ABSTRACT: This study examines the effects of information structure on auditor judgment and decision-making. Based on cognitive load theory, we predict that evidence inspired by big data such as visualizations or emails likely to lead to increased perceptions of ambiguity which in turn impacts audit-related decisions. Additionally, we examine whether those effects are moderated by time budget pressure. We conduct an experiment with 120 auditors and find that auditors presented with unstructured data, such as emails or visualizations, provide more conservative risk assessments and write-down recommendations in an inventory obsolescence setting than auditors presented with data structured in a less ambiguous, more traditional memo format. Our findings also indicate that time budget pressure moderates the effects of information structure resulting in the most conservative auditor judgments when presented with unstructured data in a high time budget pressure environment.

Keywords: big data; data analytics; task complexity; cognitive load; time budget pressure
A Potential Unintended Consequence of “Big Data”:
Does Information Structure Lead to Suboptimal Auditor Judgment and Decision-Making?

I. INTRODUCTION

"Big data" and "data analytics" are terms frequently used in the popular press and largely considered to be an important undertaking for organizations. According to Brown-Libur, Issa, and Lombardi (2015), big data collection involves gathering large volumes of both structured and unstructured data from a variety of financial and nonfinancial sources. These tools are believed to have great potential to increase both the effectiveness and efficiency of audits. In fact, many firms are beginning to use big data analyses as part of their audit procedures (e.g., PwC 2015; Schneider, Dai, Janvrin, and Ajayi 2015).

While many of the benefits of big data analyses can be clearly seen, several concerns relating to human cognitive processing limitations have been highlighted in the literature (e.g., Wang and Cuthbertson 2015; Brown-Liburd et al. 2015; Rose, Rose, Sanderson, and Thibodeau 2017). Specifically, Brown-Liburd et al. (2015) detail processing limitation concerns related to information overload, information relevance, and ambiguity. The objective of this study is to evaluate the effects of ambiguity naturally present in unstructured audit evidence developed using common themes of “big data” (such as heat maps and word clouds) on auditor judgment and decision-making. In addition, we investigate whether time budget pressure helps or hinders said judgments. Specifically, we evaluate auditors’ inventory obsolescence risk and write-down assessments when presented with information (both diagnostic and non-diagnostic) that is presented in a less ambiguous, more structured method or in a more ambiguous, unstructured format and in an environment with low time budget pressure vs. one with high time budget pressure.
We use cognitive load theory (Sweller 1988) as a basis for predicting judgment differences. According to this theory, ambiguous information is difficult for people to integrate in problem-solving activities due to stress created because of heavy cognitive loads. In these situations, people often revert to using heuristics or end information processing early in an attempt to reduce cognitive stress (Sweller and Chandler 1991). To that end, research has shown that auditors presented with complex tasks revert to conservative risk heuristics (e.g., Mascha and Miller 2010). Consequently, we predict that the increase in cognitive load resulting from ambiguity found in unstructured evidence will result in auditors assessing inventory obsolescence risk to be higher than those auditors presented with evidence that is structured.

We also assess the potential for time budget pressure to moderate the effect of information structure on auditor judgment and decision-making. Based on prior time budget literature (e.g., DeZoort and Lord 1997; Bonner 2008), we expect that increased time budget pressure will exacerbate the cognitive stress experienced by auditors that are presented with unstructured data. Because of this, we expect the effects of unstructured information on auditor inventory obsolescence risk and write-down assessments to be greater when faced with high time budget pressure than those with low time budget pressure.

The results of our study indicate significant differences among 120 auditors presented with a case involving potential inventory obsolescence problems. As predicted, auditors presented with ambiguous, unstructured evidence in the form of emails, heat maps, press releases, charts, etc. versus those presented with the same information in a structured memo provided more conservative obsolescence risk and inventory write-down assessments. Furthermore, we found that time budget pressure moderated the effects of information structure
resulting in auditors producing the most conservative judgments and decisions when presented with unstructured evidence in a high time budget pressure environment.

The study has a number of research and practice implications. From a research perspective, the study contributes to the literature related to potential concerns surrounding the use of big data in the audit process (e.g., Brown-Liburd et al. 2015; Richins, Stapleton, Stratopoulos, and Wong 2017; Rose et al. 2017). From a practice perspective, the research provides evidence on the potential for audit inefficiencies related to the use of big data. These concerns highlight the need for appropriate training concerning the use and timing of data visualization techniques in the audit process.

The remainder of the paper is organized as follows. The next section provides a review of the big data auditing literature and then describes the theory underlying our study’s hypotheses related to information structure and time budget pressure. The third section describes the research method and experimental design. The fourth section present the study’s data analysis and results. The final section provides a discussion, including limitations and ideas for future research.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Big Data and the Auditing Context

Gartner Research (2016) defines big data as “high-volume, high-velocity, and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision-making.” Audit firms are beginning to use data analytics on big data to assist in the audit process (Schneider et al. 2015; PwC 2015). For example, PwC (2015) notes that big data from a variety of different sources allows them to gain deeper understanding into the insights of a company’s transactions.
Brown-Liburd et al. (2015) detail behavioral concerns related to the use of big data in auditing. These concerns include information overload, information relevance, pattern recognition, and ambiguity. These concerns are all valid, thus the primary purpose of this study is to provide evidence into how incorporating varying types of evidence might affect auditor decision making on a common auditing task. While auditors are accustomed to reviewing financial data, and even some non-financial data, big data is largely unstructured and contain a variety of media types (e.g., emails, blogs, news articles, videos, dashboards, and social media). The heterogeneous nature of big data has led to concerns about whether auditors have the necessary skills to analyze large volumes of unstructured data properly (Richins et al. 2017). While research in the use of big data in the financial statement audit is fairly new, the basic tenets of this phenomenon have been studied in the context of fair market value measurements.

When auditors are testing fair market valuations, the basis of these estimates come from client management. Management typically employs specialists to provide reports supporting the basis of their fair value estimates, and these reports can vary wildly with respect to detail and form. There have been many studies that look to provide insight as to the issues surrounding auditing this unstructured information. As examples, Griffith, Hammersley, Kadous and Young (2015) find that auditors fail to reconcile conflicting information, and Cannon and Bedard (2017) note that auditors have trouble making recommendations regarding fair value estimates due to the subjectivity of the evidence. Further, recent research has demonstrated that auditors may fall prey to management opportunism when it comes to evidence surrounding fair market value measurements (Joe, Vandervelde and Wu 2017). Specifically, Joe et al. 2017 find that the degree of quantification in a report with both quantified and non-quantified data impacts the degree of testing suggested by the auditor, possibly because auditors are drawn to the
quantification in such reports. The issues found within the realm of fair market value estimates seem likely to pervade when auditors are faced with unstructured evidence inspired by big data analytics.

In an early paper looking at the potential impacts of using “big data”, Rose et al. (2017) found that the use of data visualizations had unintended consequences depending on when auditors viewed the analyses. Specifically, auditors had difficulty recognizing patterns when viewing big data visualizations prior to the collection of traditional audit evidence that led to heightened concern over misstatements and increased audit time budgets. We look to extend the literature by assessing the effects of “big data” inspired, unstructured evidence on auditor judgment and decision-making. While not explicitly tested in the fair market value setting or in the big data setting thus far, the ambiguity arising from changes in information structure could be what is driving the results.

**Impact of Information Structure**

The onset of using “big data” as part of the auditing process has the potential to shift how auditors interact with data from one of primarily using structured data to unstructured data (Richins et al. 2017). Unstructured data, by its very nature, can be ambiguous. Data ambiguity refers to the condition in which information is open to interpretation. Luippold and Kida (2012) note that the two primary determinants of data ambiguity are data sufficiency and data complexity. We contend that the complex nature of “big data” drives the ambiguity effects on financial statement auditors.

Data or task complexity commonly refer to the difficulty or structure of a task (Bonner 2008). The clarity of a task is a key component of task structure. Bonner (2008, p. 160) notes:

Clarity is affected first by the extent to which information cues are specified. For example, radiologists examining X-rays do not view a neat list of information cues, but instead have to find those cues. (Is the black spot on the film a cue to disease or just bad
photography?) Whether cues are measured already also affects clarity. Further, if cues are presented in a form similar to that stored in memory, clarity is greater.

Similarly, unstructured data is likely in a form that lacks clarity and requires auditors to find relevant information cues. Information that lacks clarity increases the cognitive load needed to measure and classify the cues (Bonner 1994).

Cognitive load theory (Sweller 1988) explains how individuals use memory and learning to solve problems, including how the processing ability of individuals is affected by the structuring of activities or tasks. Unclear tasks present an extraneous burden on problem solving ability of individuals due to an increase in cognitive load which reduces learning (Sweller, Chandler, Tierney, and Cooper 1990). In addition to learning reduction, increased cognitive load has been shown to impact decision-making in a myriad of ways. Of particular interest in the auditing setting is the propensity for heightened cognitive load to increase risk aversion and the likelihood to anchor (Deck and Jahedi 2015).

When faced with data that is either insufficient or overly complex, individuals often will seek simple ways to reduce cognitive stress. This behavior can result in individuals ending their judgment processing early or defaulting to judgment heuristics (MacDonald 1970; Sweller and Chandler 1991). For auditors, increased cognitive load will likely lead them to judgment heuristics that yield a conservative approach given the high costs of ineffective audits. In this vein, Macha and Miller (2010) find that task complexity is associated with overly high assessments of internal control risk. Further, in the experimental economics literature, researchers have consistently found that when participants are suffering from the effects of high cognitive load they are more risk averse (e.g. Whitney, Rinehart, and Hinson 2008; Gerhardt 2013; Benjamin, Brown, and Shapiro 2013; Deck and Jahedi 2015).
Following these findings, we expect when auditors are presented with “big data” inspired unstructured evidence related to an inventory write down, its more ambiguous nature will increase cognitive load and will result in the auditor taking a more conservative approach to the risk associated with inventory obsolescence than auditors presented with more traditional, structured data. Furthermore, we expect the higher risk assessments to result in increased inventory write-down decisions. Stated formally:

**H1a:** Auditors presented with unstructured evidence will assess inventory obsolescence risk as higher than those with structured evidence.

**H1b:** Auditors presented with unstructured evidence will be more likely to write down inventory than those with structured evidence.

### Impact of Time Budget Pressure

Time budget pressure refers to internally created constraints designed to produce effective results on an allocated task in an efficient manner. Auditors routinely face time budget pressure in their working environments in an effort by firms to keep audit costs relatively low (Bonner 2008). Research on the pressure effects resulting from time budgets (see DeZoort and Lord 1997 and Bonner 2008 for a review) have been mixed showing that these budgets may improve, have no effect, or reduce auditor judgment and decision-making quality. For example, Glover (1997) found positive effects of time budget pressure due to increased auditor filtering of irrelevant data while making misstatement risk judgments. Asare, Trompeter, and Wright (2000) found in an audit planning task that time budget pressure resulted in auditors decreasing the extent and depth of testing. However, overall audit accuracy was not affected by the time pressure. On the other hand, Coram, Ng, and Woodliff (2004) found that auditors subjected to high time budget pressure were more likely to accept doubtful audit evidence than those presented with low time budget pressure.
In general, the research suggests that the effect of time budget pressure on auditor judgment and decision-making is consistent with an inverted-U relationship. Smaller amounts of time pressure can improve judgment and decision-making quality up until some point at which the cognitive stress associated with increased time pressure begins to have a deleterious effect on judgment quality (DeZoort and Lord 1997). Auditors presented with unstructured data are already experiencing a heightened level of cognitive stress, which will be exacerbated with time pressure. Accordingly, we expect information structure to interact with time pressure effects such that auditors with “big data” inspired, unstructured evidence will be more influenced by time pressure. This increased pressure will result in more conservative obsolescence risk and lead to increased inventory write-down decisions. Stated formally:

**H2a:** Time budget pressure will impact an auditors’ inventory obsolescence risk more when auditors are presented with unstructured evidence (compared to structured evidence).

**H2b:** Time budget pressure will impact an auditors’ inventory write down likelihood assessments more when auditors are presented with unstructured evidence (compared to structured evidence).

III. TASK DESCRIPTION AND EXPERIMENTAL DESIGN

We use a multi-method judgment analysis to test our hypotheses and increase understanding of auditor judgments when presented with varying types of evidence. Specifically, an analysis-of-variance approach is used to evaluate auditors’ inventory obsolescence judgments. A between-subjects experimental design manipulates two factors (information structure and time budget pressure) at two levels and provides four cases to test the study’s hypotheses in an effort to minimize completion time demands.

**Participants**
The study’s participants include 126 auditors.\(^1\) We used Qualtrics Panels to access the auditor participants (see Holt and Loraas [2019] for a discussion of auditor participant sourcing with Qualtrics). We used several participant screens for the auditors, which included that their current employer be a Big 4, national, regional, or local accounting firm and that their current job title be an audit senior, audit manager, audit director or audit partner. As recommended by Qualtrics, we also included two speed checks. First, we required participants to view the background information pages for a minimum of 45 seconds. Second, participants were screened out if they completed the experiment in less than 1/3 of the median time calculated from a soft launch of ten participants.

Overall, the participants found the task to be both understandable (mean = 7.20, standard deviation = 1.84, with 0 = “Not at all understandable” and 10 = “Completely understandable) and realistic (mean = 7.30, standard deviation = 1.71, with 0 = “Not at all realistic” and 10 = “Completely realistic). Both means were significantly higher than the scale midpoint (p-value < 0.001, two-tailed). In addition, there were no significant differences in the variables across treatments (p-values 0.496 and 0.280 respectively).

**Task Description and Independent Variables**

Our experiment is adapted from an inventory obsolescence case developed by Anderson, Jennings, Lowe, and Reckers (1997). Participants were provided with information about a hypothetical client, its industry, and selected account balances. They were then told about a potential obsolescence problem with the client’s inventory before being presented with set of information items. To manipulate time budget pressure prior to reviewing the information items, half of the participants were told that the audit budget allows for extra time on inventory and to

\(^1\) Appropriate Institutional Review Board approval was received from the authors’ institution.
feel free to take as much time as needed, while the other half were told that the audit budget has been reduced and to review the information as quickly as possible. Next, to manipulate information structure, half of the participants received information items that were presented in a traditional, structured nature (i.e., summarized in an audit memo format). The other half of the participants received information items that were presented in an unstructured nature (i.e., raw client emails, trade journal articles, sentiment analyses, global sales heat maps). The set of information items was developed using suggestions by Applebaum, Kogan and Vasarhelyi (2017) on the most promising uses of data within the financial statement audit. Both sets of inventory information contained nine randomized items that contained both diagnostic and non-diagnostic information available for consideration when making a decision regarding an inventory write down (See Appendix). Participants were told to review as many information items as needed before proceeding to make an overall inventory obsolescence recommendation.

**Dependent Variables**

Participants made two inventory judgments that were used for hypothesis testing. First, they were asked to assess the likelihood of an inventory obsolescence problem using a scale with the endpoints of 0 = “Very Unlikely” and 100 = “Very Likely.” Next, they were asked to assess the likelihood that they would recommend a write down of inventory to their audit team supervisor using a scale with 0 = “Very Unlikely” and 100 = “Very Likely” as the endpoints.

**Covariate**

Prior psychology literature (e.g., Frenkel-Brunswick 1949; Budner 1962) has found that an individual’s tolerance for ambiguity leads to differences in perceptions related to how threatened they feel when presented with uncertainty. Accordingly, we attempted to control for

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2 Most participants viewed all nine information items.
individual differences related to each participant's ambiguity tolerance. After the inventory obsolescence judgments, participants were asked a set of 20 true/false questions that are designed to measure their tolerance for ambiguity. The ambiguity tolerance scale has been previously validated in prior literature (MacDonald, 1970) and used in the auditing literature (e.g., Lowe and Reckers 1997).

IV. DATA ANALYSIS AND RESULTS

Manipulation Checks

Two questions assessed the efficacy of the Information Structure and Time Pressure manipulations. The participants were asked how ambiguous they perceived the information surrounding the potential inventory obsolescence problem to be used to determine why varying types of evidence impact decision-making differentially. Overall, the participants who viewed the unstructured evidence (mean = 5.97, standard deviation = 2.15, with 0 = “Not at all ambiguous” and 10 = “Completely ambiguous”) found the information to be more ambiguous (p-value = 0.039, one-tailed) than participants who viewed the structured evidence (mean = 5.26, standard deviation = 2.17).

Participants also were asked how much audit time budget pressure they felt in completing the case to be as a check for the Time Pressure manipulation. Overall, there were no significant differences (p-value = 0.143, one-tailed) in the time pressure perception between participants in the high time pressure case (mean = 6.34, standard deviation = 2.26, with 0 = “Not at all pressured” and 10 = “Completely pressured”) and participants in the low time pressure case (mean = 5.93, standard deviation = 1.96). Because of this, we eliminated participants who were in the high time pressure case who did not perceive any time budget pressure (i.e., participants responding 0 or 1 on the 11-point Likert scale) and participants who were in the low time pressure case who perceived a strong time budget pressure (i.e., participants responding 9 or 10
on the 11-point Likert scale) as their responses indicate a lack of understanding of the case materials. This analysis resulted in six participants being removed from our analysis. Overall, our 120 remaining participants in the high time pressure case (mean = 6.52, standard deviation = 2.04) perceived greater time pressure (p-value = 0.012, one-tailed) than participants in the low time pressure case (mean = 5.69, standard deviation = 1.80).

**Participant Demographics and Control Variables**

Table 1 presents the descriptive statistics for the participant demographics and control variables. The majority of the 120 participants (57%) were at least 35 years old. Participants were distributed across a local, regional, national, and Big 4 firm (28%, 18%, 24%, and 31%, respectively). Participants’ job titles included senior auditors, audit managers, audit directors, and audit partners (39%, 40%, 13%, and 8%, respectively). Finally, the majority of participants (56%) had at least eight years of audit experience. We also tested whether ambiguity tolerance varied between the treatments, it did not (p value .715).

**Hypotheses Test Results**

Table 2 reports the results for participant responses to the likelihood of an inventory obsolescence problem. Panel A reports the descriptive statistics and Panel B presents ANCOVA results for information structure (structured vs. unstructured) and time pressure type (low vs. high) effects. H1a predicts that auditors presented with unstructured evidence will assess inventory obsolescence risk as higher than those with structured evidence. H1a is supported as the results show a significant main effect for information structure type (p=0.002, one-tailed). The results reveal no significant main effect for time pressure (p=0.457, one-tailed) nor a
significant evidence-time pressure interaction (p=0.777, two-tailed). Furthermore, ambiguity tolerance is insignificant as a covariate in the model (p=0.637, two-tailed).³

Insert Table 2 here

H2a predicts an ordinal interaction such that auditors will be more influenced by time budget pressure when presented with unstructured evidence than when presented with structured evidence. As previously mentioned, our traditional ANCOVA model does not reveal a significant interaction. However, ANOVA is not well suited for testing ordinal interactions (Buckless and Ravenscroft 1990), so contrast coding is used to test for the interactions. Panel C of Table 2 presents the contrast testing for inventory obsolescence likelihood using contrast weights of +3 for the high time pressure – unstructured; +1 for the low time pressure – unstructured and -2 for structured cells.⁴ The resulting contrast test is significant (p=0.002, one-tailed). Thus, H2a is supported.

Table 3 reports the results for participant responses to the likelihood of recommending an inventory write down. Panel A reports the descriptive statistics and Panel B presents ANCOVA results for information structure and time pressure type effects. H1b predicts that auditors presented with unstructured evidence will be more likely to recommend an inventory write down than those with structured evidence. H1b is supported as the results show a significant main effect for information structure type (p=0.030, one-tailed). The results also reveal a marginally significant main effect for time budget pressure (p=0.085, one-tailed). However, similar to the inventory obsolescence likelihood results, there appears to be no significant evidence type-time

³ All of the hypothesis results are robust to the removal of the ambiguity tolerance control variable.
⁴ The results are robust to a variety of contrast weights. For example, using contrast weights of +3 for the high time pressure – unstructured cell and -1 for the remaining cells results in similar inference (p=0.017, one-tailed).
pressure interaction (p=0.573, two-tailed) nor a significant covariate in ambiguity tolerance in
the model (p=0.562, two-tailed).

Insert Table 3 here

H2b predicts an ordinal interaction such that auditors will be more influenced by time
budget pressure when presented with unstructured evidence than when presented with structured
evidence. To test the ordinal interaction, we applied the same contrast coding that we used to test
H2a. Specifically, Panel C of Table 3 presents the contrast testing for inventory write down
likelihood using contrast weights of +3 for the high time pressure – unstructured cell; +1 for the
low time pressure – unstructured cell; and -2 for structured.5 The resulting contrast test is
significant (p=0.010, one-tailed). Thus, H2b is supported.

V. CONCLUSIONS

Unstructured data and data visualizations are powerful tools capable of playing an
integral part in financial statement audits. However, an understanding of the implications
surrounding the use of these data sources is critical for using them successfully. In an experiment
with experienced auditors, we investigate the potential for data ambiguity associated with
unstructured data to affect auditor judgments and decision-making. Additionally, we investigate
the potential for these effects to be heightened in the presence of increased time budget pressure
which is common in many audits.

We find that auditors presented with more unstructured data in the form of data
visualizations, email, and press releases concerning a potential inventory obsolescence issue
provide more conservative assessments surrounding the risk of inventory obsolescence than

5 The results are robust to a variety of contrast weights. For example, using contrast weights of +3 for the
high time pressure – unstructured cell and -1 for the remaining cells results in similar inference (p=0.008,
one-tailed).
auditors presented with the same information in a traditionally, structured format. Additionally, those conservative risk judgments led to increased recommendation decisions related to inventory write-offs. We also find that these conservative judgments and decisions are exacerbated when auditors are placed in a high time budget pressure environment.

In conclusion, our results have implications for both research and practice. From a practice perspective, firms should take care that the auditors tasked with analyzing unstructured data have ample expertise in the industry and with the client to help counteract the cognitive load that is brought about by unstructured data. If an auditor has developed extensive schema related to the client and industry, the impact of heightened cognitive load caused by unstructured data should be lessened. Further, an increase in risk aversion that is not based upon fact patterns but by data presentation could result in unnecessary and costly audit procedures.

Research wise, our results extend earlier findings that cognitive load increases risk aversion (e.g. Whitney et al. 2008, Gerhardt 2013, Benjamin et al. 2013, Deck and Jahedi 2015), by demonstrating that data ambiguity that is at the heart of big data changes potential audit outcomes. More research is needed to determine how best to counteract this effect, as it is likely that the profession will continue to incorporate more and more data as it becomes available. Our findings also contribute to the literature related to the implications of Big data/data analytics on the audit process (e.g., Brown-Liburd et al. 2015; Richins, Stapleton, Stratopoulos, and Wong 2017; Rose et al. 2017). Finally, our data contributes to the time budget pressure literature (e.g., DeZoort and Lord 1997; Bonner 2008) by providing evidence on the interactive effects of time budget pressure and task complexity.

Our study does carry some potential limitations. One such limitation is that we only provide data and ask for responses to one auditing decision. Recent research has demonstrated
that an additional issue with making decisions under heightened cognitive load is the propensity to be inconsistent due to lack of focus on the stimuli (Olschewki, Rieskamp and Scheibenhenne, 2018). This could prove problematic within the auditing realm as similar data patterns should result in similar decisions, which may not occur with unstructured data. Further, as the use of big data is still relatively new, it is unclear exactly what it will look like in an audit environment, so while our experiment was deemed realistic by the auditor participants, it may not be. Even so, this study offers a preliminary insight as to how changing the evidence viewed by auditors can change the audit plan. Another limitation is that we used a third party to source our participants. However, we followed sound practice on our design, manipulation and attention checks to provide assurance that our participants were appropriate for the task.
References


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<th>Structured Evidence</th>
<th>Unstructured Evidence</th>
<th>Study Total</th>
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<td>Low Time Pressure</td>
<td>High Time Pressure</td>
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</tr>
<tr>
<td></td>
<td>22</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td></td>
<td>32</td>
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TABLE 2
Inventory Obsolescence Likelihood
Descriptive Statistics and Hypotheses 1a/2a Tests

Panel A: Cell Means (SD) for the Likelihood of Inventory Obsolescence

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<th>Structured Evidence</th>
<th>Unstructured Evidence</th>
<th>Total</th>
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<tr>
<td>Low</td>
<td>58.45 (21.83)</td>
<td>68.63 (16.84)</td>
<td>64.48 (19.49)</td>
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<tr>
<td>High</td>
<td>57.86 (23.04)</td>
<td>70.05 (18.56)</td>
<td>64.88 (21.29)</td>
</tr>
<tr>
<td>Total</td>
<td>58.12 (22.29)</td>
<td>69.40 (17.68)</td>
<td>64.70 (20.42)</td>
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</tbody>
</table>

Panel B: Overall ANCOVA for the Likelihood of Inventory Obsolescence

<table>
<thead>
<tr>
<th>Source</th>
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<th>Sum of Squares</th>
<th>F-value</th>
<th>p-value</th>
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<td>3,445.07</td>
<td>8.66</td>
<td>0.002</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>1</td>
<td>4.78</td>
<td>0.01</td>
<td>0.457</td>
</tr>
<tr>
<td>Information Structure x Time Pressure</td>
<td>1</td>
<td>32.14</td>
<td>0.08</td>
<td>0.777</td>
</tr>
<tr>
<td>Covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ambiguity Tolerance</td>
<td>1</td>
<td>89.05</td>
<td>0.22</td>
<td>0.637</td>
</tr>
<tr>
<td>Error</td>
<td>115</td>
<td>45,777.23</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Contrast Test for Hypothesized Interactiona

<table>
<thead>
<tr>
<th>Mean</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>F-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Time Pressure-Unstructured Evidence</td>
<td>70.05</td>
<td>1</td>
<td>3,594.50</td>
<td>9.091</td>
</tr>
</tbody>
</table>

*Significant p-values (one-tailed) are bolded and italicized.

a The contrast coding used for the ordinal interaction is +3 for the High Time Budget Pressure-Unstructured group, +1 for the Low Time Budget Pressure-Unstructured group, and -2 for both Structured Evidence groups.

Variable Definitions:
Dependent Variable - Obsolescence likelihood reflects responses to how likely does Trexler have an inventory obsolescence problem on a scale with endpoints of “very unlikely” (0) to “very likely” (100).
Ambiguity Tolerance reflects responses to the AT-20 Scale (MacDonald 1970)
TABLE 3
Inventory Write Down Likelihood
Descriptive Statistics and Hypotheses 1b/2b Tests

Panel A: Cell Means (SD) for the Likelihood of Inventory Write Down

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Structured Evidence</th>
<th>Unstructured Evidence</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>61.36 (21.08) n=22</td>
<td>67.56 (23.29) n=32</td>
<td>65.04 (22.42) n=54</td>
</tr>
<tr>
<td>High</td>
<td>65.00 (25.29) n=28</td>
<td>76.00 (23.17) n=38</td>
<td>71.33 (24.52) n=66</td>
</tr>
<tr>
<td>Total</td>
<td>63.40 (23.37) n=50</td>
<td>72.14 (23.44) n=70</td>
<td>68.50 (23.71) n=120</td>
</tr>
</tbody>
</table>

Panel B: Overall ANCOVA for the Likelihood of Inventory Write Down

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>F-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information Structure</td>
<td>1</td>
<td>1,976.14</td>
<td>3.60</td>
<td>0.030</td>
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<tr>
<td>Time Pressure</td>
<td>1</td>
<td>1,046.65</td>
<td>1.91</td>
<td>0.085</td>
</tr>
<tr>
<td>Information Structure x Time Pressure</td>
<td>1</td>
<td>174.86</td>
<td>0.32</td>
<td>0.573</td>
</tr>
<tr>
<td>Covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ambiguity Tolerance</td>
<td>1</td>
<td>185.72</td>
<td>0.339</td>
<td>0.562</td>
</tr>
<tr>
<td>Error</td>
<td>115</td>
<td>63,077.25</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Contrast Test for Hypothesized Interactiona

<table>
<thead>
<tr>
<th>High Time Pressure-Unstructured</th>
<th>Mean</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>F-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>76.00</td>
<td>1</td>
<td>3,095.41</td>
<td>5.676</td>
<td>0.010</td>
</tr>
</tbody>
</table>

*Significant p-values (one-tailed) are bolded and italicized.

a The contrast coding used for the ordinal interaction is +3 for the High Time Budget Pressure-Unstructured group, +1 for the Low Time Budget Pressure-Unstructured group, and -2 for both Structured groups.

Variable Definitions:
Dependent Variable - Obsolescence likelihood reflects responses to how likely are you to recommend that Trexler write down their inventory on a scale with endpoints of “very unlikely” (0) to “very likely” (100).
Ambiguity Tolerance reflects responses to the AT-20 Scale (MacDonald 1970).
APPENDIX – Case Information Items

Item A – Unstructured, Diagnostic Item

From: Vineeta Agrawal vagrawal@txelex.com
Subject: Re: Fall Trade Fair
Date: December 8, 2015 at 2:08 PM
To: Pat Kirkpatrick pkirkpatrick@txelex.com

Hi Pat,

The trade fair went well. Our booth looked great, and as always, the convention floor was packed.

Regarding the Dark Horse component, I was able to review the design. As we expected, it does appear to make our current product obsolete. I’m just glad that we knew this was coming and were able to begin R&D on the new technology even though we probably won’t be able to have anything available until the end of next year. Until then, production of our current design will continue to serve our customers as there is little else we can do at the moment.

We can discuss this more at the Christmas party.

Regards,

Vineeta Agrawal
Product Manager
Trexlex Company

On December 8, 2015, at 9:00 AM, Pat Kirkpatrick <pkirkpatrick@txelex.com> wrote:

Hi Vineeta,

I hope you had a good trip. I wanted to follow-up with you to see how the trade fair went. Also, were you able to review the Dark Horse component?

PK

Pat Kirkpatrick
Chief Operating Officer
Trexlex Company

On November 23, 2015, at 12:59 PM, Vineeta Agrawal <vagrawal@txelex.com> wrote:

Hi Pat,

I wanted to remind you that I will be attending the Fall Trade Fair in Las Vegas next week. It looks like our booth preparations are all in order, so hopefully we will get a lot of traffic.

I’m hoping to be able to get a look at the Dark Horse Technologies new electronic component while I’m out there to see how it stacks up to our component.

Regards,

Vineeta Agrawal
Product Manager
Trexlex Company

Item A – Structured, Diagnostic Item

Trexlex’s product manager confirmed that the competition has designed a technologically superior product. The manager had investigated the designs at a trade fair and found the new designs made Trexlex’s product technologically obsolete. However, Trexlex also had been developing a replacement product. Production of the old design will continue, to serve existing customers’ needs until the commercial success and cost competitiveness of the new technology is established. The product manager noted that there is little else that Trexlex can do right now as a replacement is currently unavailable, but they plan to have a competitive replacement available by the end of 2016.
Item B – Unstructured, Diagnostic Item

Entity Extraction, Sentiment Analysis\textsuperscript{a}
Dark Horse Technologies New Component\textsuperscript{b}
(Trexler Competitor)

\textsuperscript{a} Social media with hashtags #DarkHorse
\textsuperscript{b} Two weeks following Fall 2015 trade fair

Item B – Structured, Diagnostic Item

A review of an article in a leading trade journal revealed that Trexler’s main competitor, Dark Horse Technologies, unveiled a new electronic component during the 2015 Fall Trade Fair. Sentiment analysis revealed the new component to be a technologically superior product and that the design will make Trexler’s product technologically obsolete.
Item C – Unstructured, Nondiagnostic Item

Item C – Structured, Nondiagnostic Item

A review of Trelxer’s cycle counting program shows that inventory record accuracy percentages in the first five weeks of 2015 showed an accuracy of about 52%. As the program removed errors from the system, accuracy increased to about 96% by week 28. The drop in accuracy from week 28 through week 35 indicates some change in the system. Corrective action was taken about week 36 and accuracy rose again until about week 40. From week 40 through week 52 the system is stable at about 93%.
Item D – Unstructured, Diagnostic Item

From: Jaime Richards  jrichards@trexler.com
Subject: Re: Dark Horse pricing
Date: December 15, 2015 at 3:15 PM
To: Pat Kirkpatrick  pkirkpatrick@trexler.com

Hi Pat,

I read it too. Based on my discussions, I believe that their initial pricing is simply a temporary marketing strategy. My belief is that the Autoswitch will be price competitive if it gets to market. Frankly, I'm skeptical of their testing of the device and think they are prematurely marketing it. Our customers either can't or won't wait that long for a product that is not proven under production conditions.

Sincerely,

Jaime

Jaime Richards
Marketing Manager
Trexler Company

On December 15, 2015, at 1:08 PM, Pat Kirkpatrick <pkirkpatrick@trexler.com> wrote:

Hi Jaime,

I just read the press release concerning Dark Horse's pricing on the Autoswitch. The price point seems to be very aggressive. I'm interested to get your take on it.

PK

Pat Kirkpatrick
Chief Operating Officer
Trexler Company

Item D – Structured, Diagnostic Item

Discussions with Trexler’s marketing manager reveal that they believe the initial price of the competitor’s new component is simply a temporary marketing strategy. She believes the new device will be price competitive when available. Furthermore, she stressed that many customers either can’t or won’t wait that long for an item not proven under production conditions and is skeptical about the adequacy of the competition's testing of the new technological device, believing that the competition might be attempting to prematurely market the device.
Item E – Unstructured, Nondiagnostic Item

Trexler Sales Process

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Item E – Structured, Nondiagnostic Item

The sales process at Trexler can be broken down into three major components, (1) start, (2) qualify and (3) close. Transitioning between components are supplemented by (4) quotes and (5) satisfy (i.e., fulfillment). Each process and transitioning point feed into the sales pipeline as various lead times are appropriate within this industry. Key points are consistent and persistent communications with quality business prospects will keep the sales pipeline healthy and expanding.
Item F – Unstructured, Nondiagnostic Item

Non-Contract Purchases Evaluation

**Item F – Structured, Nondiagnostic Item**

Non-contract purchases have decreased from 2014 by a total of 60 purchases, from 251 in 2014 to 191 in 2015. In each month except for December 2015, non-contract purchases went down by an average of six, but December 2015 was higher than the corresponding period of 2014 by five. The most significant non-contract purchases were for memory chips ($77,000 non-contract, up 15.2% making up nearly 33% of all purchases), I/O ports ($435,000 non-contract, down 2.6%, making up all the I/O purchases), custodial services ($79,000 non-contract, up 5.3%, making up all the custodial purchases), promotional materials ($78,000 non-contract, down 3.8%, making up 42.2% of all promotional material purchases), and office supplies ($58,000, up 14.1%, making up 28% of all office supplies purchases).
Item G – Unstructured, Diagnostic Item

Autoswitch - Should You Believe the Hype?

Dark Horse Technologies unveiled their newest product, the Autoswitch, at the 2015 Fall Electronics Trade Fair. According to the company, the component allows for automatic control of switching operations. If true, the product has potential to render older manual switches obsolete. Dark Horse announced initial pricing around $40 per unit with delivery by mid-2016. However, Electronic Products has learned that production will take at least 8-20 months due to retooling and production delays.

Learn more about DARK HORSE TECHNOLOGIES (/Companies/Dark_Horse.aspx)

Item G – Structured, Diagnostic Item

An article in the leading trade journal notes that although Trexler's competitor is accepting orders, they estimate that it would take at least 8-20 months to gear up to full production (because of retooling and production delays).
Projected Sales for Trexler’s Current Component
2016-2018

Greater than 200% current sales
Between 100% - 200% current sales
Between 50% - 100% current sales
Less than 50% current sales

Trexler has an international marketing team that markets its older technology products in developing nations around the world. An analysis of international sales indicated that there is a healthy third-world market for electronic components such as the old products that Trexler is manufacturing.
PRESS RELEASE

Dark Horse Technologies Announces Automatic Switch Controller Pricing

Houston, T.X. – Dark Horse Technologies today announced pricing relating to the Autoswitch, the world’s first automatic control for electrical switch operations, that was recently unveiled at the 2015 Fall Trade Fair.

“Consumers have long been looking for a more affordable and automated way of operating electrical switches, and we’ve responded with Autoswitch, redefining today’s market in electronic switch components,” said Maria Williams, Vice President, New Product Development, Dark Horse Technologies. “Throughout our company, we have strived to give customers the best possible product on the market at the lowest possible price.”

Pricing and Availability

Dark Horse is pleased to announce that they are accepting orders of the Autoswitch at $37 per unit for the first 25,000 units on their website at www.dht.com. After the initial limited order, pricing will go up to $40.99 per unit. While a delivery date for the orders has not been established, they anticipate delivery by mid-2016.

About Dark Horse Technologies

Dark Horse builds industry leading electronic switching components designed for wide appeal. Dark Horse is headquartered in Houston, TX with offices around the globe. For more information see www.dht.com.

Contact

Dark Horse Technologies
Jennifer Smart, Public Relations 281-456-7890; jsmart@dht.com

Item I – Structured, Diagnostic Item

According to a competitors' press releases, the new electronic components are expected to sell for approximately $40, a figure below the price at which Trexler historically offered their product (that being $50). One competitor had accepted limited orders, for later delivery at $37.