ON-LINE ANALYTICAL PROCESSING (OLAP) FOR NEW VENTURE MANAGEMENT AND MONITORING: AN EXPLORATORY FIELD STUDY

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Abstract

An investigative field study is undertaken for exploring the requirements and feasibility of employing sophisticated on-line analytical processing (OLAP) tools for enhancing decision-making and monitoring of early stage enterprises. This study used a sample of two groups: 1) executives from young firms, and 2) venture capitalists. Subjects were interviewed in a semi-structured format in order to probe user requirements and discuss underlying issues. Key elements of decision support systems (DSS) are reviewed. The human element of DSS is highlighted. Overall, findings were supportive for the use of OLAP tools in this context. Findings and interpretation from this qualitative research are presented, along with suggestions for future research.

1 Introduction

1.1 Background

Start-up and early stage enterprises are faced with a myriad of unstructured and semi-structured problems that require decisions. Senior executives, venture capitalists and other investors involved with these firms must make decisions that impact the potential success or failure of each new venture. Decision-making in small firms is very often an informal process and may hinge disproportionately on the expertise or opinions of just one or two individuals. These individuals usually possess a high degree of both personal and position power. While a limited hierarchy and short chain of command can provide management flexibility, this orientation may involve biases and often lacks in-depth analysis required for effective decision-making. Poor decision-making will lead to substandard business performance.

Executives of small firms are often overwhelmed with multiple responsibilities and an overabundance of data. Likewise, venture capital (VC) firms have a difficult time understanding the dynamics and performance of several companies in their portfolios. Individual venture capitalists often participate on multiple boards simultaneously. Further complicating the monitoring roles of venture capitalists, client company executives and entrepreneurs are the main sources of information regarding company condition and potential. Information asymmetry can lead to governance and trust problems (Markman, Balkin & Schjoedt, 2001). Due to agency theory issues (Eisenhardt, 1989), ambiguous decision-making criteria may be presented to venture capitalists and board members. Owner-operators and agent managers of small firms may mislead investors regarding the state of the business due to conscious and sub-conscious motivations and self-preservation instincts.

Through the use of qualitative field study research, this study attempts to gauge the feasibility of whether senior managers and venture capitalists will engage in sophisticated data analysis in order to make better decisions. The ability to do this analysis at the desktop, especially away from the office, is a powerful decision support function. Simple yet insightful queries may enhance the quality of small company surveillance, governance, management and decision-making.

The mechanism to which this data analysis will be performed is by using on-line analytical processing (OLAP) tools. OLAP can institutionalize a great deal of routine data retrieval, thus minimizing the biases associated with selected data access. OLAP allows ad hoc queries from inside the organization via senior managers, and outside the firm by venture capitalists and external board members.

1.2 Research Question

In this qualitative study, the following research question is presented: Are on-line analytical processing (OLAP) tools applicable to management and monitoring of start-ups and early stage firms? To provide insight into this problem, interviews are conducted with a small sample (n = 24) of venture capitalists and emerging company executives.

Several questions arise when trying to determine the information needs of executives and venture capitalists, including: How are top-level decisions typically made today? Is the decision-making process currently optimized? What type of information is needed to make good decisions? What is required of the executives and active investors in these firms that will contribute to the success of a decision support system? How relevant is the technological sophistication of potential users? And, lastly, what are the expectations of this small sample of potential OLAP users with regards to training and user interfaces?

1.3 Purpose and Plan of Study

The purpose of this study is to investigate the feasibility of practitioners directly utilizing sophisticated data analysis tools (i.e., OLAP) to improve the management and monitoring of small, emerging enterprises. To accomplish this, an outline of the problem is provided. Definitions of key technical terms are included and followed by a brief review of relevant literature. A methodology is presented that describes the use of field study technique to gather primary data from practicing venture capitalists and executives of young firms. The analysis of the primary data collected from these interviews provides insight into the information needs of respondents and their propensity to engage in the use of OLAP tools. This paper explores user attitudes toward training, technical sophistication and expectations for using OLAP tools.

1.4 Definitions of Key Terms

For clarity and readability, the meanings of several technical terms used in this research are provided below:

<u>On-line analytical processing (OLAP).</u> OLAP refers to an information system that allows the user to perform a query and conduct analysis, within seconds, at a personal computer (Turban & Aronson, 2001). OLAP allows users to easily pick out desired pieces of information, often by combining different dimensions and hierarchies of data from a data warehouse (Bose & Sugumaran, 1999). Achor (2002) defines OLAP as computer-enhanced multidimensional analysis performing well beyond relational databases. Hasan et al (2000) describes OLAP as a business analysis aid for executives, while distinguishing it from OLTP (on-line transaction processing) as a process automation tool at the operational level.

Decision support system (DSS). DSS is a user-friendly computer-based information system that combines data and models to provide solutions for non-structured problems (Turban & Aronson, 2001). Items such as OLAP, data warehouses, data mining functions and intelligent agents are often components of a DSS.

Data warehouse. A data warehouse is a storage area for relational data that is specially organized. Data is clean and structured in a standardized format (Turban & Aronson, 2001). Data warehouses support OLAP applications by storing and maintaining data in multidimensional format (Sen & Sinha, 2005).

Data mining. Data mining involves searching for specific, yet unknown information within databases. Data mining is particularly proficient at discovering hidden trends in data by using pattern recognition in addition to statistical and mathematical techniques (Bose & Sugumaran, 1999). Data mining is also referred to as knowledge discovery in databases (Chung & Gray, 1999).

Intelligent Agent (IA). An IA is a knowledge-based or expert system contained within a computer-based information system. The IA improves the intelligence of an information system (Turban & Aronson, 2001). Intelligent agents can conceal the true complexity of data retrieval processes from the user (Bose & Sugumaran, 1999).

Executive Information System (EIS). An EIS is a computer-based system configured to support executive work, often by providing customized reports and summaries of business activity (Turban & Aronson, 2001).

Now that study's key terms have been identified and explained, a brief review of the relevant literature is provided next.

2 Literature Review

Decision support systems are supported by an array of sophisticated, technical tools such as data warehouses, data marts, data mining programs, online analytical processing, and intelligent agents. However, when a business commits to relying on data-driven decision making, a comprehensive and complex undertaking is required involving time, resources and money. Most important of all is the human input to the process. Senior executives must clearly define the strategies that determine the technical criteria to be used to produce needed data. The types of decisions required by the business must be defined to the best of management's ability. Good decision-making depends on a robust combination of technical and human systems (Turban & Aronson, 2001).

Khatri and Ng (2000) explored the concept of intuitive synthesis within strategic decision making in the banking, computer and utility industries. The authors point out that intuitive decision-making has largely been depicted as inferior to rational decision- making. Some scholars have reported that intuitive processes are not worthy of scientific study. On the contrary, Khatri and Ng claim that a sound theory of strategic decision-making should combine both rational and intuitive processes. Achor (2002) considered "intuitive manipulation of data" the key characteristic of OLAP.

In the work of Prietula and Simon (1989), artificial intelligence and cognitive science research revealed that intuitive processes are not abnormal (Khatri & Ng, 2000). Intuition involves a complex process evolving from extended experience and learning. Intuition should not be perceived as the opposite of rationality nor viewed as a form of guessing. Intuition is a sophisticated method of reasoning that is honed over years of specific experience (Khatri & Ng, 2000). Intuition may be construed as what makes an expert an expert.

Intuition deals with problems in a non-linear fashion and thus goes beyond the limitations of rational decision-making models. Khatri and Ng (2000) tested and found that intuitive processes worked well in unstructured, unstable environments. Unstable environments are often problematic for rational analysis. Also, intuition permits rapid decision making in lieu of time-consuming analysis. Intuitive synthesis recalls multiple, related problems and scenarios from past experiences.

Mintzberg et al (1976) claimed that poorly structured problems, like strategic problems, are not suitable for programming. However, intuitive synthesis may be better suited for strategic decision making due to the lack of complete information found in strategic analysis. The human elements found in semi-structured and unstructured decision-making may be very important.

Khatri and Ng (2000) report empirical evidence that positively relates intuitive synthesis to organization performance. Essentially, this research suggests that learned experiences over time contribute to better decision-making. This is essentially the human equivalent to neural networks and data mining. The mind forms relationships and patterns, seemingly involuntarily, in order to make a judgment for a problem or situation.

Chung & Gray (1999) describe a step-by-step process for use in data mining exercises. The authors are conscious of human involvement throughout the process. They emphasize how critical human interpretation of the knowledge discovery process is and how this can lead to improvements in data mining models. Chung and Gray outline the data mining process steps to include: 1) Understanding the application and end user goals; 2) Creation of target data set to be used for discovery; 3) Cleaning up of data; 4) Reduction of variables; 5) Choice of data mining task, i.e. regression, clustering, etc.; 6) Determination of data mining algorithm; 7) Data mining itself, or the search for patterns of interest; 8) Interpretation of patterns; and lastly 9) Knowledge consolidation and reporting.

Of the above steps, understanding applications and goals (step #1) and pattern interpretation (step #8) appear to be the most relevant to human involvement in system supported decision-making. If the goals are poorly understood, then a model and subsequent mining operation will be unlikely to yield valid patterns, useful associations, or successful queries. If the interpretation of discovered knowledge is flawed, then the data mining's effectiveness will be in question.

Davenport et al (2001) described a holistic framework describing how data is transformed into usable outcomes such as better decision-making, more effective behavior, and improved business performance. The authors point out how DSS, OLAP, EIS and data mining were designed to do useful things with transacted data. However, many companies have spent a great deal of money to process transactions and collect data, yet have not engaged in useful analysis of this data for the benefit of decision-making and business performance. Chopoorian et al (2001) claim that firms often posses the needed data but do not provide users with adequate access to the data. In one particular study, less than 10% of the companies revealed significant progress in transforming data into knowledge that resulted in significantly impacting decision-making (Davenport et al., 2001).

The managerial, or human, element is key to determining the design of analytical decision support systems. A clearly articulated strategy must precede information gathering and analysis. Semi-structured and unstructured decisions require more complex system support than is required from more predictable, highly structured decisions. Davenport et al (2000) proclaimed the importance of skills and experience in both business strategists and IT professionals. This supports the arguments of Khatri and Ng (2000) that placed great emphasis on intuition. Intuition is composed partially of past experiences, and can be a key determinant for decision-making. IT professionals, such as business analysts and data modelers, must work with decision makers to determine the objectives and inputs necessary to support given situations (Davenport et al., 2000). A model is of no benefit if it does not reflect the business condition under scrutiny. Nor is a model beneficial if it neglects those individuals in need of decision support.

There is a potential for conflicts between decision makers and OLAP tool designers. Organizational and cultural changes are often required in order for a business to revert to data-based decision-making (Davenport et al., 2000). For better chances of success, top management needs to believe in and support DSS initiatives (Turban & Aronson, 2001).

Baker and Baker (1999) discussed the virtues of data warehousing for the purposes of accessing and using data for the benefit of business decision-making. Again, a key starting point is determining what the business strategy and information needs are prior to selecting and designing data storage schemes. A data warehouse is an ideal repository for large volumes of data from every functional area of a business. Data marts, on the other hand, are highly specialized data warehouses dealing only with data regarding specific functional areas such as marketing or finance. A data warehouse guarantees that all individuals are using the same data in their respective analyses. The data warehouse should allow executives to utilize user-friendly tools like graphical user interfaces to access data without the need for information technology department personnel (Baker & Baker, 1999). Time and money must be spent to ensure successful use of a data warehouse.

Multidimensional data base architecture in a data warehouse can provide dynamic access to data by a practicing manager. A query can be performed that details a particular salesperson or territory, with the types of products sold, in conjunction with specific selling promotions and to what types of customers. This multidimensional analysis is also referred to as online analytical processing (OLAP) (Bose & Sugumaran, 1999). Knowing the type of information needed before configuring storage and access media is critical. Defining before designing requires strategic forethought and user input.

Bose & Sugumaran (1999) perceived a growing divide between robust transactional processing capability and the suspect analytical ability of users. The authors developed a web-based intelligent data miner (IDM) with the goal of performing complex data mining with a more user-friendly approach. Senior executives and business managers in particular should be able to access data on demand to support decision making without requiring the assistance of IT personnel (Bose & Sugumaran, 1999). Senior managers do not need to know the intricate algorithms and methods of sophisticated intelligent agents. Intelligent agents can mask this complexity (Spencer & Loukas, 1999) from the user via easy-to-understand graphical user interfaces.

JATLite (Java Agent Template) was used by Bose and Sugumaran (1999) to create their IDM. JATLite is a group of programs that permits the creation of sophisticated software agents. These agents can be enabled to communicate with each other over the Internet. Although these agents are complex, users can be trained to employ these tools for user-friendly data mining over the Internet. A good example of mining a blizzard of data is accessing and 'drilling down' into federal Medicare records (Bose & Sugumaran, 1999).

Literature in the OLAP domain is quite diverse with regards to scope and depth. However, reoccurring themes include the importance of user-defined objectives and user understanding of how to access, analyze and interpret data – regardless of the software tools used. Data without analysis and action is just data. Data that affords timely, effective decision-making creates a valuable component to a firm's competitive intelligence arsenal.

3 Methodology

A small sampling of venture capitalists (n = 11) and executives (n = 13) from young, emerging companies were interviewed as a means of collecting primary data. Subjects were interviewed either in-person or by telephone, with five of the subjects being interviewed by both methods. The eleven venture capitalists ranged from full partner to associate partner of firms with at least $20 million currently invested in portfolio companies. Eight venture capital firms were represented.

The thirteen senior executives interviewed represented eight different early stage medical technology companies with annual sales ranging from $0 to $15 million. This study classified a medical technology company as a firm engaged in the development and commercialization of innovative equipment aimed at the medical device, interventional therapy, medical imaging and diagnostics marketplaces. Titles for the executives in this sample included vice-president, chief operating officer, chief financial officer and chief executive officer.

Respondents were asked about critical success factors and key performance indicators that are important to the types of decisions they are likely to be involved in. The skills, knowledge and tools required to accomplish effective data analysis for decision-making were briefly reviewed. Respondents were evaluated on their current knowledge and skills base as well as their aptitude and receptiveness for learning new OLAP techniques. The process of developing a data-driven DSS and OLAP tools were also briefly explored.

Semi-structured interviews were employed purposefully for their flexibility in field study situations (Babbie, 1998). While the interview guide did not change measurably during the course of the interviews, the order and emphasis of topics changed as the interviewer gained familiarity with nuances of the research subjects and subject matter. This echoes Rubin and Rubin's (1995) statement that qualitative interviews are iterative and continuous. In a way, the interviews built upon themselves. For this reason, several respondents were contacted a second time for further questioning and elaboration. The field study interview guide developed and used for this study is provided below in Exhibit 1.

Exhibit 1. OLAP Field Study Interview Guide

1. Respondent: ________________________ Date: ________________________
2. Title: ____
3. Firm: ________________________ Firm Type: ____________________
4. Firm Location: ____
5. If VC, indicate firm's current, active investment amount: ________________________
6. Annual Revenue (000's) 2001: __________ 2002:__________ 2003:__________
7. Annual Net Profits (000's) 2001: __________ 2002: __________ 2003:__________
8. What type of information do you typically use in decision making? (Circle)

   Sales Marketing Engineering Materials/Logistics Quality Finance

9. Is this information easy to access? Yes No ________________________

Exhibit 1. OLAP Field Study Interview Guide (*continued*)

10. Are you currently satisfied with the level of information you get? Yes No ________________
    Why or Why Not? ____

11. Do you regularly access (more than 2x/week) a personal computer and the Internet? Yes No

12. Is your business networked through a server? Yes No ________________________

13. Is remote, web-based access important? Yes No ________________________

14. What critical success factors, indicators or metrics do you desire in order to gauge performance or substantiate decisions?
    ____
    ____
    ____

15. Are you familiar with any of the following terms? (Circle)

OLAP:	Yes	No	________________________
Data warehouse:	Yes	No	________________________
Data mining:	Yes	No	________________________
DSS:	Yes	No	________________________
Intelligent agent:	Yes	No	________________________
EIS:	Yes	No	________________________

    ____
    ____

    ** Review terms and concepts that respondent is not familiar with.

16. Do you see value in any of the aforementioned OLAP tools with regards to your ability to make decisions or to monitor business performance?
    Yes No
    Explain: ____
    ____
    ____
    ____

17. Can you think of any additional or related issues to discuss? Or, do you need clarification on any previous items?
    ____
    ____
    ____
    ____

Thank respondents for their time and participation.

4 Analysis

While the data gathering method was qualitative in nature, the interview guide was an effective instrument for a relatively systematic collection of data. Thoughtful elicitation from the users of a system is crucial to the development of useful information systems (Browne & Rogich, 2001).

First of all, very few of the subjects interviewed had any detailed knowledge of OLAP terms such as OLAP, data warehousing and data mining. Nonetheless, findings from the interviews revealed some very consistent attitudes towards OLAP as a means of more effective decision-making for small dynamic firms.

All eleven of the venture capitalists, regardless of their level of pre-VC industry training and experience, indicated a strong desire for sales and income related information. They felt that an enterprise's ability to drive sales growth was a primary success factor. Sales productivity could be reviewed by querying sales dollars and sales units per sales representative. This finding may be reflective of VCs' insistence on financial results and sales trends as indicators of commercial acceptance and proxies for future performance. The executives in the sample that possessed either sales/marketing responsibility or general management duties were keen on using sales figures as a critical benchmark. Ten of the thirteen executives interviewed had such responsibilities.

The five managers and two VCs that possessed extensive engineering and technical backgrounds were keenly interested in project-oriented measures such as development status and engineering milestones. Bearing in mind that this study's sample of executives was taken from the medical technology industry, feedback from the field regarding the success of early trials and product demonstrations was considered very important. For example, product development-oriented managers were more concerned with performing queries on a field representative's notes rather than sales performance measures.

As externally located stakeholders, most of the venture capitalists were more adamant about remote, web-based access to OLAP tools than their executive counterparts. This finding may be attributed to the remoteness of the VCs versus the "on-site" nature of company executives. It should be noted that the VCs in this study typically spend more of their time away from their office than the executives do. Furthermore, several of the executives that do spend significant time away from the home office (typically sales and marketing executives) were as desirous of remote DSS access as VCs.

The anticipated frequency of use for OLAP tools varied a great deal with the two groups. Senior managers wanted nearly daily, and in some cases up-to-the-minute sales numbers while venture capitalists desired less frequent (e.g., monthly) queries of firm metrics. This finding reflects the level of focus expected from the two different groups concerning an individual firm.

The majority of managers and venture capitalists wanted to utilize OLAP on their own, say from their desktops. Three VCs and three managers, who were considered the least computer-proficient of all respondents, preferred hard copy reports for review instead of interfacing directly from their computers. These same respondents were the least enthusiastic about being trained on new OLAP techniques, although in general both groups were eager to express their willingness to be trained on new techniques that enhanced their own knowledge. The VCs in particular wanted training and better data access because very few of them had in-house information technology (IT) support. Also, several of the executives communicated their disdain for "….having to wait for the IT guy to get the desired information." Bear in mind that these managers work in small companies where there is usually less than one full-time IT employee with limited expertise and resources. Incidentally, all 24 subjects in this study had personal computers and regularly accessed the Internet.

Data integrity, when explained by the interviewer, was nearly universally considered to be very important. Executives and VCs alike recounted instances of board meetings, where spreadsheet reports or financial statements did not match numbers on the board presentation. Respondents wanted to "be on the same song sheet" with regard to data. Most respondents desired a high degree of confidence that the data was uniform and correct. Seven of the eleven VCs expressed doubts about the accuracy of the numbers, especially forecasted numbers, coming from portfolio companies. This problem sometimes led to a rather awkward discussion on trust. This finding lead the researcher to posit that the use of validated

OLAP tools may actually enhance trust between the two groups (company executives and VCs) because there will be sharing of common databases and equality regarding information access.

Exhibit 2. Selected Raw Responses

Question	Venture Capitalists (n = 11)	Executives (n = 13)
What type of information do you typically use in decision making?	Sales (11) Marketing (7) Engineering (2) Materials (1) Quality (2) Finance (11)	Sales (12) Marketing (9) Engineering (5) Materials (5) Quality (6) Finance (12)
Is this information easy to access?	Yes (2) No (9)	Yes (5) No (6)
Are you currently satisfied with the level of information you get?	Yes (3) No (8)	Yes (5) No (8)
Do you regularly access (more than 2x/week) a personal computer and the Internet?	Yes (11) No (0)	Yes (13) No (0)
Is remote, web-based access important?	Yes (9) No (2)	Yes (7) No (5)
What critical success factors, indicators or metrics do you desire in order to gauge performance or substantiate decisions?	Sales; sales versus forecast (performance); sales per sales rep; accuracy of information; effectiveness of sales & marketing programs; competitive responses; pro forma financials; estimated time to profitability; ROI (return on investment); field trial performance and market acceptance criteria.	Level of customer acceptance; sales; sales versus plan; sales per account; reorder rate per account; product performance & efficacy; field intelligence on competitors; customer feedback; backorder status; release dates of new products (and performance in meeting stated objectives); development status; pre-market testing & prototype performance; cash flow; burn rate and overhead; schedules; accounts payable & receivable; bills of materials, process compliance; defect rates; cost targets and performance.
Are you familiar with any of the following terms?	OLAP: Yes (2) No (9) Data warehouse: Yes (3) No (8) Data mining: Yes (3) No (8) DSS: Yes (1) No (10) Intelligent agent: Yes (1) No (10) EIS: Yes (1) No (10)	OLAP: Yes (4) No (9) Data warehouse: Yes (4) No (9) Data mining: Yes (5) No (8) DSS: Yes (4) No (9) Intelligent agent: Yes (2) No (11) EIS: Yes (3) No (10)
Do you see value in any of the aforementioned OLAP tools with regards to your ability to make decisions or to monitor business performance?	Yes (8) No (3)	Yes (11) No (2)
Can you think of any additional or related issues to discuss? Or, do you need clarification on any previous items?	Sounds great but I do not want to be a slave to the process of all these queries; proper training is a must; could be a valuable tool for checking status of portfolio companies, but not sure how often I will actually utilize; need to avoid overkill and information overload; needs to be easy to use and not too time consuming; information needs to be accurate.	Tools must be user-friendly; have lots of graphs and an economy of presentation for usable data; data needs to be accurate and timely; trainings needs to be quick; follow-up support required; access should be password protected; precious little time available for training; frequency of use should be determined by individual users; I do not want to lose control of information – would prefer to present it myself, in person..

Lastly, nearly all respondents (when prompted) voiced the need to make OLAP tools user-friendly. Most liked the idea of menu-driven, graphical user interfaces for routine as well as ad hoc queries.

Simple user-interfaces and visual representations of output are essential elements of a computerized DSS (Lee & Ong, 1996).

While most subjects were optimistic about the use of OLAP tools, they felt training should be kept to a minimum. Many executives and VCs strongly stated that their time was limited, and that long training sessions would be unacceptable. Comments regarding training involving "…an hour or so here and there …" of a subject's time were fairly typical. OLAP tool designers and modelers should be conscious of this time constraint when approaching users.

A summary table of selected feedback from the respondents is provided above in Exhibit 2.

5 Conclusions

5.1 Discussion

Several important insights were culled from the interviews of venture capitalists and emerging company executives. Most striking was the need for more efficient access to useful information in the hope of using this information to make better decisions. Venture capitalists interviewed felt that making better decisions would result in lowering their investment risk and increasing returns. Several executives in the study strongly felt that improved decision making capability would lower business risks for their firms.

Additional contributions from the primary data gathered in the field study included the following:

- Terms and practices such as OLAP, DSS, data warehouse and data mining were not well known by the interviewees (all non-IT professionals).
- Probing of critical success factors revealed parochial leanings based on personal backgrounds and objectives. For example, a COO responsible for manufacturing was primarily concerned with data access regarding inventory, cost of goods, routings, bills of material, etc. A VC with a strong sales and marketing background was focused on data retrieval capability for sales performance, customer activity, sales by region, and measures of effectiveness for marketing programs.
- Remote/web-based access was more strongly desired by the VC participants (9 of 11 VCs, or 82%) than by the executive subjects (7 of 13, or 54%).
- Desired frequency of OLAP queries differed amongst the two study groups, with executives wanting to access company data much more frequently than VCs. This finding was expected given the difference in roles for executives and VCs.
- OLAP tool training and self-sufficiency were desired, although several respondents were quite vocal about "training time" being kept to a minimum.
- Data integrity and shared databases were viewed as important success factors.
- Lastly, user-friendly interfaces are a paramount concern.

5.2 Limitations of Study

The qualitative nature of this study, while positive with respect to its semi-structured approach, presents some limitations. The interpretations from thus study are difficult to generalize across a larger sample. The limited number of sample subjects in both the VC and the executive group provides no basis for empirical analysis. Responses from interview subjects are often subjective, and may be inaccurately recorded due to interviewer biases or perhaps transcription errors.

5.3 Implications for Research

Three steps are often used for determining of system requirements when developing an IS, including 1) information gathering with elicitation from users, 2) representation, whereby system requirements are modeled, and 3) verification that model is correctly representing requirements (Browne & Rogich, 2001). In drawing a parallel from information system (IS) design to organizational research, this paper only deals with the first phase noted above – information gathering and elicitation from users. The use of semi-structured interviews in this study mimics many aspects of designing an effective IS.

Additional research is required to better understand and exploit the value of user input. Future studies should be undertaken that explores the effectiveness of system modeling and design. Empirical analysis on outcomes of such processes of IS design in this domain will be beneficial to practitioners and researchers alike. Lastly, further investigation into the use of OLAP and DSS as a mediator of trust is warranted.

6 References

Achor, T. (2002). Using online analytical processing tools. *CPA Journal, 72*:64.

Babbie, E. (1998*). The practice of social research*. (eight edition). Belmont, CA: Wadsworth.

Baker, S. & Baker, K. (1999). The best little warehouse in business. *The Journal of Business Strategy, 20*: 32-37.

Bose, R. & Sugumaran, V. (1999). Application of intelligent agent technology for managerial data analysis and mining. *Database for Advances in Information* Systems, 30: 77-94.

Browne, J. & Rogich, M. (2001). An empirical investigation of user requirements elicitation: Comparing the effectiveness of prompting techniques. *Journal of* Management Information Systems, 17: 223-249.

Chopoorian, J., Witherell, R., Khalil, O. & Ahmed, M. (2001). Mind you business by mining your data. S.A.M. Advanced Management Journal, 66: 45-51.

Chung, H. & Gray, P. (1999). Special section: Data mining. *Journal of Management Information Systems, 16*: 11.

Davenport, T., Harris, J., DeLong, D., & Jacobson, A. (2001). Data to knowledge to results: Building an analytic capability. *California Management Review, 43*:117-138.

Eisenhardt, K. (1989). Agency theory: Assessment and review. *Academy of Management Review, 14*:57-74.

Hasan, H., Hyland, P., Dodds, D. & Veeraraghavan, R. (2000). Approaches to the development of multi-dimensional databases: Lessons from four case studies. *Database for Advances in Information Systems, 31*: 10-23.

Khatri, N. & Ng, A (2000). The role of intuition in strategic decision making. *Human Relations, 53*: 57-86.

Lee, H. & Ong, H. (1996). Visualization Support for data-mining. *IEEE Intelligent Systems and their Applications, 11*:69-75.

Markman, G., Balkin, D. & Schjoedt, L. (2001). Governing the innovation process in entrepreneurial firms. *Journal of High Technology Management Research, 12*:273-293.

Mintzberg, H., Raisinghani, D. & Theoret, A. (1976). The structure of 'unstructured' decision processes. *Administrative Science Quarterly, 21*: 246-275.

Prietula, M. & Simon, H. (1989). The experts in your midst. *Harvard Business Review, 67*(1):120-124.

Rubin, H. & Rubin, R. (1995). *Qualitative Interviewing: The Art of Hearing Data*. Thousand Oaks, CA: Sage.

Sen, A. & Sinha, A. (2005). A comparison of data warehousing methodologies. *Communications of the ACM, 48*: 79-84.

Spencer, T. & Loukas, T. (1999). From star to snowflake to ERD. *Enterprise Systems Journal, 14*: 62-67.

Turban, E. & Aronson, J. (2001). *Decision Support Systems and Intelligent Systems*, *6th Ed*., Prentice Hall; Upper Saddle River, NJ.

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