# Exceptions and Other Rare and Irregular Events: Two Modes of Learning in Business Intelligence (Research in Progress)

Joseph W. Clark
USC Marshall School of Business
joseph.clark@usc.edu

## Abstract

*Irregular and unpredictable events are increasingly important design elements of several of the latest business intelligence technologies, such as complex event processing (CEP), business performance management (BPM), and the real-time enterprise (RTE). Theories of individual and organizational learning from irregular events – exceptions, interruptions, surprises, accidents, and so on – tend to conform to one of two contradictory patterns. I draw these theories together to understand the complementary processes by which learners derive knowledge and insight from irregular events. I identify contingency factors that bias learners toward one of the two cognitive modes – incorporation of multiple events into a generalized understanding, or expansion of individual events into rich analytical conversations – and propose "exception design" levers by which BPM dashboard implementers can adjust these factors and influence the way users create knowledge in business intelligence. A pilot experiment lends some support to the hypothesis that frequency and ambivalence are designable aspects of exceptions that affect learning. The author seeks feedback and suggestions for a more effective research design.*

## 1. Management by exception

The over-arching question in the study of decision support systems and business intelligence is how individuals, and organizations, turn incoming data and information into knowledge and insight that guides better decision-making. These phenomena are often imagined as continuous processes, called sensemaking [17] or organizational learning [9], but they can also be perceived as the cumulative results of numerous, discrete, and irregular events – exceptions, interruptions, accidents, surprises, and so on – that each have different kinds of impacts on knowledge, frames of reference, and routines. Lampel, Shamsie, and Shapira [8] recently highlighted the dearth of research on how rare and unusual events impact organizational thinking, citing the pervasive assumption that irregular events are either statistical outliers or just discrete manifestations of underlying, continuous processes. It is important that information systems researchers set aside this assumption and build theories about how business knowledge and insight are built up from a series of irregular events.

This is imperative for the information systems field in particular, because the *event* is an increasingly important design element in leading-edge DSS paradigms such as business performance management [4], complex event processing [10], and the real-time enterprise [5]. A number of management researchers have studied the effects on organizations of irregular events – exceptions, anomalies, accidents, interruptions, crises, surprises, and the like – but these strands of research have not yet been drawn together and brought to bear on the design of information technology or the science of business intelligence. Recent business success stories suggest that prior theories may be inadequate to explain all of what happens in an event-based business intelligence practice.

I am specifically interested in business performance management (BPM), a management and technology framework that revolves around *exceptions*. Based on the principle "what gets measured, gets done", BPM implementation involves identifying key performance indicators (KPIs) and developing personalized digital dashboards to enable users throughout an organization to monitor and act on exceptions [4]. Advocates claim that BPM empowers companies to improve strategic decision-making as well as operational management, claims that challenge prior theory on the limitations of management by exception. In a classic criticism, Argyris [1] argued that management by exception can only result in "single loop learning" and dysfunctional management; in effect, what gets measured, gets done, but measuring alone can't tell you whether you're measuring the right things in the right ways.

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We need theory that explains why exception-based business intelligence systems have proven successful for so many firms despite the theorized limitations of management-by-exception. A key insight from a widespread literature review is that theories of learning from irregular events (such as exceptions) tend to conform to two recurring but contradictory theory logics [8]. In one view, learners generalize from specific events to derive knowledge that can be applied to the general class of similar events; in the other view, the salient features of specific events attract the attention, motivate cognitive effort, and provide unique data for the creation of new knowledge. Few researchers have explored how these two important but dramatically different epistemologies work side-by-side in business intelligence practice. I contend that both modes of knowledge creation are important, and the real challenge is employing the right methods for the right problems. Research suggests that a number of important contingencies may influence which mode(s) of sensemaking an individual employs in a given situation: cognitive biases, time constraints, impact, relevance, and so on.

However, prior research does not address whether and how *technology* is a contingent factor. Can the affordances of a business intelligence package push users toward (or away from) one or the other pathway to learning from exceptions? In this study, I argue that BPM offers a number of levers by which exceptions can be designed to do exactly that. In the next section, I review the literature on irregular events and explicate the two main theories of how people learn from them. Following that, I develop propositions about how exception design can be used to influence learning, and describe a pilot project to test the propositions.

## 2. Theory review

### 2.1. Two modes of knowledge creation

Many researchers have studied the effects of irregular events on organizational learning or sensemaking – exceptions, anomalies, accidents, interruptions, crises, surprises, and so on – and this disconnected literature evidences two recurring types of theory logic.

In the first, learners classify each event as an instance of a more general type, incorporating the new data into their understanding of the general class. For example, the emergency landing of a US Airways flight on the Hudson River in January 2009 could be viewed as an instance of the "flight accident" category, and combined with knowledge about other accidents, would help a learner to estimate the probability and cost of similar accidents, draw inferences about their causes, and hypothesize about factors that can prevent future ones. In this mode of learning, which I term *generalization*, learners focus their attention on those aspects of the event that are similar to other events, so they can draw broadly applicable lessons. They manage the deluge of information by, in effect, throwing away data that is idiosyncratic to any one event.

In the second type of theory, learners' attention is drawn not to the similarities but to the specific, unique features of certain irregular events, which can be exploited for unique learning opportunities. If an event has particular salience or is seen as "critical", learners are motivated to expend time and effort to gather more information, seek out alternative perspectives, and to employ imagination and creativity to convert the idiosyncratic experience into new knowledge [11]. For example, US Airways would have realized the "Miracle on the Hudson" posed a unique opportunity to learn from a successful water landing, and taken advantage of it by collecting many types of data, sharing it throughout the organization, and evaluating its usefulness for pilot evaluation, crew training, aircraft design, and so on. Since this theory of learning involves turning small data points into large conversations by adding attention, data, and cognitive effort, I term it *expansion*.

Whether the topic is exceptions, interruptions, crises, or some other type of irregular events, the two types of theories are remarkably consistent. To my knowledge, however, no one identified these parallel but contradictory views in the literature before Lampel et al [8] discovered several instances of each view in submissions to a special journal issue on rare events and organizational learning. According to Lampel et al, the two views actually represent processes of learning that coexist and serve distinct learning purposes, despite "irreconcilable epistemologies". They argue, and I concur, that both theories are partly correct – sometimes we need to draw inferences from the similarities across events, and sometimes we should treat events as unique in order to exploit their potential for rich, inductive learning. The challenge for learners is to determine where to focus their attention, and how to use their finite cognitive resources, to effectively glean knowledge and insight from the discrete events that make up the barrage of data and information they are exposed to every day. The challenge for theory is to understand how these two modes of knowledge creation work together, and which needs are served by each.

## 2.1. Meeting knowledge needs

Lampel et al justify the contradictory theories by arguing that the two modes of learning from rare events necessarily coexist and interact. The expansion mode, which they call the “enacted salience view”, is a sensemaking process necessary for the determination of organization structure and the formation of meaningful categories of data; the generalization mode, which they call the “probability estimates view”, uses these categories to classify and generalize about events. In turn, expansion depends on lessons learned through generalization, in order to judge which events have extraordinary salience. “Ultimately, therefore, whether we see rare events as probability estimates or as enacted salience depends on whether we consider classification or sensemaking as the dominant process.” [8, p. 838].

The notion of two complementary processes of learning from irregular events gives us a good way to think about how business users of BPM dashboards generate knowledge and insight from exceptions. On the one hand, they incorporate exceptional data points into their beliefs about averages, performance trends, and predictions about the future; on the other hand, particularly salient exceptions may attract their attention, motivating them to drill down, analyze more details, and potentially modify their assumptions and even measurements. This model resonates with other theories of complementary learning processes, such as exploitation and exploration [11], single-loop and double-loop learning [1], and interactive and diagnostic use of information systems [13,14]. In each of these theories, individuals or organizations are faced with the dual tasks of refining their performance given existing measures and assumptions, and modifying those measures and assumptions as they become obsolete. The primary problem faced by learners is to properly balance their use of the two learning modes. The proper balance is endangered by a host of biases and contingent factors.

A number of studies identify conditions that affect or bias the balance between generalization and expansion, both in individuals and organizations.

**Table 1. Contingencies that affect generalization/expansion balance**

| Article | Summary of conclusions |
|---|---|
| Lampel, J., Shamsie, J., & Shapira, Z. (2009). Experiencing the Improbable: Rare Events and Organizational Learning. Organization science, 20(5), 835-845. | The type of learning triggered by rare events depends on the attention they receive. Attention is allocated based on the potential impact of an event, and the breadth of its relevance to learners’ priorities. Rare events that attract more attention are scrutinized more “richly” (expansion). |
| Starbuck, W. H. (2009). Perspective--Cognitive Reactions to Rare Events: Perceptions, Uncertainty, and Learning. Organization science, 20(5), 925-937. | Learners see idiosyncrasies and exogeneity in rare events instead of seeing them as generalizable to a class of events. The more rare/unusual the event, the stronger these perceptions. |
| March, J. G., Sproull, L. S., & Tamuz, M. (1991). Learning from Samples of One or Fewer. Organization science, 2(1), 1-13. | Three aspects of an event may make it “critical” – its place in history, its place in the development of belief, and its metaphorical power. Organizations learn from critical events by experiencing them richly – discovering more aspects, more interpretations, and more preferences (expansion). |
| Beck, T. E., & Plowman, D. A. (2009). Experiencing Rare and Unusual Events Richly: The Role of Middle Managers in Animating and Guiding Organizational Interpretation. Organization science, 20(5), 909-924. | Habitual ways of interpreting events tend to miss the novelty of rare and unusual ones. A number of cognitive biases – selective perception, availability bias, wishful thinking, hindsight bias, etc – act to preserve prior beliefs. The article explores the roles of middle managers in overcoming these biases in organizations. |
| Simons, R. (1991). Strategic Orientation and Top Management Attention to Control Systems. Strategic Management Journal, 12(1), 49-62. | Top managers employ interactive information systems to focus attention on issues of strategic uncertainty (expansion) while using diagnostic information systems (generalization) to track other issues. |
| Plambeck, N., & Weber, K. (2009). CEO Ambivalence and Responses to Strategic Issues. Organization science, 20(6), 993-1010. | CEOs who assess an issue as either strictly positive or strictly negative are less likely to take action than those who experience ambivalence (assess the issue as partly positive and partly negative). Ambivalence increases the number of actions taken in response, as well as the scope, novelty, and riskiness of those actions. |

(For simplicity, this article mostly focuses on individual learning from exceptions. The problem of *organizational* learning is analogous but different.) For Starbuck [15], learning from rare events requires attention to similarities (generalization); the problem for learners is that attention is biased toward the idiosyncrasies (expansion), and the more rare or unusual the event, the stronger the bias. For Beck and Plowman [2], the strength of existing beliefs is an important contingency that favors habitual ways of interpreting events (generalization) and impairs learners' ability to discover novelty (expansion). March et al [11] argue that learners focus attention intensively (expansion) on events deemed "critical" due to one or more contingencies: their place in history, their place in the development of belief, and their metaphoric power. Table 1 lists several findings about contingencies identified by prior literature on irregular events.

## 3. Exception design

The position of this paper is that, in the case of management by exception, technology design can also influence the allocation of attention and sensemaking effort to similarities between exceptions (generalization) and to their salient unique features (expansion). BPM practitioners and consultants can often be heard talking about "designing" an exception – an intriguing notion. The term "exception" implies an irregular, unpredictable event – something that cannot be designed – but in fact BPM's exceptions are built on several design decisions: the choice of phenomena that bear monitoring, the measurements (KPIs) that capture the salient aspects of the phenomena, the targets and ranges of acceptable values for KPIs, and the design of dashboards and alerts. Any or all of these decisions could be levers to adjust the way users derive insight from business intelligence.

I focus on two possible levers in this article – one that could allow exception designers to increase the likelihood of learning by generalization, and one that could allow exception designers to increase the likelihood of learning by expansion.

**Proposition 1: The frequency of exceptions, which can be adjusted by raising or lowering exception thresholds, is correlated with learning by generalization.** A number of sources in the literature identify the "rareness" of an event, or the degree of surprise or arousal it triggers, as a learning bias [e.g. 15]. The more rare or unusual an event is, the more likely it will attract individual attention; the less unusual, the more likely it will be considered in combination with others of its class. We extrapolate that when KPI tolerance ranges are wide, and only a few extreme cases are highlighted with "green lights" or "red lights" as exceptional, users will be biased toward expanding individual cases into unique knowledge creation. Complementarily, when the thresholds for exceptions are low, similar exceptions will be relatively frequent and users will be biased toward learning by incorporating them into more generalized understandings.

**Proposition 2: The cognitive effort needed to assess exceptions, which can be adjusted by the content and form of KPIs, is correlated with learning by expansion.** Dual-process cognitive theories, like the heuristic-systematic model (HSM) [6,3], hold that humans process information in one of two ways, constrained by situational factors and finite cognitive resources: systematically, an intense and systematic learning mode requiring significant effort (like expansion), or heuristically, a simplifying mode of information processing that economizes on attention and cognition (like generalization). Drawing on the dual-process paradigm, Plambeck & Weber [12] argue that when strategic issues are easy to assess as positive or negative, CEOs tend to process them quickly with little attention, but when issues evoke ambivalent (simultaneously positive and negative) assessments, CEOs are forced to focus their attention and process the issues more systematically and creatively. In a BPM implementation, designers have many choices of KPIs and methods of measurement. By choosing KPIs that make exceptions easy to assess as simply positive or simply negative, they can influence users to view exceptions in broad strokes and create knowledge by generalization. By choosing KPIs that evoke ambivalent assessments, on the other hand, they can encourage users to drill down and explore the unique features of each exception, creating knowledge by expansion.

In the next section I describe an experimental pilot study that tested whether manipulating these exception design "levers" could influence the types of learning that result from BPM dashboard use.

## 4. Research design

### 4.1. Hypotheses

Based on the propositions above, I test two hypotheses:

H1: The frequency of exceptions on a digital dashboard will be positively related to the amount of "generalization" learning experienced by users.

H2: The ambivalence of exceptions on a digital dashboard will be positively related to the amount of "expansion" learning experienced by users.

### 4.2. Potential covariates

As my theoretical propositions rely on dual-process cognitive theory, other variables that affect cognitive resources and cognitive load are expected to affect the learning processes that dashboard users will utilize. A few of these may have particularly strong effects, and will be controlled for in my analysis:

- Strength of prior beliefs: Beck & Plowman [2] argue that strongly-held beliefs will encourage learners to rely on habitual ways of categorizing – the generalization mode.

- Perceived time pressure, and perceived information overload: Subjects who feel the need to hurry, or who feel overwhelmed by data, will feel the need to economize on cognitive resources, pushing them toward a generalization mode.

- Dashboard usability: A dashboard that does not frustrate or distract the user frees up cognitive resources, enabling the user to more easily use an expansion mode.

### 4.3. Experiment design

I designed a digital dashboard for a fictional telesales manager, based on my own experience as an IT developer for a call center and recent liberature on best practices in dashboard design for call centers [7,16]. I created four versions with the same design and (fake) data, varying the frequency and ambivalence of exceptions: high-high, low-low, high-low, and low-high. See Appendix A for screenshots.

Frequency of exceptions was manipulated by adjusting thresholds. For example, the low-frequency condition might have highlighted the top and bottom ten percent of operators according to a certain metric, while the high-frequency condition would have highlighted the top and bottom *twenty* percent as green (good) or red (bad) exceptional performers.

Ambivalence of exceptions was manipulated by the emphasis on KPIs. For the high-ambivalence dashboards, exceptions were individually highlighted on each metric. For example, call center operators could be exceptional on calls per hour, closing rate, or average order amount. The low-ambivalence condition was induced by using a summary metric, total sales per hour, and basing red or green highlighting solely on the summary metric. Based on Plambeck & Weber [12], ambivalence is the cognition of not being able to easily assess an issue as simply positive or negative. See Figures 1 and 2.

**Operators**

| name | calls/hour | closing rate | avg. order | sales $/hour |
|---|---|---|---|---|
| Anderson | 9.3 | 80.4% | $52.21 | $391.55 |
| Brown | 14.3 | 65.8% | $78.31 | $734.20 |
| Clark | 15.8 | 57.1% | $73.52 | $661.70 |
| Davenport | 16.8 | 59.0% | $50.75 | $501.11 |
| Ericson | 18.1 | 83.4% | $61.60 | $931.65 |
| Fujita | 18.3 | 37.0% | $52.95 | $357.41 |
| Garfield | 10.5 | 51.2% | $96.26 | $517.40 |

**Figure 1. High ambivalence condition**

**Operators**

| name | calls/hour | closing rate | avg. order | sales $/hour |
|---|---|---|---|---|
| Anderson | *9.3* | *80.4%* | *$52.21* | **$391.55** |
| Brown | *14.3* | *65.8%* | *$78.31* | **$734.20** |
| Clark | *15.8* | *57.1%* | *$73.52* | **$661.70** |
| Davenport | *16.8* | *59.0%* | *$50.75* | **$501.11** |
| Ericson | *18.1* | *83.4%* | *$61.60* | **$931.65** |
| Fujita | *18.3* | *37.0%* | *$52.95* | **$357.41** |
| Garfield | *10.5* | *51.2%* | *$96.26* | **$517.40** |

**Figure 2. Low ambivalence condition**

My experiment employed Qualtrics online survey software, which has a randomization function. Each subject who logged in to take the online "survey" was randomly assigned one of the four dashboard versions, but otherwise their experiences were the same. See Appendix B for questionnaire text. The data collection had four steps:

1. Subject reads a vignette describing the telesales manager's job, his goals, the way he is evaluated, and encouraging the subject to play the role of the manager and use the dashboard to identify some facts or insights he can act on.

2. Subject answers some pre-exercise questions to "warm up" the role-playing task and measure a few possible moderating variables, such as "strength of prior beliefs".

3. Subject is given a (randomized) link to open the digital dashboard and asked to take "as much time as you like" examining the dashboard, and write down 5 to 10 "ideas,

insights, and discoveries" that are relevant and actionable for the sales manager.

4. Subject answers some post-exercise questions including manipulation checks, and measures of other possible moderating factors: "perceived time pressure", "dashboard ease of use", and "perceived information overload". It ended with and an open-ended question to catch anything I missed, such as a technical problem with the survey software, or feedback that could help me improve the experiment design.

The five to ten "insights" produced by each subject in the third step were subsequently coded by the researcher for counts of "generalization" and "expansion" insights. See Appendix C for the coding scheme.

## 4.4. Sample

Part-time MBA students who had just completed a course on information management were invited to participate in the experiment. These students had been taught about a number of case studies of organizations turning data into actionable knowledge, and were familiar with concepts such as key performance indicators and critical success factors. They were offered a small incentive – a drawing for a $100 gift certificate – and out of approximately 300 students, 56 replied. 40 of these completed the entire experiment, but unfortunately only 18 responses were usable. The other 22 responses did not correctly understand the instructions, using step three of the experiment to comment on the design or technology of the dashboard instead of drawing "insights" about the data in the case. Table 2 shows the number of usable responses in each condition.

**Table 2: Responses in each condition**

| | few exceptions | many exceptions | |
|---|---|---|---|
| high ambivalence | **4** | **5** | 9 |
| low ambivalence | **7** | **2** | 9 |
| | 11 | 7 | |

## 4.5. Summary statistics

Table 3 summarizes the dependent variables – each representing a count of generalization-type or expansion-type "insights" generated by subjects.

**Table 3. Summary of DVs**

| variable | min | max | mean | median | std.dev |
|---|---|---|---|---|---|
| GENERALIZATION | 0 | 6 | 2.667 | 2.5 | 2.058 |
| EXPANSION | 0 | 9 | 2.278 | 2.5 | 2.372 |

Table 4 summarizes expected covariates:

**Table 4. Summary of covariates**

| construct [variable] "question text" (options) | min | max | mean | median | std. dev. |
|---|---|---|---|---|---|
| Strength of prior beliefs [CSF_CERTAINTY] "How certain are you that you've identified the right factors?" (1 to 3) | 1 | 3 | 1.944 | 2 | 0.725 |
| Dashboard usability [DASHBOARD_EASYTOUSE] "The digital dashboard was easy to use." (1 = strongly disagree, 5 = strongly agree) | 2 | 5 | 4.000 | 4 | 0.840 |
| Dashboard usability [DASHBOARD_FRUSTRATING] "The dashboard's design was frustrating." (1 to 5) | 1 | 4 | 2.333 | 2 | 0.907 |
| Perceived time pressure. [FELT_TIMEPRESSURE] "I felt time pressure during the exercise." (1 to 5) | 1 | 4 | 2.278 | 2 | 0.958 |
| Perceived information overload. [DATA_TOOMUCH] "There was too much data to make sense of." (1 to 5) | 1 | 4 | 2.389 | 2 | 0.916 |

## 5. Results

Table 5 is a correlation matrix for these variables. We note that although the coding scheme allowed for insights to be categorized as exhibiting both generalization and expansion, this rarely occurred, and the two dependent variables showed a strong inverse correlation.

**Table 5. Correlation matrix.**

| | GENERALIZATION | EXPANSION | CSF_CERTAINTY | DASHBOARD_EASYTOUSE | DASHBOARD_FRUSTRATING | FELT_TIMEPRESSURE | DATA_TOOMUCH |
|---|---|---|---|---|---|---|---|
| GENERALIZATION | 1 | -0.49 | 0.617 | -0.24 | 0.315 | 0.557 | -0.55 |
| EXPANSION | -0.49 | 1 | 0.009 | 0.236 | -0.24 | -0.27 | 0.191 |
| CSF_CERTAINTY | 0.617 | 0.009 | 1 | 0.000 | 0.030 | 0.616 | -0.23 |
| DASHBOARD_EASYTOUSE | -0.24 | 0.236 | 0.000 | 1 | -0.77 | 0.073 | -0.15 |
| DASHBOARD_FRUSTRATING | 0.315 | -0.24 | 0.030 | -0.77 | 1 | 0.023 | 0.189 |
| FELT_TIMEPRESSURE | 0.557 | -0.27 | 0.616 | 0.073 | 0.023 | 1 | -0.40 |
| DATA_TOOMUCH | -0.55 | 0.191 | -0.23 | -0.15 | 0.189 | -0.40 | 1 |

### 5.1. Models

The first hypothesis relates the generalization learning mode to the frequency of exceptions and expected covariates:

$$\begin{aligned} \text{GENERALIZATION} = \beta 0 + \beta 1{*}\text{FREQUENCY} + \\ \beta 2{*}\text{CSF\_CERTAINTY} + \\ \beta 3{*}\text{DASHBOARD\_EASYTOUSE} + \\ \beta 4{*}\text{DASHBOARD\_FRUSTRATING} + \\ \beta 5{*}\text{FELT\_TIMEPRESSURE} + \\ \beta 6{*}\text{DATA\_TOOMUCH} + \varepsilon \end{aligned}$$

Regression analysis (conducted with “R”) produced the following estimates and test statistics:

```
lm(formula = GENERALIZATION ~ FREQUENCY +
CSF_CERTAINTY + DASHBOARD_EASYTOUSE +
DASHBOARD_FRUSTRATING + FELT_TIMEPRESSURE
+

Coefficients:
   Estimate Std. Error t value Pr(>|t|)
(Intercept)
   -1.3641     3.6195  -0.377  0.71344
FREQUENCY
   1.2400     0.6946   1.785  0.10182
CSF_CERTAINTY
   1.2172     0.5141   2.368  0.03731 *
DASHBOARD_EASYTOUSE
   0.1465     0.5724   0.256  0.80271
DASHBOARD_FRUSTRATING
   1.0365     0.5340   1.941  0.07831 .
FELT_TIMEPRESSURE
   0.4545     0.4451   1.021  0.32914
DATA_TOOMUCH
   -1.1964     0.3614  -3.311  0.00695 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01
‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.207 on 11
degrees of freedom
Multiple R-squared: 0.7773
Adjusted R-squared: 0.6558
F-statistic: 6.398 on 6 and 11 DF
p-value: 0.004158
```

The second hypothesis relates the expansion learning mode to the ambivalence of exceptions and to expected covariates:

$$\begin{aligned} \text{EXPANSION} = \beta 0 + \beta 1{*}\text{AMBIVALENCE} + \\ \beta 2{*}\text{CSF\_CERTAINTY} + \\ \beta 3{*}\text{DASHBOARD\_EASYTOUSE} + \\ \beta 4{*}\text{DASHBOARD\_FRUSTRATING} + \\ \beta 5{*}\text{FELT\_TIMEPRESSURE} + \beta 6{*} \\ \text{DATA\_TOOMUCH} + \varepsilon \end{aligned}$$

Regression analysis produced the following estimates and test statistics:

```
lm(formula = EXPANSION ~ AMBIVALENCE +
CSF_CERTAINTY + DASHBOARD_EASYTOUSE +
DASHBOARD_FRUSTRATING + FELT_TIMEPRESSURE
+ DATA_TOOMUCH)

Coefficients:
```

```
   Estimate Std. Error t value Pr(>|t|)
(Intercept)
   -1.05248    7.38471  -0.143    0.889
AMBIVALENCE
   0.94337    1.46998   0.642    0.534
CSF_CERTAINTY
   0.94062    1.09276   0.861    0.408
DASHBOARD_EASYTOUSE
   0.56517    1.18100   0.479    0.642
DASHBOARD_FRUSTRATING
   -0.07874    1.14506  -0.069    0.946
FELT_TIMEPRESSURE
   -0.80256    0.94137  -0.853    0.412
DATA_TOOMUCH
   0.32681    0.76514   0.427    0.678

Residual standard error: 2.566 on 11
degrees of freedom
Multiple R-squared: 0.2425
Adjusted R-squared: -0.1707
F-statistic: 0.5868 on 6 and 11 DF
p-value: 0.7348
```

### 5.2. Interpretation of results

Given the small number of usable cases from the sample, we cannot read too much into the results of the statistical analysis; however, we do make some interesting observations. First, in both cases the hypothesized relationships were not statistically significant but were in the right directions. The "generalization" model had a very high R-squared and showed significant relationships with three of the five expected covariates, suggesting that the model as a whole is accurate. The biggest surprise is that "perceived information overload" is *negatively* related to generalization, contrary to our expectation that dashboard users who felt overwhelmed with data would be more inclined to the learning mode that economized on cognitive effort. Perhaps the perception of data overload should be viewed as a dependent variable of cognitive learning style. Since no subjects actually received more or less data than others, the perception of "too much data" may have resulted from users eschewing the cognitive shortcut of generalization.

I explored the data for explanations of why the "expansion" model was a far worse fit, having a low R-square and no statistically significant relationships. I discovered a high correlation (0.571) between EXPANSION and one of the first survey questions intended to help subjects "warm up" to the roleplaying expertise – TELESALES_EXP ("Do you have any work experience related to telesales?"). Following Beck & Plowman [2], I expected that strongly-held prior beliefs, such as those developed from experience, would bias users toward relying on already-known "categories", a generalization mode. The first regression confirms this expectation, showing that a user's certainty that he "knows what to look for" (CSF_CERTAINTY) is positively related to generalization. However, the correlation between EXPANSION and TELESALES_EXP seems to show that *actual experience* (not just "certainty") seems to have the opposite effect – it biases users toward deeper exploration of the data and an expansion mode of learning. I explore further by estimating the following regression:

$$EXPANSION = \beta 0 + \beta 1*AMBIVALENCE + \beta 2*TELESALES\_EXP + \varepsilon$$

And suddenly, we see a statistically significant effect of AMBIVALENCE on EXPANSION, as predicted by proposition 2:

```
lm(formula = EXPANSION ~ AMBIVALENCE +
TELESALES_EXP)

Coefficients:
   Estimate Std. Error t value Pr(>|t|)
(Intercept)
   0.9792     0.6393   1.532  0.14646
AMBIVALENCE
   1.6667     0.8772   1.900  0.07683 .
TELESALES_EXP
   4.1875     1.3956   3.001  0.00896 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01
'*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.861 on 15
degrees of freedom
Multiple R-squared: 0.4568
Adjusted R-squared: 0.3844
F-statistic: 6.307 on 2 and 15 DF
p-value: 0.01029
```

Perhaps the lesson here is that, while users who think they know what to look for in the data are more likely to use a generalization strategy (viewing data in terms of the categories they already believe exist), people who have actual experience are less likely to rely on these categories. Instead, their experience enables them to notice the subtle differences between cases and encourages them to "drill down" for a more nuanced understanding of individual exceptions.

## 6. Conclusions from pilot test

The data appear to show that the two modes of learning are both present in BPM use. My analysis support the conclusions that *frequency* and *ambivalence* are two designable attributes of exceptions that affect a dashboard user's mode of learning, and also indicate that dashboard usability, perceived information overload, and the strength of prior beliefs about "knowing what to look for" are important biases as well. Actual experience with a problem, in contrast to the strength of prior beliefs, appeared to influence users toward an expansion mode of learning.

However, this pilot study has serious limitations which must be noted. First, the experiment was conducted on a relatively small sample, and the participants were volunteers, so there may have been selection biases at work. Furthermore, many of the responses were not usable, due to subjects misunderstanding the task's instructions. Another limitation is that the study uses a sample of MBA students, with artificially-generated data, instead of employing real-world dashboard users in a real business task. Finally, the coding of "insights" as cases of generalization or expansion was made by a fallible researcher. These challenges weaken my statistical analyses and the inferences I draw.

This project is research in progress, and I hope to elicit feedback from conference participants on how to design a stronger study. The main challenge is how to measure a cognitive variable, learning style, without relying on subjective judgments like my coding of participants' "insights", but it would also be valuable to think about how to conduct a field (or quasi) experiment with greater external validity.

## 7. Discussion

The objective of this study is to examine Lampel, Shamsie, and Shapira's [8] discovery that two theories of learning necessarily complement one another in explaining how humans distill knowledge from rare and irregular events, and to apply that theory to the "exception" design element of business intelligence dashboards. From the literature, several biases that cause learners to favor one learning mode or the other have been identified, and I have argued that the IT artifact itself can also be manipulated in order to direct a user's learning mode.

This research contributes the concept of complementary "generalization" and "expansion" learning modes to the information systems field, as well as enriching the notion of "exception design" to something more than just a computer graphics topic. I hope that it is the beginning of a new conversation about how BPM and business intelligence in general affect the way users derive knowledge from data and information.

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