QUALITY OF DATA, INFORMATION AND KNOWLEDGE IN TECHNOLOGY FORESIGHT PROCESSES

(Research Paper)

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Abstract: Futures research means observation and understanding of today's operational environment as well as identification and positioning of future opportunities. Lots of technology foresight and assessment initiatives are being made, probably in virtually all countries of the world. Articles concerning foresight rarely include assessments of what kind of materials they are based on. If they do, descriptions are general by nature, and there is no assessment of their real usability and applicability. Quality of results is not assessed in detail – not to mention quality of foresight-related data, information and knowledge more generally. This paper discusses ways in which data, information and knowledge quality considerations are related to technology foresight processes. They are illustrated by means of evaluating results of an empirical case study: a technology foresight survey undertaken in Finland in the summer of 2005. The research responds to arising societal and academic interest by combining the fields of (i) futures research and (ii) data, information and knowledge quality. Future-oriented considerations are not routine tasks, and it is especially challenging and important to ensure that these processes benefit from data, information and knowledge of good quality. The paper also outlines further research that should be done if foresight processes are to utilize and produce good quality data, information and knowledge.

Key Words: Data Quality, Information Quality, Knowledge Quality, Futures Research, Technology Foresight

INTRODUCTION

To many researchers of data, information and knowledge quality, futures research and foresight studies probably do not seem relevant with regard to their own field. They often represent exact sciences, where technical solutions can be found. Scientists interested in futures research, again, have not been particularly interested in attempts to measure how accurate their works are. Few foresight exercises have been vigorously evaluated by external evaluators – even internal reviews are still rare. A few limited attempts have been made to assess outcomes and impact of foresight. This thinking appears to be gradually changing, however [cf. 17]. The basic philosophy does still remain different; the primary goal in foresight studies is not to produce accurate forecasts as such, but rather to participate in development, affect and contribute to it – and thus to open up and widen actors' mental horizons [7, 28].

Across the world, lots of technology foresight and assessment initiatives are being made. Lots of money is used for making those. In a pilot project to map foresight competencies in Europe, it was found out that of those where data were available (84 foresight exercises), 20% cost more than 250,000 euros, with 7% costing more than 500,000 euros. Only 4% of exercises cost less than 50,000 euros [17]. Should we overlook approaches and initiatives based on quality thinking to improve their basic materials, results and usability of results in practice? This paper argues that we should not. The integration of the two fields would undoubtedly benefit policy-makers in their struggle to identify long-term trends, debate possible future scenarios and determine what priorities are worthy of investment and resource allocations.

Futures research means observation and understanding of today's operational environment as well as identification and positioning of future opportunities. When properly conducted and utilized, futures research may provide valuable competitive advantage for companies and other organizations; it is not something mystic or magic [cf. 17]. Foresight studies have been part of organizational life for a long time already, if the concept means benefiting from market studies or studies on competitors. Yet, small-scale foresight studies only give hints of trends related to one's own narrow field of operations. It has been claimed that flexible integration of technology foresight and assessment practices into the strategy work of individual organizations – companies and research institutions – is needed in order to better manage the technological development and to create long-term competitiveness [8]. It has been noted that foresight studies are used for wiring up innovation systems [7].

Futures research has been characterized as a scientifically oriented field of knowledge [22]. Foresight studies and knowledge management are said to be close to each other. However, also novel types of foresight methodologies are needed to support traditional foresight methodologies, such as the Delphi method and scenario-building. Quantitative methodologies are also needed in foresight activities. [32.] Therefore, considerations of data, information and knowledge quality are argued to be highly relevant in this field.

Articles concerning foresight do not normally include assessments of what kind of materials they are based on. If they do, the descriptions are general by nature, and there is no assessment of their real usability and applicability. Quality of results is not assessed in detail – not to mention quality of foresight-related data, information and knowledge more generally. Moreover, a stakeholder analysis is usually done at a relatively general level, without a detailed consideration of whose needs are responded to, how the results are rooted into practice, and how materials produced in foresight processes are interpreted to benefit the stakeholders.

Research in data, information and knowledge quality is widening and entering into new fields, which is reflected also in certain new topics for the International Conference of Information Quality in 2007. This paper is in line with the new topics introduced. This paper discusses ways in which data, information and knowledge quality considerations are related to technology foresight processes. They are also illustrated by means of evaluating an empirical case study.

BACKGROUND

Quality of Data, Information and Knowledge

Most definitions refer to a datum as the most basic descriptive element representing a perception or measurement about some object of interest. By itself, a datum's value typically lacks content, meaning or intent. Information is more than just a set of data; it is the output of a process that interprets and manipulates data into some prescribed format. Some authors prefer to use the term information product, as opposed to information, which is frequently used interchangeably with data [36]. The phrase, information product, emphasizes the idea that this item is determined by more than just its input data, but also by the procedures used to construct it. While data records may be more likely to follow a life cycle with separate phases, certain information products as well as the next concept, knowledge, seem to be more associated with a continuous life cycle. [27] Although this continuity is important also in this paper, we use the term information for reasons of simplicity.

Pierce, Kahn and Melkas [27] discuss the hierarchy of data, information and knowledge, and quality dimensions associated with those. There is also a thorough conceptual discussion in [24]. The difficulties in articulating knowledge are reflected in the many categories used to explain knowledge, such as

1. Explicit knowledge: Knowledge expressed as words or numbers. This type of knowledge is codified and well defined.
2. Tacit knowledge: Knowledge expressed as insights, intuitions and hunches. This type of knowledge is highly personal and hard to formalize.
3. Self-transcending knowledge: The ability to sense the presence of potential, to see what does not yet exist. It can also be described as tacit knowledge prior to its embodiment.

The third type of knowledge, self-transcending knowledge, was introduced by Scharmer [29]. Scharmer cites Michelangelo, who when talking about his sculpture of David, said: “David was already in the stone. I just took away everything that wasn’t David”. The ability to see a David where others just see rock is the essence of self-transcending knowledge. Today’s business and other leaders are often faced with the challenge of figuring out what in their environment may contain the potential new “David” and how to take away everything that isn’t “David”. Scharmer argues that the knowledge management discussion of the next decade will revolve around the interplay of the three forms of knowledge – explicit, tacit and self-transcending.

In addition, these three types of knowledge can further be classified according to whether the explicit, tacit or self-transcending knowledge can be described as

1. Declarative knowledge: Facts, know-what comprehension
2. Explanatory knowledge: Rationalization, know-why knowledge
3. Procedural knowledge: Instructions, know-how understanding
4. General/organizational knowledge: Knowledge that is easily transferred and possessed by large numbers of people.
5. Specific/individual knowledge: Knowledge that is difficult to transfer and thus is possessed by very few people. [27.]

The idea that knowledge is much more than information stems from the view that knowledge consists of an assortment of inputs: information, experiences, beliefs, relationships and techniques that an individual mentally synthesizes together to determine what a specific situation means and how to handle it [2]. For instance, if a factory manager wishes to anticipate what his/her customers like to buy in five or ten years (that is, utilize foresight), she/he cannot solely rely on analyzing information like the end of year sales report or consumer market survey to acquire this understanding. Using his/her own internal reasoning, she/he will combine the assessment of this information with other accumulated experiences to come up with an answer and a direction for how to act. That is, if the manager is, in general, keen to acquire future-oriented understanding. Based on this reasoning, this research is based on the opinion that knowledge should be treated as a process by which justified true beliefs about relationships among ideas, experiences, and information relevant to a particular area are used to obtain awareness about how to recognize and manage a particular situation [2; cf. 27]. Information can similarly be seen as a process [24].

Data quality and information quality have been studied overwhelmingly by researchers interested in computing, management information systems, databases and their management, data security and data warehouse quality, to mention a few. Researchers have concentrated on company environments and business information [cf., e.g., 5, 9, 15, 26, 34, 35, 36]. Studies in heterogeneous innovation networks consisting of organizations from different sectors have not been undertaken. Neither have studies related to foresight processes been undertaken.

According to Pierce, Kahn and Melkas [27], data, information products and knowledge are of high quality if they are fit for their intended use in conducting business operations, decision making and planning. They discuss what the relationship between data quality, information quality and knowledge quality is. The answer to this question is critical in advancing the research in this area. According to them, most people agree that improvement in data quality should result in some quality improvement in the information that is formed from these data. It seems reasonable that improvements in information should in turn raise the quality of knowledge. The authors ask, however, whether high quality data are the only prerequisite for better information quality. Is it true that good quality information "automatically" turns into knowledge and if so, what kind of knowledge? Do the quality characteristics of data and information influence the types of knowledge that an organization can create and apply? Should quality improvement begin with data, or are there other factors that dictate where to begin the improvement process? How does the improvement process compare between data, information and knowledge? Should the quality improvement efforts be done as one cohesive process, parallel initiatives, or integrated whenever possible? [27.] These are all important questions. What about the special challenges related to these concepts versus foresight processes and technology assessment – future-oriented activities that are based on a relatively uncertain foundation?

Three common approaches that have been used to identify the quality dimensions associated with data are identified in Table 1. Using these three approaches, information quality researchers have demonstrated that data quality is multidimensional in nature and can be portrayed according to the quality of the values collected, accessibility, presentation, application and level of system support for the data [34, 36, 37]. Although not always explicitly stated in the literature, it seems reasonable that one can replace data with information or knowledge area when discussing these dimensions, and their general meanings continue to apply [27]. This paper takes the intuitive approach in the case study as well as the system approach in the theoretical study.

Approach	Definition	Examples
Intuitive	Selection of quality attributes in a specific study is based on the individual's experience or intuitive understanding about what attributes are important.	[36]
System	Focuses on how the output of a process may become deficient.	[34]
Empirical	Collects input from consumers to determine the characteristics they use to assess whether the end product is fit for use in their tasks.	[37]

Table 1 – Common approaches used to identify data quality dimensions (source: [27]).

Foresight Activities

Malaska [20, 22] claims that futures research has no domain of empirical observation of its own, but accumulated empirical knowledge gained by any science can and should be utilized in futures research. A futures knowledge system encompasses three different kind of modes of knowing (see also Figure 1):

- A syntactical mode with its emphasis on methodologies to acquire knowledge
- A semantic mode that emphasises issues, contents of study, meanings and subjects
- A pragmatic mode that becomes evident when we look at implications for action, decision-making, policy formulation, management or leadership

This paper focuses on the syntactical mode with its emphasis on methodologies. The disposition presented in Figure 1 only includes knowledge, but we widen the view by including also data and information.

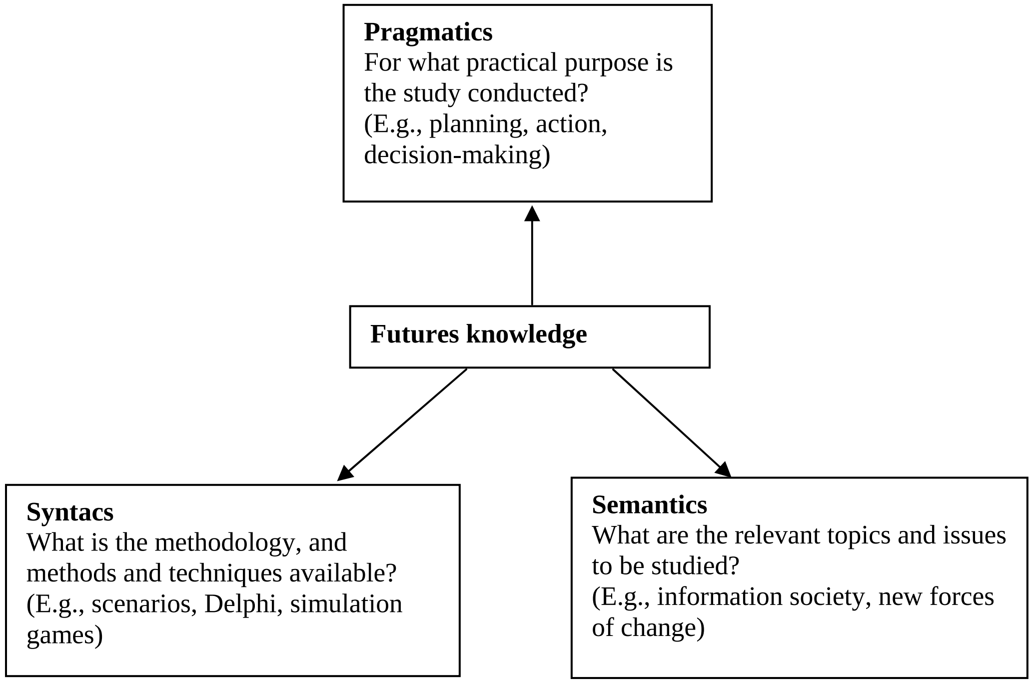

Figure 1 – A threefold disposition of the futures knowledge system (adapted from [21]).

A central subcategory of futures research is technology foresight and assessment. Foresight can be defined as "a systematic, participatory, future intelligence gathering and medium to long-term vision building process aimed at present day decisions and mobilizing joint actions" [10, 11]. Its basic philosophy has changed somewhat during recent years. Previously, more focus was laid on an approach that stressed outside objectivism during the foresight and assessment process, but nowadays the so-called constructive technology foresight and assessment has gained more popularity. It means that also those who will utilize or produce emerging technologies take part in the technology foresight process in order to influence the shaping of those technologies [8].

Foresight is a process that attempts to broaden the boundaries of perception in four ways:

1. By assessing the implications of present actions, decisions, etc. (consequent assessment)
2. By detecting and avoiding problems before they occur (early warning and guidance)
3. By considering the present implications of possible future events (pro-active strategy formulation)
4. By envisioning aspects of desired futures (normative scenarios) [30].

According to Horton [14], a successful foresight process consists of three consecutive phases (see also Figure 2):

1. Phase one comprises the collection, collation and summarisation of available information and results in the production of foresight knowledge.
2. Phase two comprises the translation and interpretation of this knowledge to produce an understanding of its implications for the future from the specific point of view of a particular organization.
3. Phase three comprises the assimilation and evaluation of this understanding to produce a commitment to action in a particular organization.

Horton's classification does not include data or the different types of knowledge. Moreover, it mainly concerns individual organizations. Technology foresight is often undertaken at larger levels, which also implies far greater challenges in, for instance, stakeholder analyses, collection of information, managing the whole foresight process, and dissemination of results.

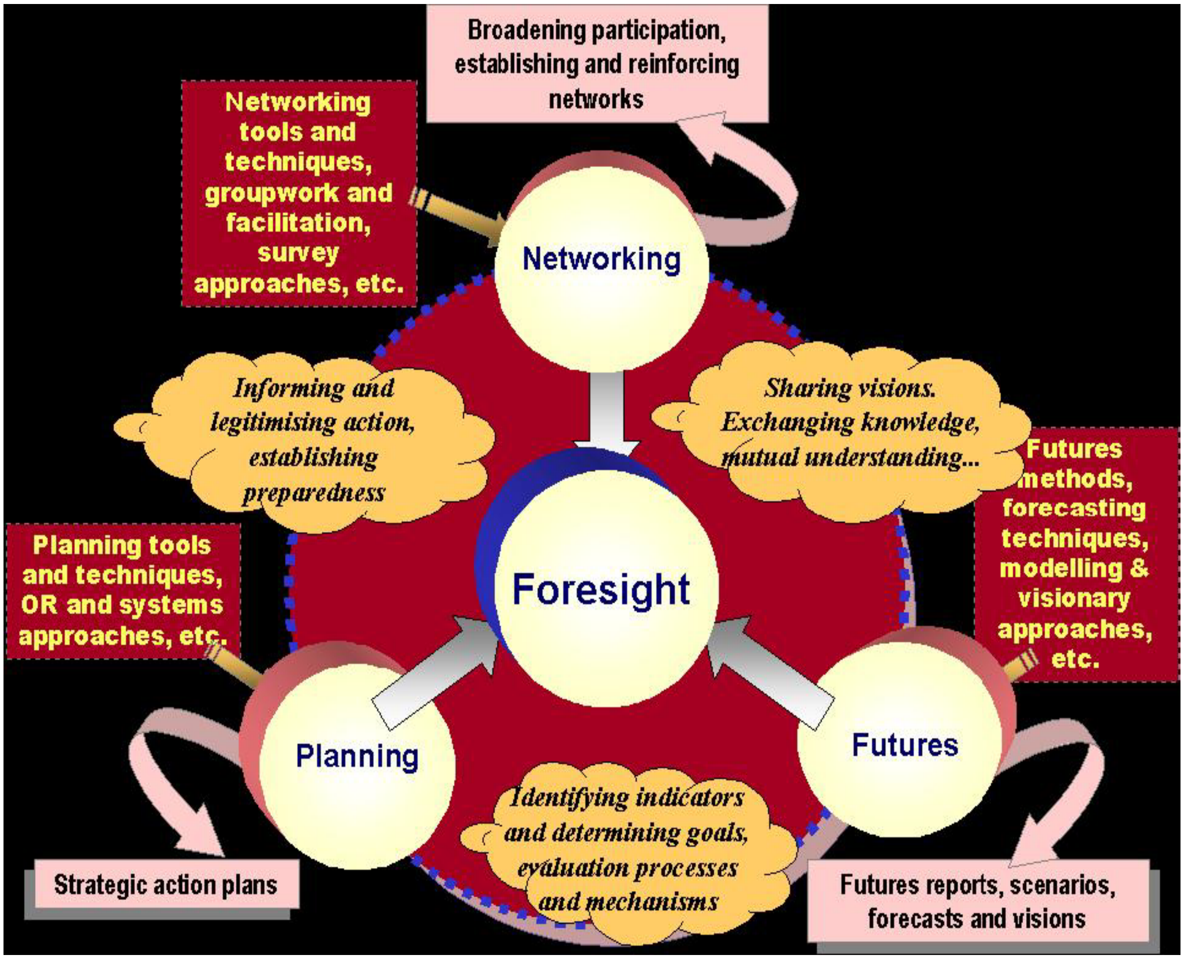

Figure 2 – Foresight's triple base (source: Miles, 2002; in [17]).

Special attention has been paid to technology foresight and assessment processes during recent years also at national and international levels. Joint Research Centre of European Commission published in 2003 an unusual report on mapping foresight competence in Europe [17]. Hundreds, sometimes thousands of people are involved in foresight exercises, and are drawn from a wide variety of backgrounds, often within the same exercise. According to the report, knowledge of many of the large national foresight exercises, such as those carried out in Germany and the UK since the early 1990s is reasonably good, and useful lessons have been learnt from them. By comparison, knowledge of activities at other territorial levels, such as regions, is often very limited, as is knowledge of national activities that focus upon a small number of business sectors or socio-economic issues. There are some good reasons for this knowledge shortfall – many of these exercises are relatively parochial, with little or no international profile; many are conducted and written up in a language other than English, thus affecting their diffusion; and up until now, no systematic attempt has been made to identify these activities, let alone describe and characterize them. There is thus a concern that technology assessment and foresight procedures of today do not serve the technology-political decision-making or the strategy processes of companies well enough [8]. The regional level needs to be emphasized, too, as well as the inclusion of a wide variety of actors and organizations – not only companies – in the foresight processes. Foresight does not concern technology only, but may naturally be undertaken in connection to other issues as well.

RATIONALE & PURPOSE

In order to increase usability of foresight studies and contribute to successful conduct of them, assessing the hierarchy of data, information and knowledge and the quality of those is necessary, in our view, at all stages of foresight processes. Otherwise, a “black hole of interpretation and implementation of foresight studies” may come into existence [cf. 31]. Resources are also wasted, if foresight studies are not conducted efficiently and effectively.

In this paper, the focus is on assessment of results of foresight studies. Other stages are briefly referred to in the discussion. Following Pierce, Kahn and Melkas [27], we also consider the following questions in relation to foresight activities:

- Is high quality data the only prerequisite for better information and knowledge quality?
- Is it true that good quality information “automatically” turns into knowledge?
- Should quality improvement begin with data, or are there other factors that dictate where to begin the improvement process? How does the improvement process compare between data, information and knowledge? Should the quality improvement efforts be done as one cohesive process, parallel initiatives, or integrated whenever possible?

This paper looks into analysis and reporting of foresight results from an empirical point of view. Research methods include literature studies as well as use of empirical results from a technology foresight survey undertaken in Finland by Helsinki University of Technology, Lahti Centre and Lappeenranta University of Technology, Lahti Unit in the summer of 2005. The empirical results are utilized to illustrate present limitations of foresight processes. Methods of the survey are described in detail in a later section. The survey has not been undertaken and the results have not been collected for this research, and the paper does not report or analyze the results as such – it evaluates their quality.

This paper attempts to reduce the gap between futures research, on the one hand, and data, information and knowledge quality, on the other hand. It advocates combining approaches and methodologies from different fields in a novel way. Combining the research fields of, on the one hand, quality of data, information and knowledge, and on the other hand, foresight and technology assessment corresponds well to arising societal needs as well as academic interest. The importance of foresight and technology assessment is more and more emphasized these days at various levels. The paper serves also the purpose of outlining further research that should be done if foresight processes are to utilize and produce good quality data, information and knowledge.

METHODS OF THE TECHNOLOGY FORESIGHT SURVEY EVALUATED

Lahti region in Southern Finland has set a goal to be the leading area in practice-based innovation activities in Finland, and the framework of network-facilitating innovation policy has been adopted in the region in order to promote innovation activities. The Lahti region's future competitiveness is seen to be greatly dependent on its ability to promote practice-based innovations, due to the absence of a whole university and very low research inputs in the region. The region has 200,000 inhabitants.

The situation in the Lahti region has forced it to develop new tools to trigger innovation processes. One aim of the network-facilitating innovation policy is to search for structural holes between the regional knowledge-base and the future-oriented knowledge-base found in the surrounding research centres; that is, to absorb the surrounding future-oriented knowledge to the regional innovation system. Therefore, as part of regional innovation policy, a resource-based technology foresight process was carried out in 2005. In general, the existing resource configurations in a region set the basis for future development, and, therefore, regional foresight processes have to be tightly connected with an audit of the region's resource base [13]. Bearing this in mind, the technology foresight process was planned to be carried out in three phases:

Phase 1:	Defining the regional development platforms and clusters to be assessed and identifying the related technologies
Phase 2:	Exploring the future opportunities for the clusters and technologies using the Delphi process
Phase 3:	Organizing future-oriented innovation sessions in order to disseminate the results of the Delphi process within the clusters

In the Lahti region, the cluster-based development strategy was adopted during 2004–2005. Strong current clusters in the region are mechatronics, environmental, grain, wood, furniture and plastics clusters. The development resources during the coming years will mainly be allocated to the development of these clusters, and especially the environmental cluster. The aim of the regional technology foresight was to create an open, exploratory foresight process, the limits of which are drawn on the basis of the regional cluster strategy. The focus was on mechatronics, environmental and plastics clusters. The process is depicted in Figure 3.

The importance of technology signals[1] was assessed during the first Delphi round of the foresight process. Signals were categorized into three main generic technological categories: ICT, nano- and biotechnologies. These pervasive technological fields can be thought of as important for large sectors of industries and clusters, since they influence the pace and direction of innovation in or across many areas. Development of the necessary knowledge capacity and competencies in these enabling technologies is expected to affect future competitiveness and innovation potential across value chains and sectors [12]. The primary data on the technology signals were collected from several sources – the most important being the signal bank of MIT Technology Review.

The selection criteria for the primary technology signals were three-fold: first, the signals had to have an explicit or at least a potential connection to the most important clusters in the Lahti region. Second, the signals ought to be hybrid by nature, reflecting the prevalent paradigms for technological convergence and fusion. Hybrid signals – it can also be argued – have a potential value for several clusters, not just one or two. Third, the chosen signals should be concrete enough, so that they could be presented in a questionnaire in a thesis-like form in order to characterize the content and the social context of a technology in question (see also [1]). Altogether some 200 technology signals were "muddled through", and 33 were selected to be further investigated during the Delphi process. The selection of technology signals, construction of technology theses and selection of expert panelists proceeded simultaneously [33].

In the foresight process, the Delphi method was used to collect expert opinions from outside of the region. Delphi is a method that emphasizes respondents' expertise on a certain research topic. The insights are based on collective expert opinions that are considered to be more reliable than a single expert opinion. [16, 23.] Linstone and Turoff [19] characterize Delphi as "a method for structuring a group

[1] The definition of technology signal is analogical to that of weak signal, only in this case, the content of the signal is related to technology.

communication process, so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem”. The Delphi process does not – in a strict sense – produce knowledge about the future, but it tells about the experts’ present expectations concerning the future and thus produces basic input materials to discussions concerning the future. The information it provides also creates a basis for building scenarios or regional innovation processes.

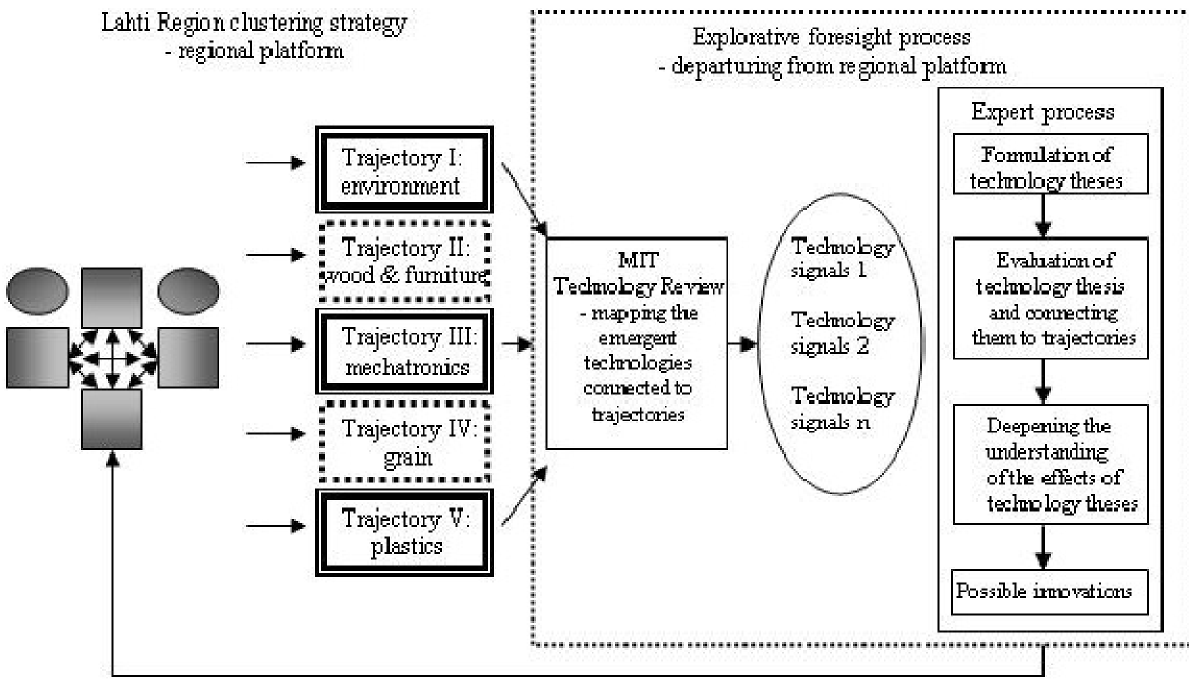

Figure 3 – Technology foresight process in the Lahti region (source: [33]).

As the method places such a great emphasis on respondents’ expertise, one of the most challenging phases of implementation of this method is selection of expert panelists (see [15]). There are several options in selecting the Delphi panel. In the study evaluated here, the composition of the panel was science and research oriented. The panel was built up by searching through web-pages of organizations, mainly universities and other research organizations that are active in doing research related to the technologies and technology signals that were relevant in the foresight process in question (see Figure 3). Altogether 300 respondents from Finland and abroad were selected to the panel. One idea behind this kind of panel building was the will and need to mobilize and integrate expertise from outside of the region into the foresight process. This was considered to be important when trying to avoid the possible tendency for technological lock-ins and path dependency [13].

The first round of the Delphi process was carried out in April 2005. Altogether 63 experts responded to that round. The general purpose of the first round was to collect expert views on the technology signals, i.e., emerging technologies that have a plausible potential to produce effects in the regional clusters of the Lahti region. The second round that focused on industrial effects of the technology signals was carried out in July-August 2005. It concentrated on five technology signals that were found to be the most promising during the first round. The main idea was to gain insights of possible product, process or business innovations that could utilize the technology signals focused on. Altogether 49 experts responded to the second round questionnaire.

The survey produced also results as responses to open questions. One could anticipate that these responses would be ways to codify respondents' *tacit or self-transcending knowledge.* However, there were great differences in the types, quality and usability of the open responses, which led us to pay closer attention to them as an illustrative case of foresight results. Of the wealth of results obtained with the help of the survey, the present paper thus discusses the open responses with a special emphasis on their quality. They comprise some nine pages. This type of material reveals and reflects strengths and weaknesses that foresight studies – especially those based on the use of the Delphi method – typically encounter concerning the quality of their empirical results.

METHODS OF ANALYSING THE QUALITY OF SURVEY RESULTS

For our analysis, the open responses were divided into three categories, based on whether they are "data-like", "information-like" or "knowledge-like". The "data-like" category includes responses that by themselves lack content or meaning. "Information-like" responses are more than just a set of data, but they are not yet "knowledge-like", i.e. an assortment of inputs synthesized together and reflecting awareness about how to recognize relevant trends related to the future.

The categorization was done with the help of the quality dimensions of

- relevancy
- timeliness
- completeness
- objectivity
- applicability

The list of dimensions was adapted on the basis of the framework of analysis for analysing information quality introduced in Melkas [24]. This study was based on significant works in the field of information and data quality. The list of dimensions in it is quite comprehensive and provides a sufficient basis for selecting the relevant dimensions for the present paper. A special dimension that was added to this research is *applicability in companies and other organizations*. This is central for the usability of results of foresight processes. Applicability was assessed in a preliminary manner based on the researchers' intuitive views. A complete assessment would include interviews with company representatives. This paper also includes certain quotes from the open responses to illustrate how the categorization was undertaken.

Important quality dimensions such as accuracy are not included in this categorization exercise, as it cannot be assessed at the time of the foresight process. Concise and consistent representation, for instance, are not relevant in the case of open responses. Applicability, again, contains nuances reflecting also accessibility, value added, interpretability, ease of understanding, ease of operation, and believability. An assessment of reputation would benefit from looking into the respondents' backgrounds, which is beyond the scope of this paper. The list of quality dimensions should thus be reasonably complete for an assessment of this kind.

The first coding was done in February 2006, and the second after two months in April 2006, to double-check the coding results. The second coding was done so that the researcher no longer remembered the first coding. In these two codings, there were some responses that were difficult to place in one of the three categories. This two-phase coding helped in deciding how to code "the uncertain ones". Those uncertain ones (27 responses out of altogether 272 responses) were once more assessed in June 2006 to make sure that they were correctly placed in the second coding.

RESULTS OF THE QUALITY ANALYSIS

The coding showed very clearly how big differences there are in the quality of the open responses. In typical foresight studies, these differences are hardly documented or discussed when reporting on the results. Although things and trends related to the future are highly uncertain, an increasing attention to quality issues is necessary in order to improve validity and reliability of results of foresight processes.

Table 2 shows how the responses were coded as "data-like", "information-like" and "knowledge-like". An ideal situation would be such that all the responses could be classified as "knowledge-like" – preferably reflecting self-transcending knowledge, and, in addition, of high quality as analysed with the help of each quality dimension. Although it is difficult to determine how the different quality dimensions really are fulfilled, the directions seem clear.

Innovations related to (type of technology)	**Data-like responses (% of all responses)**	**Information-like responses (%)**	**Knowledge-like responses (%)**
ICT technologies	33	51	16
Nanotechnology	46	49	5
Biotechnology	31	56	13

Table 2 – The survey responses as categorized by their quality and content.

The percentage of knowledge-like responses is relatively low for all the technologies. Should the percentages for data-like and knowledge-like responses be vice versa, the situation would seem much better, but the percentages above show an alarmingly high share of data-like responses. Examples of such data-like responses are (quotes from the responses for the different technologies)

- for innovations in ICT technologies: *"e-Home"*, *"mobile applications in business"*, *"transportation, new applications of wireless technology"*, *"rich call"*, *"security applications"*, *"intelligent and communicative interfaces at home"*
- for nanotechnology: *"optical computers"*, *"new screens for home and leisure"*, *"textiles and clothing, protective materials"*
- for biotechnology: *"development of healthy foodstuffs"*, *"first aid"*

Although the corresponding technology theses are not shown here due to lack of space, the above shows that these type of responses do not give a basis for consideration and judgement by themselves. They are thus "data" by nature.

Examples of information-like responses are

- for innovations in ICT technologies: *"entertainment and ubiquitous communication: nice toys, but no real impact on the efficiency of society and commerce"*, *"possibility of production or action in toxic environments without human exposure; reduced harm to health and environment; assessment and clean-up of highly toxic environments inaccessible or dangerous to humans"*
- for nanotechnology: *"environmental monitoring, home security (detectors for dangerous materials of all sorts"*, *"most probably use for military purposes, at least initially; the military is strongly seeking*

new stronger and lighter materials for a number of purposes (body armor, ground vehicles, aircraft, etc.)"

- for biotechnology: *"embedded health monitor and biomarker detector: detects risks or symptoms of diseases early", "targeted and personalized drug delivery for complex diseases: devices target both the location, timing and the dose, to optimise and personalize the efficiency of the treatment"*

These show more potential for interpretability and conversion into knowledge in organizations. Knowledge-like responses, again, are the following, for instance

- for ICT: *"All applications just a stepping stone towards more development. By 2010, 3G will be almost forgotten about. The importance factors for the industries listed is not really about the impact on those sectors – but a question of how important is the sector itself (and will it still exist as such by 2030??)* [… the response continues with industry-specific issues]
- for nanotechnology: *"Package safety of foodstuffs and healthcare materials (including care for elderly people) is important > applications securing safe storage and quality control"*
- for biotechnology: *"Significant applications in medication (personalized medication); however, need to be combined with other information (a holistic analysis comprising the person's living environment etc.). In food industry, (right food for the right group of people, personalized food) may however be more of a marketing issue than a real health benefit (impact of living environment and habits are more significant)."*

The above knowledge-like responses, although they are brief samples, reflect the respondents' tacit knowledge and deeper consideration of the technologies in question.

As to the individual quality dimensions utilized, the biggest weaknesses appear to be associated with completeness and applicability. The responses are not always very clear in that they would fully describe the respondents' intentions and ideas. This has to do with applicability, too – when we think of the usefulness of these results in organizations such as companies, their applicability in visioning and planning for the future is not necessarily high. The high share of data-like responses exacerbates this problem.

The foresight process discussed in this paper was regional, which has its impact on the applicability of the results, too. In regional processes, a stakeholder analysis is much more difficult to undertake (and is usually omitted) than in processes that serve one or a few organizations only. There may be no understanding of who the stakeholders really are in regional foresight processes. If the process aims to serve an industrial cluster, for instance plastics industry, that kind of a cluster may be too obscure as a single actor. In future studies, an issue to be investigated is whether stakeholders can, generally speaking, be targeted and served in a sufficient manner at all in regional or otherwise larger processes – or is a company level process always necessary? Who pays for such processes? Who does the work, with quality? It may often be a practical compromise that foresight processes are undertaken at a cluster or regional level.

DATA, INFORMATION AND KNOWLEDGE QUALITY AT OTHER STAGES OF FORESIGHT PROCESSES: DISCUSSION AND LIMITATIONS

Supported by the evaluation in this paper, we argue that a successful foresight process would require considerations of data, information and knowledge quality at all stages of the process. Firstly, thorough data, information and knowledge of good quality would be needed among those who design and conduct the process and as the basis for individual expert opinions (see also Figure 4). A thorough discussion of those is beyond the scope here, but one example is the need to include different kind of people in foresight processes – not only highly educated persons from managerial positions, as often is the case. Moreover, if possible, an optimal cognitive distance between the experts should be reached [cf. 25]. Through this, the necessary data, information and knowledge conversion processes may be facilitated.

Secondly, quality of responses should be thoroughly assessed, such as in this paper. Poor response quality may be a sign of

- poor quality expertise in the subject areas among respondents, or
- poor quality of the technology (or other type of) theses (inadequate definitions of concepts or unclear expressions etc.), or
- other factors

Transparency is needed in discussing the results in order to improve validity and reliability of results of foresight processes. Thirdly, quality of implementation needs careful attention. For instance, in the case presented in this paper, simply using the Delphi method is not enough. The results of the Delphi process must be again rooted back into the clusters to support practical innovation processes in companies. It has been noted that different parties in an innovation system are continuously attempting to assess significance of technology and its development from the point of view of their own operations, and therefore, the great challenge in foresight activities is to link foresight processes better into the decision processes that these activities aim to support in different organizations [28].

In the Lahti region, this is to be done in Phase three of the foresight process in question (cf. Methods of the technology foresight survey evaluated) by organizing some 60 future-oriented thematic innovation sessions in the region. In the innovation sessions, the aim is to assimilate and transform the foresight information and knowledge gained during the Delphi process into future-oriented innovation knowledge to be exploited by companies (see Figure 3). This task is not easy to fulfill. It has often been seen how difficult it is to reach a fruitful dialogue between participants of the innovation sessions, since their knowledge interests are too far from each other, which threatens the spanning of the structural hole. The innovation potential is clear, but the innovation processes are inadequate due to lack of communication and absorptive capacity [cf. 6, 38]. Information and knowledge brokerage functions are needed [cf. 3, 4]. A discussion of these implementation issues is, however, beyond the scope of this brief paper.

Returning to the research questions from Pierce, Kahn and Melkas [27], this research implies that in technology foresight, high quality data are not a sufficient basis for better information and knowledge quality. Technology foresight processes are complicated and involve many different kind of actors, whose backgrounds are heterogeneous. This research also contributed to confirming that good quality information does not automatically turn into knowledge. Conversion processes are multi-dimensional, even chaotic by nature. Quality improvement is necessary at all stages of a foresight process. Given the many actors involved, it seems that parallel quality improvement initiatives might be most efficient. It is also largely a question of awareness-raising among those involved so that they would acknowledge issues related to data, information and knowledge quality.

The results of this paper are claimed to be both scientifically and practically relevant. This research reduces the gap between futures research, on the one hand, and data, information and knowledge quality, on the other hand. Combining these research fields corresponds to arising societal needs as well as academic interest. The importance of foresight is more and more emphasized these days at various levels – national, international, regional and micro-level (individual organizations).

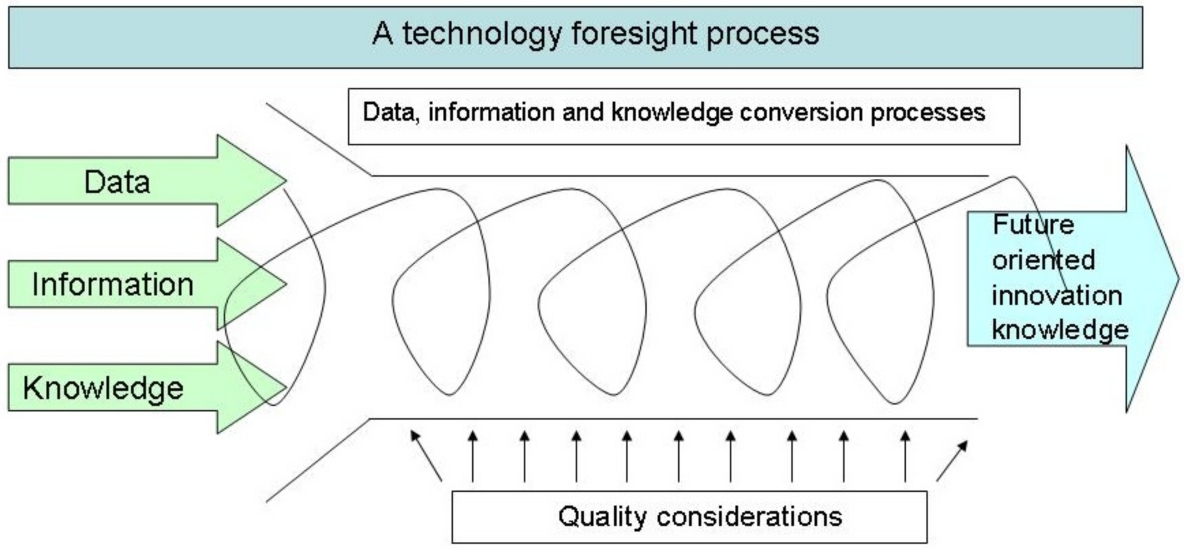

Figure 4 – Data, information and knowledge in foresight processes.

The paper also outlined further research that must be done if foresight processes are to utilize and produce good quality data, information and knowledge. Future-oriented considerations are not routine tasks, which makes it especially challenging to ensure that these processes benefit from data, information and knowledge of good quality. Improving the quality of knowledge, in particular, requires a holistic approach to the entire foresight process that includes also an understanding of the role that quality improvement in data and information can play.

The results of the research will be applicable in further research as well as in practice – when planning new foresight and technology assessment processes. The full results of the foresight process that was discussed in this paper contain much more than the open responses evaluated. The process produced interesting results for companies and other organizations. However, to illustrate the weaknesses and shortcomings in the quality, the open responses provided a good study material.

This paper has been built with the idea of introducing the concepts of data, information and knowledge quality into the new field, futures research. The aim was to discuss ways in which this could be done. Creating a framework for the integration of the two fields – futures research and quality of data, information and knowledge – would be a next step on the way to theory development. This would also benefit technology-related organizations in the Lahti region and elsewhere as well as improve futures research in general. Lessons learned from evaluating this foresight process may already be used in improving the methodology for future rounds of the regional foresight process that are planned to be carried out in the coming years in the Lahti region.

CONCLUSION

Quality of materials utilized and produced in foresight processes is highly variable. Quality matters should be taken into account at all levels, both among those who undertake and participate in foresight processes and those who use the results. A stakeholder analysis as well as an analysis of data, information and knowledge quality should be made at the beginning of the process as well as concerning the results and their implementation. Foresight should be seen as one form of data, information and knowledge management.

An interpretation process, where the results produced by foresight processes are converted into materials and information that can be utilized and turned into knowledge among stakeholders – such as companies – is also of utmost importance. This interpretation process should be a joint undertaking between researchers and practitioners and be included at the end of a foresight process. Otherwise foresight processes produce materials that do not benefit their potential users, resulting in the "black hole" of interpretation and implementation.

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