Futures 44 (2012) 206–217

Contents lists available at SciVerse ScienceDirect

Futures

journal homepage: www.elsevier.com/locate/futures

Weak signals analysis, knowledge management theory and systemic socio-cultural transitions

Jari Kaivo-oja

Finland Futures Research Centre, University of Turku, Tykistökatu 4 D, ElectroCity, 7th Floor, FIN 20520 Turku, Finland

ARTICLE INFO

Article history:
Available online 15 October 2011

ABSTRACT

The theoretical goal of this article is to narrow the gap between existing knowledge management theories and theories of weak signal analysis, and partly wild card analysis. The following theories and associated theoretical frameworks are discussed in the article: (1) Environmental Scanning Model, (2) Nonaka's Knowledge Management Theory, (3) Gammelgaard's and Ritter's Knowledge Retrieval Matrix, (4) Boisot's Information Space Model and (5) Vejlgaard's Diamond Shaped Trend Model. These various and nevertheless complementary perspectives are important for the further development of weak signal analysis, knowledge management theory and knowledge management practices in modern organisations as well as for anticipation and decision-making in policy-making arenas. There are still many theoretical and empirical challenges in these fields of scientific knowledge. A general conclusion is that all these frameworks provide interesting new perspectives for modern futures studies as such. Another conclusion is that there are various knowledge management (KM) and scanning frameworks available for implementing weak signal analysis. However, this paper, its observations and conclusions also imply that a more generalised approach to weak signal analysis needs to be developed and that modern KM theories should be used when developing new futures studies/foresight methodologies. According to the theoretical guidelines presented in this article, it is possible to make the suggestion that it would be wise to integrate the latest developments in weak signal analysis into knowledge management theory and vice versa.

© 2011 Published by Elsevier Ltd.

1. Background

In recent years there has been an active discussion about the role of weak signal analysis in organisational and institutional foresight systems and strategic decision-making. Three decades ago Igor Ansoff initiated a strategy literature discussion on weak signals. Since then, weak signals and related emerging issues have been discussed by many researchers (see, e.g. Ansoff [1–5], Webb [6], Coffman [7–11], Blanco and Lesca [12], Harris and Zeisler [13], Day and Schoemaker [14], Mendonça et al. [15], Mannermaa [16,17], Hiltunen [18–20], Kuusi et al. [21], Nikander [22], Moijanen [23], Ilmola and Kuusi [24], Uskali [25], Brummer [26], Kuosa [27], and e Cunha and Chia [28], Kuosa [29], Mendonca et al. [30], and Giland [31]). There has also been a concurrent renaissance in strategic planning, within the special context of strategic flexibility, agility emphasis and peripheral vision. Weak signal analysis can be considered a useful dimension of knowledge management processes in organisations. In different organisations and social contexts weak signal analysis is performed in a variety of ways. Some organisations tend to ignore the weak signals they receive, while others have active knowledge management models that allow the analysis of weak signals. A few organisations have even developed quite proactive knowledge

E-mail addresses: jari.kaivo-oja@tse.fi, jari.kaivo-oja@utu.fi.

0016-3287/$ – see front matter © 2011 Published by Elsevier Ltd.
doi:10.1016/j.futures.2011.10.003

processes for handling weak signals. In this sense knowledge management (KM) is closely connected to the weak signal analysis of organisations, in particular through the way organisational cultures and management models impact upon viability and the future. All new ideas, inventions and innovations are based on knowledge and knowledge management.

One aim of this article is to provide a deeper theoretical background for understanding the critical role of weak signal identification and detection in actual social and corporate transformation processes. The article is organised as follows: Section 2 addresses some key issues in knowledge management theories and discusses the role of weak signal analysis from a knowledge management perspective based on the four main theoretical strands that have constructed the domain over the last 15 years. This section will address not only the basics of KM, environmental scanning, wild card and system's approaches but also the key contributions of weak signal analysis. Section 3 considers how knowledge management theories and transitions in organisations and society focus on, but they are also put in perspective by life-cycle and diamond shaped approaches to KM, with strong implications for early detection of change. Section 4 turns attention to the role of knowledge in the making of futures. Section 5, in conclusions, presents the current challenges facing the integrated development of knowledge management theory and weak signal analysis.

Knowledge management can be defined as the deliberate design of processes, tools, structures, etc., meant to increase, renew, share, or improve the use of knowledge represented in any of the structural, human and social elements of intellectual capital [31]. During recent decades several KM theories have been developed, in particular the seminal approach of Nonaka and Takeuchi, as well as the elaborations of Boisot, can enrich weak signal analysis. In addition to consideration of the direct connection between KM and weak signal analysis, this article examines two specific perspectives: one where KM, environmental scanning and even wild cards can be linked to weak signal analysis, and two, the innovative and management-oriented approach of Snowden's multifaceted Cynefin model. This systematic examination of the mutual reinforcement between KM and weak signal analysis will allow us to emphasize some promising avenues for coping with major managerial and decision-making problems that may occur when using weak signals, as well as bringing to bear some of the essential contributions of KM. Other tools will also be envisaged such as various types of classificatory matrices and the diamond-shaped model for staging early detection approaches, with the idea of showing how management, decision-making and policy-making can in reality tap into a broad array of methodological options. The whole sequence outlines a generic claim, namely that a strong linkage between KM and weak signal analysis is essential for understanding most societal or organisational changes.

2. Main KM approaches and their enriching linkage with weak signal analysis

2.1. Nonaka and Takeuchi KM model

One important milestone in the KM field is Nonaka's and Takeuchi's book "The Knowledge Creating Company" [33]. This book presents basic KM concepts. The most widely accepted and widely quoted approach for classifying and organising knowledge from a KM perspective is the Nonaka–Takeuchi "knowledge matrix" or (so-called SECI model).

At the heart of Nonaka's theory is the premise that there are two types of knowledge: (1) tacit and (2) explicit. Tacit knowledge is subjective and experience based knowledge that cannot be expressed in words, sentences, numbers or formulas. Tacit knowledge is often context specific. It is possible that weak signals can take either the form of tacit knowledge or explicit knowledge. An important idea stemming from Nonaka's theory is that each type of knowledge can be converted. For weak signal analysis Nonaka's theory provides a useful perspective on knowledge transfers. There are different kind of knowledge transfers, and obviously also weak signals, which can be transferred through socialisation, externalization, internalization and combination. The process that transfers tacit knowledge in one person to tacit knowledge in another person is socialisation. It is experiential, active and a "living thing," involving capturing knowledge through direct interaction with customers and suppliers outside the organisation and people inside the organisation. This depends on having shared experience, and results in acquired skills and common mental models. Socialisation is primarily a process between individuals. The process for making tacit knowledge explicit is externalization. One case is the articulation of one's own tacit knowledge through ideas or images, in words, metaphors, and analogies. A second case is eliciting and translating the tacit knowledge of others, e.g. customer, experts, into a readily understandable form, i.e. explicit knowledge.

Another important aspect of Nonaka's KM theory is the critical role of enablers. According to Nonaka, within a company, there are five enablers for knowledge creation: (1) vision, (2) strategy, (3) structure, (4) system and (5) staff. What is the relevance of Nonaka's theory to weak signal analyses? Nonaka and Takeuchi emphasize the fact that without analyzing tacit knowledge and without internalizing and socialising incoming knowledge, there is hardly any robust early detection of weak signals. Nonaka's theory indicates that it is possible that weak signals are the receiving of either tacit or explicit knowledge. When work is being conducted on the analysis of a weak signal, the critical role of enablers should be taken into consideration with regard to how best disseminate the new information as well as discerning the best alternative knowledge conversion processes.

2.2. The Boisot's I-Space contribution

Another famous contribution to the KM field was Max Boisot's knowledge management theory, called Information Space theory [34–37]. Boisot [34] proposed a model of knowledge asset development along similar lines to that of Nonaka and

Takeuchi. However, Boisot's model introduces a new extra dimension, abstraction, in the sense that knowledge can become generalised in different situations. This new KM model produces a richer scheme allowing the flow and transformation of knowledge to be analysed in greater detail.

The Information Space concept (or I-Space) of Max Boisot is a conceptual framework that allows physical and information goods to be represented together and to evolve over time; sometimes they become integrated, while at other times they are more differentiated from each other. Different concepts and representations lead to different theories and policies. As we move further into a knowledge society, it is becoming clear that we will need models and representations that better match changing realities and hence that are more policy-relevant than anything currently available. The activities of codification, abstraction, diffusion, absorption, impacting, and scanning, all contribute to learning. When they take place in sequence, which to some extent they must do, they make up six phases of a Social Learning Cycle (SLC): [34–37].

(1) Scanning: insights are gained from generally available (diffused) data.
(2) Problem-solving: problems are solved giving structure and coherence to these insights (knowledge becomes 'codified').
(3) Abstraction: the newly codified insights are generalised to a wide range of situations (knowledge becomes more 'abstract').
(4) Diffusion: the new insights are shared with a target population in a codified and abstract form (knowledge becomes 'diffused').
(5) Absorption: the newly codified insights are applied to a variety of situations producing new learning experiences (knowledge is absorbed and produces learnt behaviour and so becomes 'uncodified' or 'tacit').
(6) Impacting: abstract knowledge becomes embedded in concrete practices, for example in artefacts, rules or behaviour patterns (knowledge becomes 'concrete').

In his Information Space Model, Boisot developed an interesting application of the laws of thermodynamics in which knowledge assets that are highly abstract, highly codified and undiffused are seen to be the most ordered and so have the lowest rate of entropy production and therefore the maximum potential for performing value-added work. This interesting theoretical element of Boisot's theory helps us to integrate futures studies methodology and associated theories into the laws of thermodynamics. In this sense Boisot's theory requires very special attention from the futures studies community [34,35].

This thermodynamic analogy points to the elusive and dynamic nature of knowledge. It seems that what is happening is a cycle of events in which data are filtered to produce meaningful information and this information is then abstracted and codified to produce useful knowledge. As the knowledge is applied in diverse situations it produces new experiences in an uncodified form that produces the data for a new cycle of knowledge creation. This substantive aspect of Boisot's KM theory is very important for weak signal analysis [34,35,37].

What seems obvious from both Boisot's Information Space Model and Nonaka and Takeuchi's "knowledge matrix" [33] is that the process of producing and developing knowledge assets within organisations is always changing. In addition, the research findings of futures studies and foresight analysis have an impact upon organisational dynamics and change. Organisations are living organisms that must constantly adapt to their environment. This means that the KM strategy identified as appropriate at one moment in time will need to change as knowledge moves through an organisational learning cycle to a new phase. The rate at which this cycle operates will vary from one social fabric to another. Thus, in some rapidly evolving sectors or social fabrics new knowledge is being created and applied in rapid succession, while in some more established sectors the cycle time of innovation is much slower. This dynamic aspect of cycles is very important for successful weak signal analysis. Established and less-established social organisations need therefore to have different kind of abilities when analysing and handling weak signals in their environments.

Scanning is one important element of a *Social Learning Cycle* (SLC) and means identifying threats and opportunities held within generally available but often fuzzy data, i.e. weak signals. Scanning patterns such data into unique or idiosyncratic insights that then become the possession of individuals or small groups. Scanning may be very rapid when the data are well codified and abstract and very slow and random when the data are un-codified and context-specific. Boisot's SLC thus includes a weak signal concept, which is the interesting aspect of his theory for this paper [31]. In Boisot's theory, codifying and problem-solving are important dimensions of learning, as they require, first, clear problem identification, then suggestions for further treatment. The process of giving structure and coherence to such problematic insights is precisely the process of codification. In this phase they are given a definite shape and much of the uncertainty initially associated with them is eliminated. Problem-solving initiated in the un-codified region of the I-Space is often both risky and conflict-laden. Abstraction is often connected to scientific thinking. Generalising involves the application of newly codified insights to a wider range of situations. This involves reducing them to their most essential features, i.e. conceptualising them. Problem-solving and abstraction often work in tandem. Diffusion (especially technological diffusion) is an important part of socio-cultural evolution. It means sharing the newly created insights with a target population. The diffusion of well codified and abstract data to a large population will be technically less problematic than that of data which are uncodified and context-specific. Only a sharing of context by a sender and a receiver can speed up the diffusion of uncodified data. Absorption requires a long learning process before it can happen. Applying new codified insights to different situations can be done by either "learning by doing" or "learning by using". Over time, such codified insights come to acquire a penumbra of uncodified knowledge which helps to guide their application in particular circumstances. Impact is closely related to the absorption process. The embedding of abstract knowledge is important in concrete KM practices. Such places where abstract knowledge is embedded are artefacts, in technical or organisational rules, or in behavioural practices. Absorption and impact also often work in tandem [33,34,36].

Boisot has also noted that organisations have two conflicting knowledge management strategies: information hoarding and information sharing. These are important issues, when we discuss weak signal analysis and its impact on societies. Agents adopt two quite distinct strategies for dealing with the paradox of value. Information hoarding means that an organisation realises that diffused information has no economic value, and thus they attempt to slow down the SLC by refraining from codifying or abstracting too much and by building barriers to the diffusion of newly codified abstract information, e.g. through patents, copyright, secrecy clauses, etc. Slowing down a SLC allows the extraction of value from information in a controlled way. Information sharing implies recognition that the subsequent processes of absorption, impacting and scanning create diffused information that prepares the ground for further learning and knowledge creation. Thus an organisation willingly shares its information and watches how it is used by others. They gain first-mover advantages in being the first to initiate a new SLC and extract value from the process by participating in a succession of SLCs instead of dwelling as long as possible on a single one. Hoarding and sharing strategies can be mixed in an organisation, which often makes things even more complex [33,34,36].

We can conclude that Boisot's knowledge management theory will have a fundamental impact on the further development of weak signal analysis in futures studies because it conceptually includes weak signal analysis. Weak signals are a critical part of the scanning process and one key element of a systematic SLC model. Boisot's I-Space theory includes the fundamental idea that weak signal analysis is a starting point for the other SLC processes of codifying, abstraction, discussion, absorption and impacting, which often happen after the scanning process. This is a fundamental element of Boisot's contribution to knowledge management theory. In this sense Boisot's theory includes the fundamental idea that social learning processes are not possible without scanning and weak signal analysis [36,37].

2.3. Scanning options: weak signals wild card and other open issues

In Fig. 1 below, the impact–uncertainty matrix is presented. It helps us define the role of weak signal analysis as well as the role of wild card analysis. The concept of weak signal analysis is wider than the theoretical concept of wild card analysis. Weak signals are connected a variety of options from moderately uncertain to very uncertain events and issues, while wild card analysis focuses on very uncertain events and on potential events that are likely to have rather significant impacts. It should also be noted that other standard methodologies in futures studies are focused on different types of futures events.

There are many alternative ways to perform weak signal analyses. A conventional way has been to use environmental scanning analyses and Ansoff's filters [1–5]. Typically, environmental scanning includes a broad range of personal and organisational activities. It is the process of screening a large body of information for some particular bit or bits of information that meet certain screening criteria [42]. Aguilar [43, p. 1] has defined environmental scanning as "an activity for acquiring information." Aguiral [43, p. 18] has also noted that "scanning involves simply an exposure to and perception of information. The scanning activity could range from gathering data in the most deliberate fashion – as by an extensive market research program – to undirected conversation at the breakfast table or the chance observation of an irate housewife throwing your product into trash barrel." Well-known KM field researcher Choo argues that environmental scanning analyses information about every sector of the external environment that can help management to plan an organisation's future [44]. Cook [45] notes that "environmental scanning is the practice of searching a wide array of information sources on a regular basis for symptoms of change." For example, some people scan headlines in newspapers or magazines for particular kinds of articles, and when they find that information, they stop scanning and read the article. Then they resume environmental scanning. Choo [44, pp. 112–113] has also noted that some of the signals would be (1) weak (difficult to detect), many would be (2) confusing (difficult to analyse) and others would be (3) spurious (not indicative of a true change).

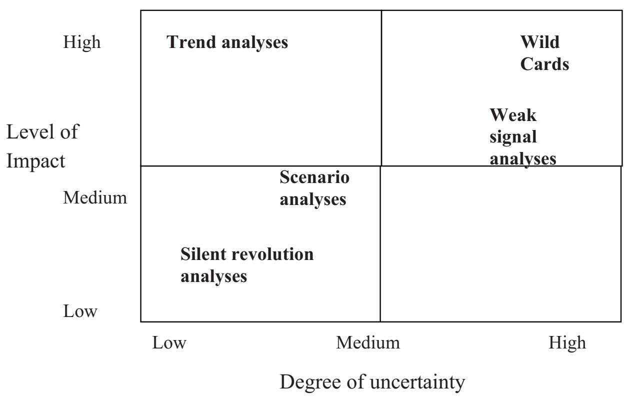

Fig. 1. The impact–uncertainty matrix and futures research methods.

Ferguson argues that few changes in the environment occur spontaneously: they start as ideas. These ideas eventually obtain a public expression in the press, radio, television, university conferences, and scientific journals [46]. Dator describes in his article changes in the following way: "The world around [them] has emerged according to various kinds of "S" curves of growth – from nothing but some crazy idea, to a frail and flimsy emergence, through a slow initial growth and then rapid middle growth, to a hard omnipresence, to steady prolonged "commonsense" existence, and/or to eventual decay and death" [47, p. 205]. One interesting interpretation is that we can see weak signal analysis as the beginning of a conventional S-curve process. The S-curve hypothesis is also closely related to innovation diffusion models and life cycle models. In this sense weak signal analysis probably plays a very important role in innovation diffusion processes and the product and service cycles of global markets.

In organisations, there can be also *passive scanning and active scanning*. *Passive scanning is an unconscious form of scanning.* Whatever a particular individual's interests, goals, personal values, or professional objectives, it is an element of human nature to respond to incoming information that might be important. This kind of spontaneous scanning at an almost unconscious level is passive scanning. In this scanning procedure no effort is made to select a particular information resource to scan. Thus, the criteria of passive scanning are obscure, unspecified, and often continuously changing. Only ad hoc decisions are made on the results of this type of scanning. *Active scanning is a conscious mental activity*. The components of active scanning are quite different from those of passive scanning. For example, the searching or screening process requires a much higher level of professional attention. In the active scanning process experts participate in a process and broadly discuss weak signal information. Also expert survey or the Delphi methodology can be utilised. The information resources scanned are specifically selected for their known or expected richness and relevance to the desired information. These resources may include some, but usually not all, of the regular incoming resources of passive scanning. A typical active environmental scan (ES) process has several distinct steps [48]:

1. searching for information resources;
2. selecting information resources to scan;
3. identifying criteria by which to scan;
4. scanning; and
5. determining the appropriate action to take based on the scanning results.

According to the literature, there are some elements and sources of ES that are more appreciated when anticipating changes than others. Aguilar [43, p. 68] found in his study that managers relied almost as much on inside sources as on outside sources for important external information. Personal sources greatly exceeded impersonal ones in importance. Aguilar draws the conclusion that scanning processes for important external information appears to rely heavily on a manager's personal network of communications [43, pp. 68–69]. Heikell drew similar conclusions about the importance of managers' personal networks on the basis of an extensive literature review regarding sources in scanning activity [49]. Choo's, El Sawy's and Keegan's research findings also point in this direction [51, p. 255], [52,53]. Choo has specified that information from human sources may be preferred when dealing with ambiguous, unstructured problem situations [50, p. 141]. Ansoff's filters approach to weak signal analyses also draws attention to the sense making processes [1–5,24]. Ansoff understood that all scanning systems, both conscious and unconscious, have filters. Ansoff described his filter construction through three concepts: (1) a surveillance filter, (2) a mentality filter and (3) a power filter. The three critical steps of theoretical progress of the Ansoff model (addressed in detail elsewhere in this special issue) are worth stressing here because it further underscores the link between KM and weak signals analysis. This can be seen in a number of ways.

Firstly, in technology foresight, Debackere and Rappa have suggested that a technological paradigm typically emerges in two phases: *in the bootlegging process and in the bandwagon process*. In the bootlegging process weak signals are taken seriously by powerful managers, but in the bandwagon process a weak signal is first neglected and after some period taken more seriously [53]. Organisations that allow bootlegging to happen in markets can gain competitive advantages with this strategic approach. The fundamental strategic problem in many organisations is that it is impossible to know if weak signals are causing an organisation to make the right kinds of strategic decisions. One problem is that in many organisations the scanning process filters are passive, non-systematic and limited to very narrow environments. Thus, much or perhaps most of the filtering of signals takes place in organisations without an explicit or guided process.

Secondly, Ansoff's approach has been systematized and developed further by Ilmola and Kuusi [24]. Ilmola and Kuusi presented a comprehensive analysis of the filtering processes and mechanisms that operate within the forecasting and vision building processes in organisations operating in turbulent environments. They also integrated many aspects of complexity theory, sense-making theory and strategic decision making theory from Ansoff's traditional filter approach. Ilmola and Kuusi also discussed key concepts of weak signal analysis and have found some concepts to be very important. In particular, *the width and depth of a filter* are important starting points in their weak signal analysis [24, p. 919]. Ilmola and Kuusi make 3 propositions, which are relevant for weak signal analysis. They are: (1) the open scope of the briefing increases the width of a filter, (2) a multi-step process increases the depth of a filter and promotes strong argumentation, and (3) social interaction as a processing method will increase the depth of a filter but reduce the width of that filter [24, p. 914]. Thus the important elements of weak signal analysis are open scope filtering, multi-step processes inside organisations and social interaction as a processing method.

A third and complementary approach, which deserves the same attention is the attempt by scholars Hiltunen and Kuusi [18–21,24,56,57] and their semiotic-based weak signal model (Peirce's semiotic theory). This model aims to create multi-level points of view on signalling processes so as to help produce meaning and reinforce analytical options arising from early detection. Their approach proposes a rather original view on ''the signification model of the future sign'' (discussed in more detail by other authors in this special issue).

2.4. Snowden and the Cynefin approach

The fourth and final set of connections between KM and weak signals analysis explored in this article was conceived at IBM's Cynefin Research Centre [38] by Snowden et al. [38–41]. The Cynefin framework originated in the practice of knowledge management as a means of distinguishing between formal and informal communities, and as a means of talking about the interaction of both structured processes and uncertain conditions. The framework is particularly useful in collective sense-making in that it is designed to allow shared understandings to emerge through the multiple discourses of a decision-making group. In the Cynefin model there are 5 different domains: (1) *ordered domain*: known causes and effects, (2) *ordered domain*: knowable causes and effects, (3) *un-ordered domain*: complex relationships, (4) *un-ordered domain*: Chaos and (5) transition domain [41, pp. 467–470; 38–40] (see Fig. 2).

Weak signals can be identified in any of these 5 domains.

2.4.1. Weak signal analysis in Domain 1

One can use a structured predictive approach when analysing weak signals, but only if clear cause and effect relationships are dominant. Here reductionism may work well. In science reductionism is an approach to build descriptions of systems out of the descriptions of the subsystems that a system is composed of, and ignoring the relationships between them. If there is no clear cause and effect mechanism this approach can lead to incorrect conclusions and decisions [41, p. 468].

2.4.2. Weak signal analysis in Domain 2

In this domain as well a weak signal analysis can be performed using system theory. Both hard and soft systems theory methods can be used to do it properly. Snowden suggests that a working decision model can be used here is: to sense incoming weak signal data, analyse that data, and then respond in accordance with scientific expert advice or an interpretation of that analysis. Structured statistical and other qualitative techniques are in this case desirable, but assumptions must be open to examination and challenge. Snowden provides also a serious warning that this is the domain in which engrained patterns are most dangerous, as a simple error in an assumption can lead to a false conclusion that is difficult to isolate and may not be seen. This informed warning made by Snowden is very important for proper weak signal analyses, because the effects of such causes can be extremely surprising [41, p. 468]. Especially useful in Domain 2 may be data mining tools and statistical outlier analyses.

2.4.3. Weak signal analysis in Domain 3

In the un-ordered Domain 3 complex relationships are concrete reality. This is the domain of complexity theory, which studies how patterns emerge through the interaction of many agents. Many futurists have noted that complexity theory helps us to understand how futures emerge. Weak signals can be identified in conditions of complexity, but making decisive conclusions is laden with risk because systemic patterns can change dynamically and move in very surprising directions. Snowden suggests that the decision model in this space be used to create probes to make the patterns or potential patterns more visible before we take any further action [41, p. 469]. When we analyse weak signals in the Domain 3, we must

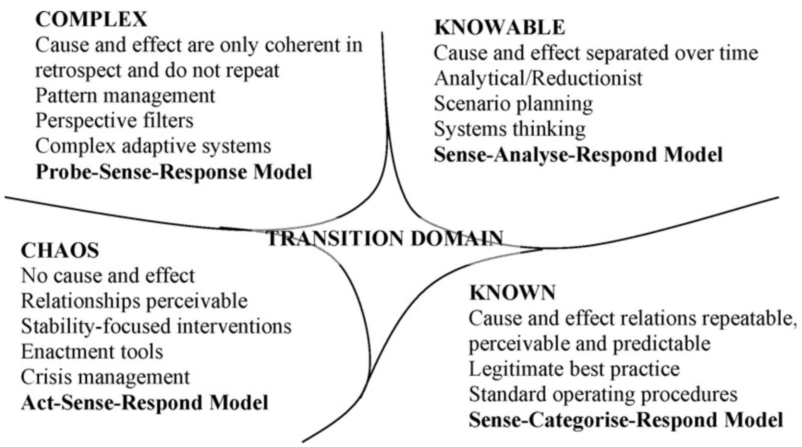

Fig. 2. Cynefin domains, modified by the author [41, p. 468].

understand that complex systemic change is a multidimensional phenomena. Basic system theory includes a big idea. Systemic change includes such issues like *imitation, inertia, sub-optimization*, *change of game and change of paradigm*. Thus, for example, emerging imitation of some behaviour can be a weak signal, which leads some organisations to inertia and sub-optimization.

2.4.4. Weak signal analysis in Domain 4

How is it possible to do weak signal analyses in chaotic conditions? According to Snowden the chaotic domain is, in a very real sense, uncanny in that there is a potential for order but few can see it. If somebody can see changes, s/he rarely does anything unless they have the courage to act. In known space it pays to be canny, that is, to know how to work the system in all its intricacies. In chaotic space, a canny ability gets you nowhere (there is no system to be worked). In the Domain 4 you need a different type of ability, one that is uncannily mysterious, sometimes even to its owner. Canny and insightful people tend to succeed in their own lifetimes; uncanny people tend to be recognised and appreciated only centuries later, because during their time their actions appeared to be either insane or pointless. Both these types of people somehow identify weak signals but they draw very different and unique conclusions from to them [41, p. 469].

2.4.5. Weak signal analysis in Domain 5

In the transition domain there are various alternative processes possible. The domain of disorder is a very problematic domain because decision-makers are looking at the same situation from different points of view. In this domain it is not possible to say how a weak signal actually should be interpreted. Individuals tend to compete to interpret the central space on the basis of their personal preferences for action. It is typical in this domain that some people with stable order seek to create or enforce some rules. Experts seek to conduct research and accumulate empirical databases. Policymakers seek to increase the number and range of their contacts. They typically rely on the current social capital of their networks. Persons having authoritarian or needs associated with dictatorship are eager to take advantage of a chaotic situation and seek absolute control. If a weak signal is regarded as very important more people seem to want to pull it towards the domain where they feel most empowered by their individual capabilities and perspectives. Hence, the wisest way to handle weak signals, in the domain of disorder, is to build up good stakeholder networks, which are able to handle problematic situations in a diplomatic way [41, pp. 469–470].

Snowden's theory is a good starting point for sense-making in a complex and complicated world. In particular, Cynefin's 5th Domain tells us why weak analysis is not an easy strategic issue for organisations. The most important insight of Snowden's theory is that *five different weak signal analysis models can be found within it*. In the KNOWN domain, weak signal analysis is conducted by using the Sense–Categorise–Respond model. In the KNOWABLE domain weak signal analysis is conducted by following the Sense–Analyse–Respond model. In the COMPLEX domain weak signal analysis is conducted according to the Probe–Sense–Respond model. In the CHAOS domain weak signal analysis is difficult to conduct and must follow the Act–Sense–Respond model. In the DISORDER domain conflicts in decision-making are recognised as part of reality. In this domain, the networked co-operation of stakeholders and experts and their interactive dialogue are the key elements of weak signal analysis [38–41].

In wrapping up this section it is clear that all three knowledge management theories as well as the impact–uncertainty matrix underscore the relationship between weak signals practices and the broader processes of decision making addressed by KM. This insight also provokes the observation that weak signal identification and detection may play a critical role in social transformation processes. Overall the connections linking weak signals, KM and societal transformation merit further attention by futures researchers. One of the aims of this article is to draw attention to these connections and offer some thoughts on how to elaborate the nature of the relationships and avenues for further research.

3. Socio-cultural transitions in organisations and society: a link between weak signal analysis and trend analysis

Why do we consider that knowledge management theories and transitions in organisations and society belong to a same overall field of concern? Obviously, it can be concluded, on the basis of the discussions above, that knowledge management systems have direct and indirect impacts on future developments. For example, *active environmental scanning leads to different kinds of decision-making processes than passive environmental scanning systems*. Furthermore, knowledge management systems have an important impact on sense-making in organisations [54,55,57,58] as was noted by Igor Ansoff himself in his filter theory [1–5,24]. In spite of this finding, many organisations use traditional linear planning methods, which include strong assumptions about presumably efficient, well-focused strategic plans and clearly defined visions, missions and strategy implementation. This kind of linear strategy model reduces an organisation's sensitivity and ability to address socio-cultural shifts and changes in its environment. It may also decrease organisation's creativity and innovation capabilities. In this way knowledge management systems have an impact on their organisation's capability to adjust to a changing environment.

A typical transition process in a society can be tracked step by step by the Diamond-Shaped Trend Model, presented by Vejlgaard [59, pp. 63–69]. The model stages six different personality profiles: (1) trendsetters, (2) trend followers, (3) early mainstreamers, (4) mainstreamers, (5) late mainstreamers and (6) conservatives (see Fig. 3). According to Vejlgaard, the size of trendsetter group is 5% of a population, whereas trend followers are 10% of a population, early mainstreamers 20% and the

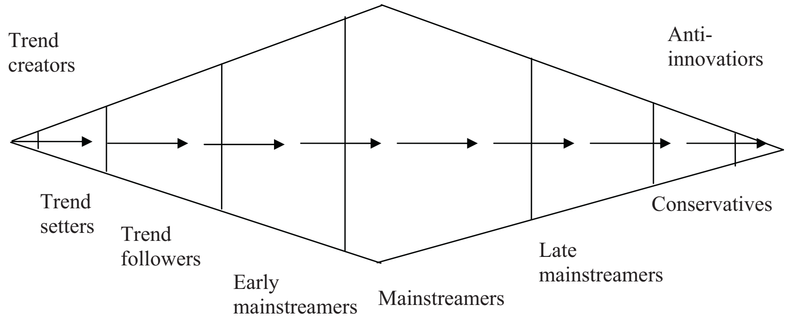

Fig. 3. The Diamond-Shaped Trend Model [59, p. 64].

critical mass of a population, mainstreamers, 40% of the total population. Finally, late mainstreamers are 15% and conservatives, 10% of a population. There can also be a seventh social group, *anti-innovators*, who do not want to adopt new ideas or inventions. This social group is not interested in any kinds of weak signals or wild cards. The strongest social tension exists between anti-innovators and trend creators. A strong social tension exists also between trend setters and conservatives. There are always some social groups that do not accept any weak signal at all or at least the changes they announce, e.g. groups such as the Amish in the United States. Such groups periodically re-emerge with new claims and rhetoric, climate change is now giving fuel to some such perspectives. Trend creators and anti-innovators account for about 1% of the population according to Vejlgaard's field evaluations [59].

These profiles can also be called trend groups. According to this DST-model of social transition processes all people are part of a trend process. Weak signals are in fact mostly created by trendsetters according to the DST model. Trendsetters are a very small group, but very inventive and innovative. After the first changes and weak signals are detected, trendsetters start adopting these signals and ensure that there will be a trend; then early mainstreamers adopt it in their turn, shaping it in their own terms. In this way, weak signals are always an original source of trends, which can transform societies. The Diamond-Shaped Trend Model can be used to represent the entire population and its forms of uptake regarding weak signals [59, pp. 63–69, 75].

There are always some ideas produced by trend creators, which are not adopted by trend setters. In this case weak signals stay weak signals. The trend process starts when the different trend groups are inspired from the top (or left-hand side) of the DST model. The model is a simplified representation of a more complex process. In the DST model the critical group is the trendsetter group. Some social groups are important trendsetters. Such influential groups include artists, celebrities, the wealthy, gay men, designers, the young and style conscious subcultures and other sub-groups of trendsetters [59, p. 56]. All these constituencies can in their own time and context be envisaged as potential proxies for early detection of emerging trends, they constantly interplay with weak signals.

4. Foresight methodology and knowledge management systems

Theories of knowledge management can be a fruitful starting point for understanding weak signal analysis in real-life contexts. Some organisations can be characterized as knowledge activists and even innovation activists. In many of these cases, such organisations appear to consciously use different kinds of weak signal analysis to achieve their objectives. However, in many organisations, active environmental scanning or weak signal filtering and processing remain under-developed. In rapidly changing environments, this may be problematic. O'Reilly has found that the quality and accessibility of a source affects its use in scanning [58]. Saunders and Jones summarize some of the characteristics that have been cited in literature as a reason for selecting information sources. These characteristics are: urgency, accessibility, cost, feedback, channel capacity, symmetry of channel capacity, time, the speed of message handling, information richness, and "social presence". In a more complex analysis building upon the DST model as well as some of the previously examined approaches, e.g., the Cynefin concept, these dimensions play a critical role for effectively linking KM and weak signals [see e.g. 60, pp. 32–33].

Two approaches, in particular, are discussed in the literature in relation to knowledge transfer: personalization and codification strategies (see Fig. 4). These two approaches have also been related to the use of weak and strong ties between individuals [61,62]. Weak ties cover distant, infrequent relationships between individuals, whereas strong ties refer to very close, frequent, long lasting, personalized relationships, which in turn reflect the personalization approach. Weak ties between units are helpful for searching or scanning for information, whereas strong ties are needed to transfer complex knowledge [63–65]. This kind of observation is very important in the context of weak signal analysis. Weak ties are helpful in scanning processes, but strong ties are needed if we want to handle complex knowledge. Complex knowledge is hard to encode and decode through communication technologies [65], so that an individual can retrieve "additional and peripheral" knowledge through electronic means. Complex knowledge is likely to be transferred through socialisation processes in which knowledge is transferred mainly in tacit form from one actor to another [66].

		Use of personalization strategy: Low	Use of personalization strategy: High
Use of organisational codification strategy	High	Database	Virtual communities of practice
	Low	Individual memory	Social capital

Fig. 4. Knowledge retrieval matrix [67, p. 16, 79].

In knowledge management one important distinction is made between the use of personalization strategy and the use of organisational codification strategy. This leads to a classification that is very important for foresight methodology, as it one potential way of determining which kind of foresight tools and methods can be best used in weak signal analysis.

In weak signal analysis, we can use databases as well as quantitative and qualitative data analysis as starting points. Taking into account the large amount of fragmented information considered, the use of information technology in this respect is viewed as central to the internalization of knowledge. New digital technology applications are providing interesting possibilities for us. These novel knowledge technology platforms (like Google+ and Twitter) provide a repository of codified knowledge and, in the long run, the technology reduces the individual effort needed to retrieve information, and finally reduces the effort required by individuals who are often separated in time and by their physical environment from the knowledge they require. In fact, through the use of various databases, many people, at least with written documents, serve as primary sources of information for the individual knowledge worker. The risk of data overflow has thus emphasized the need to reduce data into recognisable patterns of information through the use of computer algorithms [67, p. 6, 7]. As we know computer algorithms are today widely used in the Internet and in digital web 2.0 applications. From this perspective weak signal analysis and filtering is now easier than before. The media and journalists also play important role in various processes of weak signal identification, analysis and filtering [68–70].

Another knowledge-based strategy is to ask virtual communities to define relevant weak signals. According to Wenger [71, p. 4]: 'Communities of practice are groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis'. It is often the passion for something interesting that brings people together, since an individual naturally seeks to share insights and build knowledge in areas of interest to them [72]. This differs from informal networks of people who just communicate, share information and build relationships. The group intends to build practices and develop domains of knowledge with a unique perspective. Given this uniqueness, newcomers to a community need to learn how to function within the entity [73,74].

Assessments of communities of practice have often revealed evidence that such communities can efficiently transfer tacit and complex knowledge amongst its "club" members [75,76]. Virtual communities are very similar to communities of practice – a group of frequently interacting individuals sharing a common practice. The difference is that the communication and coordination of work takes place in cyberspace through information and communication technology (ICT). The community is therefore socially relational but without necessarily a specific geographic point-of-reference in common [77]. Like communities of practice, virtual communities operate with informal goals, a common language, shared understandings and reasonable levels of trust. Thus, trust is also a basic background factor for weak signal analysis. The establishment of virtual communities of practice can enable codification and personalization strategies to be combined in ways that are potentially advantageous for knowledge management. Sometimes, virtually connected teams build a relationship through face-to-face meetings before they effectively collaborate electronically [72]. This is typical in ambient R&D projects. Many KM experts think that this kind of KM approach is the best one, because it includes a high use of the personalization strategy and a high use of the organisational codification strategy. This theoretical viewpoint and background experience is important for effective weak signal analysis. Sharing weak signals requires some critical level of trust.

The third option is to rely on individuals and their personal memories. According to memory research, individual memory is developed through a person's observations, experiences, and actions and consists of semantic, episodic and skill-based memory [79, p. 135; 80,81]. To define these forms of memory, we can note, on the basis of modern memory research, that, firstly, *semantic knowledge* refers to general knowledge stored in a network of concepts, whereas *episodic knowledge* applies to individual experiences, and thirdly *skill knowledge* encompasses the implicit knowledge of how to do things [79, p. 135, 136; 80,81]. Knowledge of this type makes sense to the individual and is codified at this level, rather than at the organisational level. This kind of skill knowledge is not part of the wider organisational memory, since it is not stored anywhere [79, p. 136; 80]. Skill to handle weak signals is a very specific form of skill. The potential existence of a knowledge store is a critical issue in weak signal analysis, because there are many pieces of information or knowledge, which include weak signals, but if they are stored, but not analysed or filtered by human beings. This kind of special knowledge can only be brought to bear on present activities, resulting in organisational behaviour changes

[73, p. 136; 75,76]. Gammelgaard and Ritter have noted in their article that 'the simultaneously low degrees of organisational codification and personalization strategies reveal isolated retrieval processes drawing on individual memory alone. An example is those experts who solely retrieve information from their personal memory, and make use of neither personal networks nor databases' [73, p. 136].

Knowledge management strategy based just on individual memory is not necessarily the best one for weak signal analysis. First, this strategy is very vulnerable, because if one person is responsible to remember a huge amount of weak signals, this person will probably be overloaded with information and knowledge. This kind of special person can also be recruited to another organisation with his valuable skills and capabilities. Of course some individuals have exceptionally large memory capacities, but they are exceptions to the common rule. A very large memory capacity is needed to define which weak signals are actually new and interesting. However, in any case, such strategy is not sustainable and always difficult to transmit or share if needed. Thus, organisational capacity to filter and analyse weak signals is still a challenging question, if we think this critical issue from knowledge management perspective.

The fourth option is to rely on social networks and social capital in defining interesting weak signals. Nowadays social media provides new possibilities for this. Addressing a knowledge management perspective, Daniel et al. [84, p. 116] define social capital as: '...a common social resource that facilitates information exchange, knowledge sharing and knowledge construction through continuous interaction, built on trust and maintained through shared understanding'. In addition, there must be a series of connections between individuals and organisations; they must perceive themselves as part of a social network where there is a sense of trust across different connections. There are many forms of trust, social trust, economic trust and political trust. Typically, social or interpersonal trust can be based upon immediate, first-hand experiences of other people, whereas political trust is more generally learned indirectly and at a distance. Economic trust is connected to market transactions and their reliability. With high levels of social capital and trust an organisation is better positioned to receive useful weak signals. So called *confidential information* or *confidential knowledge* includes often more relevant weak signals than normal information or knowledge without confidentiality character. Sometimes very critical weak signals are *business secrets*.

All of these aspects of connecting KM to foresight methodologies reinforces the observations of Ilmola and Kuusi's [24] regarding how to undertake effective weak signal analysis through (1) opening up the scope of the briefing, thereby increasing the width of the filter, (2) utilising a multi-step process, thereby increasing the depth of the filter that promotes strong argumentation and introduces social interaction as a processing method. Of course there are some tradeoffs. Open filtering systems promote the width of weak signal analysis. Deep filtering systems, on the other hand, promote the depth of the filtering process. The challenge in organisations is to develop both *proper open filters and deep filters* by using an integrated filtering model [24].

According to these guidelines, we can make the suggestion that it would be wise to integrate the latest developments in weak signal analysis into knowledge management theory and vice versa.

5. Conclusions

The goal of this article has been to narrow the gap between existing knowledge management theories and theories of weak signal analysis and partly wild card analysis. A general conclusion is that all frameworks provide interesting new perspectives for modern futures studies as such. Another conclusion is that there are various frameworks available for implementing weak signal analysis. However, this paper, its observations and conclusions also imply that a more generalised approach to weak signal analysis needs to be developed and that modern KM theories should be used when developing such methodologies.

Building on the preceding discussion here are a few observations regarding potential fields for further research:

1. Nonaka's theory indicates that it is possible that weak signals are received in either the form of tacit knowledge or explicit knowledge. Another important idea stemming from Nonaka's theory is that each type of knowledge can be converted by different processes, which are socialisation, internationalization, externalization, and combination.
2. An important aspect of Nonaka's knowledge management theory is the critical role of enablers. According to Nonaka, within a company, there are five enablers for knowledge creation: (1) vision, (2) strategy, (3) structure, (4) system and (5) staff. Thus, when an individual works on developing a weak signal analysis, the critical role of the various enablers should be taken into consideration, as should the alternative knowledge conversion processes that were defined by Nonaka.
3. According to the Knowledge Retrieval Matrix developed by Gammelgaard and Ritter [67,78], a new and very important knowledge-based strategy is to ask virtual communities to define relevant knowledge and also relevant weak signals. This kind of KM approach is seen as useful because it combines personalization and organisational codification strategies. This knowledge management theory is important starting point for effective weak signal analysis of organisations.
4. In his theoretical Information Space Model, Boisot has developed an interesting application of the laws of thermodynamics in which knowledge assets that are highly abstract, highly codified and undiffused are seen to be the most ordered and so have the lowest rate of entropy production and therefore the maximum potential for performing value-added work. This interesting theoretical element of Boisot's theory could help to integrate futures studies' methodology and associated theories into the laws of thermodynamics. In this sense Boisot's I-Space theory requires special attention from the futures studies community.

5. The most important implication of Snowden's theory is that there are five different weak signal analysis models.
6. In weak signal analysis there have been promising steps taken towards progress in understanding and anticipating change. Just to name one such innovative approach, let's mention in particular, the future sign analysis suggested by Hiltunen and Kuusi making best use of the three dimensions of weak signals. Several others could be also evoked here. This expanding theoretical approach to weak signal analysis could also benefit from the research tradition of knowledge management. With respect to that, Vejlgaard's Diamond-Shaped Trend Model can be seen as an important integrative model between weak signal theory and conventional trend analysis.

These various and nevertheless complementary perspectives are important for the further development of weak signal analysis, knowledge management theory and knowledge management practices in modern organisations as well as anticipation and decision-making in policy-making arenas. There are still many theoretical and empirical challenges in these fields of scientific knowledge.

References

[1] I.H. Ansoff, Managing strategic surprise by response to weak signals, California Management Review XVIII (2) (1975) 21–33.
[2] I.H. Ansoff, Strategic issues management, Strategic Management Journal 1 (1980) 131–148.
[3] I.H. Ansoff, Strategic Response in Turbulent Environments. Working Paper No. 82-35, European Institute for Advanced Studies in Management, August, 1982.
[4] I.H. Ansoff, Implanting Strategic Management, Prentice/Hall International, 1984,, p. 510.
[5] I.H. Ansoff, Conceptual underpinnings of systematic strategic management, European Journal of Operational Research 19 (1985) 2–19.
[6] J.R. Webb, An evaluation of Igor Ansoff's theory of weak signal management by means of an investigation and forecast of future developments in the ophthalmic laser environment, Doctoral thesis, University of Strathclyde, 1987.
[7] B. Coffman, Weak Signal Research, Part I: Introduction, Journal of Transition Management, MG Taylor Corporation, 1997. www.mgtaylor.com/mgtaylor/jotm/winter97/wsrintro.htm.
[8] B. Coffman, Weak Signal Research, Part II: Information Theory, Journal of Transition Management, MG Taylor Corporation, 1997. www.mgtaylor.com/mgtaylor/jotm/winter97/infotheory.htm.
[9] B. Coffman, Weak Signal Research, Part III: Sampling, Uncertainty and Phase Shifts in Weak Signal Evolution, Journal of Transition Management, MG Taylor Corporation, 1997. www.mgtaylor.com/mgtaylor/jotm/winter97/wsrsampl.htm.
[10] B. Coffman, Weak Signal Research, Part IV: Evolution and Growth of the Weak Signal to Maturity, Journal of Transition Management, MG Taylor Corporation, 1997. www.mgtaylor.com/mgtaylor/jotm/winter97/wsrmatur.htm.
[11] B. Coffman, Part V: A Process Model for Weak Signal Research, Journal of Transition Management, MG Taylor Corporation, 1997. www.mgtaylor.com/mgtaylor/jotm/winter97/wsrprocm.htm.
[12] S. Blanco, H. Lesca, Environmental scanning: designing a collective learning process to track down weak signals, in: Presentation in Actes de la 3e Conferénce de l'AIS Amérique (Association for Information Systems), Indianapolis, USA, 1997.
[13] D.D. Harris, S. Zeisler, Weak signals: detecting the next big thing, The Futurist 36 (6) (2002) 21–29.
[14] G. Day, P. Schoemaker, Scanning the periphery, Harvard Business Review (November) (2005) 135–148.
[15] S.S. Mendonça, M.P. e Cunha, J. Kaivo-oja, F. Ruff, Wild cards, weak signals and organizational improvisation, Futures 36 (2004) 201–218.
[16] M. Mannermaa, Toolbox ja heikot signaalit,(Toolbox and weak signals), Futura 13 (2) (1999) 32–37.
[17] M. Mannermaa, Heikoista signaaleista vahva tulevaisuus,(A Strong Future from Weak Signals), WSOY, Porvoo, 2004.
[18] E. Hiltunen, Heikot signaalit – teoriakatsaus,(Weak signals – a theoretical review), Futura 14 (2) (2000) 72–77.
[19] E. Hiltunen, Heikkojen signaalien käyttö yrityksissä,(The application of weak signals in companies), Futura 15 (1) (2001) 45–50.
[20] E. Hiltunen, The future sign and its three dimensions, Futures 40 (3) (2008) 247–260.
[21] O. Kuusi, E. Hiltunen, H. Linturi, Heikot tulevaisuussignaalit – Delfoi tutkimus,(Weak signals: a Delphi study), Futura 14 (2) (2000) 78–92.
[22] I.O. Nikander, Early warnings – a phenomenon in project management. Dissertation for the degree of Doctor of Science in Technology, Helsinki University of Technology, Helsinki, 2002.
[23] M. Moijanen, Heikot signaalit tulevaisuuden tutkimuksessa,(Weak signals in futures studies), Futura 17 (4) (2003) 38–60.
[24] L. Ilmola, O. Kuusi, Filters of weak signals hinder foresight: monitoring weak signals efficiently in corporate decision-making, Futures 38 (8) (2006) 908–924.
[25] T. Uskali, Paying attention to weak signals – the key concept for innovation journalism, Innovation Journalism 2 (4) (2005) 33–49.
[26] V. Brummer, Innovaatioaihioiden verkkopohjainen ideointi ja monikriteerinen seulonta (Internet based generation and multicriteria screening of innovation ideas). MSc Thesis (Engineering), Department of Physics and Mathematics, Helsinki University of Technology, Helsinki, 2005. www.sal.hut.fi/Publications/pdffiles/TBRU05.pdf.
[27] T. Kuosa, Heikko signaali vai merkityksetön kohina: Pattern management – ontologisesti uusi lähestymistapa heikkojen signaalien tarkasteluun ja tulkintaan,(A weak signal or meaningless noise: pattern management – an ontologically new approach to examining and interpreting weak signals), Futura 19 (4) (2005) 115–120.
[28] M.P. e Cunha, R. Chia, Using teams to avoid peripheral blindness, Long Range Planning 40 (6) (2007) 559–573.
[29] T. Kuosa, Futures signals sense-making framework (FSSF): a start-up tool to analyse and categorise weak signals, wild cards, drivers, trends and other types of information, Futures 42 (2010) 42–48.
[30] S. Mendonca, M.P.E. Cunha, F. Ruff, J. Kaivo-oja, Venturing into the wilderness: preparing for wild cards in the civil aircraft and asset-management industries. LRP, Long Range Planning, International Journal of Strategic Management 42 (2009) 23–41.
[31] B. Giland, Early Warning, Using Competitive Intelligence to Anticipate Shifts, Control Risk and Create Powerful Strategies, American Management Association, New York, USA, 2004.
[33] I. Nonaka, H. Takeuchi, The Knowledge-creating Company – How Japanese Companies Create the Dynamic of Innovation, Oxford University Press, Oxford, 1995.
[34] M. Boisot, Information Space: A Framework for Learning in Organizations, Institutions and Culture, Routledge, London, 1995.
[35] M. Boisot, Knowledge Assets: Securing Competitive Advantage in the Information Economy, Oxford University Press, Oxford, 1998.
[36] M. Boisot, B. Cox, The I-Space: a framework for analyzing the evolution of social computing, Technovation 19 (1999) 525–536.
[37] M. Boisot, I.C. MacMillan, K.S. Han, Explorations in Information Space: Knowledge Actor and Firms, Oxford University Press, Oxford, 2008.
[38] D. Snowden, The paradox of story: simplicity and complexity in strategy, Scenario and Strategy Planning 1 (5) (1999) 16–20.
[39] D. Snowden, Liberating knowledge, in: Liberating Knowledge CBI Business Guide, Caspian Publishing, 1999, pp. 9–19.
[40] D. Snowden, The new simplicity: context, narrative and content, Journal of Knowledge Management 5 (10) (2002) 11–15.
[41] C.F Kurtz, D.J. Snowden, The dynamics of strategy: sense-making in complex and complicated world, IBM Systems Journal 42 (3) (2003) 462–481.
[42] W.L. Renfro, J.L. Morrison, Scanning the external environment: organisational issues. applying methods and techniques of futures research, in: L. James, Morrison, L. William, Renfro, I. Wayne, Boucher (Eds.), New Directions for Institutional Research No. 39, Jossey-Bass, San Francisco, 1983.
[43] F.J. Aguilar, Scanning the Business Environment, Macmillan, New York, 1967.

[44] C.W. Choo, Wei Chun, Information Management for the Intelligent Organization: The Art of Scanning the Environment, 3rd ed., Information Today, Inc., Medford, NJ, 2001.
[45] L. Cook, The state scanning network: an issue identification system for state policy managers, Futures Research Quarterly (1986) 65–77.
[46] S.D. Ferguson, Strategic planning for issue management: the communicator as environmental analysts, Canadian Journal of Communications 18 (1) (1993) http://www.cjc-online.ca/index.php/journal/article/viewArticle/716/622.
[47] J. Dator, Universities without 'quality' and quality without 'Universities', On the Horizon 13 (4) (2005) 199–215.
[48] J.L. Morrison, W.L. Renfro, W.I. Boucher, Futures Research and the Strategic Planning Process. Implications for Higher Education, ASHE-ERIC Higher Education Reports, 1984 http://horizon.unc.edu/projects/seminars/futuresresearch/.
[49] M. Heikell, Scanning the Business Environment for Detecting Weak signals, Teknillinen korkeakoulu, Täydennyskoulutuskeskus, Informaatiopalvelun kurssi 12, Helsinki, 1986.
[50] C.W. Choo, Information Management for the Intelligent Organization – The Art of Scanning the Environment, Information Today Inc., Medford, 1995.
[51] O.A. El Sawy, Personal information systems for strategic scanning in turbulent environments: can the CEO go on-line? MIS Quarterly (March) (1985) 53–60.
[52] W.J. Keegan, Multination scanning: a study of the information sources utilized by headquarters executives in multinational companies, Administrative Science Quarterly 19 (September (3)) (1974) 421–441.
[53] K. Debackere, M. Rappa, Science and industry: network theory and paradigms, Technology, Analysis & Strategic Management 6 (1) (1994) 21–37.
[54] K.E. Weick, Sense-Making in Organizations, Sage, Thousand Oaks, CA, 1995.
[55] P. Anderson, Complexity theory and organization science, Organization Science 10 (3) (1999) 216–232.
[56] C.S. Peirce, Some consequences of four incapacities, Journal of Speculative Philosophy (1868) 140–157, www.peirce.org/writings/p27.html (opened: 20.06.06).
[57] O. Kuusi, E. Hiltunen, Signification Process of Future Sign. E-Books 4/2007, Finland Futures Research Centre, Turku School of Economics, Turku, 2007.
[58] C.A. O'Reilly, Variations in decision makers' use of information sources: the impact of quality and accessibility of information, Academy of Management Journal 25 (December (4)) (1982) 756–771.
[59] H. Vejlgaard, Anatomy of a Trend, McGraw-Hill, New York, 2008.
[60] C. Saunders, J.W. Jones, Temporal sequences in information acquisition for decision making: a focus on source and medium, The Academy Management Review 15 (January (1)) (1990) 29–46.
[61] M.T. Hansen, The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits, Administrative Science Quarterly 44 (1) (1999) 82–111.
[62] A. Rindfleisch, C. Moorman, The acquisition and utilization of information in new product alliances: a strength-of-ties perspective, Journal of Marketing 65 (2) (2001) 1–18.
[63] M.S. Granovetter, The strength of weak ties, American Journal of Sociology 78 (6) (1972) 1360–1380.
[64] H.K. Steensma, K.G. Corley, On the performance of technology-sourcing partnerships: the interaction between partner interdependence and technology attributes, Academy of Management Journal 43 (6) (2000) 1045–1067.
[65] G.P. Huber, Organizational learning: the contributing process and the literatures, Organization Science 2 (1) (1991) 88–115.
[66] P. Cohendet, F. Kern, B. Mehmanpazir, F. Munier, Knowledge coordination, competence creation and integrated networks in globalised firms, Cambridge Journal of Economics 23 (2) (1999) 225–241.
[67] J. Gammelgaard, T. Ritter, The Knowledge Retrieval Matrix: Codification and Personification as Separate Strategies, CKG Working Paper 10/2004. Department of Management, Politics and Philosophy, The Center for Knowledge Governance, Copenhagen Business School, Copenhagen. Denmark, 2004.
[68] J. Kaivo-oja, Futures of journalism profession: scenario analyses of innovation journalism based on critical drivers in the today's media world, in: The 6th Conference of Innovation Journalism. The Journalism Succeeding with Innovation, University of Stanford, Innovation Journalism 6 Conference Paper, Stanford, 2009 www.innovationjournalism.org/./KaivoojaFuturesofJournalismdraft.
[69] T. Uskali, Weak signals in innovation journalism – cases Google, Facebook and Twitter, in: The 6th Conference of Innovation Journalism. The Journalism Succeeding with Innovation, University of Stanford, Innovation Journalism 6 Conference Paper, Stanford, 2009 http://www.innovationjournalism.org/archive/injo-6-6.pdf.
[70] S. Inkinen, J. Kaivo-oja, Understanding Innovation Dynamics. Aspects of Creative Processes, Foresight Strategies Innovation Media and Innovation Ecosystems. eBook 9/2009, Finland Futures Research Centre, Turku School of Economics, Turku, 2009 http://ffrc.utu.fi/julkaisut/e-julkaisuja/eTutu_2009-9.pdf.
[71] E. Wenger, Communities of Practice: Learning, Meaning and Identity, Cambridge University Press, Cambridge, 1998.
[72] R. McDermott, Why information technology inspired but cannot deliver knowledge management, California Management Review 41 (4) (1999) 103–117.
[73] J. Lave, E. Wenger, Situated Learning: Legitimate Peripheral Participation, Cambridge University Press, Cambridge, 1991.
[74] I. Nonaka, R. Toyama, N. Konno, SECI Ba and leadership: a unified model of dynamic knowledge creation, in: I. Nonaka, D.J. Teece (Eds.), Managing Industrial Knowledge: Creation, Transfer and Utilization, Sage Publications, London, 2001, pp. 13–43.
[75] J.S. Brown, P. Duguid, Organizational learning and communities-of-practice: toward a unified view of working, learning and innovation, Organization Science 2 (1) (1991) 40–57.
[76] M.S. Gertler, Tacit knowledge and the economic geography of context or the undefinable tacitness of being (there), Journal of Economic Geography 3 (1) (2003) 75–99.
[77] M.K. Ahuja, K.M. Carley, Network structure in virtual organizations, Organization Science 10 (6) (1999) 741–757.
[78] J. Gammelgaard, T. Ritter, The knowledge retrieval matrix: codification and personification as separate strategies, Journal of Knowledge Management 9 (4) (2005) 133–143.
[79] M.M. Alavi, D. Leidner, Review: knowledge management and knowledge management systems: conceptual foundations and research issues, MIS Quarterly 25 (1) (2001) 107–136.
[80] E.W. Stein, V. Zwass, Actualizing organizational memory with information systems, Information Systems Research 6 (2) (1995) 85–117.
[83] E.W. Stein, V. Zwass, Actualizing organizational memory with information systems. Information Systems Research 6 (2) (1995) 85–117.
B. Daniel, R.A. Schwier, G. McCalla, Social capital in virtual learning communities and distributed communities of practice, Canadian Journal of Learning and Technology 29 (3) (2003) 113–139.