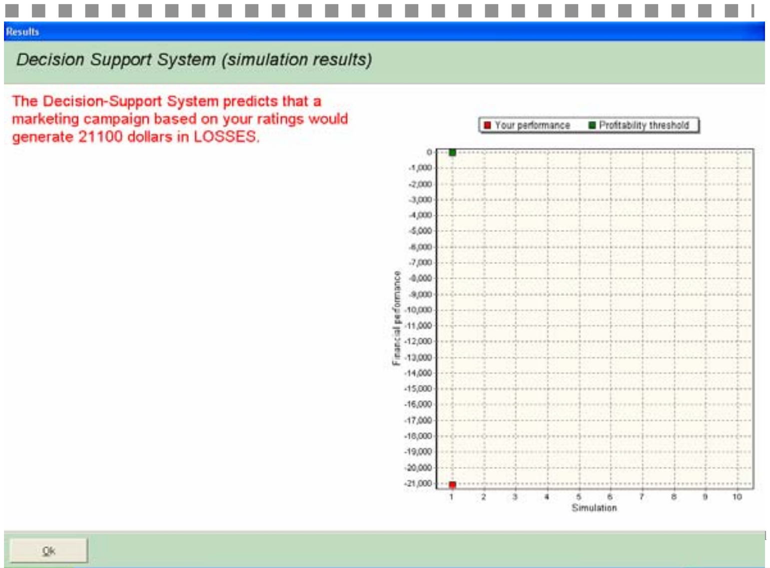
Part 1 – Using the DSS

Figure 4: Sequence of Steps in the Experiment

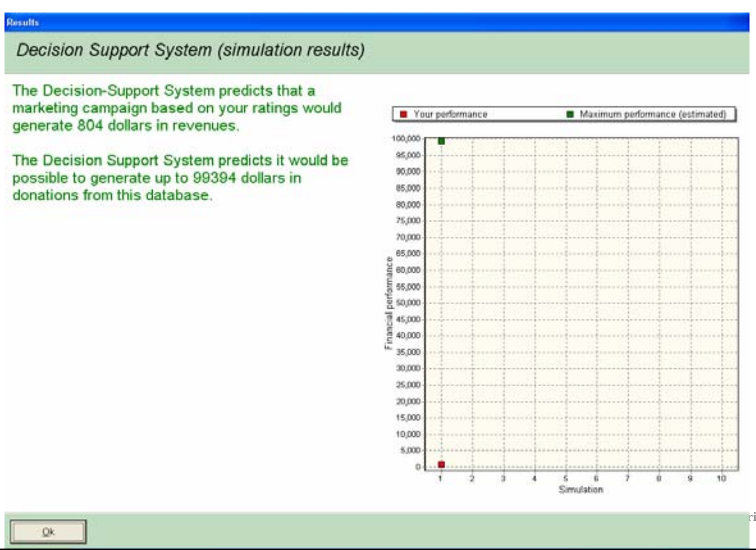


- 10 simulations using the DSS, each yielding their mental model
- Manipulated feedback after each simulation
- Four conditions:
  1. Outcome feedback (expected performance of rating strategy)
  2. Upside potential feedback (expected outcome+expected perf of DSS strategy)
  3. Corrective feedback (expected outcome+suggestions on how to change weights)
  4. ALL feedback (1+2+3)

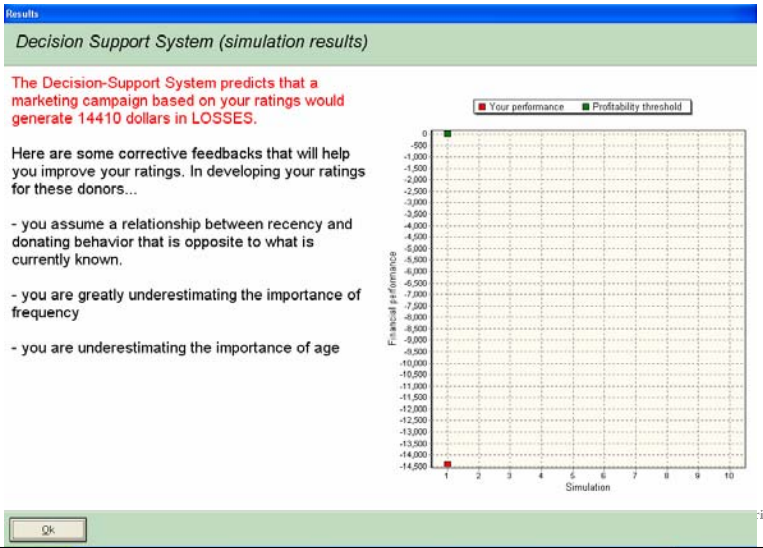
Using the DSS – Outcome feedback



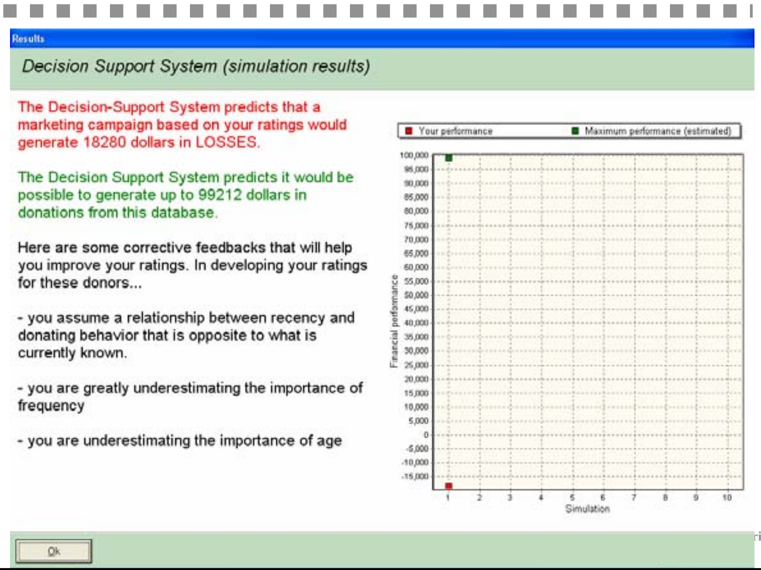
Using the DSS – Upside feedback



Using the DSS – Corrective feedback

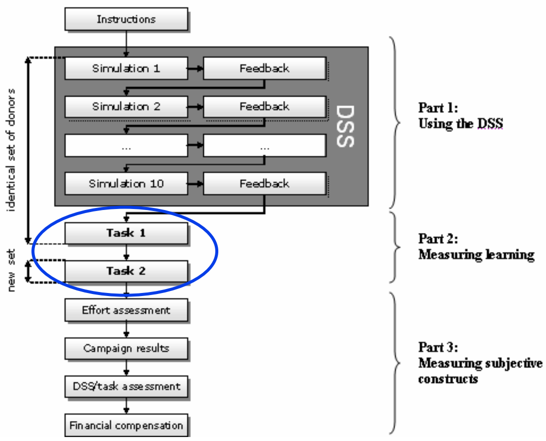


Using the DSS – ALL feedback



Part 2 – Measuring Learning

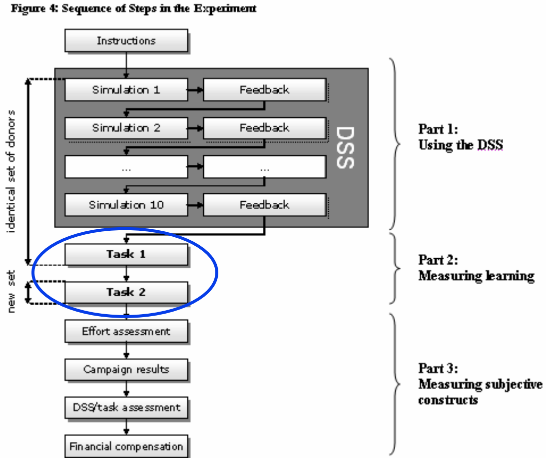
Figure 4: Sequence of Steps in the Experiment



- Task 1: immediately after ten simulations, same donors
- Task 2: After Task 1, but with different set of 20 donors

Part 2 – Measuring Learning

Figure 4: Sequence of Steps in the Experiment



- Task 1: immediately after ten simulations, same donors
- Task 2: After Task 1, but with different set of 20 donors
  - Measured learning by comparing mental model in Task 2 with initial mental model
  - Measured mechanistic learning by comparing mental model in Task 2 with mental model in Task 1

Part 2 – Measuring Learning

Mental Model accuracy:

Euclidian distance between mental model and true model

TRUE MODEL: $\beta = \{-20, 40, 10, 30\}$

MENTAL MODEL: $\beta' = \{-25, 35, 20, 10\}$

MENTAL MODEL ACCURACY: $$\mathrm{ED}_t = \left[\sum_j \left\{ \beta'_{jt} - \beta_j \right\}^2 \right]^{0.5}$$

$$WED_t = \left[\sum_j \omega_j \cdot \left(\beta'_{jt} - \beta_j \right)^2 \right]^{0.5}$$

Part 2 – Measuring Learning

Mental Model accuracy:

Gap between mental model and true model

$$WED_t = \left[\sum_j \omega_j \cdot \left(\beta'_{jt} - \beta_j \right)^2 \right]^{0.5}$$

Deep learning:

Change between Task 2 mental model and initial mental model

$$DL = -\left(WED_2 - WED_0 \right)$$

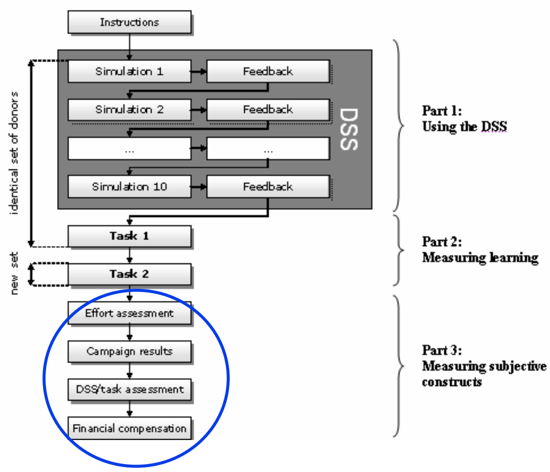
Mechanistic Learning:

Change between Task 2 mental model and Task 1 mental model

$$ML = \left(WED_2 - WED_1 \right)$$

Part 3 – Measuring Subjective Constructs

Figure 4: Sequence of Steps in the Experiment

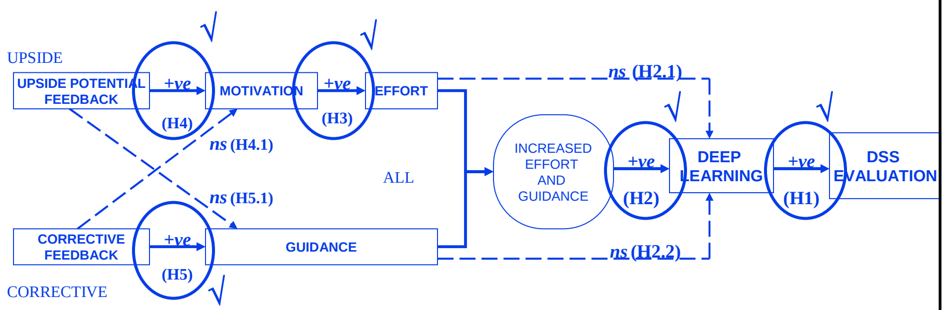


- Effort
  - I was totally immersed in addressing this problem.
  - I took this task seriously.
  - I put in a lot of effort.
  - I wanted to do as good a job as possible no matter how much effort it took.
- Motivation
  - The DSS motivated me to do better.
- Guidance
  - The DSS gave clear guidance on how I could do better.
- DSS evaluation
  - I would definitely recommend a DSS like the one I had available to direct marketers.

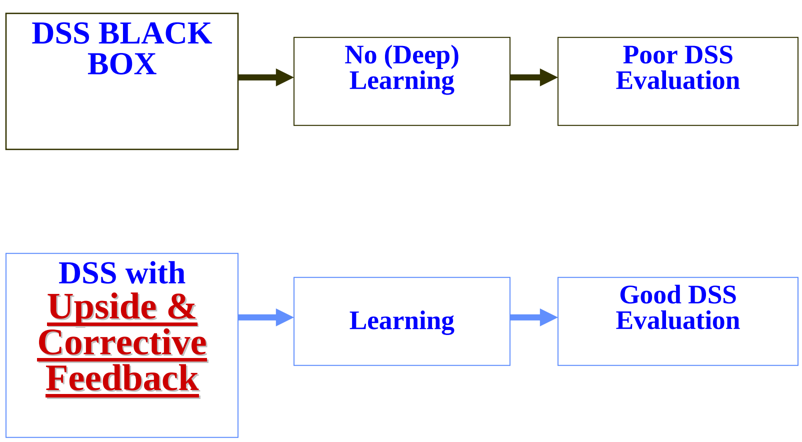
Sample & Experimental Procedure

- 61 MBA students, randomly assigned to each of four conditions
- Paid 0.015% of actual performance on each of the two tasks plus $15 participation fee
- Earned between $23-$44, average of $38.
- Time of 14 to 80 minutes, average of 42 minutes.

SUMMARY RESULTS



Implications



DSS Design Implications

Decision-makers must be motivated to change

- *"Why should I change my mental model?" "What is the upside?"*
- **DSS design must incorporate upside potential (incentive)**

AND

Decision-makers must be given guidance to change their mental models

- *"How should I change my mental model?"*
- **DSS must calibrate, evaluate, and correct manager's mental model**

Lembersky et al (1986).. Edelman Prize winner at Weyerhauser

"We had to gain the understanding and acceptance of the woods foremen. The foremen used VISION to see the results of cutting and allocating a sample of stems from their region using their old instructions. Then, they were given the new instructions and asked to re-cut the same set of stems. They were also encouraged to experiment with any other cutting patterns of their own invention.

The experienced field expert sponsored and participated in these foreman activities. With their value demonstrated, the foremen readily embraced the new instructions and saw the implications of the dynamic programming algorithm."

Take Aways…
DSS/OR Model Success Depends on…

- **Technology factors:** The model/DSS must be objectively good, appropriate for the problem AND well designed: ***Feedback and Upside potential.***
- **Personal factors** Users must have personal incentive and absorptive capacity to use models
- **Organizational factors** Multiple stakeholders, multiple/conflicting objectives/incentives, resource limitations, inertia???

  ➔ **All must be accounted for to facilitate on-going DSS/OR Model success**

Horses for Courses???

Degree of Visibility	Standalone	Integrated
Visible (Interactive)	1 **Standalone Models** Example: Marketing Engineering tools (www.mktgeng.com) Example: Conjoint Analysis tool (www.sawtooth.com)	3 **Integrated Model Systems** Example: Group Decision System (Group Analytic Hierarchy Process)
Hidden (Embedded)	2 **Component Objects** Example: Automated Software Agent (Price comparison agent)	4 **Integrated Component Objects** Example: Revenue Management System (www.therubicongroup.com) Example: Marketing Optimization System (www.marketswitch.com)

Degree of Integration

..With Different Adoption/Impact Profiles?

Impact Length	Local Only	Wide Applicability
One time/ Short Term	1 Eg Syntex Labs	3 Eg ASSESSOR
Long Term	2 Eg Rhenania	4 Eg American Airlines/ Revenue Mgt

Transportability

The Answer….It Depends…
(But we are learning about the dependencies)

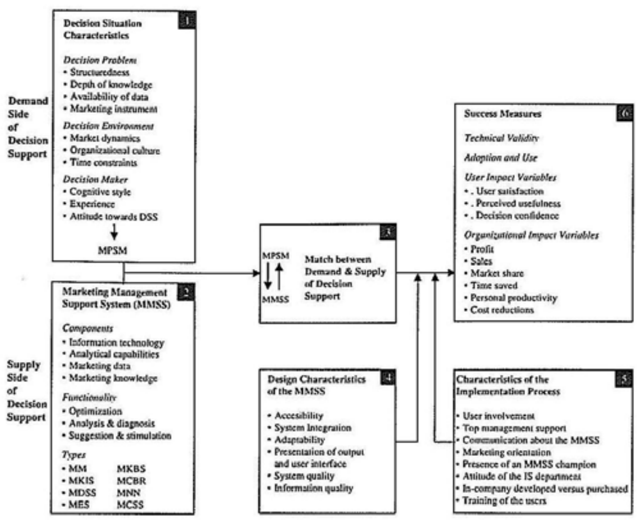


Figure 9.1 An Integrating Framework of Factors That Determine the Success of Marketing Management Support Systems (*Source:* adapted from Wierenga, Van Bruggen, and Staelin 1999)

The Real 5 Stages of Organizational Adoption of a New Model…

1. Exaltation
2. Disenchantment
3. Search for the Guilty
4. Punishment of the Innocent
5. Distinction for the Uninvolved