Detecting Weak Signals by Internet-Based Environmental Scanning

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Firms in highly dynamic environments focusing on innovation in their products and services, often encounter elevated amounts of uncertainty regarding the future direction of technological change. Finding reliable and imbedded information enhances a firm's ability to tackle new markets and take advantage of possible hidden opportunities. To reduce uncertainty, obtain hidden knowledge, and gain competitive advantage, environmental scanning, which is one of the main components of foresight, is recommended by scholars of strategic management. The process of detecting weak signals for shedding light what one authority calls "blurry future zones" (Day & Schoemaker, 2005, p.1) has currently been receiving attention in environmental scanning studies. Some studies emphasize the importance of the subject; yet they offer few practical methodologies for actual cases. To help address this gap, this research introduces a new approach for detecting weak signals during Internet-based environmental scanning by applying the Cluto toolkit (see Section 4.7) plus using human judgment. This novel methodology is applied to the application of Micro Tiles, a recent innovative product of a digital display company located in Ontario, Canada, Christie Digital Company.

In the conduct of this exploratory research, about 40,000 HTML pages were retrieved from the Internet in a search during 2009. To extract weak signals information from the retrieved unstructured texts, documents were grouped into a number of clusters by the CLUTO software. Two subject matter experts compared and evaluated the cluster results for the purpose of finding potentially relevant information in regard to the company's strategic intent. Analyzing the clusters, the experts reduced the number of clustered documents from the original corpus into smaller sets with the goal of finding more relevant and unexpected documents (weak signals). The relevancy and expectedness of information in documents were two measurements as related to weak signals. The trends of the study indicate that as anticipated both experts found more unexpected documents in the smaller sets rather than the larger ones. Moreover, regarding one expert's analysis, the smaller sets contain documents that are more relevant to the domain of interest. Overall, according to one expert, documents existing in the smaller sets display more weak signals.

This emerging methodology offers a practical procedure to apply web-based information in the development of a company's environmental scanning procedures. Using this methodology, managers can employ both computer tools and human sense-making methods to detect potential weak signals and reduce certain biases in the detection process.

Keywords: environmental scanning, foresight, weak signals, document clustering, CLUTO

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Dedication

This thesis is dedicated to my father, who supported me in all aspects of my life, and to my mother, for her motivation and encouragement.

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Chapter 1
Introduction

Firms in highly dynamic environments focusing on innovation in their products and services often encounter problems relating to rapid change and increasing discontinuities. There have been various historical examples in which firms could not "sense and respond" (Haeckel, 2004, p.1) to future changes, and therefore lost significant revenue. As Day and Schomakher (2005) discussed, between 2001 and 2004, Mattel lost 20 percent of its worldwide share because of failing to recognize the rapid maturing of preteen girls and their preference for dolls that look like their older siblings and ideal pop stars rather than three-to-five-year-old children.

Due to environmental uncertainty, managers frequently have difficulties shaping companies' strategies, and are thus unable to deal with strategic surprises (Schwarz, 2005). The major responsibilities of today's managers are to make decisions and to formulate and implement strategies (Schwarz, 2009). In the domain of strategic management, a key effective strategic formulation and means of comprehending future changes is to conduct environmental scanning (Abebe, Angriawan, & Tran, 2010). The concept of environmental scanning was first introduced by Aguilar in 1966 "as the acquisition and use of information about events, trends, and relationships in an organization's external environment, the knowledge of which assisted management in planning the organization's future course of action" (Aguilar, 1967; Choo & Auster, 1993; Choo, 2001, p.1). Various scholars have studied the effects of environmental scanning on the performance of firms. Decker, Wagner, and Scholz (2005) stated that, there is a strong relationship between environmental scanning and business success. Environmental scanning has also been linked to improvement in organizational performance (Choo, 1993).

One of the important fundamentals of conducting environmental scanning is detecting weak signals of change. The weak signal concept was introduced by Igor Ansoff in 1975 to overcome the problems of long-range planning. Weak signals are defined as "warnings (external or internal), events and developments, which are still too incomplete to permit an accurate estimation of their impacts and/or to determine their full-fledged responses" (Ansoff, 1982, p. 12). Detecting weak signals enables firms to respond rapidly to environmental changes. By probing weak signals, firms are able to be vigilant in avoiding possible surprises, and may be heedful of any signs of change, future threats, and opportunities. An organization must scan the environment frequently to identify any signals of

change and carry out planning and actions in response to that change as early as possible (Ansoff, 1984, 1975). Weak signals detection will find future problem areas and opportunities. Nonetheless, four questions still remain: How can firms detect early warning signs of coming changes? How can they convert environmental threats into opportunities? Is there a support tool that can help managers detect blind spots? Is there a way to find appropriate information for improved decision-making?

In a survey of high-tech French companies, Blanco and Lesca1 (1997) found that weak signals detection was a major problem encountered by managers, and concluded that the use of support tools would be helpful. Schwarz (2005) studied why implementation of weak signals in German corporations failed, and discovered that the problems related to a:

> Lack of participation of potential future users in the implementation phase, a lack of joint understanding of the nature of trends, differing and unrevealed requirements of trends by various interested parties, a broad misconception of the weak signals concept and trends, an excessively heavy reliance on alleged hard data, a lack of interaction among users, and finally a missing link to the strategic functions in an organization. (p. 22)

In strategic management literature, certain researchers have proposed practical methods for detecting weak signals. Decker et al. (2005) performed a study to detect weak signals by conducting an environmental scanning on the Internet, but his approach was limited to only 50 documents. Similarly, Uskali (2005) tried to find weak signals in the financial news of one Finish daily newspaper. Although Uskali argued that there were weak signals in the journalistic texts, he was unable to propose a systematic approach for future research.

The role of the Internet in weak signals detection is significant. The World Wide Web is considered a useful tool for detecting weak signals in environmental scanning processes (Decker et al., 2005). External environmental information such as customer market, business, research institute, journal article, politic, and technology is shown on the web, before its effects are observed in the real world. Although the World Wide Web is a considerable source of information, observing significant amounts of data on the Internet consumes much time and effort, which ultimately cannot be accomplished by an ordinary person (Decker et al., 2005). As a result, the purpose of this research is to propose a model for detecting weak signals of change during Internet-based environmental scanning. The specific aim is to find public web pages containing weak signals related to the topic of interest. This research sought information related to the potential applications of Micro Tiles for

digital media in theatre production. Micro Tiles is a recent innovative product of the Christie Digital Company (see Appendix A). About 40,000 web pages related to the application of Micro Tiles were retrieved from the Internet in 2009 for the purpose of finding weak signals in the corpus. The relevancy and expectedness of documents were two measurements applied for defining weak signals; that is, the more relevant and unexpected the document, the more it tended to be a weak signal. To narrow the amount of retrieved information (from 40,000 webpages), methodological document reduction was performed with both computer (CLUTO) and human judgment. CLUTO is a software package applied for clustering huge numbers of documents. Two subject matter experts compared and evaluated the cluster results for the purpose of finding any possible weak signals in regard to the company's strategic intent. Applying this method, the number of documents was reduced in three iterations--from 38,030 to 12,789 to 7,718 and finally to 1,510 documents. To test the following propositions, 40 sample web pages from the 38,030 text corpus (the large sample), 40 sample web pages from the 7,718 text corpus (the medium sample), and 40 sample web pages from the 1,510 text corpus (the small sample) were chosen randomly. These arbitrary samples were then shown to the two experts who have specialized knowledge of Christie Micro Tiles and digital media for theater production. The experts were asked to judge each web page in terms of relevancy and expectedness. The experts (1 and 2) evaluated the documents independently, without any communication during the procedure. Subsequently, the following propositions were expressed:

> P1: After data reduction with CLUTO, human judgment can determine whether a randomly drawn sample of documents comes from small, medium or large datasets.
>
> P2: There is a relationship between data reduction and the perceived relevancy of the documents (the smaller the dataset, the higher is the relevancy of the documents in the dataset).
>
> P3: There is a relationship between data reduction and the perceived expectedness of the documents (the smaller the dataset, the higher is the unexpectedness of the documents in the dataset).
>
> P4: The ratio of relevant to irrelevant documents in the small dataset is greater than that in the medium one.
>
> P5: The ratio of relevant to irrelevant documents in the medium dataset is greater than that in the large one.

P6: The ratio of unexpected to expected documents in the small dataset is greater than that in the medium one.

P7: The ratio of unexpected to expected documents in the medium dataset is greater than that in the large one.

After the evaluation by the judges, results indicated the following: according to Expert 2, the distribution of relevant documents was not the same across the three databases. For the small dataset the distribution of relevant documents was greater than that for the medium one, and for the medium dataset, the distribution was greater than that for the large one, which supported the propositions. According to Expert 1, the distribution of relevant documents was the same across the three databases, which did not support the propositions. According to both experts, the distribution of unexpected documents was not the same across the different databases. For the small dataset the distribution of unexpected documents was greater than that for the medium one and for the medium dataset, it was greater than that for the large one, which again supported the propositions.

Although this exploratory study is limited to the involvement of just two experts and one dataset, these trends suggest that the proposed model could be applied for detecting weak signals of change in organizations. This research indicates that the proposed model reduced the documents to the subset that contained more unexpected information, and implies that environmental scanning on the Internet can be a useful tool for detecting weak signals of future changes and should be adopted by firms that depend on their innovative capability.

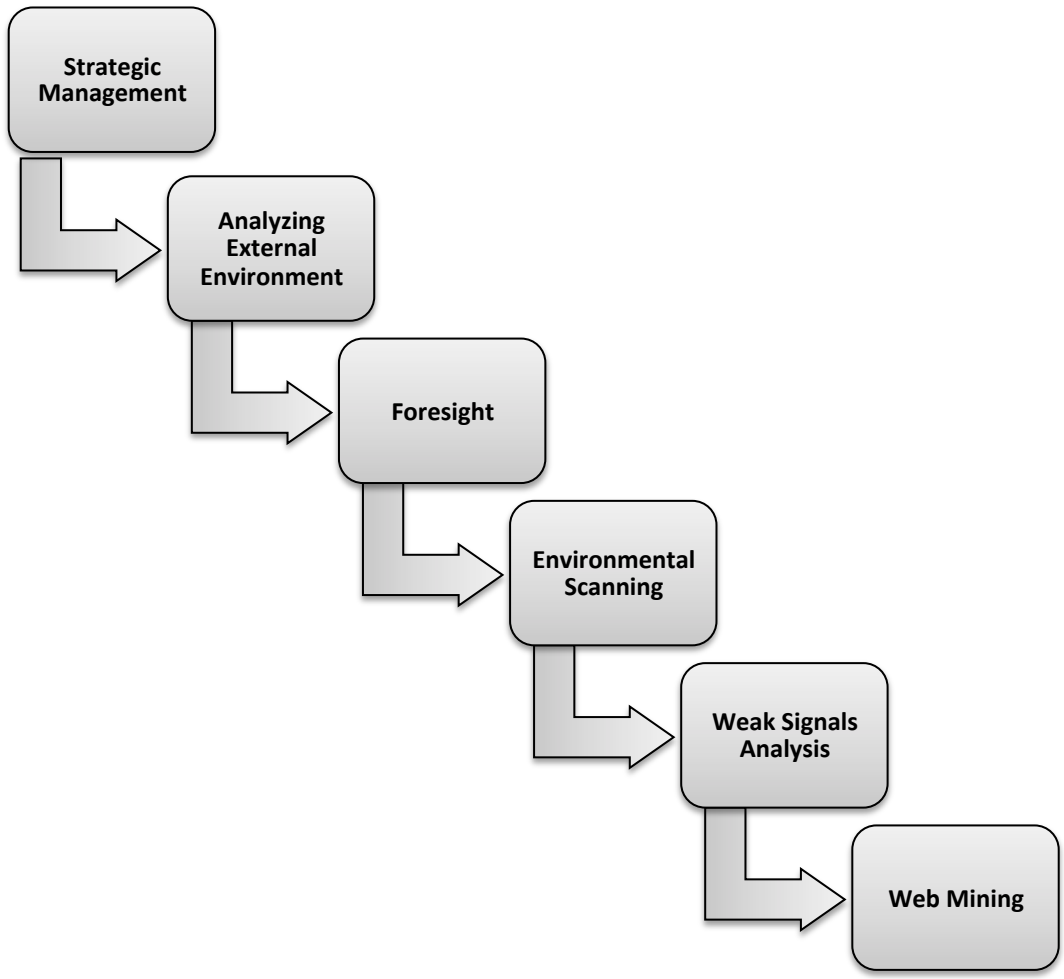
The rest of the paper is organized as follows. Chapter 2 describes the academic literature related to strategic management, foresight, environmental scanning, weak signals, document clustering, and web mining. In Chapter 3, a hypothetical model is constructed to test the feasibility of detecting weak signals in large document corpus. Experimental procedures of a case study then were tested in Chapter 4. In Chapter 5, the results of the analysis were presented. Finally, Chapter 6 summaries the key trends and offers some suggestions for future research.

Chapter 2

Literature Review

The research question examined in the thesis is to better understand a business problem that can be solved by computer science tools. The literature review consists of two parts. The first part deals with the necessity of detecting weak signals toward "corporate foresight" (Rohrbeck, 2011, p.1), with the ultimate goal of enhancing the strategic perspective of the firm, while the second part introduces the main document-clustering algorithms. This chapter describes academic literature within the following areas: strategic management, foresight, environmental scanning, weak signals analysis, and web mining (Figure 1).

Figure 1: Literature Review Framework



2.1 Strategic Management

Strategic management is a relatively new field of study and suffers from a lack of consensus in terms of an exact definition. The concept originated for the most part in the middle of the 1960s and early 1970s from various managerial perspectives (Pettigrew, Thomas, & Whittington, 2002). Alfred Chandler realized the importance of looking at long-term perspectives in future studies and emphasized the combination of different management areas (Chandler, 1962). Philip Selznick suggested combining organizational internal factors with external ones and introduced SWOT analysis to find strengths, weaknesses, opportunities, and threats to organizations (Selznick, 1957). Igor Ansoff revolutionized the strategic management concept by defining the concept of "weak signals" for the early detection of changes in the environment, and emphasized the use of continuous scanning to have real time strategic vision (Ansoff, 1975). Ansoff introduced the concept of "strategic issue management" as a way of responding to highly turbulent environments and summarized the evolutionary phases of five modern management systems with their purposes, strengths and limiations (Table 1). While debate still exists regarding a precise definition of strategic management, the stance adopted in this paper mirrors that of Igor Ansoff as well as the following implicit consensual definition by Nag, Hambrick, and Chen: "The field of strategic management deals with the major intended and emergent initiatives taken by general managers on behalf of owners, involving utilization of resources, to enhance the performance of firms in their external environment" (Nag et al., 2007, p. 944).

2.2 Technology Foresight

In order to have a better strategic view of the firm and to survive in an increasingly competitive environment, foresight processes have been widely recommended by most strategic management scholars (Voros, 2003; Rohrbeck, 2011). Horton stated that "foresight is the process of developing a range of views of possible ways in which the future could develop, and understanding these ways sufficiently well to be able to decide what decisions can be taken today to create the best possible tomorrow" (Horton, 1999, p. 1).

As Cuhls (2003) mentioned, the terms *foresight* and *forecast* have been used interchangeably in most studies, even though there are remarkable differences between the two concepts.

In forecasting, only one possible option for the future is defined, as if there is only one present and thus only one future. Today, the study of the future not only tries to predict the future, but also takes an active role in shaping the future. Instead of having only one possible option for the future, in foresight studies, different potential futures are assessed.

Table 1: Evolution of the Strategic Management System

	Control	**Long-range planning**	**Strategic planning**	**Strategic management**	**Strategic issue management**	**Surprise management**
Purpose	Control deviation and manage complexity	Anticipate growth and manage complexity	Change strategic thrusts	Change strategic thrusts and change strategic capability	Prevent strategic surprises and respond to threats/opportunities	Minimize surprise damage
Basic assumption	The past repeats itself	Past trends continue into the future	New trends and discontinuities	Expect resistance New thrusts demand, new capabilities	Discontinuities are faster than response	Strategic surprises will occur
Limiting assumption	Change is slower than the response	The future will be like the past	Past strengths apply to future thrusts and strategic change is welcome	The future is predictable	Future trends are acceptable	Future trends are acceptable
	← Periodic →				← Real time →	

Note. Adopted from Ansoff (1980, p. 13)

Typically, one option is selected, and the meaning of that option is interpreted for the current situation. In this case, the organization could define how to change current strategies in order to reach that option. Therefore, foresight is a flexible procedure with more open research questions being shaped during the planning process. It is highly dependent on the opinions of experts and is generally

more qualitative than quantitative (Cuhls, 2003). The major differences between foresight and forecasting are outlined in Table 2.

Table 2: Summary of Differences Between Forecasting and Foresight

Foresight	Forecast
Basic points, needs, and research questions are still open and looked for as part of the foresight process	Basic points, topics and research questions must be clarified in advance
More qualitative than quantitative	More quantitative than qualitative
Looks for 'information' about the future and for networking, makes use of the distributed intelligence	Questions regarding what the future in the selected area might look like
Brings people together for discussions about the future and for networking, and makes use of the distributed intelligence	More result-oriented, can also be performed by individual people or in single studies (depends on methodology)
Criteria for assessments and preparation for decisions	Not necessarily assessments, different options and choices or the preparation for decisions
Communication about the future as an objective	Describes future options; results more important than the communication aspects
Long-, medium- and short-term orientation with implications for today	The major points are long-, medium- and short-term orientation as well as the path into the future
Finds out if there is consensus on themes	No information about consensus necessary
Experts and other participants, very dependent on opinions	Mainly 'experts' and/or strict methodologies, less dependent on opinions

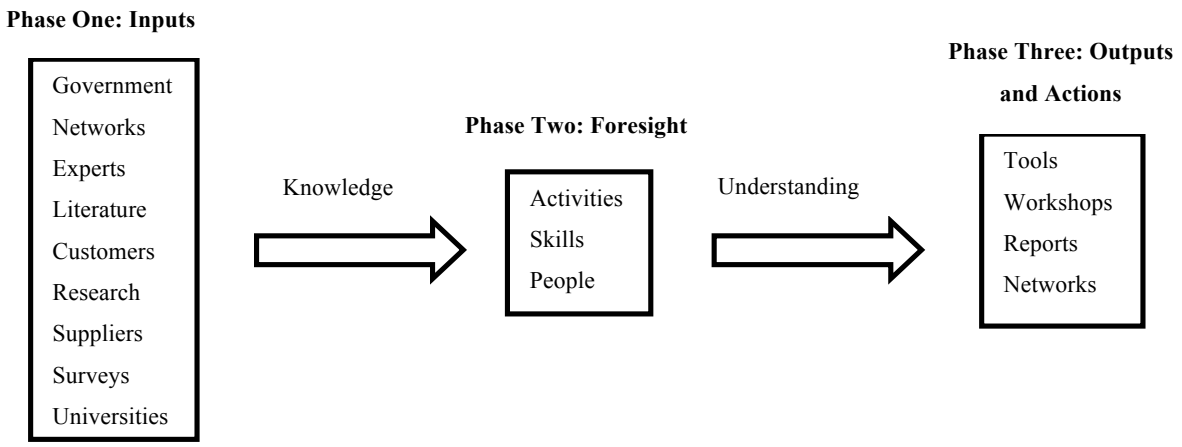
Note. Adopted from Cuhls (2003)

Horton (1999) defined three phases in the foresight process: inputs, foresight, and outputs or actions. The first phase consists of collecting information from sources such as experts, publications, reports, personal, or business networks. To gather information, Horton (1999) suggested various methods, including environmental scanning, the Delphi method, and informal conversations. The second phase consists of two categories: translation and interpretation. Translation involves converting information summarized in phase one into the format that is comprehensible by the organization. In this phase, the jargon and irrelevant information should be eliminated and the

essentials should be presented in the organization's language. Interpretation is the crucial realm of the foresight process and basically answers the question of "so what?" and recognizes what all the information means for the organization. Interpretation consists of evaluating the retrieved knowledge and testing various possible futures in the context of the organization. Using a third party in the interpretation process is essential for identifying ambiguities, creative thinking, and posing questions challenge managers perception. The third phase conveys the generated results in an appropriate format to managers who have the authority to take actions in the organizations. The typical formats are reports, seminars, informal networks, or roadmaps (Voros, 2003). A more detailed framework of the foresight process is shown in Figure 2.

This research has been conducted with the aim of gaining technological foresight for strategic management within the specified company. To reach this goal, environmental scanning procedures, which are the main methods of providing input for the foresight process, have been applied. In the next chapter, these environmental scanning procedures are briefly discussed.

Figure 2: A Successful Foresight Process



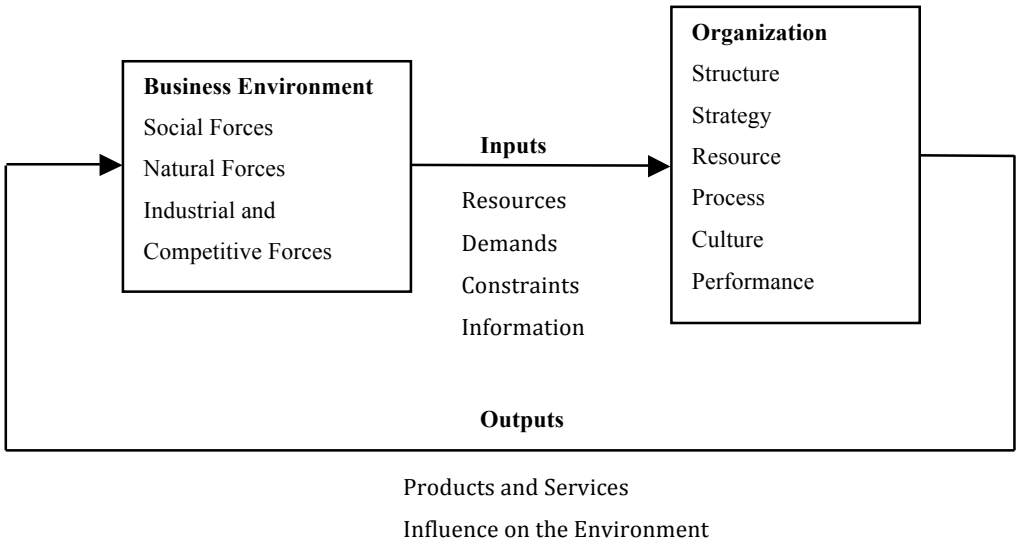
Note. Adopted from Horton (1999)

2.3 Environmental Scanning

As mentioned in Section 2.2, performing environmental scanning provides input for foresight processes. In this section, the relation between organization and environment is defined. The definition and modes of environmental scanning are then explained.

Many scholars have been trying to understand the relation between organizations and the environment. Kahalas (1977) was a pioneer in connecting system theory with organizational theory. Subsequently, many scholars have viewed organizations as open systems that continuously exchange inputs and outputs with the environment (Kahalas, 1977; Choo, 1995). To better understand the relationship between organizations and the environment, Liu (1998) refered to Porter's view of an organization and presented clearly the interaction between the organization and the environment, as shown in Figure 3 (Porter, 1985, 1991).

Figure 3: The Relation Between an Organization and Business Environment



Note. Adopted from Liu (1998)

As defined in Figure 3, the environment provides the input for the organization, including resources, labor, capital, raw material, and energy. The environment also defines the potential market, imposes constraints, and provides information for the strategy processes of the organization. This environmental information is the main consideration of this study. Simultaneously, the organization also affects the environment by producing scarce products and giving services. In the open system view of the organization, the environment affects and is affected by the organization in a "continuous interactive process" (Liu, 1998, p. 296). This environmental information is the key element of the environmental scanning process, and the basic concept of this research. The environmental scanning concept was first introduced by Aguilar (1967) and is now understood to be "the acquisition and use of information about events, trends, and relationships in an organization's external environment. The knowledge of this assists management in planning the organization's future course of action (Aguilar,

1967; Choo & Auster, 1993; Choo, 2001, p. 1)**.** This process of gathering and analyzing information from a company's external environment includes social, regulatory, technological, political, economic, and industrial areas.

Organizations scan the environment in order to reduce "chances of being blind-sided in the marketplace, avoid possible surprises, identify threats and opportunities, gain competitive advantage, and improve long- and short- term planning" **(**Albright, 2004, p. 40; Choo, 2001, p. 1).

In the last couple of decades, scholars have studied the effects of environmental scanning on organizational strategy and performance. Choo and Auster (1993) and Daft, Sourmunen, and Parkes (1988) found that managers who perceive greater environmental uncertainty tend to do more scanning. Based on evidences from literature, Choo (2001) concluded that environmental scanning is linked to improved organizational performance. In a recent survey of 84 Southern Nigerian companies, Olamadea, Oyebisib, Egbetokuna, and Adebowa (2011) found that the basic objectives of environmental scanning for 94 percent of organizations were to reduce uncertainty, test the appropriateness of actions already taken, and update existing knowledge. Monitoring and analyzing the environment helps the firm to find technological and market opportunities and therefore can increase the ability of firms to enter new domains (Daft et al., 1988). Danneels (2008) discovered that environmental scanning positively influences the ability of a firm to build new competencies by building the basis for managing discontinuous change. Zahra and George (2002) stated that "absorptive capacity is the ability of the firm to recognize the value of, acquire, assimilate, and apply knowledge from external sources" (p. 186). This capacity can be increased by environmental scanning processes (Cohen & Levinthal, 1989). Environmental scanning brings information from various sources into the firm, which increases the knowledge of the firm and helps employees to find new opportunities (Damanpour, 1991). However, scanning not only enhances the organizational performance, but also increases the level of communication among employees. Consequently, according to Choo (2001), scanning has impact on four areas of the organizations: communication of shared vision, strategic planning, management, and future orientations.

2.3.1 The Modes of Environmental Scanning

Organizations gather information about their environment by various channels, including personal relationships with colleagues and knowledge experts, trade and professional literature, and by participating in professional and trade activities (Danneels, 2008).

Daft and Weick (1984) stated that depending on managers' beliefs, organizations interpret the environment in two diverse ways: first is the analyzability of the external environment, and second is "the extent to which an organization intrudes into the environment to understand it" (Daft & Weick, 1984, p 288). Since organizations may vary in their beliefs toward analyzability and the degree of intrusiveness into the environment, four patterns of environmental scanning have been defined: undirected viewing, conditioned viewing, enacting and searching (Daft & Weick, 1984; Augilar, 1967).

Undirected viewing is the form of scanning by which companies perceive the environment as un-analyzable and therefore seek information without any specific purpose. This kind of scanning is casual, with managers finding information through their personal contacts and sometimes by chance. Another form of scanning is conditioned viewing, by which organizations perceive the environment as analyzable but are unable to perform active searching; in this kind of scanning organizations rely on their initial documentation, reports, and publications that have grown over time, and because in some periods they found that this information was useful to them, they now are conditioned to use it. Enacting is the form of scanning by which an organization perceives the environment to be un-analyzable, yet intrudes into the environment to affect it. In this form of scanning, organizations experiment and test the environment and modify their traditional beliefs about the environment. In this mode, organizations want to create the potential market instead of finding the market demands. The final form of scanning is discovering which takes place when the organization perceives the environment to be analyzable and actively tries to collect information from the environment. In this form of scanning, managers purposefully seek information about a specific issue (Daft & Weick, 1984; Aguilar, 1967).

This thesis considers the last two forms of scanning (enacting and discovering) to be the target forms of scanning.

2.3.2 Types of Environmental Scanning

There are various means of scanning the environment. The use of a specific information source by managers is often related to its accessibility (Choo, 1993). Managers perform environmental scanning via face-to-face interaction and telephone communication. They may also perform impersonal environmental scanning by reading newspapers, magazines, company reports, television broadcasts and online databases. Research has found that executives' external networks and

personal contacts are the main sources for obtaining information (Aguilar, 1967; Daft et al.,1988). However, these forms of scanning are less than systematic and may lead managers to make wrong decisions. Nowadays, using the Internet to acquire information from companies' environments has become dominant.

2.3.3 Internet as an Environmental Scanning Tool

The Internet continues to be an exciting information source for many companies. The acquisition of vast amounts of information available on the Internet has grown dramatically. By using the Internet for environmental scanning, organizations can get diverse information free of charge. Studies have assessed the impact of using Internet sources on varying organizational aspects. Teo and Choo (2001) found that the Internet has a positive impact on the quality of competitive intelligence information and ultimately on organizational strategic benefits. Perry, Taylor, and Doerfel (2003) examined how organizations integrate the Internet in crisis situations and found that it can help organizations with conducting better environmental scans and finds much more useful information than they obtain from traditional sources, thus aiding in preparation for possible crises. Alallak (2010) described the Internet as a useful marketing tool, one which helps organizations to collect information from customers for better and faster customer value. Although the market environment has strategic importance for organizations, environmental scans on the Internet should not be restricted to the market environment (Tan, Teo, Tan, & Wei, 1998; Decker, Wagner, & Scholz, 2005). For example, organizations should scan their customers and their competitors in order to understand what their customers want and what their competitors offer.

Decker et al. (2005) noted that trends in political, social, technological, and other trends are on the Internet before their consequences become clear to the public. However, managers typically avoid performing systematic environmental scans because, in their opinion, the process might be too complex or the organization might encounter information overload. Nevertheless, it is argued that using the Internet in overall business strategies and competitive markets, companies may increase revenues, reduce their costs, and promote managerial effectiveness (Teo & Choo, 2001). Therefore, organizations that frequently carry out environmental scanning on the Internet are likely to be better at responding to environmental changes (Tan et al., 1998).

The aforementioned reasons found in the literature were the main incentives to conduct an Internet-based environmental scanning procedure.

2.4 Weak Signals

Ansoff (1975) introduced a concept called weak signals for preventing long-range-planning or strategic-planning problems (Kuosa, 2010; Ilmola & Kuusi, 2006). Ansoff (1982) defined weak signals as "warnings (external or internal), events and developments, which are still too incomplete to permit an accurate estimation of their impact and/or to determine their full-fledged responses" (p. 12). According to Ansoff (1975), for a firm to be able to respond rapidly to uncertain environment, it should be prepared ahead of time to respond to any signs of information about possible threats and opportunities; if the firm waits until the information becomes adequate enough for all to respond, it may encounter the crisis. On the other hand, if it accepts vague information, the information may not be complete enough to support strategic planning. To overcome this problem, the organization must scan the environment frequently to identify any signal of change and make feasible plans and actions as early as possible (Ansoff, 1984; 1975).

Ansoff (1975) categorized information into two groups: strong signals and weak signals. Weak signals can become clearer and strengthen over time to become strong signals or they might vanish. Ansoff (1984) introduced three filter mechansims that organizations may apply to make sense of weak signals. According to Rossel (2009), organizations may transform the flow of perceived signals into knowledge by using the following filters:

1) An observation filter (or surveillance filter) defines the area for observing and collecting data and includes methods of information acquisition.

2) A cognitive filter (also called a mentality filter) defines the area for evaluating the information that is passed from the first stage and is relevant to the firm.

3) A power filter is applied when the managers, players, or decision makers of the organization come together to determine and analyze information that is passed from the last two stages.

In other words, the filters outline three steps in detecting weak signals. These steps include the selection of the data, the sources of information, the domain in which weak signals should be defined, and in the interpretation phase, how managers or experts should make sense of the signals.

Although Ansoff's weak signals theory has contributed to the development of the strategic management field, other researchers have also focused on this issue in recent decades. Ilmola and

Kuusi mentioned that the "weak signals approach is experiencing a renaissance in strategic planning" (Ilmola & Kuusi, 2006, p. 908). Still, there are major problems related to the description, interpretation, and detection of weak signals. No specific procedure, definition, and practical example related to this concept exists in the literature (Hiltunen, 2008). Uskali (2005) offered different definitions of weak signals in the literature such as "a sign, which is slight in present dimensions but huge in terms of its virtual consequence", and "a factor for change hardly perceptible at present, but which will constitute a strong trend in the future" (p. 4). Hiltunen (2008) also provided other names for weak signals, including wild cards, seeds of change, emerging issues, and early indicators.

Although the role of weak signals has been emphasized in futures studies, their detection does not guarantee success. Use of weak signals depends mainly on the observer's mindset and hence is more subjective than objective; therefore, weak signals will not exist without a receiver's attention (Hiltunen, 2008). Decker et al. (2005) stated that "a challenge in weak signals detection results from the fact that the originators of fragmented information are probably outsiders to the organization in question, and even to the industry under consideration" (p. 191). Moreover, the receivers, managers in organizations, are biased and they tend to observe strong signals rather than weak ones (Decker et al., 2005; Blanco & Lesca, 1997; Hiltunen, 2008).

In a survey of high-tech French companies, Blanco and Lesca1 (1997) found that weak signals detection was a major problem encountered by managers and that the use of a support tool would be helpful. Moreover, although weak signals may be recognized in organizations, managers may not act on such signals because they do not wish to cope with potential consequences; therefore, they may be more ready to disregard the information (Blanco & Lescal, 1997).

2.4.1 The Importance of Weak Signals Detection

According to Reger, the following are the main reasons for paying attention to early indication of future changes in technological developments/trends:

"1-Increasing speed of innovation and product life cycles

2-Globalization of markets and technology

3-Growing R&D expenditures to come to a new product or process and the risk of misdirected spending

4- Diffusion of new technologies developed in certain branches into other ones and the fusion of different technologies" (Reger, 2001, p. 533).

2.4.2 Role of the Internet in Weak Signals Detection

Day and Schoemaker (2005) have suggested that firms monitor blogs, chatrooms and websites when collecting information from customers and complainers and, in this way, develop better peripherial vision. Managers should also pay attention to employees' suggestions, lost-sales reports, and postmorterms on contracts won by competitors to find useful information. The World Wide Web is considered to be a valuable tool for detecting weak signals in environmental scanning processes (Decker et al., 2005). Information about the external environment including, customers markets, businesses, research institutes, journal articles, politics, and technology is available on the web long before its effects are observed in the real world. However, the huge amount of information on the public web is hazy and noisy, and it consumes time to find the right information through regular search engines such as Google or AltaVista (Decker et al., 2005).

Therefore, in this research, environmental scanning of the public web was considered to be the main method for detecting weak signals. To analyze the information on the web, web mining, text mining and document clustering techniques were applied; the following sections of the literature review include a general clarification of web mining and knowledge discovery methods from the web.

2.5 Web Mining and Web Information

With the huge amount of information available online, the World Wide Web is one of the largest sources from which organizations can gain useful information from customers, competitors, and the external business environment, and from which to gain perspective for business decision-making (Purandre, 2008). The fact that the web is popular, dynamic, huge, and convenient causes the problem of information overload, which makes it difficult to find relevant information and to create new knowledge out of the available information (Kosala & Blockeel, 2000; Kobayashi & Takeda, 2000). To find relevant information, a user can put the particular query into the desired search engines, and the query response is a list of web pages that are similar to the user's topic. However, the retrieved results often have two key problems: low precision and low recall. Precision refers to the portion of retrieved documents that are relevant. Recall refers to the portion of relevant documents that are retrieved. Low precision is the user's inability to find the relevant information from the retrieved documents and low recall is the user's inability to retrieve all the relevant documents.

Fortunately, web mining techniques can be used to help solve the above problems (Kosala & Blockeel, 2000).

2.5.1 Web Mining

Web mining is the "use of data mining techniques to automatically discover and extract information from Web documents services" (Kosala & Blockeel, 2000, p. 2). It overlaps heavily with information retrieval, machine learning, statistics, pattern recognition, and data mining (Chakrabarti, 2003).

2.5.2 Types of Web Mining

It has been shown that web mining can be divided into three types (Purandre, 2008):

- Web Usage Mining

  This is the process of understanding usage history on the Internet such as how many times the link has been observed, which web pages users have seen or what people have done after leaving a particular pages.

- Web Structure Mining

  To understand the similarity between sites, web structure mining is used to analyze the nodes and connections among websites and discover and make patterns from the structure of the webpages based on the hyperlinks within them.

- Web Content Mining

  This is the process of finding useful information from unstructured text files, audio files, images, videos and hyperlinks on the web. Web text mining is one of the most popular research areas of web content mining and overlaps with information retrieval. This research addresses web text mining.

2.5.3 Web Text Mining

Text mining, a relatively new research area, is a particular form of data mining (Zanasi, 2002). It is the process of extracting information from large collections of unstructured text documents. More than 80 percent of information is stored in text; therefore, text-mining techniques are extremely beneficial for business purposes (Gupta & Lehal, 2009). With an enormous amount of

information available on the web, text mining is growing rapidly and has been given wide attention. Web text mining includes mining, extraction, and integration of useful data, information, and knowledge from web page contents (Castellano, Mastronardi, & Tarricone, 2007). Although text mining and data mining have differences, their basics are similar. In the following sections the definition of data mining is first addressed. Following this, the differences between data mining and text mining are described.

2.5.4 Definition of Data Mining

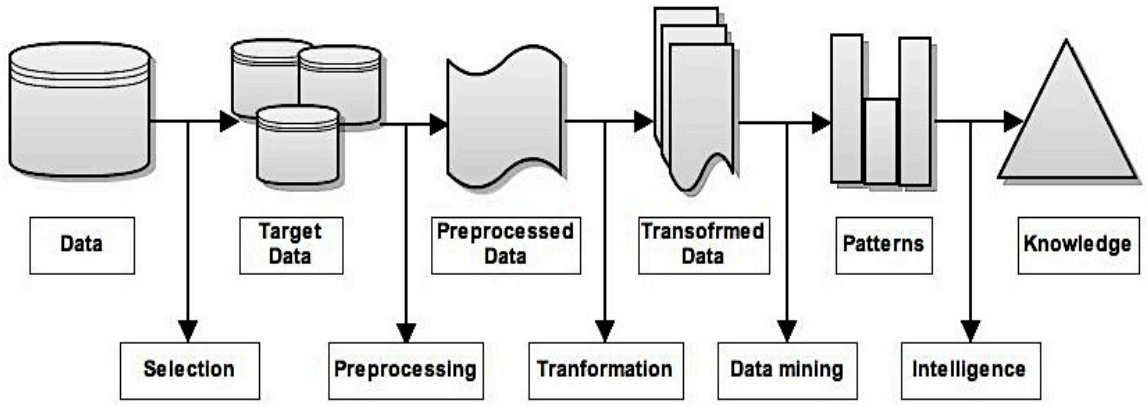
Fayyad, Piatetsky-Shapiro, and Smyth (1996) defined Knowledge Discovery in Databases (KDD) as the "nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data" (p. 2). From their point of view, KDD is the overall process of discovering useful information from data, while "data mining is a step in the KDD process that consists of applying data analysis and discovery algorithms that, under acceptable computational efficiency limitations, produce a particular enumeration of patterns (or models) over the data" (p. 41). The KDD process typically contains the following steps: data selection, pre-processing, transformation, data mining, and interpretation of results (Fayyad et al., 1996).

Data selection is the process of selecting the database to be analyzed. Pre-possessing includes data cleaning and removing noise from data. Transformation is reducing data and finding useful features related to the goal of the project. The next step is finding the appropriate data mining rules such as classification or clustering, and the last step is interpreting the detected patterns by data mining processes or visualization of the extracted pattern (Fayyad et al., 1996). The KDD process is shown in Figure 4.

2.5.5 Differences Between Data Mining and Text Mining

Data mining methods require relational databases, highly structured formats for data, and extensive data preparation. Text mining methods aim at discovering knowledge from unstructured data such as e-mails, full-text documents and HTML files (Gupta & Lehal, 2009). Since a text mining process is relatively similar to a data mining process, Fayyad's (1996) steps of the KDD process are applicable to text mining. In this research, KDD steps were applied for extracting knowledge from HTML files.

Figure 4: KDD Process



Note. Adopted from Fayyad et al. (1996)

2.5.6 The Process of Knowledge Discovery in Text

Document collection: Like data selection in KDD steps, this is the process of selecting and collecting documents that are required to be analyzed (Fan, Wallace, & Rich, 2006).

Preprocessing: This is the process of transforming documents into the appropriate format for analyzing. This step varies depending on the purpose of analysis and the characteristics of the documents (Fan et al., 2006).

Text mining: This concerns using different algorithms to extract information from the text. Text mining includes various techniques such as feature extraction, clustering, summarization, text categorization, text association, or information visualization (Choudhary, Oluikpe, Harding, & Carrillo, 2009). In this study, document clustering is used for text mining purposes.

2.6 Document Clustering

Document clustering is one of the most applicable methods of text mining and used to group large amounts of documents into a number of clusters. During clustering, documents are partitioned into disjoint subsets of clusters so that the documents in each cluster are similar to one another, and the documents of each cluster are very different from those of other clusters (Vidhye & Aghila, 2010). In clustering, a document set is based on unsupervised data, which means that no training set is

required; hence, there is no clear objective of a perfect clustering method (Croft, Metzler, & Trevor, 2010).

2.6.1 Forms of Document Clustering

Generally, two types of clustering algorithms have been found: hierarchical and partitional. Hierarchical approaches produce clusters in a nested sequence of partitions. Therefore, the result of hierarchical clustering can be displayed as a tree, called a dendogram. Dendograms can show the merging splitting process (Steinbach, Karypis, & Kumar, 2000). In partitional clustering, a desired number of clusters are initially defined. Each object is assigned to one cluster until the appropriate objective function is optimized.

The differences between these methods relate to the performance of their objective functions. In both methods, an algorithm begins with the initial number of clusters and then tries to improve the clustering performance by changing the relevant objective function (Croft et al., 2010).

There are generally two types of algorithms for each clustering type, and they are briefly explained in the following sections.

Hierarchical Clustering

2.6.2 Divisive Clustering

Divisive clustering is a top-down approach, which begins with a whole set of documents as a single set of clusters. It then partitions documents into two or more clusters until it reaches a total of K clusters (Croft et al., 2010)

2.6.3 Agglomerative Clustering

Agglomerative clustering is a bottom-up approach, which begins with each document as a separate cluster. It then joins two or more clusters to form a new cluster until there are a total of K clusters (Croft et al., 2010).

Partitional Clustering

2.6.4 K-means Algorithm

In the K-means algorithm, the number of clusters at the beginning and at the end does not change. Therefore, the clustering algorithm starts and ends with K clusters. In every single iteration, each document is either kept in the same cluster or assigned to a different cluster until the K clusters are reached. It has been found that partitional clustering algorithms, of which the classical example is K-means, perform better for large document datasets because of their low computational requirements (Cutting, Pederson, Karger, & Turkey, 1992; Steinbach et al., 2000). Due to the large document dataset, in this study, the K-means algorithms associated with the application software are used. The following steps illustrate the logic behind the K-means clustering.

1- Select K points as the initial centroids
2- Assign all points to the closest centroid
3- Recompute the centroid of each cluster
4- Repeat steps 2 and 3 until the K clusters are reached.

2.6.5 Vector Space Model

In most clustering algorithms, documents are represented using a *term frequency-inverse document frequency* (*tf-idf*) vector-space model (Salton, 1989). A vector space model is an algebraic way of representing text documents in a matrix format for automatic indexing. In a vector space model, a set of n documents with m terms is represented as n×m term document matrix. Terms are defined as a set of documents' words. Each document corpus contains distinct words and each dimension relates to a separate term. Each document d is represented as a vector d in the term-space. Q is the set of corpus words.

$$d_j = (w_{1.j}, w_{2.j}, w_{3.j}, \ldots, w_{m.j})$$
$$q = (w_{1,q}, w_{2,q}, \ldots, w_{m,q})$$

Usually each document is represented by its weight factors. The weight factor is used to represent a document in a mathematical format based on the frequency of the words occurring in a document and the length of the document. Therefore a tf-idf (term frequency-inverse document frequency) is used as a statistical weight measurement.

$W_{ij} = tf_{ij} \times log^{\frac{N}{n}}$

where

W_{ij} = weight of term T_j in document D_i

tf_{ij} = frequency of term T_j in document D_i

N = number of documents in collection

n = number of documents where term T_j occurs at least once

By using the above equation for finding documents' term weights, each document vector is normalized by its unit length.

2.6.6 Similarity Measurements

A critical goal in document clustering is locating the similarities between documents. There are two main approaches for finding document similarities: the first method discovers the distance between documents, called the Euclidean distance. The second method calculates the cosine function between documents (Zhao & Karypis, 2004). Finding the cosine similarities between documents is more common, and computes the cosine of angles between the vectors of documents (Andrews & Fox, 2007). In this study, the cosine similarity between documents was used, as explained in the methodology section. The following equation is utilized to find the cosine measure between the documents:

$\cos\ (d_1, d_2) = \frac{(d_1, d_2)}{\|d_1\|.\|d_2\|}$

where

dot is the vector dot product and

$\|\ \ \|$ is the length of the document

In K-means clustering, the centroid of the documents in each cluster must be calculated. According to Steinbach et al. (2000), using the mean as the centroid for computing the documents in a K-means algorithm is easier than using the median, although calculating median is also acceptable. In a K-means algorithm, the following equation is used to find the centroid of a set of documents (S):

$$c = \frac{1}{\|S\|} \sum_{d \in S} d$$

Where

S is the set of documents

d represents each document

Calculating the cosine similarity between the cluster centroid and a document is similar to calculating the average similarities between the document and all other documents in the cluster. Therefore, the following equations are used in the K-means algorithm to discover the similarity between two centroid vectors and between the documents in a centroid vector (Steinbach et al., 2000).

$$\cos\ (d, c) = \frac{(d,c)}{\|d\|\|c\|}$$

$$\cos\ (c_1, c_2) = \frac{(c_1,c_2)}{\|c_1\|\|c_2\|}$$

2.6.7 Bisecting K-means

A bisecting K-means algorithm initially splits the documents into two clusters and then further splits the documents from one of the clusters until the K clusters are reached.

2.6.8 Clustering Performance

Clustering evaluation is another challenging issue in document clustering. There has been little agreement among scholars on the best clustering algorithm (Andrews & Fox, 2007). Generally, research has been shown that a hierarchical algorithm produces better results but takes more time and space. It is often not practical for large document collections. A K-means algorithm has been demonstrated to reach the optimum solution faster, and so is more practical for large document collections but produces lower quality results (Steinbach, et al. 2000; Chakrabarti, 2003). Steinbach, et al. (2000) found that a bisecting K-means could produce clusters that perform better than those produced by regular K-means and those produced by agglomerative hierarchical clustering techniques. K-means is a simple clustering algorithm that runs quickly but is sensitive to its initial seed; however a bisecting K-means algorithm can overcome this problem. Based on the above information from the literature, K-means and bisecting K-means algorithms were used in this study.

2.6.9 Pre-Processing

Pre-processing is used to reform a dataset into a format that is appropriate for clustering. Pre-processing steps take a text file as an input and give tokens (terms) as an output. In this way the text is ready for building a vector space model (Andrews & Fox, 2007). Pre-processing contains several steps:

Term Filtering: This includes removing punctuation and characters that will not give useful information.

Tokenization: This "splits sentences into individual tokens, typically words. More sophisticated methods, drawn from the field of Natural Language Processing (NLP), parse the grammatical structure of the text to pick out significant terms or chunks (sequences of words), such as noun phrases" (Andrews & Fox, 2007, p. 6).

Stemming: This is the process of reducing words to their root forms. For example, "constructing", "construction" and "constructed" are all similar to the stem "construct". There are several stemming algorithms. For example, Porter's stemming algorithm is a standard one that is used in this study.

Stop Word Removal: "Stop words" are typical words that carry less important meaning than keywords. For example, "a", "an", "the" are common stop words.

Pruning: Some words in documents occur rarely, although they might convey important messages. In pruning, these words are removed based on a pre-defined threshold (Andrews & Fox, 2007).

In this study, the pre-processing steps were used. The details are discussed further in the methodology section.

Chapter 3
Propositions

The importance of detecting weak signals by conducting systematic environmental scanning has been discussed in Section 2.4.1. In highly uncertain environments, accessing reliable and imbedded information will enhance a company's capabilities to tackle new markets and take advantage of possible hidden opportunities. Consequently, it is increasingly important for innovative firms to find new information and detect weak signals of change because, as Vasudeva and Anand (2011) argued, ground-breaking firms often encounter high amounts of uncertainty regarding the future direction of technological change (as cited in Henderson & Clark, 1990; Tushman & Anderson, 1986).

Innovation is a critical step in the performance capabilities of firms, enabling the ability to cope with a turbulent environment and gain competitive advantage (Zhaou & Wu, 2010). When surrounded by a dynamic environment and restricted to only internal organizational knowledge, it can be challenging for managers to make sense of the future market for their products.

Scholars have suggested that the required knowledge for innovative firms mostly exists outside of a firm's technical expertise (Vasudeva & Anand, 2011); hence, it would be advantageous for managers in highly changeable environments to have so called "peripheral vision" (Day & Schoemaker, 2005). The greatest challenge faced by companies in developing their peripheral vision is detecting weak signals, which stands for the "blurry zone at the edge of the organization's vision" (Day & Schoemaker, 2005, p. 1). One hypothetical approach is to guide the firm toward the seeking of new, reliable, and external information which could enhance absorptive capacity and ultimately increase innovation capability (Vasudeva & Anand, 2011). Absorptive capacity is the "ability of the firm to recognize the value of the new information, assimilate it, and apply it to the commercial end" (Cohen & Levinthal, 1990). This ability is a critical driver, implying that for a firm to be inovative, it must build a robust level of prior related knowledge. According to the authors, this prior knowledge refers to an awareness of scientific or technological improvements in the field. Cohen and Levinthal (2009) pointed out that building absorptive capacity depends upon individuals' absorptive capacity and the transformation of knowledge between individuals and subunits of the organization. The authors explained that some sort of overlap between indivudals' knowledge enhances effective communication, while diversity of knowledge is needed because varied problem solving abilities,

learning skills, and mindsets will yield innovation and allow indivuals to make "novel linkages and connotations" (Cohen & Levinthal, 1990 , p. 131).

The model proposed in this study explores the possibility of detecting weak signals of technological change by conducting environmental scanning of the public web, and then performing data reduction using clustering techniques (CLUTO) along with human judgment. Just as with a proof of concept, the aim was to investigate the feasibility of the proposed model and some indication of its potential for future research and practical application. Specifically, our probe was of a use case related to the application of Micro Tiles, a recent innovative product of the Christie Digital Company—in applications of digital media for theatre production.

"A proof of concept initiative supports feasibility studies that test an idea to mitigate the risk of further research investments" (Ontario Centres of Excellence, 2011, para. 1). Such studies involve a limited number of projects (case studies) with specific subjects and are intended to encourage further work pursuing a particular line of testing. If a study is intended to establish a new line of theory, it should make clear what that new theory is, how it relates to existing theories and evidence, why the new theory is needed, and what the intended applications of the theory are. Accordingly, this study was intended to establish a new line of product use, to develop novel approaches, and to perform the trial run on a use case (the application of Micro Tiles) and thereby to gauge the viability of pursuing further research on related topics.

Another significant factor in the research was the selection of experts who were involved during the study. A dictionary defines experts as those "having, involving, or displaying special skill or knowledge derived from training or experience" (Merriam-Webster, 2011). According to Ericson and Lehmann (1996), it takes approximately ten years for an individual to attain expert performance and involves different variables, including deliberate practices, parental influence, motivation, coach/teacher role, feedback, age of initiation of the skills, and performance. Deliberate practice plays a key role in Ericson's definition of expertise and involves many hours of intense practice of tasks or activities. Studies have shown that experts are domain specific, implying that experts in specific areas accumulate knowledge over a long time and that being expert in one specific area does not necessarily guarantee superior performance in other areas. Armstrong (2005) shed light on the definition and characteristics of experts by reviewing literature and derived several characteristics of experts that distinguish them from non-experts, including superior performance in a specific domain, pattern recognition ability in the domain of expertise, rapid problem solving, broader perspective in problem solving, and ability to monitor, adjust and correct their performances.

The above definition and characteristics were fundamental to the selection of experts in the technical aspects and applications of Micro Tiles. Our several assessments found only two available and suitable experts. The chosen experts were knowledgeable in the digital media area, possessed more than twenty years of experience in the domain, were involved in the exploration of applications for Micro Tiles, but were not employees of the Christie Digital Company.

Furthermore, this study uses the World Wide Web to conduct environmental scanning and gain preliminary information related to detecting weak signals, as described in Section 2.4.2. The challenges of weak signals were therefore related to the facts that a) a weak signal has no exact definition, 2) labeling a sign or information as a weak signal is subjective rather than objective; hence, it is hard to find a robust measurement tool, and 3) the estimated timeline of a signal occurring is not clear. In other words, are interpreters looking for a potential signal that will occur two, or four, or ten years from now, or has the signal just occurred? Or was it stored in the report and website and then interpreted? Moreover, interpreters of weak signals are constrained by time and effort; therefore, it is impossible to fully test the accuracy of their detections in real-time.

Day and Schoemaker (2005) stated that "Looking at everything means looking at nothing" (p. 3). In the huge dataset of approximately 40,000 web pages involved in this study, it was difficult to find potential signals. To find the proverbial needle in the haystack and narrow down the retrieved amount of information, it was decided to perform a methodical document reduction with computer (CLUTO) and human judgment. This was done by assuming that the ratio of relevant to irrelevant and unexpected to expected documents in the smallest set was greater than the ratio in the largest one.

The relevancy and expectedness of information in documents were two measurements as related to weak signals. Weak signals detection is mostly dependent on the mindset of the observer or the interpreters. Time, relevancy, expectedness, and observer's mindset were used as dependent variables for finding any sign of a weak signal, considering the fact that the variables do not have equal weights in the assessment. Formulating this concept, we have

$W(x) = W(R(x), E(x), T)$
$R(x) = R(O, T)$
$E(x) = E(O, T)$
where

W: Weak Signal, R: Relevancy, E: Expectedness, T: Time, O: Observer's mindset, x: One potential sign

If there is a signal in the environment at any moment, labeling it as a weak signal depends on whether or not the sign is relevant and unexpected to the domain of use. The relevancy and expectedness depends upon the mindset of the observer and the moment in which they interpret the sign. The expectedness is negatively associated with the weak signals, which means that the more unexpected the sign, the more it tends to be a weak signal.

In this study, having more relevant and unexpected documents in the smallest set was expected. Therefore, the following propositions were expressed:

P1: After data reduction with CLUTO, human judgment can determine whether a randomly drawn sample of documents comes from small, medium or large datasets.

P2: There is a relationship between data reduction and the perceived relevancy of the documents (the smaller the dataset, the higher is the relevancy of the documents in the dataset).

P3: There is a relationship between data reduction and the perceived expectedness of the documents (the smaller the dataset, the higher is the unexpectedness of the documents in the dataset).

P4: The ratio of relevant to irrelevant documents in the small dataset is greater than that in the medium one.

P5: The ratio of relevant to irrelevant documents in the medium dataset is greater than that in the large one.

P6: The ratio of unexpected to expected documents in the small dataset is greater than that in the medium one.

P7: The ratio of unexpected to expected documents in the medium dataset is greater than that in the large one.

To test the propositions, data concerning a project related to the application of Micro Tiles (Appendix A) in digital media in theatre production were applied.

Chapter 4
Methodology

This chapter discusses the approaches used in this research. The first section outlines the study's design, and the second section explains the procedure of the study. Real digital media data were used for testing the propositions. The following sections explain the processes of research design and gathering data. A brief description of Micro Tiles is also provided in Appendix A.

4.1 Research Design

In July 2009, a research team met at the Lower Ossington Theatre in Toronto, Canada to introduce Micro Tiles to potential users, specifically to theatre professionals, before its introduction into the general marketplace.

Members included University of Waterloo researchers, a team of Christie Digital Company employees, representatives of professional theatre companies and faculty theatre members of the Universities of Toronto, York, Waterloo, Ryerson, and Brock, and the colleges of Humber and Sheridan.

The aim of the July 2009 meeting was to find information related to the potential applications of Micro Tiles for digital media in theatre production. Evidence was gathered through face-to-face interviews, written surveys, and reparatory grid interviews, and generally focused on "how this particular technology might extend the industry's artistic vision and business plans" (Hauck, J. Goodwin, D. Goodwin, Guild, & Sparkes, 2011, p. 2). One specific aspect of the meeting was to formulate queries, which could be used subsequently in the search engine to provide potential information to help achieve the aforementioned goals.To formulate the queries, a team of eight experts were asked: what combination of keywords in the World Wide Web would likely lead to the relevant information for the use of Micro Tiles for digital media in theatre production. The selection of keywords happened before the Ossington event—they were elicited from a set of experts who were at a workshop held at University of Waterloo to look at the tiles and design the production that was shown at that event.

Each member of eight experts was asked to write four queries, with each query containing two to five key words separated by Boolean arguments. These requirements are evident in the form entitled "Keyword Descriptions for Boolean Search" as shown in Appendix G. On the first round, 32

queries were introduced and after revision, for clarification, 48 were finally selected. Definitions of Boolean operators are provided in Appendix B.

4.2 Queries

Searching for relevant information on the public web can be an overwhelming task for many users. Historically, various web search strategies have been used in order to retrieve appropriate information from web pages. Holscher and Strube (2000) proposed a diagram (Figure 5) which depicted actions directly involved in search engine interactions. According to the authors, experts changed their search engines, changed existing queries, and requested additional result pages if they did not find relevant documents. Another popular web search strategy is Boolean search (Ford, Miller, & Moss, 2002). Holscher and Strube (2000) found that web experts made use of advanced search options, such as Boolean search and phrase search much more frequently than did average users.

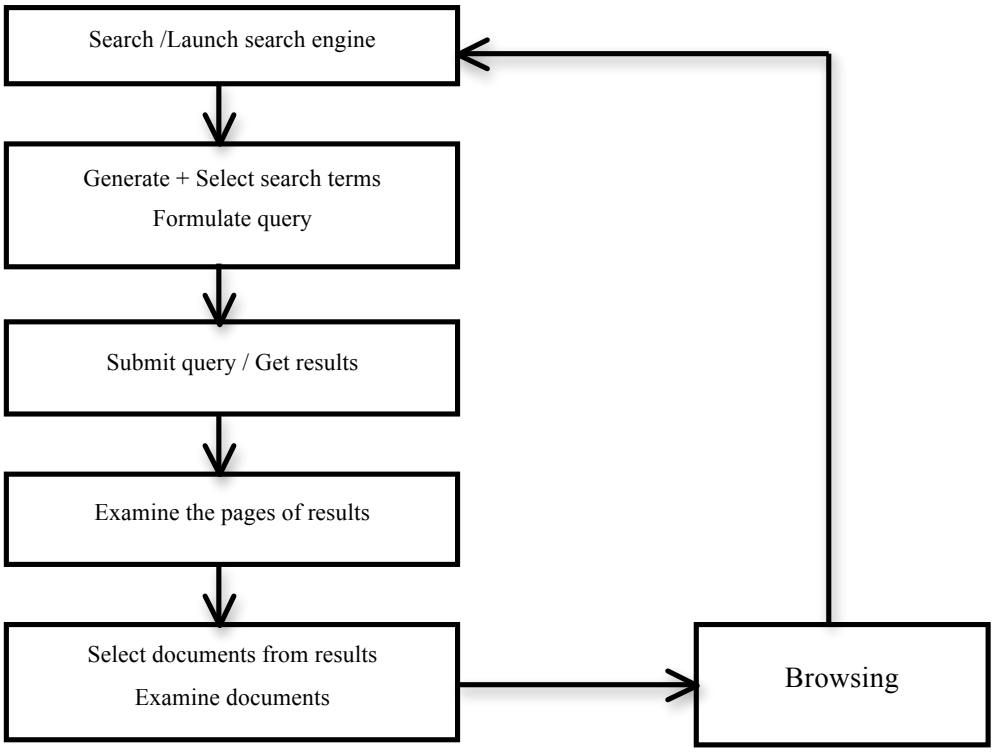
After the proposed 48 queries were written, they were then entered into DEVONagent (Mac search engine software). It was chosen because of "its abilty to handle the Boolean operators and also features the number of operators such as NEAR or BEFORE that are only found on high-end databases" (DEVONtechnologies, 2011, p. 80). DEVONagent's unique features and its advantages over regular search engines such as, Google, Yahoo, and AltaVista, are illustrated in Appendix B.

Each query was run separately by first copying the queries from the log document and then pasting them into DEVONagent. DEVONthink (Appendix C) finally stored and organized the retrieved web pages. Any duplicated documents were removed by DEVONthink (Castillo, 2009).

4.3 Samples

This study used samples of web pages that were retrieved through a systematic search procedure in 2009. All steps, including selecting search engine, queries, and pre-processing procedures, are discussed in this chapter.

Figure 5: Close of Direct Interaction With Search Engine



Note. Adopted from Holscher & Strube (2000)

4.4 Analyzing Phase

The stored web pages in DEVONthink must be analyzed in order to find relevant information and detect weak signals.

Document clustering methods (Section 2.6) were applied to find groups of similar documents. From these groups, expected and irrelevant documents were removed, while unexpected, and relevent documents were kept. Accordingly, the clustering toolkit (CLUTO) was used to conduct the clustering function. CLUTO's unique features and its applications are provided in Section 4.7.

In addition, as described in Section 2.6.9, pre-processing steps were performed prior to the clustering phase in order to convert the web pages format into one that was appropriate for the clustering software. The steps involved for pre-processing the documents are explained in Section 4.5.

4.5 Pre-processing Phase

Only textual information in web pages was considered in this study; hence, each HTML web page was converted into plain text file with the DEVONthink functionality of striping HTML tags. A script was then used to remove line breaks and aggregate all separate text files into one file, in which each line of the file represented one document. The same steps were also performed to aggregate the URLS.

For aggregating the documents, a scripting language (Apple script) and the following command lines were used, as evidenced in Appendix H. Apple script was applied to merge text files at the beginning; however, after merging several text documents, the merging process decelerated. Hence, the following command line was used for the remainder of the merging:

CAT f1.txt f2.txt f3.txt > f4.txt

The next steps in pre-processing the documents were removing the stop-words, stemming, and creating the vector space matrix (Section 2.6.5), which is the most common document representation model used in text mining. This process was completed with Doc2mat file (Section 4.6).

4.6 Doc2mat File

Doc2mat file is a Perl script that converts a set of documents into the vector space matrix made compatible with CLUTO's clustering algorithm. The synopsis is

Doc2mat [options] doc-file mat-file

"Doc-file" stores the documents using one document at each line format. Therefore, the total number of documents in the document-term matrix is equal to the number of rows in the file doc-file. "Mat-file" stores the generated CLUTO compatible mat file, as well as the file-stem for the label file if it is applicable.

Doc2mat does word stemming (Porter's stemming algorithm (Porter, 1980)), stop-word elimination, and the tokenization process

"The Doc2mat algorithm begins by replacing all non-alphanumeric characters with spaces. Following this, the white-space characters are used to break up the line into tokens. Each of these

tokens is then checked against the stop-list, and if they are not there they get stemmed. The tokenization and stemming process may be slightly different in relation to various options in Perl script" (Karypis, 2003, "Doc2mat").

Operating the Doc2mat file, the CLUTO's inputs (including the vector space matrix and ClabelFile) were produced. Tokenization approaches are defined in Section 2.6.9. The entire methodology process is also depicted in Figure 6.

- All words were stemmed
- Stop words were eliminated
- Words consisting of numbers were retained
- Words containing fewer than three letters were removed
- The remaining words were stemmed using the Porter-stemming algorithm (Porter, 1980).

4.7 CLUTO

Karypis (2002) defines CLUTO as "a software package for clustering low and high dimensional datasets and for analyzing the characteristics of various clusters" (p. 4). It uses various clustering methods based on partitional, agglomerative, and graph-partitioning algorithms. CLUTO calculates objective functions relating to certain criterion function, and optimizes (minimizes or maximizes) particular clustering criterion functions that are defined at the beginning of the clustering procedure. CLUTO uses seven criterion functions that can be applied both for partitional and agglomerative clusterings.

CLUTO has the capability of comparing relations between documents within clusters and among different clusters. It has been observed that CLUTO can perform effectively on high dimensional datasets in terms of the number of documents and number of dimensions: "Moreover, since most high-dimensional datasets are very sparse, CLUTO directly takes into account this scarcity and requires memory that is roughly linear on the input size" (Karypis, 2002, p. 4).

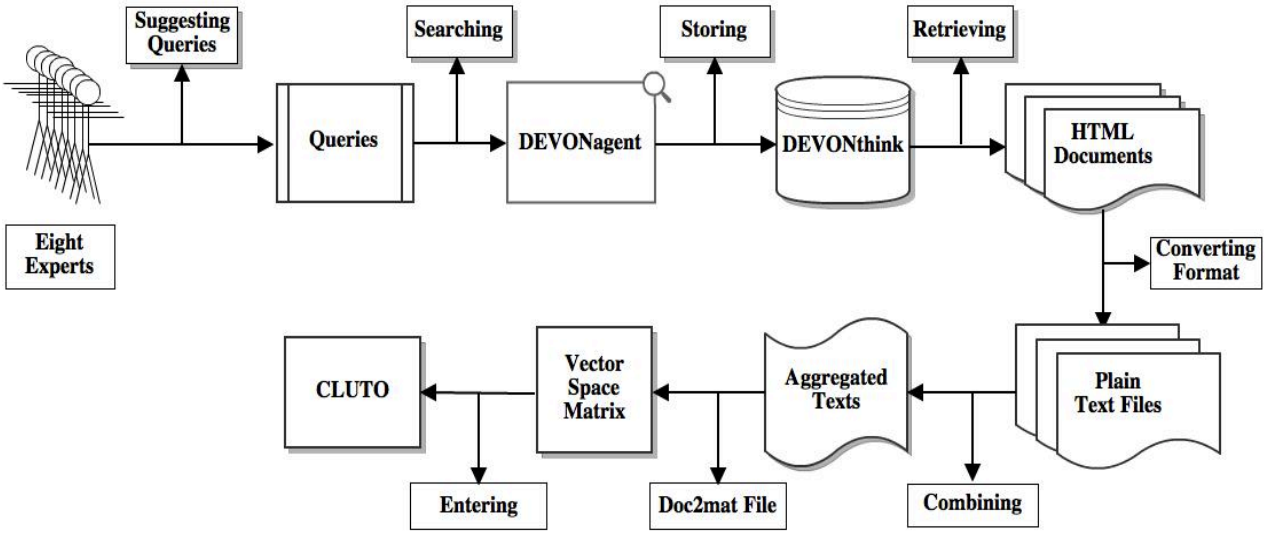
CLUTO analyzes and clusters with its "stand-alone" programs Vcluster and Scluster (Karypis, 2002, p. 6). Vcluster receives a vector space matrix as an input, while Scluster receives a similarity matrix (or graphs) between documents as an input. Vcluster and Scluster are performed by placing the following lines in the command-line:

Vcluster [optional parameters] MatrixFile NClusters

Scluster [optional parameters] GraphFile Nclusters

The matrix file is the vector space matrix (2.6.5). The Nclusters are the number of clusters known a priori.

Figure 6: Methodology



4.8 Clustering Algorithm Parameters

In CLUTO, multiple optional parameters specify the behavior of different clusters. In general, clusters can be grouped into three categories. The first category controls different aspects of the clustering algorithm; the second category controls the type of analysis, and the third category controls the visualization of the clusters (Karypis, 2002).

4.9 CLUTO Input

CLUTO takes a vector matrix file and an optional column label (clabelfile) and classifies labels of the documents. The column label is the file that stores the label for each column of the vector space matrix. In document clustering, the columns of the vector space matrix are the terms produced from documents. Therefore, if the total terms of the matrix are n, the column label file has exactly n lines.

4.10 CLUTO Output

Regarding clustering results, CLUTO can produce two kinds of output. The first kind covers the clustering results with various measurements, while the second kind generates hierarchical trees if the related option has already been defined in the command line.

4.11 Cluster Numbers

In K-means algorithms, clustering numbers should be defined a priori, making these the most challenging part of the clustering method. Zhao and Karypis (2004) pointed out that no ideal clustering numbers are suggested by the literature and that the best clustering numbers should be found by the user through various experiments. The performance of a criterion function depends on the degree of obtaining balanced clusters and the degree in which they can operate effectively with different clustering tightnesses (Zhao & Karypis, 2004). For the purpose of this research, through various experiments and due to our large dataset, it was decided to use the number of clusters that resulted in no cluster exceeding 10 percentage of the overall document count (Figure 8).

4.12 Cluster Algorithm

Zhao and Karypis (2002) evaluated agglomerative and partitional algorithms and found that for large document datasets, partitional clustering algorithms performed better than agglomerative ones with low computational requirements.

CLUTO has 18 different optional parameters. Using these parameters, CLUTO finds the appropriate clustering solution. For example, one of the options is *–clmethod*. The *–clmethod* parameter defines the document clustering method. *–clmethod* consists of six different optional methods for clustering documents. In this research, the **rbr** and **direct** methods have been used, as described in the following:

Rbr: In this method, a vector space matrix is at first clustered into two parts. One part is selected and bisected further until the ideal K clusters are found. In the end, the overall solution is "globally optimized" (Karypis, 2002, p. 8).

Direct: In this method, CLUTO initially clusters the whole document into the ideal K clusters. This method is usually slower than the rbr method; however, for cluster numbers less than

20, it achieves superior results. Increasing K, the repeated bisection method performs better than direct clustering (Karypis, 2002).

4.13 Cluster Criterion Functions

There are seven different clustering criterion finctions that define the optimization formula for clustering methods. For the mathematical definition of CLUTO's clustering criterion functions refer to Appendix D.

Differing criterion functions can lead to completely different results (Karypis, 2002). I2 and H2 produce very good clustering solutions (Karypis, 2002). Zhao and Karypis (2004) evaluated the performance of different criterion functions for partitional clustering algorithms and found that I2 performs better than the I1 criterion function. However, the selection of appropriate criterion functions depends mainly on the application area. Therefore, it might be useful to perform experimentation before selecting one criteria function (Karypis, 2002). Hence, for the current database and with regards to Karypis (2002) suggestion, both H2 and I2 were used as the criteria functions and shown to the experts for interpretation. Since there were only slight differences in the interpretation results, I2 was used as a default criterion function.

4.14 Procedure

The procedure essentially aimed at moving the documents from the original corpus to a subset that contains more relevant and unexpected documents to the domain of use. Relevancy and expectedness were two measurements used for defining weak signals. In addition, the choices of CLUTO's options were based on the reasons provided in Sections 4.11, 4.12, and 4.13. However, certain choices such as the selection of appropriate number of clusters were based on the experts' judgments as explained in the following.

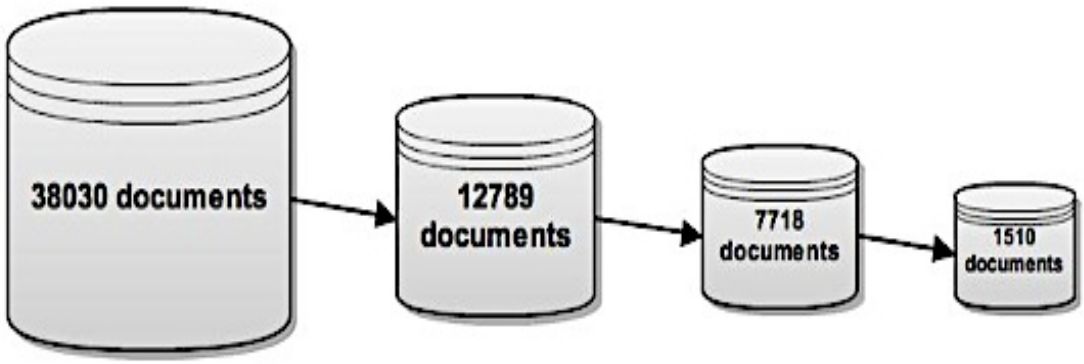
It was decided to begin with 10 as an initial number of clusters since the target cluster size was 10% of the documents. If any cluster size exceeded 10 percent of the overall documents, then one was added to the number of clusters, and they were clustered again. This process was continued until all cluster sizes were less than 10 percent of the overall documents (Figure 8).

The CLUTO clustering results were reviewed by two experts to select the clusters that were not relevant for Christie Digital's preliminary goal, and that were not useful in detecting weak signals. During the procedure, each expert used individual and independent judgment. Only the clusters

chosen by both experts to be dropped were finally removed from the document corpus. The corresponding documents and URLs were then removed from the document set, and the clustering process was performed again. This process continued in three iterations, which significantly reduced the number of documents. The number of documents remaining after each reduction is shown in Figure 7. The scripting language Python was used for selecting and removing the documents from the document corpus (see Appendix F).

Based on the experts' judgments, dropping and clustering iterations were stopped after three repetitions. The original set contained 38,030 documents, the second set contained 12,789 documents, the third set contained 7,718 documents, and the last set contained 1,510 documents. Three iterations were judged to be necessary for data reduction, yet sufficient for detecting weak signals.

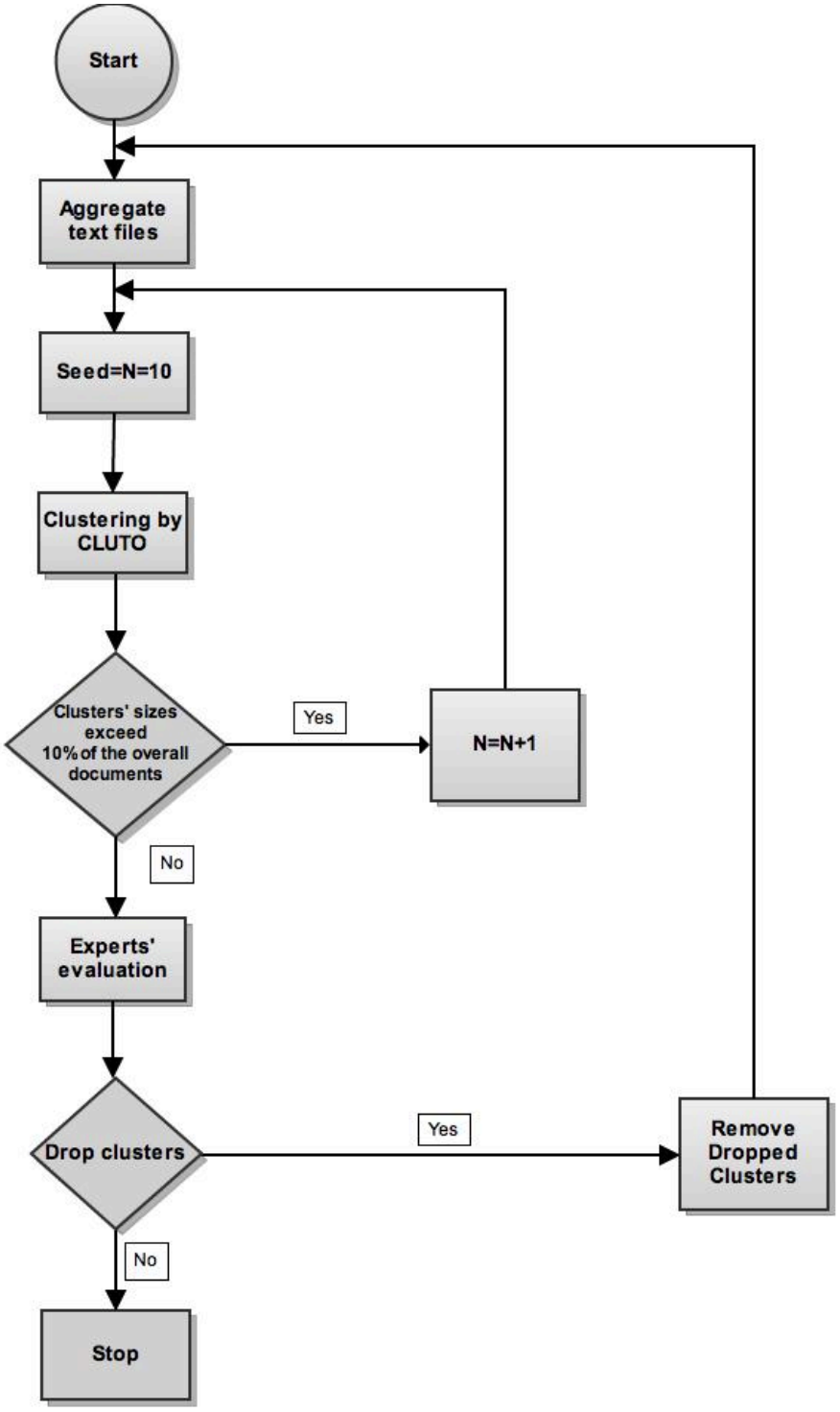
Figure 7: The Number of Documents Remaining After Each Reduction



4.15 Judgment Procedure

Due to the impracticality of evaluating each document separately, it was decided to gather 40 random samples from each set of the 38,030, 7,718, and 1,510 document sets in order to test the propositions. Basically, the aim was to collect samples from the large (38,030), medium (7,718) and small (1,510) datasets, and then compare the yielded results by checking the relevancy and expectedness of the documents. We could thus discover whether the smallest document set had more relevant and less expected documents.

Figure 8: Document Reduction Flow Chart



To conduct the procedure, each set of 40 samples was categorized into four groups of ten samples; therefore, 120 sample web pages were placed into 12 anonymous folders with each folder containing 10 web pages. Unique identification codes were assigned to each web page in the database (e.g., 1, 2, 3,etc.), and alphabetical codes were assigned to each folder of 10 web pages (e.g., A, B, C, etc.). These codes were chosen to prevent the experts from understanding the original sources of each document. The experts were then given a form (Appendix J), and were asked to judge the corresponding document set (38,030, 7,718, and 1,500) regarding each group of 10 documents and classify each web page in terms of relevancy and expectedness. The experts evaluated the documents independently, without any communication during the procedure (Figure 9).

As can be seen in Appendix J, the form captured the expert's name, the alphabetical set number, and the date that the evaluation was conducted. In the table (Appendix J), each document number refers to each web page. The experts had to choose whether the website's information was clearly relevant, maybe relevant or irrelevant, using the definition of relevancy provided below the table, or whether it was clearly unexpected, somewhat unexpected, or expected in terms of the application expectedness definition. For "clearly relevant" and "clearly unexpected" documents, associated probability was defined to be more than 70 percent. For "maybe relevant" and "somewhat unexpected" documents, probability was between 30 and 70 percent, and for "irrelevant" and "unexpected" documents, the probability was defined to be less than 30 percent. Finally, responses were converted into 80, 50, and 20 scales, in which 80 stood for relevant/expected, 50 for maybe relevant/somewhat unexpected, and 20 for irrelevant/clearly unexpected documents.

Having consistency in document sets, relevancy, and expectedness were defined as follows:

- **Technical Relevance for Firm's Product Management:**

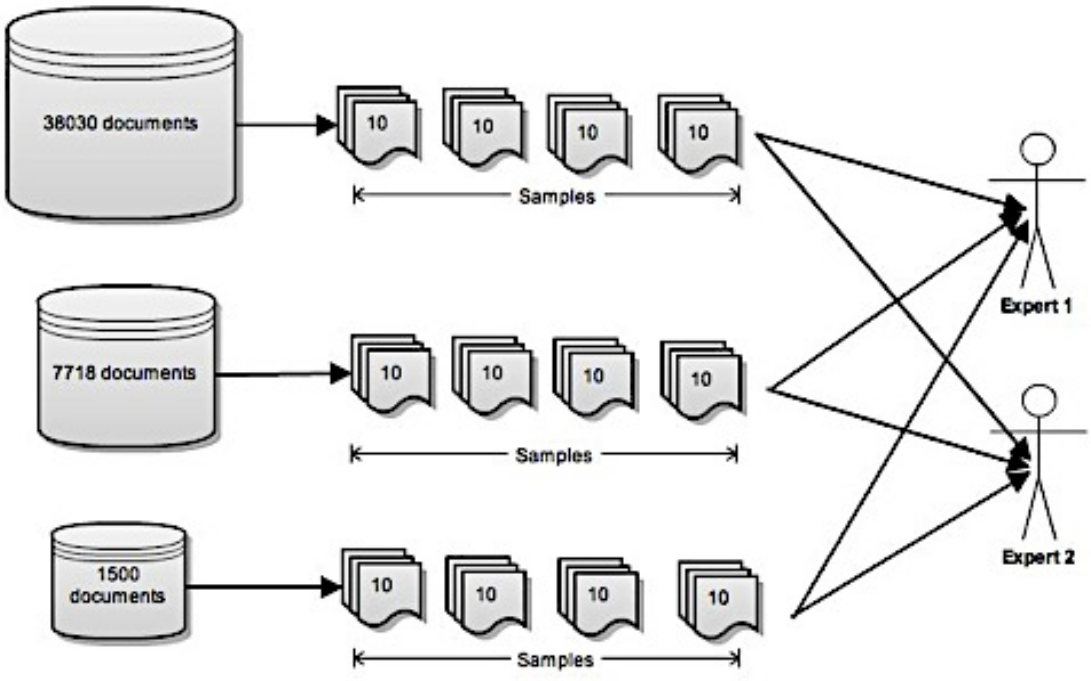
  How likely is the Christie Digital product management team to find the information relevant to Micro Tiles?

- **Application Expectedness for Theatre Professionals:**

  How likely is the UW creative/theatre production team to be inspired by the novel or unique application of Micro Tiles?

The information provided by the experts was then analyzed by statistical software (SPSS). Chapter 5 reports the results of the clustering by CLUTO and statistical analysis of human judgments.

Figure 9: Experts Judgments Procedure



Chapter 5
Results

This chapter provides the results of the study. The first part explains CLUTO's results in different iterations of the data reduction, and the second part describes the sampling results and the relevant statistical analysis for testing the propositions. Appendix E displays the set of 48 queries and the corresponding number of search results provided by the DEVONagent search engine.

5.1 Descriptions of CLUTO Results - First Iteration

Table 3 displays the summary of CLUTO results at the first iteration. The number of documents is 38,030, and the number of clusters is 25.

Table 4 indicates part of the Vcluster output of CLUTO for the first iteration. As can be seen in the table, the first part of the CLUTO's report describes the optional parameters used in the clustering. From this table it is clear that CLUTO prints information about the matrix such as its name, number of rows (number of documents), number of columns (number of tokens), and number of non-zeros in the matrix. Next, CLUTO reports on the options used to find the clustering.

For the first iteration, the followings parameters were applied:

- **CLMethod:** Due to the small number of clusters, the direct method was used (see Section 4.12).
- **CRfun:** The I2 criteria function was used (see Section 4.13).
- **SimFun:** The similarity between the documents was computed by using the cosine function of their vectors (see Section 2.6.6).
- **Number of clusters:** The desired number of clusters was reached at 25 (see Section 4.11)
- **RowModel:** This parameter selects the model to scale the various columns of each row. In this study, the columns of each row in the matrix were not scaled.
- **Col Model:** The columns of the matrix were labeled according to inverse-document-frequency (IDF) (see Section 2.6.5).
- **GrModel:** This is related to graph-partitioning based algorithm and was not applied here.

Table 3: Summary of CLUTO Output - First Iteration

Cluster Number	Internal Similarity	External Similarity	Size	Descriptive Words
0	0.504	0.010	406	Meetup, green, organ, environ, inappropri
1	0.278	0.018	419	syndic , digg , newslink , myyahoo, 2008
2	0.258	0.018	426	publish, volum, ingentaconnect, ingenta author
3	0.188	0.013	317	fhwa , highwai , transport , feder , trail
4	0.172	0.006	796	und, der , die , ein, von
5	0.176	0.017	1431	led , displai , inquiri , sell, outdoor
6	0.14	0.012	658	hair, laser, skin, treatment , remov
7	0.143	0.021	998	signag , digit , network, kiosk , retail
8	0.127	0.022	983	patent , inventor, usernam , apparatu ,password
9	0.109	0.020	1150	projector, dlp , cinema , christi , digit
10	0.092	0.009	874	hled , str , nky , vyhledat, zboz
11	0.099	0.016	752	monitor , multi , request, multipl, uv
12	0.089	0.014	1112	mobil , pda , accessori , batteri , gp
13	0.095	0.022	1468	bnet , manag, tag, result, window
14	0.086	0.014	3544	laser , beam, optic, engrav, photon
15	0.079	0.014	1538	theatr, plai, ticket , actor, stage
16	0.058	0.017	2339	energi , climat , environment , warm , environ
17	0.046	0.013	3019	environment, environ , water, australia , wast
18	0.051	0.019	2218	camera , dvd , digit, soni, video
19	0.051	0.019	2082	displai , lcd, panel , monitor , www
20	0.04	0.018	2712	art , artist , student , music, cultur
21	0.034	0.013	1288	perform, vehicl , car, clock, brake
22	0.029	0.01	1153	ieee, sql, code, bibtex, cocoa
23	0.031	0.014	1959	wikipedia , answer, edit , dictionari,articl
24	0.032	0.019	3557	ol , technolog , comput , displai, comp

Note. Number of documents: 38,030, number of clusters: 25

Table 4: CLUTO's Report Regarding the Applied Method

Vcluster (CLUTO 2.1.2) Copyright 2001-06, Regents of the University of Minnesota
Matrix information ----------
Name: final09.mat , #Rows: 38030, #Columns: 699159, # NonZeros: 15287034
Options ----------
CLMethod=Direct, CRfun= I2, SimFun= Cosine, #Clusters: 25
RowModel=None, ColModel=IDF, GrModel=SY-DIR, NNbrs=40
CSType=Best, Ntrials=10, Niter=10

- **CStype:** This parameter defined the method to be used for selecting the next cluster to be bisected by CLUTO's repeated-bisecting algorithms. CStype has two options: "LARGE" and "BEST". "LARGE" chooses the largest cluster to be bisected further, and "BEST" chooses the cluster that gained better value of the clustering criterion function to be bisected further. In this study, the "BEST" option is used.
- **Niter:** In each clustering step, CLUTO clusters documents in different iterations until it reaches the appropriate clustering solution. Niter option defines the maximum number of "refinement iterations" that CLUTO uses to find the appropriate clustering solution. The default value is 10. The appropriate range is between five and 20 (Karypis, 2002, p. 15).
- **Ntrials:** By default, the value was 10, indicating that CLUTO computed 10 different clustering solutions. Each solution had a different set of seed objects. Among these solutions, CLUTO selects the clustering solution that had the best value of the criterion function (Karypis, 2002).
- **NNBr:** This was the parameter related to a graph-partitioning based algorithm. The default value was 40. Because no graph-partitioning algorithm was applied in this study, the parameter remained as the default value.

Table 5: Part of CLUTO's Statistical Report

25-way clustering: $[I2 = 1.00e + 004]$ [37199 of 38030]					
Cid	Size	ISim	ISdev	Esim	ESdev
0	406	+0.504	+0.083	+0.010	+0.003
1	419	+0.278	+0.118	+0.018	+0.003
Descriptive & Discriminating Features					
Descriptive: meetup 93.1%, green 0.2%, organ 0.2%, envion 0.2%, inappropri 0.1%					
Discriminating: meetup 51.5%, laser 2.9%, display 1.0%, led 0.7%, digit 0.7%					

Table 5 displays part of CLUTO's statistical report. The first line of the report relates to the value of the I2 criterion functions.

"The column labeled "size" relates to the number of documents belonging to each cluster. The column labeled "ISim" displays the average internal similarity of each cluster, and the columns labeled "ISdev" display the standard deviation of average internal similarities. The column labeled "ESim" displays the average similarities of the documents of each cluster and the rest of the documents (external similarities), and the "ESdev" shows the standard deviation of the average of external similarities. For example, 0.504 in Table 5 indicates that the average internal similarity between the documents in cluster number 0 is 0.504.

For our textual analysis, *the –showfeatures* option was also applied. This feature displays the set of words (columns of the vector space matrix) that best describes the similarities of the documents within each cluster and the set of words that best describes the differences between each cluster and the rest of the documents. There is a percentage number beside each word, which describes the percentages within cluster similarity that the corresponding word could explain. For discriminating among words, the percentage number indicates the percentage of differences that the particular word could explain regarding the cluster and the rest of the documents. Therefore, there is a large overlap between the descriptive and discriminative features. The words are also listed in decreasing descriptive and discriminative order. The default number of words that could be displayed is five; however, with the *–nfeatures* parameter, the number of observed words could be changed" (Karypis, 2002, p. 19).

Table 6: Experts' Suggestions Regarding Removal of Clusters - First Iteration

Cluster Number	Expert 1 Suggested Themes	Expert 1 Judgment	Expert 2 Suggested Themes	Expert 2 Judgment
0	**Environment**	**Dropped**	**Meeting/conferences**	**Dropped**
1	**New sites**	**Dropped**	**New sites**	**Dropped**
2	**Database**	**Dropped**	**Publishing**	**Dropped**
3	**Transportation**	**Dropped**	**Transportation**	**Dropped**
4	**German**	**Dropped**	**German**	**Dropped**
5	**Ecommerce**	**Dropped**	**Retailing**	**Dropped**
6	**Cosmetic**	**Dropped**	**Health/medical**	**Dropped**
7	Signage	Kept	Signage	Kept
8	**Patent Database**	**Dropped**	**Patents**	**Dropped**
9	Suppliers	Kept	Suppliers	Dropped
10	**Unknown**	**Dropped**	**Unknown**	**Dropped**
11	Multi-Monitors	Kept	Multi-monitors	Kept
12	**Ecommerce/Mobile**	**Dropped**	**Mobile**	**Dropped**
13	**Network Software**	**Dropped**	**Software**	**Dropped**
14	**Engraving**	**Dropped**	**Lasers**	**Dropped**
15	Theater sites	Dropped	Theater	Kept
16	**Environment**	**Dropped**	**Energy/Environment**	**Dropped**
17	**Environment**	**Dropped**	**Environment**	**Dropped**
18	**Ecommerce**	**Dropped**	**Photography**	**Dropped**
19	Display	Kept	Display	Kept
20	Art	Kept	Art	Kept
21	**Automotive**	**Dropped**	**Automotive**	**Dropped**
22	**Database**	**Dropped**	**Engineering/data**	**Dropped**
23	**Database**	**Dropped**	**Wiki/reference**	**Dropped**
24	Theater	Kept	Theater	Kept

Note. Number of documents: 38030, number of clusters: 25

5.2 Dropped Clusters by the Experts - First Iteration

Table 6 indicates the clusters dropped by the two experts. Next to each cluster the corresponding themes provided by each expert are shown. In general, the cluster themes that were neither perceived as facilitators in detecting the weak signals nor reaching the goal described in the Chapter 3 were removed from the corpus. The dropped clusters are bolded.

5.3 Remaining Documents – First Iteration

The following table outlines the total number of documents that were clustered by CLUTO, the number of documents dropped by experts, and the number of remaining documents. The total number of documents that CLUTO could cluster was less than the original number of 38,030 because in almost every clustering, CLUTO could not assign some documents to any clusters.

Table 7: Remaining Documents - First Iteration

Iteration 1	
Total documents	37,199
Dropped documents	24,410
Remaining documents	12,789

5.4 CLUTO Results - Second Iteration

CLUTO's parameters in the second iteration were similar to the first one. The number of clusters was 17, and the total number of documents clustered was 12,789 (Table 8).

Table 8: Summary of CLUTO Output - Second Iteration

Cluster Number	Internal Similarity	External Similarity	Size	Descriptive words
0	0.608	0.005	158	Request, uv, cooki, server, header
1	0.245	0.02	282	Ol, cdt, amol, light, diplai
2	0.141	0.023	437	Monitor, multi, multipl, compu, screen
3	0.120	0.023	895	Signag, digit, network, kiosk, retail
4	0.119	0.022	813	Prjector, dlp, lamp, project, lumen
5	0.116	0.022	374	Cinema, Christi, imax, barco, projector
6	0.108	0.021	227	Wearable, nomad, comput, gesturetek, xybernaut
7	0.069	0.017	501	Film, min, vote, Egyptian, cinematheque
8	0.067	0.016	1234	Theatr, plai, ticket, stage, actor
9	0.063	0.022	976	Art, artisit, culture, danc, perform
10	0.06	0.022	1002	Lcd, display, tft, plasma, monitor
11	0.054	0.020	742	Display, www, com, print, zibb
12	0.044	0.019	777	Brail, intel, window, comput, keyboard
13	0.042	0.021	1102	Student, univers, disable, research, scienc
14	0.040	0.021	977	Control, designlin, system, equip, sensor
15	0.035	0.021	1187	Busi, market, company, announc, indstri
16	0.035	0.021	1105	Comment, post, 2008, blog, game

Note. Number of documents: 12,789, number of clusters: 17

5.5 Dropped Clusters by the Experts – Second Iteration

Clusters dropped by the experts at second iteration are shown in Table 9. As can be seen in the table, Expert 1 did not suggest the themes associated with each cluster, but only provided information about the clusters that should be removed. Therefore, N/A, which stands for "Not Applicable", has been written in the column "Expert 1 Suggested Themes". The dropped clusters are bolded.

Table 9: Experts' Suggestions Regarding Removal of Clusters - Second Iteration

Cluster Number	Expert 1 Suggested Themes	Expert 1 Judgment	Expert 2 Suggested Themes	Expert 2 Judgment
0	**N/A**	**Dropped**	**Request/Info**	**Dropped**
1	N/A	Kept	Technology	Dropped
2	N/A	Kept	Multi-monitor	Kept
3	N/A	Kept	Signage	Kept
4	N/A	Kept	Projector	Dropped
5	N/A	Kept	Cinema	Dropped
6	N/A	Kept	Mobility	Dropped
7	N/A	Dropped	Film	Kept
8	N/A	Dropped	Theatre, Stage	Kept
9	N/A	Kept	Art	Kept
10	N/A	Kept	Technology	Dropped
11	**N/A**	**Dropped**	**Digital**	**Dropped**
12	**N/A**	**Dropped**	**Computing**	**Dropped**
13	**N/A**	**Dropped**	**Education**	**Dropped**
14	N/A	Kept	System control	Dropped
15	**N/A**	**Dropped**	**Business, Marketing**	**Dropped**
16	**N/A**	**Dropped**	**Blogs**	**Dropped**

5.6 Remaining Documents - Second Iteration

The total, dropped, and remaining number of documents in the second iteration is shown in Table 10.

Table 10: Remaining Documents - Second Iteration

Iteration 2	
Total documents	12,789
Dropped documents	5,071
Remaining documents	7,718

5.7 CLUTO Results - Third Iteration

In the third iteration, the same clustering algorithm was initially used; however, the results were not satisfactory, and the experts could not make-sense of them. Thus, we changed the CLUTO's algorithm method. As described in Section 4.12, direct method does not perform well for cluster number more than 20; therefore, instead of direct method, rbr method was applied. The CLUTO's results in the third iteration are shown in Table 11.

Table 11: Summary of CLUTO Output - Third Iteration

Cluster Number	Internal Similarity	External Similarity	Size	Descriptive words
0	0.383	0.025	97	Christi, projector, roadster, cinema
1	0.242	0.021	277	Ol, Cdt,amol,light,displai
2	0.237	0.021	96	Designlin,nomad,technlin,europ
3	0.193	0.026	287	Monitor, multi, multipl, compu, dual
4	0.191	0.031	186	Signag, kiosk, digit, gesturetek,self
5	0.166	0.024	109	Imax, theater, movi, regal, cinema
6	0.140	0.023	172	Wearabl, comput, xybernaut, devic,cloth
7	0.130	0.029	225	Dlp, projector, rear, project, dpi
8	0.126	0.027	213	Cinema, barco, digit, scroll, projector
9	0.120	0.027	565	Projector, dlp, lumen, lamp, project
10	0.112	0.020	270	Min, film, Egyptian, cinematheque
11	0.112	0.027	693	Signag, digit, network, content, player
12	0.099	0.019	133	Kmv,minicom, rgb,consol, switch
13	0.095	0.016	195	Vote, prison, quatermass, drama, episod
14	0.092	0.023	223	Touch, planner, touachscreen, display, lcd
15	0.090	0.023	188	Multi, wall, screen, monitor,displaylink
16	0.085	0.024	487	Art, artist, culture, creative, exhibit
17	0.076	0.024	482	Theatr, stage, art, bai, actor
18	0.078	0.027	372	Plasma, display, lcd, crt, crystal
19	0.073	0.024	430	Lcd, tft, display, Toshiba, panel
20	0.061	0.017	715	Theatr, plai, ticket, London, shakespear
21	0.057	0.024	541	Art, danc, music, perform, artist
22	0.048	0.023	762	Control, equip, system, sensor, embed

Note. Number of documents: 7718, number of clusters: 23

5.8 Dropped Clusters by the Experts - Third Iteration

Table 12 shows the clusters dropped by the two experts after the number of documents was reduced to 7,718. The dropped documents are bolded.

Table 12: Experts' Suggestions Regarding Removal of Clusters - Third Iteration

Cluster Number	Expert 1 Suggested Themes	Expert 1 Judgment	Expert 2 Suggested Themes	Expert 2 Judgment
0	Christie	**Dropped**	Vendor Specific	**Dropped**
1	Display tech	**Dropped**	Technology	**Dropped**
2	Exhibits	**Dropped**	Technology	**Dropped**
3	Computer monitors	**Dropped**	Components	**Dropped**
4	Signage	**Dropped**	Signage	**Dropped**
5	Imax	**Dropped**	Imax	**Dropped**
6	Wearable electronics	**Dropped**	Wearable Computers	**Dropped**
7	Projectors	**Dropped**	Projection video	**Dropped**
8	Movie theater	**Dropped**	Cinema projection	**Dropped**
9	Projectors	**Dropped**	Projection technology	**Dropped**
10	Movies	**Dropped**	Tech Spec	**Dropped**
11	Signage	**Dropped**	Digital Signage	**Dropped**
12	Unknown	**Dropped**	Technology	**Dropped**
13	Movie	**Dropped**	Prison voting	**Dropped**
14	Other displays	**Dropped**	Touch Screens	**Dropped**
15	Computer monitors	**Dropped**	Multi wall projection	**Dropped**
16	Art	Kept	Digital Art	Kept
17	Theatre	Kept	Theatre Stage	Kept
18	Displays	**Dropped**	Technology	**Dropped**
19	Displays	**Dropped**	Technology	**Dropped**
20	Tickets	**Dropped**	Theatre Signage	**Dropped**
21	Art	Kept	Performance arts	Kept
22	Control	**Dropped**	Control Systems	**Dropped**

Note. Number of documents: 7718, number of clusters: 23

5.9 Remaining Documents - Third Iteration

The total, dropped and remaining number of documents in the third iteration is shown in Table 13.

Table 13: Remaining Documents - Third Iteration

Iteration 3	
Total documents	7,718
Dropped documents	6,208
Remaining documents	1,510

The experts suggested stopping the clustering processes for the following reason: After three iterations, the number of documents was reduced significantly, and irrelevant information, as intended initially, was removed from the document corpus. Additional dropping eliminated the valuable and necessary information. For these reasons, the clustering procedure was stopped.

5.10 Statistical Analysis

For obtaining 120 samples from three databases, random numbers were generated by Excel and are shown in Table 14. As can be seen in the table, for each document corpus (38030, 7718, 1510), 40 random samples were generated. As explained in Section 4.15, each set of 40 samples was categorized into four groups of ten samples; therefore, 120 sample web pages were placed into 12 anonymous folders with each folder containing 10 web pages.

Table 14: Random Numbers Generated by Excel

	38030 documents				7718 documents				1510 documents			
Number	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	27609	35340	12519	28022	1708	5392	308	2899	460	1292	621	1407
2	28972	1228	13669	21394	4562	4106	906	6840	507	1133	761	1392
3	36059	25878	20808	17287	1215	322	2943	5049	1441	1341	933	1223
4	6705	24395	32457	19378	19	4539	6197	6873	982	22	1395	1318
5	11601	37501	18135	10029	3165	5484	3561	467	748	1279	454	689
6	15253	19074	4157	4323	5755	6142	7009	7021	343	1163	1281	726
7	16821	718	5701	35353	4518	754	7162	5004	740	766	1413	759
8	8696	532	343	22739	3554	3611	4192	5707	681	1180	116	766
9	20355	28026	14444	19683	5438	2681	4956	6407	1123	1509	735	1422
10	22499	20770	608	21808	4454	359	535	7258	1213	47	723	695

5.11 Summary of the Experts Judgments

The information provided from the forms completed by the experts (Appendix J) was analyzed by SPSS. Experts' judgments regarding the recognition of the original sources of the

samples are provided in Table 15. From this table, it is clear that Expert 1 judgment was 100 percent correct, and Expert 2 recognition was 87.5 percent correct.

Table 15: Comparisons of the Experts' Judgments With the Actual Database

Expert 1	Expert 2	Actual Database
Small	Small	Small
Medium	Medium	Medium
Large	Large	Large
Small	Small	Small
Large	**Medium**	**Large**
Large	Large	Large
Small	Small	Small
Medium	Medium	Medium
Large	**Medium**	**Large**
Small	Small	Small
Medium	Medium	Medium
Large	Large	Large

5.12 Judgments' Frequencies

In Table 16, the experts' judgments are shown in terms of relevancy and expectedness of the documents.

Table 16: Summary of the Experts' Judgments

	Expert 1 Frequency	Expert 1 Percentage	Expert 2 Frequency	Expert 2 Percentage
Relevant	2	1.7%	14	11.7%
Maybe Relevant	14	11.7%	18	15%
Irrelevant	104	86.7%	88	73.3%
Total	120	100%	120	100%
Clearly Unexpected	7	5.8%	10	8.3%
Somewhat Expected	32	26.7%	18	15%
Expected	81	67.5%	92	76.7%
Total	120	100%	120	100%

As can be seen, Expert 2 found more relevant documents than Expert 1 in the 120 samples. However, both experts found roughly the same results regarding the expectedness of the documents.

The validation of the author's judgment is analyzed in the following sections. Tables 17 and 18 indicate the cross tabulation tables of both experts depicting each of the three datasets in terms of relevancy and expectedness of the documents. For example, the first number in the first row and first column of Table 17 shows that, in a small dataset, both experts found 14 "Irrelevant" documents. The fifth number in the first row of that table also shows that, in medium dataset, Expert 2 found three "Irrelevant" documents; while Expert 1 found three "Maybe Relevant" documents.

Table 17: Cross Tabulation Table for Relevancy of the Small, Medium, Large Datasets

		Expert 1								
		Irrelevant			**Maybe Relevant**			**Relevant**		
		Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Expert 2	**Irrelevant**	14	31	34	0	3	4	N/A	N/A	2
	Maybe Relevant	12	4	N/A	1	1	N/A	N/A	N/A	N/A
	Relevant	9	0	N/A	4	1	N/A	N/A	N/A	N/A

Table 18: Cross Tabulation Table for Expectedness of the Small, Medium, Large Datasets

		Expert 1								
		Unexpected			**Somewhat Unexpected**			**Expected**		
		Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Expert 2	**Unexpected**	3	N/A	N/A	7	N/A	4	0	N/A	2
	Somewhat Unexpected	3	N/A	N/A	6	3	N/A	N/A	1	N/A
	Expected	1	N/A	N/A	6	5	5	9	31	35

The bar chart diagrams (Figures 10, 11, 12, and 13) represent the experts' judgments in terms of the relevancy and expectedness of the datasets. As can be seen in Figure 10, according to Expert 2, the relevancy of the documents for the small dataset was more than that of the medium dataset and the relevancy of the medium dataset was more than that of the large dataset. In contrast, according to Expert 1 only two websites were completely relevant in the whole set (Figure 11). However, in terms of expectedness, both diagrams yielded roughly the same results (Figure 12, Figure 13).

Figure 10: Expert 2 Judgment for Relevancy of the Documents

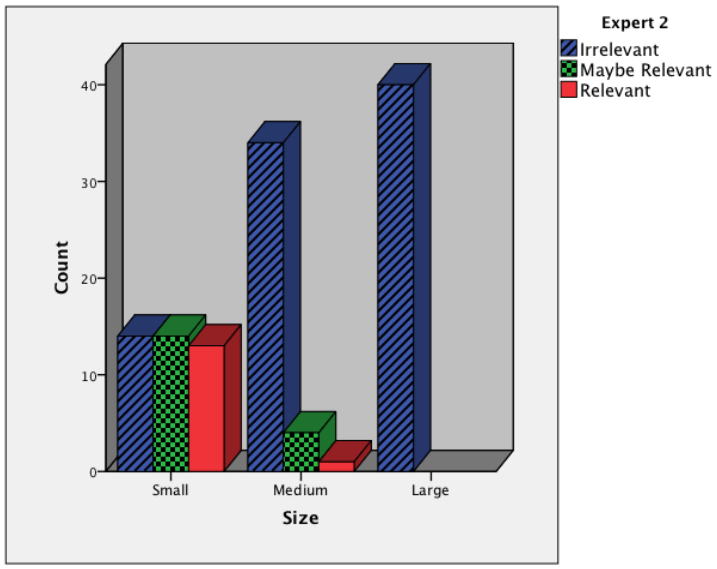


Figure 11: Expert 1 Judgment for Relevancy of the Documents

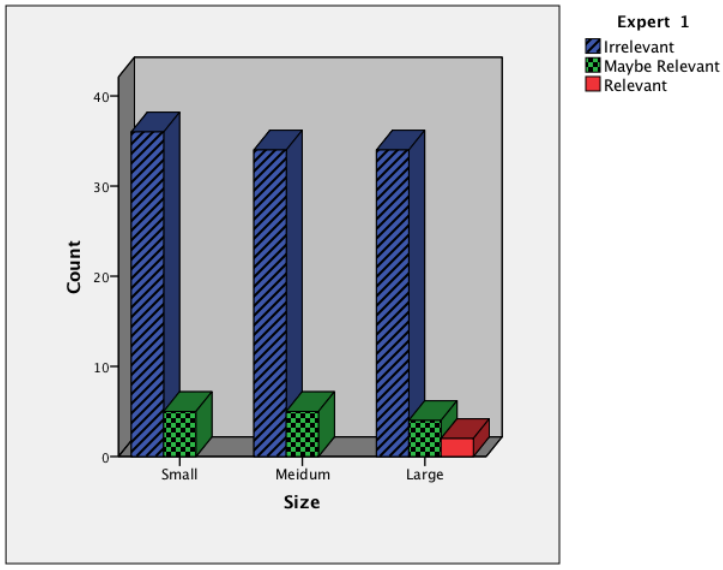


Figure 12: Expert 2 Judgment for Expectedness of the Documents

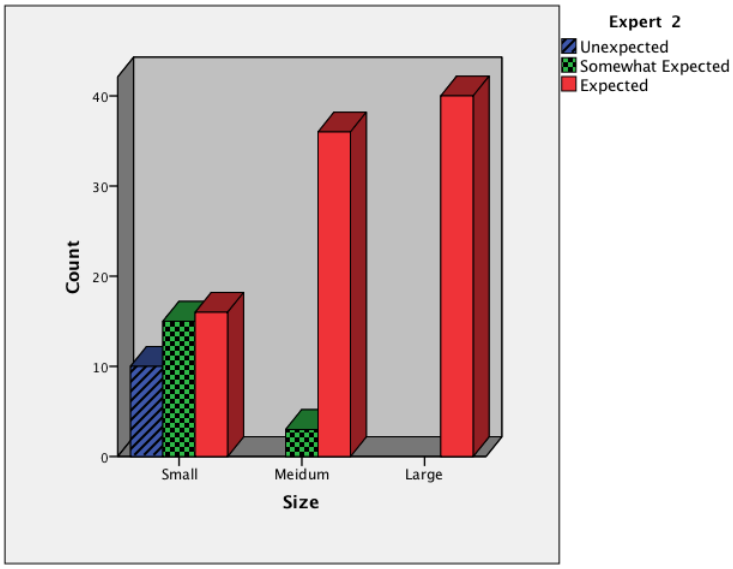
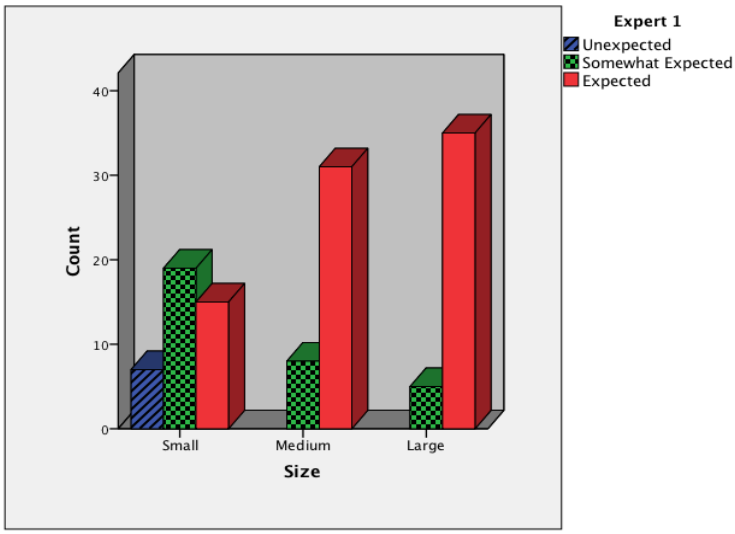


Figure 13: Expert 1 Judgments for Expectedness of the Documents



An aim was to explore possible disparities between the judgments in terms of relevancy and expectedness of the documents between the whole set (120 samples) and each of the three databases (i.e., small, medium, large). Since the applied scale was in ordinal measurement, and the normality of the dataset was not presumed, the Wilcoxon-ranked test was performed. The Wilcoxon test is an alternative test for paired t-tests and is used when the paired t-test assumptions are violated. It can be used when the population cannot be assumed to be normal or when the data are in the ordinal scale.

Table 19: Statistical Analysis for Comparing Two Judgments

	Relevancy				**Expectedness**			
	Small	**Medium**	**Large**	**Overall**	**Small**	**Medium**	**Large**	**Overall**
Z Wilcoxon value: 2* vs. 1*	4.54	0.707	2.271	3.233	2	1.663	2.236	1.333
Two tailed P-value: 2* vs. 1*	**0.000**	0.48	0.023	**0.001**	0.841	0.103	0.025	0.182
Mean 2	49.25	25.25	20	31.5	54.5	77	80	70.5
Mean 1	23.75	23.75	26	24.5	55.25	74	76.25	68.5
Spearman's Correlation 2 vs. 1 Kappa	0.379	0.285	N/A	0.171	0.453	0.458	N/A	0.582
P Correlation value 1 vs. 2	0.016	0.074	N/A	0.062	0.003	0.003	N/A	**0.000**
Correlation 2 vs. actual	N/A	N/A	N/A	0.875	N/A	N/A	N/A	0.875
Correlation 1 vs. actual	N/A	N/A	N/A	1	N/A	N/A	N/A	1

Note. Correlation significant at the 0.01 level (2-tailed); *2 stands for Expert 2, and 1 stands for Expert 1; Confidence Interval = 95%; N/A means that the statistical analysis could not be performed because at least one variable was constant, or the variable was not chosen.

The results and the P-values of the analysis are shown in Table 19. Prior to that, the paired t-test was also applied, and the yielded results were compared with Wilcoxon test results. Both results were relatively similar, possibly because the number of samples was 40 for each database, and based on central limit theory the population can be assumed to be normally distributed. In Table 19, the means of the Expert 1 judgment and Expert 2 judgment for the presented variables are also provided. It is clear that the degree of relevancy and expectedness indicated by Expert 2 was greater than that of Expert 1, which means that Expert 2 found more relevant and less unexpected documents in the whole 120 samples than Expert 1.

Inter-rater reliability counts the degree of agreement between judges. In Table 19, an analysis was performed to define the amount of consensuses in the ratings given by the two judges. Due to the

ordinal nature of our data, Spearman's rho (a non-parametric test) correlation was used for finding the correlation between the paired datasets. Spearman correlation is used when the variables are not assumed to be normally distributed and yet are assumed to be ordinal. Kappa statistic could not be used in this case because the rating scale had natural ordering (e.g., clearly relevant, maybe relevant, irrelevant). In terms of relevancy, there was slight agreement between the experts, $r(120) = 0.171$, $p > 0.01$; however, in terms of expectedness, the two judges were significantly correlated with each other $r(120) = 0.582$, $P < 0.01$.

As can be seen in the last two rows of Table 19, Expert 1 recognized the original database sources of all the samples correctly, $r(120) = 1$, while the correlation of Expert 2 judgment with the original dataset was 0.875.

To test whether the distribution of relevant documents between different datasets is the same, the Krusal-Wallis test (the non-parametric alternative of one way ANOVA), was applied for the following reasons:

- The nature of our data was non-parametric.
- The comparison included three independent groups (datasets).
- The comparison included three sets of scores (i.e. relevancy, maybe relevant, irrelevant) that came from different groups.
- The provided data was ordinal.

The results of the analysis are shown in Table 20. The following results are yielded from Table 20.

Regarding Expert 2, the distribution of relevant documents is not the same across the three databases. For the small dataset it is greater than that of the medium one, and for the medium dataset it is greater than that of the large one.

Regarding Expert 1, the distribution of relevant documents is the same across the three databases.

Regarding both experts, the distribution of unexpected documents is not the same across the three databases. For the small dataset it is greater than that of the medium one, and for the medium dataset it is greater than that of the large one.

Cross tabulation analysis was also performed to analyze the experts' judgments in terms of the relevancy and expectedness of the each of the three databases. Chi-square test of independence was also achieved initially to compute the statistical significance of the cross-tabulation table (3×3), and to determine whether there is a significant relationship between the data reduction and relevancy of the documents, or whether there is a significant relationship between data reduction and having more unexpected documents.

Table 20: Kruskal-Wallis Test for Comparison of the Three Datasets

		Chi-Square	Significance Level (P-value)
Relevancy	Expert 1	0.223	0.894
	Expert 2	48.089	0.000
Expectedness	Expert 1	31.806	0.000
	Expert 2	46.939	0.000

Note. Degree of freedom: 2, significance level: 0.05

For any Chi-Square test, the data must satisfy the following two assumptions:

- The sample must be randomly selected from the population.
- The sample size, n, must be large enough so that the expected count in each cell is greater than or equal to five.

Regarding our dataset, the second assumption was violated; therefore, for each pair of the dataset the contingency table (2 ×2) was provided as an alternative for Chi-Square test. The P-values of the analysis for testing the relevancy of the documents are shown in Table 21. For some values, Fisher's Exact test was not applicable because the associated expert's judgment was constant. Thus, there was no difference in one of the categorical variables and, therefore, it was impossible to perform Fisher's statistical analysis. In both tables, the P-values of the bolded numbers are less than 0.05 (significance level), which indicates a significant association between the variables. To be precise, the following results could be derived from Table 21.

5.13 Regarding Expert 2 Judgments

The number of relevant documents was not equally distributed between the pair databases.

- The ratio of maybe relevant/irrelevant documents in the small dataset was significantly larger than that in the medium one.

- The ratio of relevant/irrelevant documents in the small dataset was significantly larger than that in the medium one.
- The ratio of maybe relevant/irrelevant documents in the small dataset was significantly larger than that in the large one.
- The ratio of relevant/irrelevant document in the small dataset was significantly larger than that in the large one.

For the other values ($P > 0.05$), there was no significant relationship between the variables.

Table 21: The P-values of Fisher Exact Test for Contingency Table Between Paired Variables

Pairwise Datasets	Relevancy		
	Variables	**Expert 1**	**Expert 2**
Small vs. Medium	R* vs. M*	N/A	0.355
	M vs. I*	1	**0.001**
	R vs. I	N/A	**0.000**
Small vs. Large	R vs. M	0.455	N/A
	M vs. I	1	**0.000**
	R vs. I	0.493	**0.000**
Medium vs. Lar ge	R vs. M	0.455	N/A
	M vs. I	1	0.052
	R vs. I	0.493	0.467

Note. * R stands for Relevant, M for Maybe Relevant and I for Irrelevant documents, N/A means no statistical analysis was provided because at least one expert's judgment was constant. Degree of freedom=1, significance level: 0.05

In addition, in terms of expectedness, the following results are derived from Table 22.

5.14 Regarding Both Experts' Judgments

- The ratio of somewhat unexpected/expected documents in the small dataset was significantly larger than that in the medium one.
- The ratio of unexpected/expected documents in the small dataset was significantly larger than that in the medium one.
- The ratio of somewhat unexpected/expected documents in the small dataset was significantly larger than that in the large one.

Table 22: The P-values of Fisher Exact Test for Contingency Table Between Paired Variables

Pairwise Datasets	Expectedness		
	Variables	**Expert 1**	**Expert 2**
Small vs. Medium	Ex vs. SE	**0.003**	**0.000**
	SE vs. UE	0.16	0.533
	Ex vs. UE	**0.001**	**0.000**
Small vs. Large	Ex vs. SE	**0.000**	**0.000**
	SE vs. UE	0.562	N/A
	Ex vs. UE	**0.001**	**0.000**
Medium vs. Large	Ex vs. SE	0.378	0.116
	SE vs. UE	N/A	N/A
	Ex vs. UE	N/A	N/A

Note. * Ex stands for Expected, SE for Somewhat Expected and UE for Unexpected documents, N/A means no statistical analysis was provided because at least one expert's judgment was constant. Degree of freedom=1, significance level: 0.05

Chapter 6
Discussion and Conclusions

The purpose of this exploratory study is to find a potential method for detecting weak signals by using Internet-based environmental scanning in a domain of interest. The aim was to investigate the feasibility of the proposed model and some indication of its potential for future research and practical application. Specifically, the study proposed to locate weak signals of information about the application of Micro Tiles, a recent innovative product of the Christie Digital Company, from the World Wide Web. The degree of relevancy and expectedness of the documents were two measurements defined for evaluating weak signals. In an effort to reduce the information retrieved from the Internet and detect weak signals, clustering techniques was used to reduce the available data and CLUTO was the analysis package.

The initial information retrieved from the Internet was reduced in three iterations; that reduction yielded three subsets of documents: small, medium, and large. Obtaining 40 random samples from each of the three databases, the author asked the two experts to judge on the degree of relevancy and expectedness of the documents in each subset. Based on the opinions of Expert 2, the small dataset contained more relevant and unexpected documents than the medium one did, and the medium dataset contained more relevant and unexpected documents than the large (original) set did. Findings by Expert 2 supported the preliminary propositions, indicating that applying the proposed model makes it possible to find weak signals from document corpus. Similarly, in terms of expectedness, according to Expert 2, the small dataset had more unexpected documents than that for the two others, thus supporting the proposition.

In addition, when 40 random and anonymous samples of documents in groups of ten, from each of the three small, medium, and large datasets were presented; Expert 1 was 100% correct and Expert 2 was 87.5% correct for guessing from which corpus the samples were drawn.

In contrast, in terms of relevancy, the findings by Expert 1 do not imply that the smallest set contained more relevant documents. Regarding Expert 1 judgment, only two “clearly relevant” documents existed in the large dataset.

Possible reasons for this discrepancy are:

- The threshold differences set by the experts because the relevancy threshold for Expert 1 was clearly higher than the relevancy threshold of Expert 2.

- Perspective differences could have existed between the two experts for assessing the documents. One expert had an engineering background and evaluated the relevancy of the documents in terms of their possible contribution to design new Micro Tiles, while the other expert had a product management perspective and was interested in information that deployed the application of Micro Tiles.
- The two experts assessed the documents independently. For more consistent evaluation, it may be beneficial to have group meetings among experts. In this way, judges could justify and adjust their reasons based on mutual opinions and consensus.
- According to Cohen and Levinthal (1990), although overlapping individual ideas is beneficial, new knowledge originates from the diversity of knowledge within individuals. Therefore, using judges with different expertise, despite their being inconsistent, would enhance the absorptive capacity of the firm.

The trends of this study suggest that the proposed model successfully reduced the documents into the smallest set that contained more unexpected results. These trends are appealing as they offer a cost-effective way of conducting environmental scanning on the Internet. Information on the Internet is free of charge and the applied software is open source; therefore, organizations can access and make sense of the hidden information easily and earlier than their competitors. In addition, this systematic approach aligns perfectly with the huge number of documents in a timely manner, and applies easily in any environment. It can be used to overcome the problems of weak signals detection in environmental scanning processes introduced by Ansoff (1975) because it is a way of moving from the traditional point of view of strategic management to a more modern one as displayed in Table 1. Complying with Ansoff's real time strategic view of a firm (1980), this method aims at preventing strategic surprises, minimizing surprise damage and responding to threats and opportunities ahead of time.

The experimental process of the method also aligns with the basic essentials of the foresight process introduced by Cuhls (2003). Being dependent on the opinions of the experts, communicating about the future, being flexible in shaping the future, comprising both qualitative and quantitative procedures, and bringing people together for discussion about the future are the main rationales of labeling this method as foresight. In addition, this method incorporates with three phases of the foresight process defined by Horton (1999), including inputs, foresight, and outputs (Section 2.2). The Internet was applied to provide the input and the clustering toolkit (CLUTO) was used for converting retrieved information from the Internet into the format comprehensible to the experts

(Translation). The experts, who were not employees of the Christie Digital Company, were involved in the project to interpret the results and make sense of them (Interpretation). The obtained knowledge could further be presented to the managers of Christie Digital Company in various formats, including presentations, reports, or roadmaps (Output).

Environmental scanning on the Internet not only enhances the peripheral vision of a firm, but also increases a firm's absorptive capacity by amplifying its knowledge acquisition. Knowledge acquisition "refers to the firm's routines and processes that allow it to analyze, process, interpret and understand the information obtained from external sources" (Zahra & George, 2002, p. 189). This external information brings diversity of knowledge to a firm and intensifies its cumulative absorptive capacity, ultimately enabling the firm to assimilate and exploit new knowledge whenever it is required. As Zahra and George indicated in 2002, the attributes of knowledge acquisition capability are intensity, speed, and direction. A firm's knowledge acquisition ability associates significantly with the intensity and the speed of acquiring the required knowledge. As organizations are restricted by internal resources, acquiring knowledge and the learning process is slower than usual, thus it might take several years to build robust absorptive capacity. In addition, because the direction of acquiring knowledge is complex and heterogeneous, firms should have individuals with diverse backgrounds and varied expertise to successfully utilize external technologies.

6.1 Limitations

- The trends of this study are restricted by the mindsets of two experts. More consistent results could certainly be obtained by having multiple experts with varied expertise and knowledge in digital media and theatre production. Assessing the documents through commonality in a group meeting would improve the degree of communication. Similarly, the article by Talke (2007) clearly explained that a corporate mindset is an essential element affecting innovative activities of a firm; he indicated that proactive, analytical, aggressive and risk averse management actions are positively associated with a new product performance toward market and technology perspective.
- A second limitation of the study involves the number of samples chosen from each dataset. The analysis of the experts was based on only 40 samples. Obviously, for more accurate results, it would have been better to examine more samples.
- A third limitation of the study is related to the selection of clustering algorithms and the number of clusters. While the algorithm and the number of clusters was logically chosen, better clustering results might be obtained through alternative methods. All steps

involved in the clustering process, including term filtering, tokenization, stemming, and stop word removal affected the clustering results; thus, changing these steps could modify the results. Moreover, in the K-means algorithm, the clustering number has to be defined a priori. Because no ideal clustering number is defined in the literature, selection of the proper clustering number is a challenge; hence, the alternative numbers might also improve the results.

- Judging based on the analysis of one software product is another limitation of the study. Although CLUTO has performed well with our huge number of documents, alternative software might yield different results. It is worth mentioning that, initially, other text mining software was tested; however most of them did not perform well with large document collections, and could not offer clustering solutions.

6.2 Future Research

Three possible areas could be explored in future research including:

- Proposing powerful theoretical models to describe weak signals, their advantages, and problems could guide strategic managers toward better insights about their peripheral vision. Still weak signals theory suffers from lack of a precise definition in the literature (see Section 2.4), and proposing a robust model that clearly defines its elements and applications would be useful.
- As discussed in the methodology section, we entered the queries into the search engine in year 2009. Information on the Internet is changing constantly; we can therefore enter the queries into the search engine at special intervals and thus compare the results. For example, one possible way is to put the queries into the search engine each year and compare different years' results to determine whether the same results will be obtained in subsequent years or not. Selecting another search engine and applying the method for another innovative product could also lead us to alternative results.
- In addition, alternative practical methods to detect weak signals by Internet-based environmental scanning or any other systematic procedure could help organizations take advantage of hidden opportunities and avoid future surprises. Although the importance of detecting weak signals is emphasized in literature, few practical methodologies for its detection were suggested. Further research into the developing and commercializing of a robust tool for detecting weak signals in a real time is advised. Such a tool would detect

weak signals in real-time from huge amounts of data, including, blogs, complainers and competitor's boards, and websites.

The following method proposed by Day and Schoemaker (2002), however, may be applied by organizations to clarify whether they need to utilize a tool for detecting weak signals or not. However, we still emphasize the need for future studies to find a support tool for detecting weak signals.

Day and Schoemaker (2002) proposed a peripheral vision tool that assist managers to calculate their existing capability and need for peripheral vision, and hence help them to locate their organizations in quadrants as vulnerable, vigilant, focused, and neurotic. According to the authors, a vulnerable organization has low capability and high need for peripheral vision. A vigilant organization has high capability and high need for peripheral vision. A focused organization has low capability and low need for peripheral vision, and a neurotic organization has high capability and low need for peripheral vision. Only a vulnerable organization should actively enhance its peripheral vision and detect weak signals. For other types of organizations, different kinds of strategies should be applied. Thus, we recommend that managers use this tool for calculating their organization's capability and need for peripheral visions, and find whether the organization is vulnerable, vigilant, focused or neurotic. Simultaneously, future study proposing a robust tool to detect weak signals is recommended.

Appendix A: Micro Tiles

Christie Digital is a global visual technology company that provides a range of display technologies and solutions for various application areas including cinema, business environments, control rooms, and other high demanding organizations (Christie, 2011).

Currently, Christie Digital designs and delivers innovative display products known as Micro Tiles to its market. Micro Tiles are small display units that are composed of modular 306 × 408 (16"×12") dimensions and weigh only 20 lb (9.4 kg). Micro Tiles lock together quickly and easily to build a large display unit; hence, this flexibility allows a product to be built in just about any environment. Due to Digital Light Processing (DLP) technologies, Christie's Micro Tiles offer colour ranges which are superior to the those of usual Liquid Crystal Display (LCD) and plasma technologies. With Micro Tiles, audiences are able to perceive high resolution images in various positions regardless of whether they sit away from, close to or at an angle to the display. Each Micro Tile has a sensor inside which enables the detection of another unit, and thus the size and layout of the displayed image is arranged in terms of its whole size. Micro Tiles have high resolution and low servicing and maintainance costs; thus, each Micro Tile can be replaced or removed in less than 15 minutes from the front without shutting down the whole display. In addition, the radio frequency remote control can be managed via the menu command on the displays from a distance of up to 100 metres. Micro Tiles can be applied in diverse places such as hotels, public spaces, museums, sporting events, live theatres, and other areas requiring display solutions (Christie Micro Tiles, 2010).

Figure 14[a]: A Unit of Micro Tile

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Figure 15[b]: An Example of a Micro Tile Display

Figure 16[a]: Dimensions of Micro Tiles

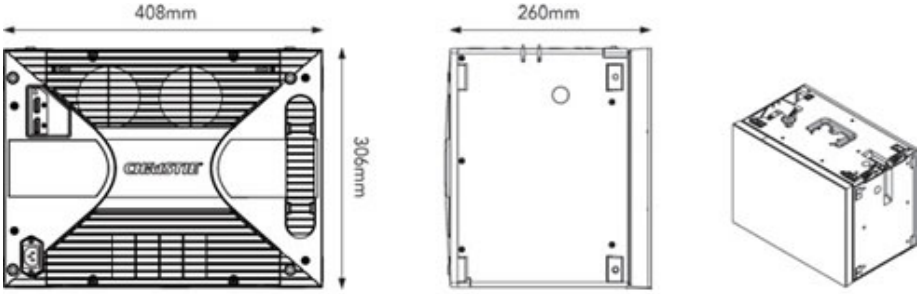

Figure 17[c]: Micro Tiles Easy Wall Installation and Services

Note.[a] Adopted from (Christie Micro Tiles, 2010). [b]Adopted from (Josiah, 2009). [C]Adopted from (Christie Digital System, 2011)

Appendix B: DEVONagent

DEVONagent provides a clean Mac-like user interface for finding information in the public web with the use of more than 130 plug-ins for popular search engines, databases, and search tools. As it performs its search, DEVONagent identifies pages that have broken, are out of date, or are related to advertisements, and then filters these out before displaying the search results. Its unique high-end Boolean search operators allow AND, OR, BEFORE, NEAR, NEXT, AFTER as well as parentheses and wildcards to make search results more accurate. DEVONagent downloads each page instead of displaying only the link. Searching with DEVONagent usually takes longer than searching with regular search engine tools; however, ultimately the reader saves time by not needing to go through every page and filter manually. DEVONagent assists the user in finding, collecting, and organizing information while tightly integrating it with DEVONthink (Appendix C) for building an organized archive of web pages (DEVONtechnologies, 2011).

As mentioned in the DEVONagent manual (DEVONtechnologies, 2011), there are several appealing reasons for using DEVONagent:

- Getting improved search results
- Spending less time on searching for relevant results
- Searching more specifically
- Archiving searching and continuing at a later time
- Working effectively with Apple script and DEVONthink

Boolean Operators

- **Syntax:** *Term 1 BOOLEAN OPERATORS Term 2*
- **AND:** contains term 1 and term 2
- **OR:** contains term 1 or term 2
- **NOT:** does not contain term
- **AFTER:** term 1 occurs after term 2
- **BEFORE:** term1 occurs before term 2

Appendix C: DEVONthink

DEVONthink is based on a powerful artificial intelligence architecture that helps users to find, store, organize, edit, analyze, and archive the documents on a Mac. It is a good option for handling huge collections of data, since with only a few simple clicks it assists the user to gain a broader view of the files and discover the relationship between them. DEVONthink Pro "allows user to pull the signal out of an ocean of noise, and creates elegance, perspective, and order, out of information overload" (DEVONtechnologies, 2011, p. 8).

Appendix D: The Mathematical Definition of CLUTO's Clustering Criterion Functions

Criterion Function	Optimization Function
I_1	$maximize \sum_{i=1}^{k} \frac{1}{n_i} (\sum_{u,v \in S_i} sim(v,u))$
I_2	$maximize \sum_{i=1}^{k} \sqrt{\sum_{u,v \in S_i} sim(v,u)}$
ε_1	$minimize \sum_{i=1}^{k} n_i \frac{\sum_{u \in S, v \in S_i} sim(v,u)}{\sqrt{\sum_{u,v \in S_i} sim(v,u)}}$
$\mathcal{G}_1$	$minimize \sum_{i=1}^{k} \frac{\sum_{u \in S, v \in S_i} sim(v,u)}{\sum_{u,v \in S_i} sim(v,u)}$
$\mathcal{G}_1'$	$minimize \sum_{i=1}^{k} n_i^2 \frac{\sum_{u \in S, v \in S_i} sim(v,u)}{\sum_{u,v \in S_i} sim(v,u)}$
$\mathcal{H}_1$	$maximize \frac{I_1}{E_1}$
$\mathcal{H}_2$	$minimize \frac{I_2}{E_1}$

Note. Adopted from (Karypis, 2002, p. 10). k is " the total number of clusters. S is the total objects to be clustered, S_i the set of objects assigned to the *i*th cluster, n_i is the number of objects in the *i*th cluster, v and u represent two objects, and $sim(v,u)$ is the similarity between two objects" (Karypis, 2002, p. 10).

Appendix E: Forty-eight Queries Suggested by the Experts

No	Query	Number of Documents
1	modular AND projector OR video BEFORE display	3075
2	adaptive BEFORE theatrical OR theatre BEFORE set OR environment	9427
3	adaptive BEFORE optics BEFORE video AND projector AND display	58
4	adaptive OR modular AND video BEFORE technology	646
5	adaptive OR modular AND display BEFORE technology	759
6	laser AND projection	1275
7	digital AND media AND performance AND projection AND led	158
8	digital AND theatre AND live AND lcd	247
9	drama AND innovation AND performance AND technology AND display	92
10	display AND technology NOT cinema NOT television	2616
11	telemetric AND theatre AND digital	188
12	tile AND led AND display AND video NOT television	172
13	lcd AND laser AND video AND display AND theatre	120
14	presence AND resolution AND experience AFTER digital AND projection	140
15	laser OR oled OR foled AND modular AND digital display	139
16	wearable AND display AND digital NOT ubiquitous AND computing	707
17	telepresence AND modular AND mobile AND scalable NOT corporate	52
18	advert* AND techno* AND screen NOT billboard	63
19	architect AND screens AND projection AND digital NOT animation	109
20	drama AND digital arts NOT animation AND laser AND projection	51
21	drama AND projection OR experiment OR laser	5017
22	digital AND display AND indoor	788
23	digital BEFORE display AND theatre OR performance	2500
24	performing BEFORE arts AND digital AND innovation	326
25	digital AND interaction AND public AND performance	620
26	projection AND theatre AND performance AND movie AND TV	96

Forty-eight Queries Suggested by the Experts – Continued

No	Query	Number of Documents
27	installation AND performance AND art AND theatre AND stage	251
28	intermedial AND technology AND projection AND led AND display	20
29	virtual AND scenary AND lighting AND projection AND surface	6
30	multi AND screen AND display	1358
31	realtime AND network AND display	271
32	lambda AND display AND wall AND visualization	84
33	digital AND signage AND network AND control	1037
34	digital AND signage AND array AND control	346
35	modular AND (projectOR OR video) BEFORE display	403
36	adaptive BEFORE (theatrical OR theatre) BEFORE (set OR environment)	19
37	(adaptive BEFORE optics) BEFORE (video AND projectOR AND display)	6
38	(adaptive OR modular) AND (video BEFORE technology)	669
39	(adaptive OR modular) AND (display BEFORE technology)	535
40	(presence OR experience) after digital AND projection	547
41	resolution AFTER digital AND projection	673
42	(laser OR oled OR foled) AND modular AND "digital display"	73
43	wearable AND display AND digital AND (computing NOT ubiquitous)	661
44	advert and techno and screen not billboard	43
45	(drama and "digital arts" not animation) and laser and projection	29
46	drama and (projection or experiment or laser)	237
47	(digital before display) and (theatre or performance)	1101
48	(performing before arts) and digital and innovation	220

Appendix F: Python Code for Removing the Clusters

This is the Python code for removing the clusters used in the methodology procedure. When each expert suggested removing some clusters, this code was applied to find the documents included in those clusters. The documents and the related URLs were removed by the following code.

```
import sys
        inputFile = file("2009D2-17-url")
        outputFile = file("ndocs", "w")
        inputClusterNums = file("2009D2-17.mat.clustering.23")
        outputClusterNums = file("nnums", "w")


        clustersToBeRemoved = {}
        for i in xrange(1, len(sys.argv)):
                clustersToBeRemoved[sys.argv[i]] = True


        for line in inputClusterNums:
                numCluster = line.strip()
                doc = inputFile.readline()
                doc = doc.strip()
                if(numCluster not in clustersToBeRemoved):
                        outputClusterNums.write(numCluster + "\n")
                        outputFile.write(doc+"\n")
        outputClusterNums.close()
        outputFile.close()
```

Appendix G: Keyword Description for Boolean Search

NAME: ______________ KEYWORD DESCRIPTION FOR BOOLEAN SEARCH

______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______
______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______
______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______
______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______	OR NOT AND BEFORE AFTER	______

Appendix H: Merging Scripts

Having plain text files of 48 queries, this code was applied to aggregate all plain text files into one text file. This code was also applied for aggregating the URLs of the web pages.

```
set file1Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q1_text"
set file2Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q2_text"
set file3Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q3_text"
set file4Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q4_text"
set file5Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q5_text"
set file6Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q6_text"
set file7Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:Q7_text"
set file8Path to "Macintosh HD:Users:nasimtabatabaei:Desktop:Result2010:M7_text"


set file1Text to read file file1Path
set file2Text to read file file2Path
set file3Text to read file file3Path
set file4Text to read file file4Path
set file5Text to read file file5Path
set file6Text to read file file6Path
set file7Text to read file file7Path


set finalText to file1Text & return & file2Text & return & file3Text & return & file4Text & return & file5Text & return & file6Text & return & file7Text
	writeTo(finalText, file8Path, false, string)

	on writeTo(this_data, target_file, append_data, mode) -- append_data is true or false, mode is string etc. (no quotes around either)
		try
			set target_file to target_file as Unicode text
			if target_file does not contain ":" then set target_file to POSIX file target_file as Unicode text
			set the open_target_file to open for access file target_file with write permission
			if append_data is false then set eof of the open_target_file to 0
			write this_data to the open_target_file starting at eof as mode
			close access the open_target_file
			return true
		on error
			try
				close access file open_target_file
			end try
			return false
		end try
	end writeTo
```

Appendix I: Convert HTML Pages to Plain Text Files

This code was applied for three reasons: to select the web pages of each query, to change those web pages to plain text files, and to aggregate the plain text files into one text file with the condition that each line of the text file corresponds to one web pages.

```
tell application id "com.devon-technologies.thinkpro2"
	set theDatabase to the selection

	set theTextFilePath to "/Users/nasimtabatabaei/Desktop/result_final_text" as POSIX file
	set theTextFileReference to open for access theTextFilePath with write permission

	set theURLFilePath to "/Users/nasimtabatabaei/Desktop/result_final_url" as POSIX file
	set theURLFileReference to open for access theURLFilePath with write permission

	set recordCount to 0

	repeat with thegroup in records of theDatabase

		repeat with theRecord in children of thegroup

			repeat 1 times
				try
					set theText to plain text of theRecord
					set theURL to URL of theRecord
					set recordCount to (recordCount + 1)
				on error
					exit repeat
				end try

				set theTextItems to paragraphs of theText
				set AppleScript's text item delimiters to " "
				set theText to theTextItems as string
				set AppleScript's text item delimiters to {""}

				write theText to theTextFileReference starting at eof
				write (return & linefeed) to theTextFileReference starting at eof

				write theURL to theURLFileReference starting at eof
				write (return & linefeed) to theURLFileReference starting at eof

			end repeat
		end repeat

	end repeat

	close access theTextFileReference
	close access theURLFileReference
	recordCount

end tell
```

Appendix J: Judgment Form for Evaluating the Web Pages

Examiner's name: Set Number: Date:

Document Number	Clearly Relevant (p=>70%)	Maybe Relevant (p=70-30%)	Irrelevant (p=<30%)	*Document Number*	Clearly Unexpected (p=<30%)	Somewhat Unexpected (p=30-70%)	Expected (p=>70%)
1				*1*			
2				*2*			
3				*3*			
4				*4*			
5				*5*			
6				*6*			
7				*7*			
8				*8*			
9				*9*			
10				*10*			
Total				**Total**			

***Technical Relevance* for firm's product management:**

• How likely is the Christie Digital product management team to find the information relevant to Micro Tiles?

***Application Expectancy* for theatre professionals:**

• How likely is the UW creative / theatre production team to find the information inspires the novel or unique application of Micro Tiles?

This set belongs to *Smallest/ Medium/Largest* dataset.

- ***Smallest:*** 1500 documents [_]
- ***Medium:*** 7718 documents [_]
- ***Largest:*** 38030 documents [_]

Appendix K: Sample A of the Web Pages

The following document is one sample of the web page that was evaluated by the experts. The following is the experts' judgments:

Expert 2 judgment: "Clearly Relevant", "Clearly Unexpected"

Expert 1 judgment: "Irrelevant", "Clearly Unexpected"

IAAA

Department of
Arti*Facial* Expression

Flexible and precise digital control of the human body is one of the most important challenges in the development of fully automated dance and theatre. The IAAA Department of Arti*Facial* Expression is focussed on basic research and artistic applications in this area.

The IAAA Department of Arti*Facial* Expression develops new forms of algorithmic performance art which employ the human body as a computer-controlled display device. Our current investigations focus on the human face. We study the mechanisms of human facial expression, and build innovative muscle-control technologies. The results of our R & D are demonstrated in video-installations and live performances.

Appendix L: Sample B of the Web Pages

The following document is one sample of the web page that was evaluated by the experts. The following is the experts' judgments:

Expert 2 judgment: "Maybe Relevant", "Somewhat Unexpected"

Expert 1 judgment: "Clearly Relevant", "Somewhat unexpected"

DIGITAL TIGERS

"Carpe Pixels": The Digital Tigers Story

Digital Tigers offers by far the most complete multi-monitor product line in the world.

Our mission is to provide complete multi-monitor solutions that work together seamlessly — from multi-screen desktop displays (Zenview), to desktop workstations (Stratosphere), to notebook docking stations (SideCar), to multi-monitor software utilities (Zenview Manager).

Beyond complete solutions, we also offer the industry's highest quality components at the industry's best prices. Check the specifications before you buy: you can't buy a better multi-screen display than we offer, and most of our displays are also more affordable than those of competitors.

Testimonials

"Flawless"

"My experience with Digital Tigers has been flawless. I would recommend them to anyone in

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