Eliciting Conceptual Models to Support Interdisciplinary Research

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Abstract

Constructing interdisciplinary knowledge requires knowledge sharing between researchers studying the same object from different disciplinary angles. Such sharing is particularly difficult because the knowledge is situated in different scientific disciplines. Researchers must find common ground to share, and this causes high transaction costs. This paper reports on an experiment with a method of conceptual analysis to elicit, analyse and compare conceptual models used by individual researchers, with the ultimate aim to facilitate researchers in sharing these models. Using an open coding method, we analysed the papers of two researchers from an interdisciplinary research project. The resulting conceptual models were validated in semi-structured interviews. The method was found to be effective in eliciting concepts, also those used implicitly. The interviews also revealed certain mechanisms by which researchers adopt new concepts and choose words for strategic reasons. However, the analysis costs are high, while the benefits remain as of yet uncertain.

1. Introduction

The potential of interdisciplinary research is that it can bring together knowledge from different fields in novel and synergistic ways, enabling new, integrated perspectives on complex phenomena. To realise this potential, the interdisciplinary scientific practice requires methods and tools that enhance the sharing and integration of disciplinary knowledge.

Social scientists view knowledge sharing and knowledge construction as an inherently social process in which people with different backgrounds collaboratively negotiate meaning as part of their social (professional) practice. Learning occurs through what is called “the legitimate peripheral participation of individuals in groups” [1]. Knowledge, in this view, is socially constructed, highly situated, and to an important extent implicit [2]. Hence, methods to support knowledge construction from this tradition tend to focus on group processes and uses techniques like group model building [3] and shared cognitive maps (e.g. [4, 5]).

Information scientists, on the other hand, view the sharing and building of scientific knowledge as a process in which different researchers strive for a high level of externalisation and formalisation of knowledge, which in turn makes it accessible and usable by others, and in the end enables formal (computer) modelling. Scientific researchers learn from each other by conceptually sharing and comparing the models they use. In this view, knowledge takes the form of explicit, externally available, ubiquitously accessible information. Methods to support knowledge sharing and building have therefore concentrated on making scientific work as much and readily available to others as possible, with techniques like increasingly sophisticated (on-line) repositories of knowledge [6], data mining techniques [7], and automated model comparison [8].

Both traditions offer some leads to support knowledge construction within interdisciplinary research projects. The social scientist might suggest that the researchers involved in an interdisciplinary project have specific meetings aimed at negotiating a shared understanding of their team's knowledge. The information scientist might suggest that they pool all the written documents they use and/or produce, and analyse this document base for shared concepts, linked to persons. The method of *conceptual analysis* that we propose in this paper uses elements from both views, but is expected to be less labour-intensive than the social interaction methods while suffering less from the conceptual ambiguity caused by homonyms and synonyms than information-analytical methods.

Conceptual analysis focuses on the conceptual models underlying scientific work. It aims to uncover the concepts that are necessary to describe a researcher's disciplinary knowledge and how these concepts are related, see also Jackson [9] and Guarino [10]. This produces a highly explicit account of a researcher's knowledge, which offers insights in, and

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opportunities for comparing and relating his/her knowledge to the knowledge of other researchers. The method for conceptual analysis we propose is geared to find those concepts and the relations between them that allow comparison of knowledge from different disciplinary backgrounds. It should enable two researchers from different disciplines to recognise how their disciplinary backgrounds are related, which in turn may give rise to producing new scientific knowledge.

The method we propose, in particular the construction of an overarching conceptual model that it involves, may give the impression that we believe that disciplinary differences can be resolved by unification of knowledge in a single 'true' model of reality. This is not the point we want to make. The conceptual analysis should be seen as a hermeneutic activity in the spirit of Gadamer (see [11] for an excellent primer), and the models it produces as a trigger for researchers to partake in such an activity and as a means to facilitate them in gaining an understanding of the language the other researcher uses.

In this paper we report on our first experiment with conceptual analysis in a multidisciplinary research project. We analysed the work of two researchers with as aim to (1) document our procedure for doing conceptual analysis, (2) reflect on the validity of the method, and (3) reflect on its viability. We have structured our report as follows. We start by arguing why we believe that our hunch that conceptual analysis can support interdisciplinary knowledge construction is worth pursuing. We then describe our method in more detail, rather formally on an abstract level, but also informally on a practical level. Next, we describe some selected results, permitting ourselves a few illustrative examples while focusing on those observations that reveal certain problems that seem inherent to the method. In the final section, we summarise our findings and draw some tentative conclusions.

2. Motivation

When proposing a method for conceptual analysis as a means to enhance interdisciplinary knowledge construction, we should be specific about a number of things:

1. What do we consider to be interdisciplinary knowledge?

By '*multi*disciplinary research project' we mean a project in which several researchers with different (or at most some partially overlapping) disciplinary knowledge and skills participate to produce new scientific knowledge. The project becomes '*inter*disciplinary' only when this new scientific knowledge is such that it could not have been produced if the participating researchers would all have had the same disciplinary knowledge. In other words, if we have a small multidisciplinary project with researchers a and b, trained in disciplines A and B, and individually capable of producing new knowledge K_A and K_B, this project becomes *inter*disciplinary when it produces knowledge k such that $k \notin K_A \cup K_B$ [1]. So for k to be new, it should involve knowledge not already part of disciplines A and/or B.

2. Why do we believe its construction to be difficult?

New, interdisciplinary knowledge k comes about by induction [2] from empirical observation, for instance when researchers a and b must observe some empirical phenomenon that they cannot fully explain using concepts from A or B. Furthermore, a and b need to mutually agree on the meaning of k. This presupposes that they both can meaningfully relate k to their respective disciplinary knowledge, they have sufficient understanding and awareness of each other's knowledge to be able to accept that k is related to either discipline, and agree that their understandings of k are sufficiently the same for their current purposes of collaboration (cf. [12]). In other words, they need to negotiate some common ground as to the meaning of k and its relation to their respective disciplines. Such 'grounding' processes have high transaction costs, that is, they require much time and effort from researchers, resources that can be allocated more efficiently to mono-disciplinary research. Empirical studies of interdisciplinary research [13, 14] show that such resources are difficult to mobilise. Promoting interdisciplinarity would require institutional changes (other incentive structures) or a lowering of transaction costs.

3. Why do we believe that conceptual analysis offers effective support?

A conceptual analysis offers a shared set of definitions that can be used in communication. The use of such a shared conceptual framework enables exchanging knowledge from different domains without the need for a "globally shared theory" [15], p. 908. In other words, collaborating researchers will have smaller needs to gain expertise in each other's fields. We therefore assume that the transaction costs for individual researchers a and b can be lowered if they

[1] For projects with more than two researchers, we would require that these conditions are met for at least two participants with different disciplinary backgrounds.

[2] If k could be deduced from knowledge of a or b alone, this would violate our condition that $k \notin K_A \cup K_B$.

use a conceptual analysis of their domains, because it affords more explicit knowledge about their own disciplinary knowledge A and B, and about how the concepts in A and B do (and do not) relate to each other.

Furthermore, *a* and *b* initially each speak their own disciplinary 'languages' A and B, and to achieve common ground, they must each discover what they have in common (i.e., $A \cap B$) and extend their language to A+C and B+C where C consists of the concepts needed to better understand the empirical phenomenon they investigate. We expect that the cost of (1) discovering $A \cap B$ and (2) negotiating the concepts in C can be reduced through conceptual analysis. The former because the results of a conceptual analysis of A and B are explicit and can be re-used when other researchers from A and B engage in interdisciplinary research, the latter because the process of conceptual analysis provides focus and rigour to the grounding process, which leads to a concise and unambiguous set C that is easier to relate to the concepts in A and B, especially when these also have been rendered concise and unambiguous.

Finally, the existence of homonyms and synonyms in the discourses of *a* and *b* can give rise to mutual misunderstandings, that may or may not be detected [16]. If undetected at first, such misunderstandings may pose much difficulty later in an interdisciplinary endeavour [17]. The disambiguating capabilities of conceptual analysis can facilitate the detection of such misunderstandings early, and can so limit associated costs.

4. Will conceptual analysis fit in with scientific practice?

We take the view of science as a *practice* in the sense of Wenger [1]. This means that scientists 'learn to be scientists' through participation in scientific practice. This participation starts when one enters university as a student, that is, in the far periphery of scientific practice. As one continues the route into science as a MSc. student, then as a PhD. student, and further, one learns about the scientific practice through participation [1]. A large part of this learning process will involve becoming part of a disciplinary practice, with all the inherent jargon, meanings, and opinion. In this respect, science does not differ from other knowledge-intensive professions, such as public policy making, commercial consultancy, and R&D. However, the political, strategic and commercial reasons that in these professions keep individuals from sharing knowledge freely are far less pertinent for scientists. On the contrary, in the scientific practice *not* sharing knowledge is frowned upon and knowledge externalisation is explicitly rewarded [18]. Scientists are increasingly judged by their yearly number of publications and their citation indices [19]. Another difference is that scientific knowledge is particularly formalised in comparison with other fields of profession [20]. Science uses definitions, theories, conceptual models and even formal models to capture knowledge, which implies that the extent to which scientific knowledge is situated, implicit, and contextualised, could be considerably less than in other practices [1, 21]. In sum, scientific knowledge can be argued to be generally more explicit and formalised than other professional knowledge, and therefore more amenable to conceptual analysis.

5. Why not automate the analysis?

Automatic concept elicitation and/or comparison of conceptual models would seem ideal for lowering transaction cost. Pfeiffer and Gehlert [8] provide strong arguments why automatic model comparison is infeasible. The problem lies in the formalisation of the meaning of concepts. Externalised and explicit though it may be, scientific knowledge is still situated, for instance in the context of the discipline. Even sharing fully formalised models would require the sharers to fully immerse in their interlocutor's discipline, become experts in each others' fields as it were, to be able to understand the meaning intended to be conveyed by those models. However, computer tools can support the elicitation of concepts, and formal representations of conceptual models can facilitate their sharing.

In sum, our aim is to offer researchers in interdisciplinary teams explicit information about the relation between their and others' knowledge, by enabling conceptual comparisons, and doing so without keeping meaning out of the equation, or embarking on labour-intensive group negotiations. Our hunch is that conceptual analysis is an appropriate means to this end. The questions we address in the remainder of this paper are:

1. Can conceptual analysis be used to represent a researcher's conceptual convictions?
2. Which aspects of scientific practice can threaten validity of conceptual analysis?
3. Is conceptual analysis a cost-effective method to support interdisciplinary research?

3. Method

As a small-scale exploratory test of validity and viability of conceptual analysis, we analysed the work of two researchers in an interdisciplinary research project. As data we used these researchers' written materials – published articles as well as 'grey literature' – to validate the results we conducted semi-structured interviews. We will not discuss all contents of the actual analysis, but rather give the reader an impression of the steps we took in the analysis and its validation, and a taste of its yields.

3.1. Participants

The two junior researchers that took part in our test both work on the Understanding Complex Networks theme of the Next Generation Infrastructures program (NGI), an international, multi-university, interdisciplinary research effort (see http://www.nginfra.nl) that comprises projects in fields ranging from applied mathematics to philosophy of technology, and from information sciences to spatial planning. The NGI program focuses on infrastructures for energy supply, transport, telecommunications, and water: large-scale socio-technical systems of high and increasing societal and economic importance. One researcher works on innovative methods for research, learning and intervention based on multi-actor simulation and gaming, the other on industrial ecology and agent-based simulation of infrastructure development.

3.2. Data

We asked the participants for their recent writings, which yielded three conference papers in the first project, and four conference papers and a book chapter in preparation in the other. These writings were used for the conceptual analysis of the participants' projects. Furthermore, the participants were interviewed about the conceptual analysis of their work. The interviews were recorded and analysed by the first author.

3.3. Conceptual Analysis – Formal Description

Before we describe the practical steps involved in our conceptual analyses, we introduce some formal notation to precisely describe our analysis method. A conceptual model is defined as a 3-tuple M = (C, R, Q) where C is a set of concept types, R a set of relation types between these concept types, and Q the set of question types that can be answered using M. The analysts aim to conceptually model the knowledge that is generated and/or used by the participants $P = \{p_1, \ldots, p_n\}$ (so n = 2 for our test case). To that end they peruse the scientific articles produced by each person p_i and codify the knowledge it contains in n separate conceptual models. Ideally, for each of these models $M_i = (C_i, R_i, Q_i)$,

1. C_i contains all concept types used (explicitly or implicitly) by researcher p_i
2. R_i contains all relation types between these concept types (i.e., of the type $r \subset C_i^j$ for some $j \geq 2$) used (explicitly or explicitly) by researcher p_i
3. Q_i contains the questions that researcher p_i seeks to answer

The next step is that the analysts construct one more conceptual model $\mathbf{M} = (\mathbf{C}, \mathbf{R}, \mathbf{Q})$ that can be conceived of as the 'master model', because for all i, $C_i \subseteq \mathbf{C}$ and $R_i \subseteq \mathbf{R}$. The sets **R** and **Q** each will necessarily be larger than the union of their respective subsets in the models M_i because the 'master model' should answer questions that are typically not posed by the individual researchers, so the analysts will have to define additional relation types (notably to represent incompatibility) and possibly additional concept types as well (for example, to explicitly represent the researchers and their disciplinary perspective).

The main challenge for the analysts is to define the elements of **C** and **R**. They must not only develop an adequate understanding of the concepts and relations used (explicitly or implicitly) by the researchers involved, but also resolve the problem of homonyms and synonyms (in the scientific articles produced by the researchers, identical words may denote different concepts and vice versa), choosing words to define the elements of **C** and **R** in such a way that

- the elements of **C** and **R** allow valid representation of *all* concepts and relations used by the researchers involved (completeness);
- the definitions can be understood not only by the analysts, but also by the researchers p_i and permit them to validate 'their' model M_i; and
- **C** and **R** do not contain more elements than necessary to achieve the previous two goals (parsimony).

3.4. Conceptual Analysis – Practical Implementation

Our formal description explains *what* to find, in terms of concepts. This section describes *how* we proceeded to find it.

We took a qualitative research approach (cf. [22, 23]) using open coding of the participants' writings. We did consider building the sets C_i and R_i by collecting pertinent nouns, adjectives and verbs from a text, but we expected that by doing so we would fail to detect concepts that are entailed by the meaning of certain sentences, rather than stated explicitly. Also, lists of key words would shed no light on the researcher's questions (Q_i). We therefore decided to use a more subjective approach.

We started, per author, with asking them all their publications relevant to their current project. Next we selected from the text those excerpts that in some way reflected the author's conceptual model, that is, those excerpts that contained statements about concepts (C_i), relations between concepts (R_i), and / or research questions / aims (Q_i). Before we started the actual analysis, we coded each excerpt using a small number of coding categories. These categories were based on our conviction that $M = (C, Q, R)$, and on a first exploratory reading of the data. In that sense they served as sensitising concepts [24]; also known as experiential data; Strauss, 1987), and as a starting point for working toward (C_i, R_i, Q_i). The categories we used were:

- Real-world convictions: Statements that refer to abstract and / or concrete aspects of real world
- Model-world convictions: Theoretical conclusions about real-world phenomena and aspects
- Techniques: Statements about the modelling technique in use
- Model: Statements about the model used and / or developed by the researchers
- Real-world Questions and Aims: Research questions and aims pertaining to the real-world
- Model-world Questions and Aims: Research questions and aims pertaining to scientific theory
- Case: Statements about a research case or research client.

For each category a summary was written using all *main* concepts and their relations. By ‘main’ we mean that in specific cases exemplars of a concept were not added when they did not add to, or change the meaning of the concept itself.

Based on the above, the process of analysis can now be described more formally as a series of operations performed by analysts:

1. Select the set of researchers P
2. For each $p_i \in P$, select a set A_{pi} of scientific articles (co-)authored by p_i and relevant to the interdisciplinary research project under study
3. Initialize the ‘master model’ **M**. Note that this need not imply that $\mathbf{M} = (\varnothing, \varnothing, \varnothing)$, because **C**, **R** and **Q** will still contain the generic concepts, relations and questions that will be used by analysts.
4. Initialize the conceptual model for each researcher, which here does imply that $M_i = (\varnothing, \varnothing, \varnothing)$ for I = 1..n

Then iterate over the following steps:

1. Select and peruse a scientific article $a \in A_{pi}$, searching for potential concepts
2. For each concept, determine whether there is a corresponding $c \in C_i$. If not, determine whether there is a corresponding $c \in \mathbf{C}$. If not, add c to **C**. Add c to C_i.
3. Peruse article a in search for relations involving c
4. For each relation, determine whether there is a corresponding $r \in R_i$. If not, determine whether there is a corresponding $r \in \mathbf{R}$. If not, add r to **R**. Add r to R_i.
5. Periodically check whether M_i is coherent. If it is not, see if an explanation can be found (implicit concepts and relations? poor line of argument?)

3.5. Interview Guideline

The validity of our summaries was tested in a semi-structured interview. All interviews were conducted by the first author. The interviewer informed the participant in general terms about the approach that had been taken for the content analysis, paying special attention to the seven categories that were used to structure the data. During the interview, the interviewer read aloud the category summaries for the participant's research. Three questions were asked, repeated for each of the categories:

1. Is there anything in the summary that is unclear to you?
2. To what extent does the summary match your research:
    a. Does the summary contain elements that are not part of your research? And if so, which?
    b. Does your research contain elements that are not part of the summary? And if so, which?
    c. Does the summary contain errors? And if so, which?
3. Do you have any further comments on the summaries?

The first question aimed to get any problems in understanding out of the way. The second question focused on whether the summaries (a) contained misinterpretations, (b) were complete, and/or (c) contained errors. The third question was aimed at improving the summaries.

4. Results

As the study reported is a small-scale exploratory test of validity and viability of conceptual analysis, we focused on the elicitation process and did not aspire to fill the master model $\mathbf{M} = (\mathbf{C}, \mathbf{R}, \mathbf{Q})$. Nonetheless, we wish to give the reader an idea of the type of results we obtained. We therefore start this section with an excerpt from the texts of participant p_1:

> "Infrastructures are highly complex multi-actor systems involving strategic decision-making competition and conflict, negotiation and diplomacy, tactics, logistics, operational planning."

The excerpt was from a paper on the development of simulation games to support complex decision making. It was coded "real-world convictions" and led to the following paragraph as part of the complete summary (based on all analysed writings) of the real-world convictions of p_1:

> "Infrastructures are a specific type of complex system, [. . . .] i.e. multi-actor, which means that the system has processes of strategic decision-making, which implies competition and conflict, negotiation and diplomacy, tactics, logistics, operational planning.
>
> These actor aspects are entailed:

- Actors can plan, which means that they are able to evaluate a current system state, have a concept of causality. They have a system representation that is to some extent causal.
- Actors have a representation of other actors, and they even have a representation of other actors' goals and intentions, as is entailed by their ability to act strategically.
- The existence of conflict entails that actors can deliberately choose to counter-act each other.
- Their ability to plan entails that actors are able to project the current system state into the future, and their ability to act strategically entails that they have intentionality and are to some extent able to predict other actors' behaviour.
- Their ability of diplomacy entails that the actors are able to have conscious knowledge of other actors' sensitivities, desires, aims, assets."

As an example, we will identify some concepts and relations from the above. Important concepts to be included in C_1 are 'system', 'complexity', 'infrastructure', 'actor', 'decision', 'decision-making process', 'behaviour', 'communication', 'system state', 'representation', 'goal', 'intention', 'projection', and 'theory of mind'. Foregoing the types of relation (such as 'is-attribute-of', 'is-instance-of'), we mention some of the relations to be included in R_1, starting first with the concept 'system', then with the concept 'actor'. Systems can be complex. Complex systems can be multi-actor systems. Infrastructures are an instance of a complex multi-actor system. Multi-actor systems contain multiple actors. Complex multi-actor systems contain processes. Among these processes are decision-making, communication, and projection. Actors have representations of the system. Actors have goals, desires, assets, sensitivities. Actors have representations of past system states and possible future system states. Actors prefer some future system states over other future system states. Actors have a theory of mind, a representation of other actors' actor-being. Actors have a concept of causality. Actors can reason – using their representations of systems and of other actors in those systems – to predict future states, in other words, build scenarios based on different decisions. Actors act to pursue their goals and desires. Actors can communicate with other actors in order to pursue their goals and desires. Some of the system processes stem from actor behaviours.

Although the excerpt led to the identification of concepts and relations, it did not contain any questions to be included in Q_1, that is, questions that researcher p_1 seeks to answer using C_1 and R_1. We will come back to this later.

4.1. Issues of Validity

Neither participant found any part of our summary of their writings unclear. Furthermore, neither summary contained elements that the participants thought did not belong there. However, both participants found certain elements missing: the summaries did not give an entirely complete picture of their research. This incompleteness occurred in two varieties.

First, in one case our summary was only partially complete for the *Model* category. Participant p_1 was developing a multi-player simulation game about a major international seaport as part of her research. Our summary was incomplete as to the various roles within the game:

> P1: Your description concerns only the tasks of the commercial role. . . . . This is only about negotiating, closing contracts and allotting space in the harbour. That's what the commercial department does. . . . . Some elements are missing . . . . general director and building director.

In this specific example, our analysis did not cover all elements that the participants had expected us to cover, given the data we used. In most cases, however, participants reported that they found that our summaries agreed with the papers we had studied.

Second, the summaries were incomplete due to the data set. In all but the above case, the participants agreed that our summary was as complete as could be, given the data we had had access to. However, they also both agreed that the summaries were not complete as compared to their current states of affairs:

> P1: There's the specific goal *of* the game, so to show aspects of complexity, and then there's the goal *in* the game, that's just, you've got to build this harbour and make profit as soon as possible, and then there's my research goal, which is about, what knowledge about complexity can you get from the game.
> A: I didn't get that last goal [from the papers I read]
> P1: Yeah, but it's not in [those papers] either. . . . . I'm adding that now, call it progressive insight.

In the above excerpt, the participant explains that she reconceptualised her research questions during the course of her studies, and that this new research question had not been available to us given the data we studied. This seems to have been caused by a learning effect on the part of the participants:

> P2: It's an interesting question, of how does a scientific research project evolve anyway. You're playing with something, chewing on it, blowing bubbles with it, you try things out, and some things materialise and those you write down, and other things, you, like, keep them without writing them down. . . . . It's my idea to see one's own project as evolutionary as well.

Furthermore, a participant opined that some important data is not accessible through reading research papers at all:

> P2: You miss all those things that are important but don't get written down.

In sum, using written material as a basis for conceptual analysis yields some differences between the conceptual model and the participants' current convictions. It seems that most of these differences due to learning of the participants. On the other hand, for all but one of these cases the participants said that we could not have known about this difference give the data we had at our disposal. Furthermore, according to the participants, neither summary contained any errors.

4.2. Other Issues with Content Analysis

The interview data contained a number of statements that are of import with respect to the validity of our approach. First, there is the issue of the use of different words for the same concept in different papers:

> P2: Scrap the world-vector from your analysis. . . . . I used this word in one of my first papers. I have a strong need for formalising the knowledge in my model. Being a simple engineer, the thing you do is put that in a vector. . . . . It took [a colleague] three months before he understood what I wanted with that vector, and then he said Oh, you want an ontology! . . . so that's what [the world-vector] became. . . . . So [in the beginning] the world-vector was the solution, but this is superior.

Participant p_2 initially used the word ‘world-vector’ to refer to a specific aspect of his agent-based model. He derived this word from his background as an engineer, but apparently was not entirely content with it. His colleague, an information scientist, called this same thing ‘ontology’ and explained why. Participant p_2 seems to think that the word ontology is superior to the word world-vector. In reaction, participant p_2 therefore started using the word ontology. However, there was no change to his model on the conceptual level. In this case, the mechanism leading to a change in choice of words was the participant coming across a superior term for one concept. The following change in choice of words also did not involve a conceptual change, but the mechanism is different:

> P2: That *can* be regarded as a belief system.
> A: Do you see its as a belief system?
> P2: This is also a nod to Andreas [a researcher P2 collaborates with] and his decision theory. . . . . Let's say I also put that statement there for political reasons. That language is easier to understand for decision theorists.

The interview data showed that the use of the term ‘belief system’ was chosen for a better interface with decision theorists in general, and one collaboration partner in particular. Such strategic choices do not only occur with regard to words and concepts, but also with regard to research goals:

> A: I got the impression that the goal of the simulation game was to make a contribution to the efficient realisation and operational management of [the harbour case] project.
> P1: Yes... I think that was the goal the harbour had. . . . . [The harbour] contracted us with these goals, and in our game we try to show part of that, and in turn the goal in the game is again a more efficient harbour.
> A: So that's not the same as your research goal with the game?
> P1: No, that's certainly different.

From these excerpts we conclude that choices of concepts and research questions not always are what a participant would have chosen on his/her own. In that sense, (co-authored) written materials do not represent the concepts, relations and questions of one researcher only.

With regard to time costs, the method proved costlier than we had anticipated. The reading and summarising all data cost about three weeks, although this time includes deriving codes for the data. That is, the conceptual analysis method as presented here is still being developed, and in that sense this is not a reliable estimate for the actual time costs of conceptual modelling. Nonetheless, a figure of three weeks shows that time costs are a concern.

5. Discussion and Conclusion

In this paper we have introduced a methodology for conceptual analysis as a means to support interdisciplinary research projects, and addressed certain questions regarding the validity of the method in the context of an exploratory study into its viability.

The participants commented that the analyses generally represented the data well and that our conceptual analyses did not contain any outright errors. However, the analyses were incomplete in some respects. First, because the participants continuously learn throughout their projects, and their papers can be seen as snapshots taken at some point in this process, the data we used can not yield a full account of participants' conceptual models. By consequence, the data set in this study was not entirely current with the participants' conceptual models.

Second, the participants made some comments on our analyses because it did not in all cases reflect solely their own convictions and aims. Choice of words and choice of research goals may be entered for strategic reasons, for instance for project partners or intended collaboration partners. This means that our analyses contained some traces of others' conceptual models.

Obviously there is a trade-off between validity and data availability. Published papers have a relatively high availability, even in the case of conference papers. Beyond that, data availability sharply drops. The use of personal communication, like interviews, could probably mitigate these problems, but the fact that almost all of the analysis was correct as to what was covered in the papers suggests that the extra effort might not be worth it in terms of validity.

In sum, certain aspects of the analyses cause validity problems. However, these problems are not specific to the conceptual analysis method presented in this paper, but mainly to the data set in use. In that respect, this study shares its shortcomings with any method that relies on the analysis of written data. Overall, it appears that our analyses were a good conceptual representation of what was in the data, as appears from the interviews.

With regard to labour time costs of the conceptual analysis method, our first experiences offer some doubts as to its feasibility; the labour intensiveness is high, and the results of the method with regard to constructing new knowledge still need to be produced. However, there are several reasons to expect lower future time costs. First, as this was our first try with the method, we had to develop the practical part of the method as we went along. Having done and described this, a second time around will probably go faster. Second, some learning effect is to be expected, that is, with exercise future analyses will probably cost less time for the same amount of work. Third, as researchers in interdisciplinary research settings will share some research interests, the rate at which new concepts need to be added will decrease over time, due to conceptual saturation of M.

With regard to the method, there are two important differences with automated content analysis techniques from the information sciences. Our ‘manual’ analysis has the advantage of including meaning in the analysis, but in doing so it also introduces subjectivity, because the analysis becomes subject to human interpretation, and consequently runs the risk of overinterpretation. In the case of this study we mitigated this risk by checking our results with each other (i.e., the first author performing the main analysis, and the second author keeping track of the first author's work) and with the participants in the interviews. These checks alleviate some problems of subjectivity by introducing *inter*subjectivity, that is, checking whether the analysis is shareable and transferable between different people. It should be noted that the analysis included a number of entailed concepts and relations, that is, they were not explicitly mentioned in the participants' writings, but they were included in our analyses. In that sense, our approach adds to techniques from information sciences. Still, the participants indicated that the analyses represented the data well.

The study discussed in this paper did not address issues related to the way conceptual analysis might actually support interdisciplinary research. We here offer an example of some differences and similarities from our study that shows how conceptual analysis can address this. Our analysis indicated that participant 1 writes about complex *systems*, and participant 2 about complex *problems*. These seem to be two sides of the same coin, because the concept of problem entails an unwanted, or to be improved, state of a system. Using 'problem' as a conceptual bridge between complex problem and complex system shows how the authors are interested in one same category, i.e. complexity. If we look further we see that both participants are to some extent interested in the same type of complexity, because both stress the importance of the system behaviour, i.e., being emergent, and both also emphasise the importance of actor and/or stakeholder behaviour for system behaviour.

There also are some differences in their focus of attention; Participant 1's interest in problem solving, decision making, and interaction, offers a contrast with participant 2's interest in emergence and system evolution. This difference also allows some insight in their choices for research method: the kind of system behaviour participant 2 is interested in offers little leads for a method like simulation and gaming, because that requires too many experiments to yield enough data for studying emergent patterns in system evolution. Conversely, participant 1's interest in decision-making, communication and negotiation, makes it almost impossible to substitute human participants (players in a simulation game) with computer models of behaviour.

We expect that further formalisation and in-depth analysis of the participants' conceptual models will lead to more specific insights. To date, we focused mostly on the feasibility of our method, disregarding the question concerning its cost-effectiveness. The experiment so far still seems promising in that it indeed clarifies the conceptual models, something that is appreciated also by the participants themselves. However, the expected benefits in terms of lowering the transaction costs of knowledge sharing across disciplines have not been demonstrated yet, whereas the costs of the analysis are evident in the time and effort it takes to perform the analyses.

6. References

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