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CONCEPTS AND CONCEPT LEARNING IN PHYSICS

THE SYSTEMIC VIEW

Tommi Kokkonen

Department of Physics
Faculty of Science
University of Helsinki
Finland

ACADEMIC DISSERTATION

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Supervisors

Professor Ismo T. Koponen
Department of Physics
University of Helsinki
Finland

Dr., Title of Docent Maija Nousiainen
Department of Physics
University of Helsinki
Finland

Dr., Title of Docent Terhi Mäntylä
Faculty of Education,
University of Tampere
Finland

Pre-examiners

Professor Esä Räsänen
Laboratory of Physics
Tampere University of Technology
Finland

Professor Lennart Schalk
Pädagogische Hochschule Schwyz
Goldau, Switzerland

Opponent

Professor Mieke De Cock
Department of Physics and Astronomy
KU Leuven
Belgium

ABSTRACT

Research in science education has long been concerned with a problem that students acquire conceptions which are unsatisfactory from the scientific point of view. These conceptions are also often robust and slow to change. The learning process whereby the students' conceptions undergo a change is often viewed from the point of view of conceptual change. In this thesis, this traditional problem of conceptual change is approached as a problem of concept learning, where concepts are complex structures and parts of a conceptual system. The approach is thus termed here the *systemic view*. It is influenced by recent cognitive science research on relational concepts, which are concepts characterized by their relational structure and/or the relations they bear to other concepts. Because scientific models can also be conceptualized as relational structures, relational structures are central from the viewpoint of scientific knowledge. The systemic view thus bridges the cognitive aspects of learning (students' initial knowledge) and the target knowledge, thereby illuminating the learning process that leads from initial conceptions to advanced scientific knowledge. The articles presented in this thesis consist of two empirical studies (I and II), in which students' conceptions about DC circuits are examined from the systemic view perspective. These studies develop and apply the *directed graph model*, which is a graphical representation of the different conceptual elements. It allows examining students' conceptions and their change in detail. Such graphs also act as templates for computational modelling of the learning process reported in two other articles (IV and V). The computational models allow examining structural aspects of concepts and their context-dependent dynamics. Article III examines the role of models and modelling in concept learning and suggests how seeing models as relational categories clarifies the cognitive aspects related to model-based learning. The results of the thesis show that in learning advanced scientific knowledge, students' ability to modify and revise relational knowledge is vital to the learning and acquisition of correct conceptions. A result of practical significance is the strong context and task dependence of these processes of modifications and revisions.

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LIST OF ORIGINAL PUBLICATIONS

This thesis is based on the following publications, which are referred to in the text by their Roman numerals:

I Kokkonen, T. & Mäntylä, T. (2017). Changes in University Students' Explanation Models of DC Circuits. *Research in Science Education*. Advance online publication. DOI: 10.1007/s11165-016-9586-y

II Kokkonen, T. & Nousiainen, M. (2016). Learning Physics Concepts – A Description in Terms of Relational Concepts. In H. Silfverberg, & P. Hästö (Eds.), *Annual symposium of the Finnish mathematics and science education research association 2015* (pp. 35-47). Matematiikan ja Luonnontieteiden opetuksen tutkimusseura r.y.

III Kokkonen, T. (2017), Models as Relational Categories. *Science & Education*. Advance online publication. DOI: 10.1007/s11191-017-9928-9

IV Koponen, I, & Kokkonen, T (2014). A systemic view of the learning and differentiation of scientific concepts: The case of electric current and voltage revisited. *Frontline Learning Research, 4*, pp. 140-166. DOI: 10.14786/flr.v2i2.120

V Koponen, IT, Kokkonen, T. & Nousiainen, M. (2016). Dynamic Systems View of Learning a Three-Tiered Theory in Physics: Robust Learning Outcomes as Attractors. *Complexity*, *21*(2), pp. 259–267. DOI: 10.1002/cplx.21803

The author's contributions regarding the articles included in the thesis are as follows. In articles **I** and **II**, the author was involved in designing the empirical setting and the collection of data. The author also analysed the data and was the main author of the articles. In articles **IV** and **V**, the author was involved in formulating the theoretical framework underlying the simulations, participated in the analysis of results, interpreted the results of the simulations and provided empirical data for comparisons. The author also made major contributions in writing articles **IV** and **V**. Article **III** was planned, constructed and written by the author alone.

1 INTRODUCTION

One longstanding problem in science education is that during learning, students develop an idiosyncratic and only partially correct understanding of scientific phenomena and how to conceptualize them. In explaining scientific phenomena, students often use concepts and models that have only a tangential resemblance to accepted scientific knowledge—sometimes even contradicting it. Students' own personal knowledge and concepts that differ from scientific knowledge and concepts are difficult to change even after ample instruction or when students are faced with counterevidence. The problem lies in how students' own intuitive understandings and concepts guide and restrict their further learning. Sometimes students' initial conceptions are mixed with the to-be-learned scientific concepts, forming unscientific synthetic conceptions (Vosniadou, 1994).

The nature of students' prior knowledge and its role in learning has been a major focus in science education and in its more disciplinary focused research domains (e.g. physics education research). Such research pays close attention to the nature of target knowledge, because it affects the learning processes and the ways in which teaching is designed. In physics, the target concepts and models are often abstract and complex. Grasping their meaning and learning to apply them requires that students acquire complex relational schemes and gradually form interlinked, heterogeneous knowledge elements of complex knowledge.

The students learning process where personal knowledge is transformed into scientific knowledge has often been examined from the point of view of conceptual change (Amin, Smith, & Wiser, 2014). The term conceptual change refers to the process of restructuring one's conceptual structure. In this thesis, the focus is on the part of conceptual change that involves the transformation and acquisition of concepts. In what follows, these processes are referred to briefly as *concept learning*. Concepts are here understood as learners' internal, mental representations in contrast to scientific concepts, which are collectively accepted and shared external representations (Rusanen & Pöyhönen, 2013). In traditional accounts, the conceptual change process is seen as a special kind of learning process in which students' ontological commitments, epistemological beliefs or standards of explanation undergo a change. Previous research has assumed that students have somewhat stable, recognizable initial knowledge states, which are transformed into other, stable, and hopefully more scientific knowledge states (Clement, 2008). These kinds of views on learning, however, have been criticized and challenged, and many alternatives have been proposed (see e.g. Hammer & Brown, 2008; Ohlsson, 2009) although coherent alternative views have been slow to develop.

This work focuses on a cognitively oriented approach to concept learning and specifically on the acquisition of scientific concepts in the context of physics. While many recent studies on concept learning and conceptual change have paid attention to social, cultural and affective factors, we still lack an adequate cognitive account of the process of learning of scientific concepts (Clement, 2013). Also, a persistent issue within conceptual change research is that there are diverging views about what kind of entities concepts themselves are (Rusanen & Pöyhönen, 2013; diSessa & Sherin, 1998). For instance, certain views argue that concepts are embedded in intuitive "framework theories" consisting of implicit epistemological and ontological beliefs (Vosniadou, 1994; Vosniadou & Skopeliti, 2014). These views, while receiving some support from research, put less emphasis on the structure and the relational schemes related to individual concepts, which are arguably central in grasping scientific concepts at high school and university levels (Koponen & Huttunen, 2013). Other approaches emphasize students' ontological categorizations as the key factor in learning and lean on a view of concepts where concepts are collections of features and where learning constitutes acquiring these features (Chi, 2008; 2013).

Science education research, when it is subject-matter oriented, has focused on model-based learning (MBL) approaches, which assume that models are central in concept learning. Although concept learning is one of the main goals of MBL, relatively few studies have tried to develop a cognitively justified view of MBL and how it facilitates concept learning (Louca & Zacharia, 2012; for notable exceptions, see Nersessian, 1995; Clement, 2008).

Recent developments in cognitive science have paid attention to the role of relational knowledge in cognition (Goldwater & Gentner, 2015; Halford, Wilson, & Phillips, 2010). Researchers have shown that our understanding of many concepts hinges on the relation that concepts bear to other concepts, and it is assumed that such relational knowledge also forms the foundation for many of our higher cognitive competences (Goldwater & Schalk, 2016). As relational structures are also fundamental to the target knowledge (i.e. scientific knowledge), a concept-learning approach based on relational knowledge thus forms an obvious interdisciplinary link between cognitive science research and science education. Such an approach can bridge the cognitive aspects of concept learning and its dynamics with central aspects of the target knowledge.

In this thesis, students' conceptions and concept learning are analysed by applying the systemic view developed herein. The systemic view on concept learning sees concepts predominantly as relational structures and knowledge as interconnected system of these structures. Also, according to this view, the nature of students' knowledge, cognitive aspects of learning as well as the nature of the to-be-learned knowledge (i.e. scientific concepts and models) are all equally important in learning scientific concepts. One part of this study is also to explicate the conception of concepts based on recent

developments in cognitive science and to bridge this view with views about the nature of scientific knowledge.

The specific context of the study is the learning of concepts related to direct current circuits. This context is well known from many previous studies about concept learning and allows the view developed here to be tested and evaluated. It enables us to see how the systemic view of concept learning and, more generally, the relational concepts approach may advance our understanding of concept learning in science.

The main results are presented in five articles. Articles **I** and **II** report the empirical studies and the theoretical background ideas of the interpretations of empirical results. They also show the systemic view is contextualized in the case of learning DC circuit concepts. The theoretical underpinnings based on relational knowledge and how they are related to MBL are discussed in more detail in article **III**. Articles **IV** and **V** discuss how a systemic view yields computational modelling of concept learning.

The systemic view on concept learning is based on the assumption that relational aspects of concepts are the key features in learning advanced scientific concepts. In this thesis, this view was originally developed without direct reference to relational concepts framework and psychological or cognitive theories of concepts (see articles **I,** and **IV** and **V**). Instead, the central role of relational structures was based directly on notions of the structure of the target knowledge (i.e. scientific knowledge). The relational concepts framework and research on relational representations, however, provide a cognitive basis and interpretation for the approach taken here. This connection is explicitly discussed in article **III**, which also provides the connection points between model-based learning and relational knowledge.

2 CONCEPT LEARNING

2.1 CONCEPTUAL CHANGE AND CONCEPT LEARNING

The learning of scientific concepts is often examined from the point of view of conceptual change. Conceptual change research evolved largely in the 1970s along with growing interest in how students' prior ideas might hinder learning and persist even after ample instruction (Amin et al., 2014; diSessa, 2015). It was found that students need to overcome these prior conceptions—a process often called conceptual change (Lappi, 2013). The term "conceptual change" is used broadly to denote the many kinds of transformation processes in learning, where student's initial knowledge is transformed into scientific knowledge. In this thesis, however, instead of conceptual change, the term "concept learning" is preferred, because many learning processes involve only assimilation of new facts and/or concepts but no changes happen in concepts in the learner's possession before the assimilation.

Characterization of concept learning requires: a) a representation of students' prior conceptions, b) a representation of the outcome, and c) specification of the learning mechanisms that lead from a to b (Lappi 2013). As learning is a psychological phenomenon, we need to lean on cognitive and psychological theories of concepts and learning in representing students' representations and mechanisms of change. In other words, we need a description regarding what concepts or other knowledge elements are relevant to represent students' knowledge (Koponen & Huttunen, 2013). To assess whether learning is successful or not, we need to compare how students' use concepts (i.e. how they make inferences) and how concepts are used in science (Rusanen & Pöyhönen, 2013). Of course, in practice students' inferences are compared to appropriately simplified or reconstructed scientific knowledge taught in high school or university. The interdependency between these three components are presented in Figure 1. How the separate articles **I**-**V** included in this thesis are situated within this framework is also shown in Figure 1.

Regarding the target knowledge, model-based learning (MBL) addresses the issue of the nature of scientific knowledge. In MBL, models are adopted as the central elements of scientific knowledge and knowledge construction (Gilbert & Justi, 2016; Koponen, 2007; Nersessian, 1995). While the target knowledge and the underlying aims of learning provide the context and scope of the to-be-learned knowledge, psychology of learning describes the learning of such knowledge in terms of knowledge elements and mechanisms. In the context of MBL, such an approach is rare, as there are only a handful of studies that address the cognitive processes related to learning models and modelling (Louca & Zacharia, 2012). In article **III**, I discuss in detail how a

cognitively justified view of learning of scientific concepts, the views about scientific knowledge and students' concepts can be bridged.

There has been an extensive debate about the nature of students' conceptions and the nature of the conceptual change process. Early studies examined concept learning at the level of single concepts and beliefs (diSessa, 2015). However, quite early on, research came to consider the underlying reasons for specific beliefs. Some have examined the conceptions in terms of ontologies while others described concept learning at the level of implicit theoretical beliefs (see e.g. Chi, 2013; Vosniadou, 1994).

In addition to the different elements, it is often claimed that conceptual change comes in a variety of degrees or types. For example, learning might require simple accretion or refutation of facts, changes in the underlying epistemic and/or ontological suppositions or major re-organization of concepts or conceptual elements (Chi, 2013; Clement, 2008; Rusanen & Pöyhönen, 2013). Some authors distinguish the assimilation type of learning from conceptual change, which is then described as being in some sense a "special" or more fundamental type of learning or learning process (see e.g. Chi, 2013).

In general, concepts, beliefs, and theories can be seen as examples of *declarative knowledge*, which is characterized as "knowing that" (Chi & Ohlsson, 2005). In contrast, *procedural knowledge* can be characterised as "knowing how". Examples of this kind of knowledge include knowing how to ride a bike or how to solve a physics problem (Chi & Ohlsson, 2005). Procedural knowledge is distinct from declarative knowledge in that it is task dependent not necessarily verbalisable unlike conceptual knowledge, for example. These different types of knowledge are also associated with different learning processes and different instructional implications. For example, problem-solving practice enhances procedural knowledge and leads to more efficient problem-solving performance (Richey & Nokes-Malach, 2015). In contrast, there is little evidence that practice would promote learning complex, coherence knowledge or help students to overcome misconceptions (Richey & Nokes-Malach, 2015).

The different descriptions of conceptual elements and varieties of changes stem from different theoretical considerations and interpretations of empirical data facilitated by the theories. Much research has focused on conceptual change, but no apparent consensus has emerged even about the central issues surrounding the topic. A fundamental open question concerns the notion of concept itself. There is no commonly accepted account of what concepts are, what kinds of changes in students' knowledge constitute conceptual change or about the mechanisms that bring it about (Clement, 2013; diSessa & Sherin, 1998; Rusanen & Pöyhönen, 2013). Consequently, we still lack an adequate cognitive account of conceptual change and its mechanisms (Clement, 2013; Rusanen & Pöyhönen, 2013).

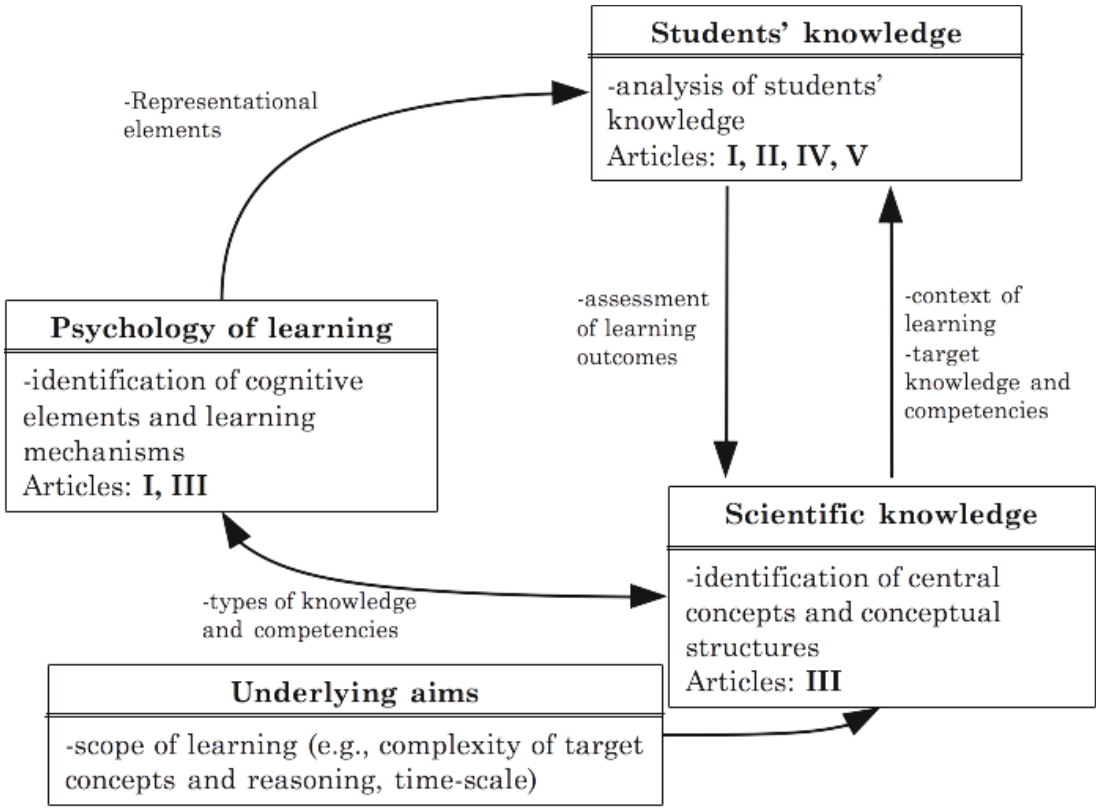


Figure 1 The relevant perspectives for examining and assessing the concept learning process.

While the different views have sometimes been conflicting, recent research has taken a more constructive viewpoint on concepts as a system consisting of multiple related features and conceptual change as a dynamic process where those features are transformed and changed in multiple ways (Amin et al., 2014; Brown & Hammer, 2008; Koponen & Huttunen, 2013).

2.2 AN EXAMPLE: STUDENTS' CONCEPTIONS OF DC CIRCUITS

Many of the early "misconceptions" studies concentrated on students' conceptions about specific topics within physics. This research examined and documented various "false beliefs" or "misconceptions" such as "the earth is closer to the sun in the summer" (Brown & Hammer, 2008; diSessa, 2015). While this perspective's influence has waned during recent years, it continues to be widely held (Brown & Hammer, 2008; diSessa, 2015). Many of these studies have been conducted in the context of DC circuits. This is one of the main reasons why the context of DC circuits was chosen for the empirical studies. The purpose was not to identify new misconceptions. Instead, the familiar and well-known context provided a good platform for developing a

new kind of approach to concept learning. Next, the research on students' DC circuit conceptions is discussed.

Although a rather mundane topic for physics experts, DC circuits have been shown to be difficult to master even at the university level, let alone earlier. In many studies regarding students' understanding of DC circuits and relevant concepts, students are asked to predict and explain the behaviour of simple circuits by ordering the bulbs according to their brightness.

The problems students have are various, ranging from the lack of relevant concepts or models to the failure to comprehend the geometry of the circuit. The simplest explanations are mere rules of thumb, such as "the bulbs are equally bright because they are connected in series/parallel". Apart from these merely descriptive statements, the most naïve intuitive explanations are based on the conception that something (electricity, current, energy, etc.) comes from a battery and is consumed by the bulbs (Borges & Gilbert, 1999; Koumaras, Kariotoglou, & Psillos, 1997; McDermott & Shaffer, 1992). Consequently, when a change is made in a circuit (a bulb is added or a switch is opened/closed), students may concentrate only on the part that has been changed and fail to consider that the change might affect other parts of the circuit as well (McDermott & Shaffer, 1992). Similarly, some students may think that the current in a circuit is not affected before it passes a component or that the current through a component is not affected by modifications to the circuit after the component (Picciarelli, di Gennaro, Stella, & Conte, 1991).

The above conceptions have been taken as students' failure to consider the circuit as a system with interacting parts. That is, students are applying what is known as "local" or "sequential reasoning". These conceptions are often accompanied by an idea that there is a decreasing amount of current going back to the battery. Also, in a simple series circuit, students often think that one bulb receives less than another, as the "first" bulb has already consumed a portion of the current. The conception that the battery acts as a source of constant current (i.e. the current does not depend on the components in the circuit) often occurs with this kind of thinking (Dupin & Johsua, 1987; McDermott & Shaffer, 1992).

Students often do not distinguish between related terms and use the terms current, electricity, voltage and power interchangeably or so inconsistently that the terms' meanings are ambiguous (Li & Singh, 2016; McDermott & Shaffer, 1992). Sometimes students explicitly understand voltage and electric current as synonymous or voltage is understood as the intensity or force of electric current or as the amount of current stored in a battery (McDermott & Shaffer, 1992; Reiner, Slotta, Chi, & Resnick, 2000). Some intuitive explanations concentrate on the number of elements in the circuit, such as "more bulbs—less current" or "less bulbs—more current" (McDermott & Shaffer, 1992). This of course fails to recognize the different connections and their respective resistances but nevertheless acknowledges the relation between the elements in the circuit and the current. More

advanced explanations can exploit some quantitative formulas but fail to understand properly their meaning and how they are applied (Li & Singh, 2016; McDermott & Shaffer, 1992). For example, students sometimes confuse individual and equivalent resistances and might substitute the equivalent resistance in the equation when calculating the power of single bulbs (Li & Singh, 2016). Also, while managing to calculate correctly the total current using equivalent resistance, students may then ignore the effect of individual resistances on the brightness of the bulbs. Students may also have a wrong interpretation of Ohm's law in that they believe that whenever the electric current is zero it implies zero voltage as well (Li & Singh, 2016). While a typical task testing students' knowledge involves predicting the relative brightness of bulbs connected in different circuits, students frequently fail to realize that the dissipated power determines the bulbs' brightness—despite it being explicitly mentioned. Thinking that the electric current or the voltage determines the brightness is of course adequate in the case of identical bulbs but leads to wrong predictions in the case of non-identical bulbs.

In summary, the studies reviewed above focused on identifying the various problems and beliefs students have about basic DC circuits and the corresponding concepts. Typically, the focus in such studies is in revealing and characterizing students' misconceptions–that is, conceptions that are wrong from the scientific point of view.

3 CONCEPT LEARNING AND THEORIES OF CONCEPTS

3.1 CONCEPTS AND CATEGORIES

Research on students' misconceptions has provided researchers and teachers alike with a characterization of the salient features of students' conceptions regarding specific content areas. Nevertheless, different conceptual change views have strived for a description of the underlying factors that give rise to the specific conceptions. On the other hand, psychological and cognitive science research has strived for a general account of concept learning. This research has focused on finding the general properties of how concepts are represented and learned.

Within cognitive science, concepts are assumed to play a role in "higher" cognitive capacities such as categorization, reasoning, planning and analogical thinking (Machery, 2009). Concepts "carve up the world", enable inferences and organize our knowledge into larger structures (Danks, 2014, p. 99). Concepts are bodies of knowledge that are stored in our memory and used in processes related to the higher capacities (Machery, 2009, p. 12). Despite this general definition, much of the research is centred around categorization. While the terms *concept* and *category* are sometimes used as synonyms, they are often distinguished. Typically, concept refers to the mental representations we have about the entities in the world whereas category means the groups of entities themselves.

Many kinds of processes can be viewed as acts of categorization: from recognizing objects and people to interpreting a phenomenon as an instance of Newton's second law (Goldstone & Kersten, 2003). Once an entity is categorized as something, we can make inferences based on our interpretation. In addition to these *inductive generalizations*, concepts are often associated with the generative nature of creative thought: new concepts can be formed from existing ones and be readily comprehensible on the basis of the parent concepts (Goldstone & Kersten, 2003).

The psychological and cognitive views on concepts of interest in this thesis focus on three types of conceptions of concepts: 1) feature-based concepts, 2) concept as embedded in theories, and 3) concepts as relational schemes. The first two views have provided the basis for two well-known approaches on conceptual change: ontological shift theory (Chi, 2008; 2013) and framework theory (Vosniadou, 1994). The third view based on relational schemes has not yet led to similar concise, established views on concept learning. The systemic view advocated in this thesis is a step in that direction. In what follows, each of these three views is briefly discussed from the viewpoint of how it is related to concept learning.

3.2 ONTOLOGICAL SHIFT AND FEATURE-BASED CONCEPTS

Some researchers maintain that many difficulties in learning the concepts of physics stem from misconceived ontologies, which are taken as taxonomic categories (Chi, 2008; 2013). Students' ontologies can be characterized as knowledge about "what kind of entities there are in the world" (Amin et al, 2014, p.59). For example, Reiner and her colleagues (2000) note that students associate the characteristics of material objects to many physics concepts, such as electric current, voltage, heat and force. They suggest that this underlies, for example, the above-mentioned prevalent conception of a battery as a storage or source of electricity which gets consumed by the components (Reiner et al., 2000; see, also, Borges & Gilbert, 1999; Koumaras, Kariotoglou & Psillos, 1997; McDermott & Shaffer, 1992).

One of the most refined and influential views about students' ontological difficulties is the *ontological shift theory* (Chi & Slotta, 1993; Chi, Slotta, & De Leeuw, 1994; Chi, 2008; 2013). The key assumption of the ontological shift view is that "entities in the world may be viewed as belonging to different ontological categories", such as "matter", "processes" or "mental states" (Chi & Slotta, 1993, p.251). Consequently, learning is a process of organizing the concepts into the correct, normative ontological categories. Categorization is thus seen as a powerful learning mechanism, as upon categorization concepts can inherit characteristics of the category, which allows for novel inferences based on the inherited attributes (Chi & Slotta, 1993; Chi et al., 1994; Chi, 2008; 2013). An entity belonging to a certain category may possess a set of ontological attributes. For example, birds "fly", "lay eggs", "have feathers", "have beaks" and so forth.

Ontological shift is closely related to the concept of *differentiation*, which means drawing a distinction between two close concepts (Smith, Carey, & Wiser, 1985). Students often conflate two closely related concepts and fail to understand them as different. Common examples include heat and temperature (Wiser & Amin, 2001) and electric current and voltage (Lee & Law, 2001).

The ontological shift view is closely linked to theories of concepts that assume that concepts are represented by a set of features describing the properties of the category members (Goldwater & Schalk, 2016). Moreover, it is typically assumed that concepts are organized into hierarchical taxonomies. Such theories differ depending on whether they assume that the features are about an average (i.e. a prototype) or a typical member (i.e. an exemplar) of the category (Machery, 2009). Categorization of entities amounts to a similarity comparison between the stimuli and the category representation.

The ontological aspects of concept learning are well documented and are deeply rooted in the psychological aspects of concept learning. However, while ontological shift as such is acknowledged, some researchers have

questioned the centrality of the ontological shift in learning scientific concepts (see e.g. diSessa, 1993; Gupta, Hammer, & Redish, 2010; Vosniadou, 1994). For example, while Vosniadou (1994) acknowledges the importance of ontological shifts, she argues that ontological change is tied to multiple changes in the knowledge system. In addition to changes in the ontological attributions, it is argued that they also need to go through epistemological changes (Vosniadou, 1994).

3.3 CONCEPTS AS EMBEDDED IN THEORIES: FRAMEWORK THEORY

According to the *framework theory* view on concept learning, conceptual structures consist of epistemic and ontological presuppositions (comprising the so-called framework theory) along with specific theories, beliefs and mental models. Framework theories constrain the lower level elements so that new information gets interpreted in the light of presuppositions (for example, new concepts get associated with a certain ontological category, as described above). Specific theories are "sets of interrelated propositions or beliefs describing the behaviour and properties of physical objects" (Vosniadou, 1994, p. 47). For example, "hotness is a transferable property of physical objects" could be a part of a student's specific theory (Vosniadou, 1994, p.48).

In the framework theory approach, concepts are assumed to be "embedded in theories" (Vosniadou, 1994, p. 46). This conception stems from the so-called *theory-theory* of concepts and concept learning (see e.g. Murphy & Medin, 1985). Feature-based theories of concepts can explain certain features of our categorization processes but they often dodge the question of why only certain features get represented and not some others (Machery, 2009). In many situations our judgements go beyond the apparent similarity and are instead based on some background or theoretical knowledge about the world (Murphy & Medin, 1985). For instance, our knowledge about animals in general might affect our categorization and similarity judgements. Similarly, it has been argued that our epistemic and ontological knowledge affects our knowledge about basics physics concepts (Vosniadou, 1994). It should be noted that prototype and exemplar theorists could endorse the view of concepts being embedded in theories, as concepts can be understood as collections of features embedded in some general theory (Machery, 2009).

3.4 RELATIONAL CONCEPTS

The framework theory approach goes beyond feature-based representations in explaining our categorization judgements and concept learning. It also

acknowledges that naive conceptions and beliefs cannot be inspected in isolation but concept learning involves changes in the interconnected elements of the knowledge structure. However, the framework theory puts little emphasis on the structure and the relational schemes related to individual concepts, which are central in grasping scientific concepts—especially at the advanced stage of learning (high school and university) (cf. Chiou & Anderson, 2010; Koponen & Huttunen, 2013). Similarly, the ontological shift view does not address the structure of knowledge but rather how students associate certain ontological attributes to the concepts and phenomena in question (cf. Chiou & Anderson, 2010; Koponen & Huttunen, 2013). Moreover, the ontological shift view seems to represent concepts as feature lists (Rusanen & Pöyhönen, 2013) while relational knowledge entails more advanced cognitive mechanisms (beyond simple feature comparison) to be learned and reasoned with (Goldwater & Schalk, 2016).

Recent cognitive science research acknowledges that many categories are characterized by their relational structure. This view stems from another version of the theory-theory of concepts according to which, concepts *are* theories (sometimes also called mini-theories)—instead of being embedded in theories. That is, concepts store some causal, functional or nomological information about the categories they represent (Machery, 2009). For instance, birds can fly *because* they have wings and this explains why these features (flying and having wings) occur together (Rehder & Ross, 2001). Relational categories consist of systems of relations linking the features without specifying them; it is sufficient that the members satisfy the relational structure (Rehder & Ross, 2001). In these kinds of categories, membership amounts to a more abstract basis for categorization and category members may be devoid of any featural similarities (in contrast to the above-mentioned views). Up until recently, these kinds of categories have been an understudied aspect of concept learning (Goldwater & Gentner, 2015).

Relational concepts capture the idea that our understanding of certain concepts, such as the "central force system", is based on the relations the concept bears to other concepts or the internal relational structure. For example, in the case of the earth and the moon, we may say that the moon is related to the earth by virtue of revolving around it. We may also construct a physical model of the situation, which can be represented by mathematical functions (Gentner, 2005).

Relational categories can be further divided into role- and schema-governed categories (Gentner, 2005; Goldwater, Markman, & Stilwell, 2011; Goldwater & Schalk, 2016). In essence, schemas denote whole relational systems whereas role-governed categories share a common role within such a system. In addition, the constituent items in schema categories (i.e. the different roles) can be grouped to form thematic categories (Goldwater et al., 2011).

Feature-based and relational concepts may become connected, as the different roles in a particular schema are typically filled with a member of the feature-based category (Goldwater et al., 2011). More specifically, relational and feature-based categories can be explicitly distinguished by defining attributes as predicates that take one argument, and relations as predicates taking two or more arguments. LARGE(x) is an attribute while LARGER(x,y) is a relation (Gentner, 1983). Furthermore, a distinction can be made between first- and higher-order relations: first-order relations relate to objects (i.e. members of feature-based categories) whereas second- and higher-order relations relate to relations (Gentner, 1983). These distinctions originate from analogical learning research, specifically from the structural alignment theory, but have been taken up (at least to some extent) by educationalists perhaps because they help to conceptualize the nature of the knowledge needed to learn science (Goldwater & Schalk, 2016; see e.g. Paatz, Ryder, Schwedes, & Scott, 2004; Richland & Simms, 2015).

Relational knowledge is vital to many of our higher cognitive competences (Halford et al., 2010). One crucial property of relational representations is that they allow us to go beyond the apparent featural similarity of entities being represented. Relational representations are *structurally consistent* in that they support the selection of relations that are conserved across instances and thus enable abstraction and, to some degree, independence from the similarity of content (Halford et al., 2010). Our inferences or categorization judgements are not bound to featural representations but we can instead rely on "deep" structural similarities that go beyond superficial details. Such structural similarities are important in physics, as physics principles and laws are often instantiated in apparently very different systems. Goldwater and Schalk (2016) have recently persuasively argued that the current research on relational categories offers promising ways for closer integration of the different research approaches to science education.

4 SCIENTIFIC KNOWLEDGE AS RELATIONAL KNOWLEDGE

Research on concept learning in science education requires that the goal of the learning is explicated; it requires a view of the nature of the scientific knowledge. Without an explicated view about the targeted scientific knowledge, the goals of science education are not recognized, nor is it possible to evaluate if these goals are achieved. As discussed earlier, to assess whether a learner has learned a concept amounts to assessing whether he or she uses the concept correctly (Rusanen & Pöyhönen, 2013). Research on concept learning should thus bridge our understanding between psychological aspects of learning and the role of students' personal knowledge in learning and our understanding of the nature of scientific knowledge (articles **I, IV**). Typically, at an advanced level (i.e. in high school or university), the learning outcomes are assessed through asking students to solve sets of problems, which are intended to be diagnostic of the most important contents of the target domain. Three connected domains of importance for learning emerge from these considerations: 1) students' personal knowledge, 2) scientific knowledge as target knowledge, and 3) learning task designs to achieve the target knowledge.

Relational knowledge, as well as being fundamental to our higher cognitive capacities, is also central in understanding the nature of scientific knowledge. Hence, the relational concepts framework offers a natural contact point for integrating theories of learning with views about the nature of scientific knowledge. In different views on scientific knowledge, relational structures are explicitly in focus, most notably in the model-based view of science.

4.1 THE MODEL-BASED VIEW OF SCIENCE AND SCIENTIFIC KNOWLEDGE

The best-known model-based view of science in science education and science education research is Giere's view, which sees scientific knowledge and scientific theories as clusters or families of related models (Giere, 1988; 1994). The models can be related to each other via sharing mutual concepts and/or relations. For example, Coulomb's law uses the concepts of force and charge while the concept of electric field relates force, charge and Coulomb's law. Models can also be hierarchically related, as some models are derived from other, more general ones. In these ways models introduce structure for the whole knowledge system (Nousiainen & Koponen, 2010; cf. Balzer, Moulines, & Sneed, 1987). Moreover, Giere (1994) suggests that models and their relational structure are central in determining the meaning of scientific

concepts and how the concepts are applied. Although he does not elaborate on the issue, he seems to imply that by applying certain "basic" models (cf. Halloun, 1996) in simple situations one learns how the concepts refer and are applied as parts of scientific models (Giere, 1994, p. 295).

Models and their relational structure are typically presented via equations, which relate the variables describing the properties of the target system (i.e. its intrinsic properties, state or interactions). Giere's account is an example of the so-called semantic view of theories, which identifies theories as consisting of classes of structures or classes of models (Lorenzano, 2013). These classes are identified on the basis of principles or laws—that is, on the basis of their relational structures (Giere, 1988; 1994; Lorenzano, 2013). In the more formal version of the semantic view, models are cast in set-theoretic terms: theory is viewed as a set of sentences (axioms) and the model is a structure in which all the statements are true (Frigg & Hartmann, 2017; Suppes, 1962). Frigg and Hartmann (2017; see, also Giere, 1988) note that especially in physics the idea that models are interpretations of more abstract laws is common. For example, Newtonian models are typically constructed by applying a general law (such as Newton's second law) to a specific system by combining it with various force function and making certain assumptions about the variables relating to the system (Giere, 1988; Frigg & Hartmann, 2017).

Certain recent views, while endorsing many of the basic assumptions of the semantic view, extend its basic ideas and see models as semi-autonomous with respect to theories instead of constitutive of them (Morrison & Morgan, 1999). These views acknowledge that in scientific practice, models are seldom straightforwardly derived from any existing theory. Instead, modelling might proceed, for example, via a *model template*, which is an "abstract conceptual idea embedded into a mathematical form or method" (Knuuttila & Loettgers, 2014, p. 298). This view also leans on the view of models as relational structures, but relaxes and alters the relation of models and theory on the one hand, and the relation of models and the target systems (or the world) on the other (Frigg & Hartmann, 2017; Knuuttila, 2011). Consequently, rather than emphasizing the structure and coherence of expert knowledge, these kinds of approaches underline more the practice of modelling and models' role in a knowledge generation.

4.2 THE MODEL-BASED VIEW OF LEARNING SCIENTIFIC KNOWLEDGE

In MBL, models and modelling are seen as essential ingredients of constructing, accepting and communicating scientific knowledge. Consequently, it has been argued that they should have an important role in science education as well (Gilbert & Justi, 2016). Models and modelling-based pedagogies are often seen as ways to engage students in "authentic"

scientific practices as well as learn about the nature of models and science more broadly (Campbell, Oh, Maughn, Kiriazis, & Zuwallack, 2015).

One of the main purposes of MBL is enhancing students' concept learning, as models can be viewed as important for constructing and communicating the meaning of scientific concepts (Gilbert, 2004). Depending on the conception of scientific knowledge (and models) one adopts, this might mean for example that theory is interpreted only through models, which contextualize the concepts and statements of the theory (Bailer-Jones, 2009). One might also view models as constitutive of theories (Giere, 1988).

Regarding concept learning, Amin and others (2014) distinguish two broad approaches using models: using ready-made models and model construction (i.e. modelling) (Amin et al., 2014; Gilbert & Justi, 2016). Using ready-made models refers to using analogies, visualizations, concrete models or simulations in order to introduce scientific ideas and concepts to students. One of the underlying key ideas in using visualizations or concrete models is helping students to ground often abstract scientific concepts and/or models. The use of analogies enhances students' understanding by showing how a novel idea or a model is like a familiar one (Duit, 1991).

In model constructing approaches, students are asked to create and apply models of their own via presenting their ideas with various external representative means (such as graphs, diagrams or equations). Model construction approaches are often embedded in collaborative and inquiry learning activities. In inquiry-based approaches, models are constructed in order to answer specific questions posed in some phenomenological context. There are various conceptualizations of the model construction activities (for reviews, see Oh & Oh, 2011; Gilbert & Justi, 2016; Louca & Zacharia, 2012). The approaches differ with respect to the amount of scaffolding, and how the nature of models (e.g. ontology, the epistemological status) and theories are conceptualized. Nevertheless, the approaches share many common traits as the process typically starts with a question or a problem and proceeds with constructing the model and making systematic observations in order to evaluate and subsequently validate the models (Louca & Zacaria, 2012). Consequently, students are engaged in phases of creating, applying and revising their models, which can result in more meaningful learning and better understanding (Oh & Oh, 2012).

In model construction approaches, the role of models as parts of theories is often emphasized, as it is noted that too often naive discovery is applied in which questions are often "arbitrary" and hypotheses are "poorly informed guesses" (Windschitl, Thompson, & Braaten, 2008, p. 946). This underscores the structure and coherence of scientific knowledge (see e.g. Hestenes, 1992). Indeed, this aspect is reflected in studies about experts' and novices' problem representations, as experts exhibit more abstract and coherent knowledge.

Concept learning is among the most important aims of MBL approaches, but still only a few studies have attempted to develop a cognitively justified

approach to understanding concept learning within MBL (Louca & Zacharia, 2012;). This aspect is discussed in articles **I** and **III** to some extent. Moreover, the use of external representations and how it affects constructing, using and learning from models is not particularly well understood (Louca & Zacharia, 2012). To this end, Perkins and Grotzer (2005) make an interesting contribution, as they discuss how students' limited repertoire of causal modelling styles is an important obstacle in learning. While students are initially inclined towards simple linear and/or sequential causality, acquiring advanced scientific concepts and models requires familiarity with more complex patterns such as constraint-based interaction (Perkins & Grotzer, 2005). Familiarity with a diverse set of modelling styles and/or complex relational patterns is of central importance in making connection across domains and noticing relational patterns in novel contexts (Perkins & Grotzer, 2005). These aspects are emphasized in the so-called generative modelling approach, which emphasizes the relative autonomy of models and especially computational methods in constructing and validating the models (Koponen & Tala, 2012).

The argument for the centrality of relational knowledge is in this section substantiated through examination of the nature of scientific knowledge. Firstly, scientific concepts are typically embedded in models, which contain information about the interdependence of the concepts. Acquiring, applying and transforming this relational information is at the core of learning scientific concepts. Relations between the concepts and how they are represented and learned should receive more attention. Unlike everyday concepts, which can be learned via contrasting the instances of the concepts, scientific concepts are often learned in problem situations where they are applied as parts of models which serve as solutions to the problems. Scientific concepts are learned in situations where they are used in relation to each other. Therefore, models and model-based-view must have a central role in the learning of scientific concepts.

5 THE SYSTEMIC VIEW OF CONCEPT LEARNING AND CONCEPTUAL CHANGE: BRIDGING DIFFERENT APPROACHES

When learning scientific concepts, students may encounter numerous problems. The target concepts are often complex and abstract, which is a challenge for students. Students often acquire conceptions that are false from the scientific point of view but are nevertheless robust and hard to change. One important question in concept learning concerns the conception of concepts, which in turn affects the aspects that are deemed central in learning scientific concepts. For example, it seems that the structure of students' concepts and how these structures change has received little attention. Nevertheless, examination of the nature of scientific knowledge and recent cognitive scientific research on concept learning implies that the structural aspects of models and concepts are central. Similarly, recent research in cognitive science research has suggested that relational representations are fundamental to our cognitive capacities and central to our understanding.

5.1 THE SYSTEMIC VIEW

In this thesis, students' concept learning is analysed from a viewpoint based on recent research on relational concepts and relational representations. A viewpoint that connects concept learning and a model-based view can be based on the relational structure of concepts and how the concepts are embedded in a system of relations. This is a key notion of the systemic view, which sees knowledge as a complex relational system.

The thesis shows how the systemic view is contextualized in the case of learning concepts of DC circuits (articles **I**, **II** and **IV**), how it connects to a model-based view of science education (articles **I** and **III**), and how the systemic view yields computational modelling which describes concept learning (articles **IV** and **V**). In the following, I provide a summary of how the systemic view bridges these different areas.

The systemic view, as discussed in detail in article **IV**, and utilized in articles **I** and **II**, considers the different relations between concepts as well as the attributes students associate with the concepts. Attributes and attributions can be constitutive of some simple beliefs associated with the concepts as well as provide information about the perceived ontologies of concepts. The attributes in the systemic view are understood similarly in the feature-based theories of concepts as well as in the ontological shift or framework theories (Slotta, Chi, & Joram, 1995; Wiser & Amin, 2001). Consequently, the initial differentiation of closely related concepts can be

conceptualized in terms of the attributes associated with the concepts; concepts can be said to be differentiated if they are associated with different sets of attributes as discussed in detail in articles **I** and **IV**. However, the study reported in article **I** suggests that only when concepts are used in law-like relations are they properly understood as different. These relations are typically manifested in scientific models, whose role in concept learning is intertwined with this role as argued in article **III** (see also, article **I**).

The close connection between the relational knowledge and model-based-approach in science teaching is not fully developed in the systemic view as presented in article **IV** but the issue is discussed in articles **I** and **III**. It suggests that the relevant aspects of models and concepts embedded in them are the types of relations as well as the kinds of relational patterns associated with the concepts. It is furthermore discussed how these are related to the construction of models, and how such a picture provides a fresh viewpoint on model-based learning in science education.

The systemic view and conception of concepts as relational schemes yields computational modelling of concept learning. Articles **IV** and **V** present two proof-of-concept types of computational models, which incorporate central ideas of the systemic view. The computational models open up the possibility of exploring and proposing grounded hypotheses about the dependence between student's initial, personal knowledge, structure of target knowledge (scientific knowledge) as well as task design and structure. The interplay between these three diverse fields is not easily approached empirically, but computational studies may help to gain insight into those connection points which are of most importance and might yield empirical approaches.

5.2 THE DIRECTED GRAPH MODEL

In discussing concept learning, articles **I**, **II**, **IV** and **V** utilize a graphical representation of concepts, thus capturing the nature of concepts as relational structures. In articles **I** and **II**, exploratory, descriptive empirical studies were conducted in the context of DC circuits. In article **I**, students' conceptions about DC circuits and related concepts as well as the changes in the explanation models students generated were examined by using the directed graph model (DGM), introduced in detail in article **IV**. The DGM is used in this thesis to represent the relational aspects of the concepts as well as the dynamics of the learning process. The DGM was developed during this thesis to facilitate visual representation of the complex structure of advanced concepts.

The DGM represents students' conceptions and explanation models as collections of different conceptual elements: models, attributes, concepts and different relational patterns. An example of a DGM (discussed in detail in article **I**) appears in Figure 2. In article **II**, the different relational patterns identified in article **I** were simplified further and used to describe features of

students' conception about DC circuits. These idealized relational patterns appear in Figure 3.

In article **I**, close attention was paid to so-called constraints, which were conceptualized as limitations in the use of attributes. In the context of DC circuits, an important set of constraints is derived from circuits' geometry. Here, the attribute "divides" can be used with the constraint "in parallel" to denote the conception that the electric current divides in junctions where two components are connected in parallel. Furthermore, it was noted that relations between concepts are not always causal but can be viewed as constraining laws. For example, Ohm's law typically has a causal reading (voltage causes current) and Kirchhoff's laws I and II are essentially constraining conservation laws.

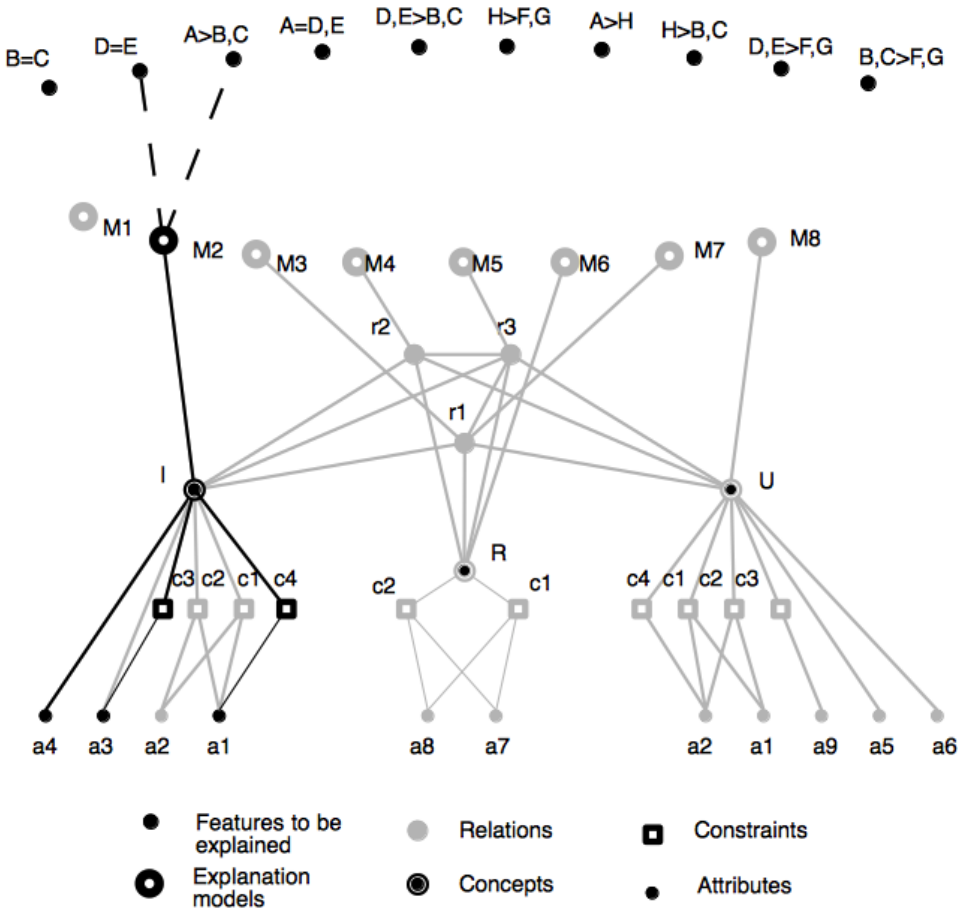


Figure 2 Template of DGM graph representing students' knowledge (article **I**). An example representing the typical conception of the consumption of current in a circuit appears in black lines. Possible (but not active) connections between conceptual elements appear in grey. Attributes (a1,…,a9), relations (r1, r2, r3), constraints (c1, c2, c3) and models (M1,…,M8) are described in article **I** in more detail. The uppermost row denotes the possible predictions/observations required by the task design (i.e. task structure). Originally published in article **I**.

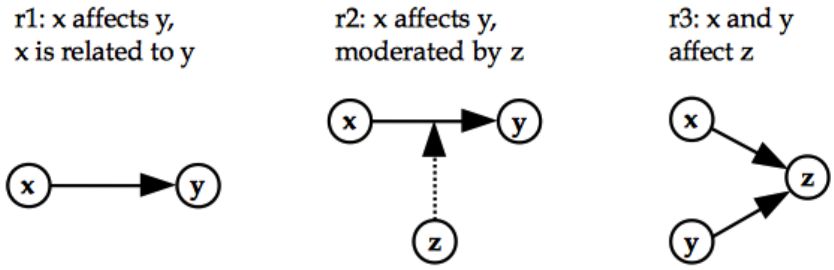


Figure 3 Diagrams of generic relational patterns appearing in students' explanations. Originally published in article **II**.

Constraints and different relational patterns (appearing in Figure 3) are relational representations. From the relational concepts framework they can be interpreted as relational representations of a different order (Gentner, 1983; Paatz et al., 2004). Kirchhoff's laws can be interpreted as first-order relations while Ohm's law can be seen as a higher-order relation relating to three concepts (see r3 in Figure 3), voltage, electric current and resistance, which are themselves relational.

5.3 EMPIRICAL STUDIES: DC CIRCUITS

The studies reported in articles **I** and **II** are descriptive exploratory empirical studies about students' concepts related to DC circuits. Here, a brief description of the methods and subsequent analysis of the data is presented. A more thorough description can be found in articles **I** and **II**. In both studies, students worked with DC circuit tasks in which one has to predict and explain the relative brightness of bulbs connected to different basic circuits. An example of the circuit used in both studies appears in Figure 4.

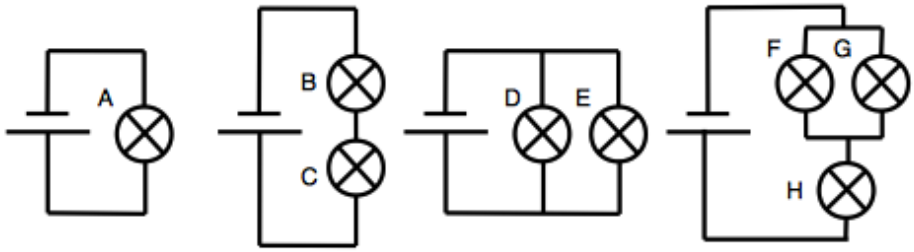


Figure 4 An example of circuits studied in articles **I** and **II**. Originally published in article **I**.

5.3.1 METHOD

In article **I**, 31 university students worked in groups of 2 or 3 with tutorial-type tasks where one must first predict and explain the order of brightness of bulbs and then construct the actual circuits to test the predictions. First, students were asked to think about their predictions on their own for a few minutes. They were then asked to explain and discuss their prediction with others. Finally, students were asked to explain their observations. In article **II**, 11 university students worked alone with pen and paper versions of similar tasks. In both studies, the majority of participants were university students minoring in physics who attended the intermediate courses intended for pre-service physics teachers.

In the group sessions, an interviewer was present at all times. The interviewers mainly asked only clarifying questions during the tutorial-type tasks and avoided "feeding" any terms and/or concepts to the students. The group sessions can be conceived as an unstructured or informal conversational interview, as there were no predetermined questions and the session was guided only by the task at hand. The interviews were videotaped and transcribed verbatim. The interviews lasted on average 23 minutes (ranging from 10 to 36 minutes).

The transcripts as well as students answers to the pen and paper versions of the tasks were analysed by means of content analysis (cf. Chi, 1997; Elo & Kyngäs, 2008; Miles, Huberman, & Saldaña, 2014). As the purpose was to identify the conceptual elements students used as well as the explanation models they generated, the analysis consisted of two coding cycles targeting patterns at different levels (Miles, Huberman & Saldaña, 2014). The first cycle consisted of condensing the essential ideas of students' verbal expressions and segmenting the condensed expressions. This was followed by the coding of the segments (i.e. identifying the names of the concepts used as well as the attributes and relations). The second coding cycle was carried out to merge the categories (attributes and relations) into meaningful patterns (i.e. explanation models). In article **II**, the analysis of the written answers consisted of identifying the relational patterns students used in explaining the relative brightness of the bulbs.

In article **I**, the different elements were combined into a graph (see Figures 2 and 5) to present how different elements were connected together in students' explanations. Two graphs were drawn for each student: one for the prediction phase and one for the explanation phase.

5.3.2 RESULTS AND DISCUSSION

In both of the studies presented in articles **I** and **II**, students made false predictions regarding the different degrees of the bulbs' brightness. They typically could provide only partial explanations for their observations. Students held false beliefs such as the electric current gets used up or consumed in the circuit, which were reflected in their predictions that one of

the bulbs connected in the series would be brighter than the other—a belief that is prevalent in previous studies about the topic (Lee & Law, 2001; McDermott & Shaffer, 1992). The belief that the battery acts as a source of constant current was found to be very common too (see also, McDermott & Shaffer, 1992).

However, the main interest of the analysis was to identify students' explanation models and their changes at a detailed level. The different models were categorized according to the concepts and relations incorporated in them. Students were also found to use a range of explanation models to account for the differences in brightness. The explanation models identified in article **I** appear in Table I. Four examples of students' conceptions represented via DGM appear in Figure 5. The interlinkages of different conceptual elements differ across students, and variations in the interlinkages are substantial. Each of the examples shown in Figure 5 represents a very different "conception" and a simple verbal description of such conceptions would be difficult.

As indicated in previous studies about the topic (see e.g. Reiner et al., 2000), students favoured rather simple models involving only one or two concepts. Typically, students generated explanations based on the electric current. As discussed by Reiner et al. (2000), students' conceptions of voltage may not be as clearly defined as their conceptions of a current, as the current lends itself more easily to concrete, materialistic associations. As a consequence, students might more readily use current-based explanations when prompted. The simplest explanations were mere rules of thumb— such as "bulbs connected in parallel are equally bright"—rather than actual explanations. As such these simple explanations are not generalizable to other contexts. However, as mentioned above, these descriptive statements might act as heuristics for students guiding the construction of more sophisticated explanations.

The different beliefs (such as "the current degrades" or "is consumed in the circuit") related to the concepts were represented as different constellations of attributes. This is related to the way in which the attributes are discussed in feature-based theories of concepts. Moreover, it is comparable to the way in which concepts' ontologies are discussed as different attributes connected to the concepts (see e.g. Slotta at al. 1995; Wiser & Amin, 2001). However, the studies presented in articles **I** and **II** distinguish between feature-like attributes and relational features unlike most studies discussing students' ontologies related to DC circuits (see e.g. Slotta et al., 1995).

The ontological shift is not discussed in this thesis in detail, but the results imply that certain beliefs held by the students might stem from simple material associations as discussed in Reiner et al. (2000). Nevertheless, it seems that at the university level, the relational schemes associated with the concepts cause students difficulties and learning at this stage can be attributed to the students' ability to apply and modify relational knowledge.

The results of this thesis align with Koponen and Huttunen (2013), who claim that law-like knowledge (i.e. causal schemes) has an important role in driving the changes in the ontological attribution of concepts.

While many students' explanations were rather simple, some of them could modify their initial predictions after observing the actual circuits. Comparing the DGMs from the prediction and explanation phases enabled analysing the changes in students' explanation models. This revealed three distinct processes that seem central to concept learning: *model switch, model elaboration* and *model refinement*. The different processes appear in Figure 6. Model switch involves switching from one explanation model (used in the predicting the brightness) to another which does not share features with the initial model. Rather than simply switching the model, model elaboration includes adding elements to the initial model. For example, a student might have initially used a current-based explanation and elaborated it to include resistance in order to account for the observations. Model refinement means merging many models into one.

The change processes which appear in Figure 6 are comparable to the way in which certain aspects of acquiring relational knowledge is discussed within cognitive science (see e.g. Halford, Wilson & Phillips, 2010; Dixon & Kelley, 2007; Corral & Jones, 2014). *Theory revision* amounts to revising a hypothesized relational structure if it fails to account for the situation at hand (Dixon & Kelley, 2007). Corral and Jones (2014) argue that (at least) two sub-processes, *schema refinement* and *schema elaboration* contribute to the revision of the relational structure. Comparably to the discussion in article **I**, elaboration means adding relations to the existing structure. Refinement amounts to stripping away unessential details corresponding to an analogical learning scenario, which results in abstracting the schema so that it contains only the structure common to the target and the source (Corral & Jones, 2014).

Table 1. *The descriptions of the explanation models that the students used in the interviews. Originally published in article* ***I.***

Model	**Description**	**Related concept(s)**	**Relations**
M1 Simple models	These models are based on a simple rule of thumb, such as: "When the bulbs are in a series, they have the same brightness."	-	-
M2 Current-based model	The only concept used in this model is the current: a current flows into a circuit and causes the bulb to burn.	*I*	-
M3 Pre-Ohmian current model	A current flowing in a circuit makes the bulbs light up, and the current depends on either the resistance of the circuit or the voltage between the ends of the battery or component.	*I, R* or *U*	r1
M4 Ohmian model	A current flowing in a circuit makes the bulbs light up. The current depends on the resistance of the circuit and the voltage between the ends of the battery or component.	*I, R*, *U*	r2
M5 Pre-electric power model	a) The brightness of the bulb depends on the current running through it and the voltage between its ends. b) The brightness of the bulb depends on the current running through it and the resistance of the bulb.	*I, R* or *U*	r3
M6 Resistance-based model	This model uses only resistance. The brightness of the bulbs is determined by the resistance of the bulbs and/or the resistance of the circuit	*R*	-
M7 Pre-Ohmian voltage model	The brightness of the bulb depends on the voltage between its ends. The voltage depends on the resistance of the bulb.	*U, R*	r1
M8 Voltage-based model	This model uses only voltage. The brightness of the bulb depends on the voltage between its ends.	*U*	-

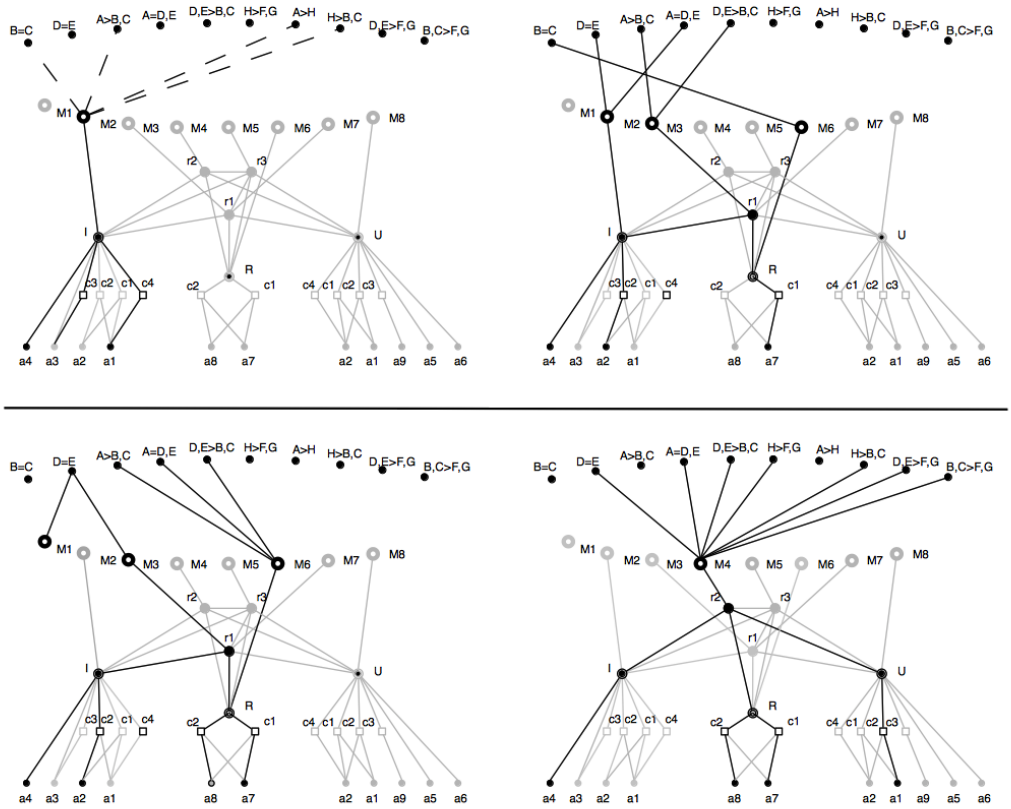


Figure 5 Examples of two students' conceptions represented via DGMs. The DGMs on the left are from the prediction stage, the DGMs on the right are from the explanation stage. Adapted from article **I.**

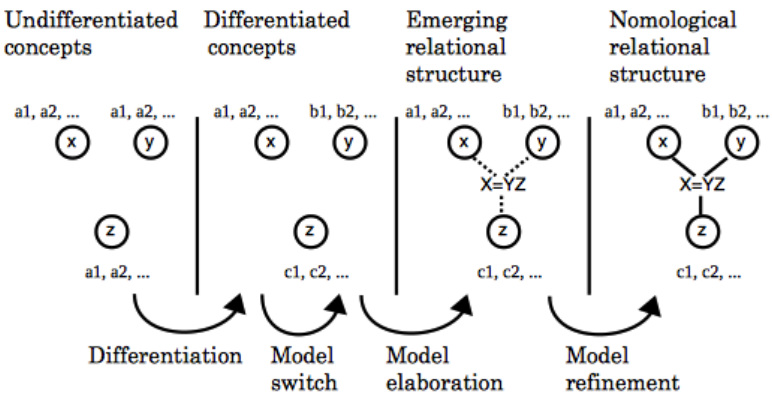


Figure 6 Changes in students' explanation models. The concepts (e.g. electric current, voltage and resistance) are denoted by x, y and z, while a1,..., b1,... and c1,… denote the attributes associated with the concepts. Originally published in article **I**.

5.4 CONCEPT LEARNING RELATED TO MODEL-BASED LEARNING

Relational schemes, according to the view developed in this thesis, are closely related to models and modelling. According to the model-based view on science education, models and modelling are key structures for learning scientific concepts and facilitating conceptual change. Despite concept learning being one of the most important aims of MBL, only a few studies have attempted to construct a cognitively justified basis for concept learning within MBL.

In the theoretical article **III,** MBL was examined from the viewpoint of the relational concepts framework. It was argued that models can be conceptualized as relational categories, which are categories whose membership is determined by a common relational structure. A "central force system" can then be thought of as a category consisting of the systems that satisfy the relevant relations. On the other hand, as models can become objects of study in their own right, the category can also be thought to consist of the models (instead of the systems) that describe a central force system. By viewing models as relational categories, I sought to illuminate the roles of models and modelling in learning scientific concepts and the related cognitive aspects in the context of MBL.

As already discussed in chapter 4, two broad approaches can be distinguished within MBL: using ready-made models and model constructing (Amin et al., 2014). In article **III**, two different dispositions towards model construction are pointed out: *constructive* and *generative modelling*. In constructive modelling approaches, models are parts of larger, more comprehensive frameworks (i.e. theories) (see e.g. Hestenes, 1992). Generative modelling, on the other hand, assumes a more autonomous role for models, where models are typically not straightforwardly derived from any existing theory (see e.g. Koponen & Tala, 2014). In contrast, modelling can draw from multiple recourses and include purely phenomenological elements. These perspectives (constructive and generative modelling) come close to semantic and artefactual views of modelling, respectively (see, Giere, 1988; Knuuttila, 2011; Lorenzano, 2013).

Conceptualizing models as relational categories underscores the importance of relational knowledge in learning the concepts in the context of MBL. Firstly, constructing and applying models requires grasping the relational structure embedded in specific models. Secondly, acquiring the interconnected and coherent knowledge structure, which is emphasized in constructive modelling approaches, entails learning the relations between the models. Making connections across different hierarchies of models (see e.g. Halloun, 1996; Hestenes, 1992) also requires relational knowledge, as abstraction is enabled by relational representations (Halford et al., 2010). Teaching should support the learning of such knowledge.

The ability to construct and identify relational schemes in novel situations is central in generative modelling approaches where models are seen as semi-autonomous (see e.g. Koponen & Tala, 2014; Lehrer & Schauble, 2015). This also includes transferring schemes from one context and/or domain to another, as well as using multiple different external representations. From the viewpoint of relational categories, general relational knowledge is vital in this kind of modelling. Also, generative modelling requires a developed repertoire of "modelling styles"–for example, expertise in modelling with constraint equations. Consequently, the choice of external representations (or modelling tools) is also of central importance because it affects what is or can be learned from the model. For instance, mathematics can assist in students' conceptual development (Amin et al., 2014; Lehrer, Schauble, Strom, & Pligge, 2001; Lehrer & Schauble, 2015) and therefore it should not be treated as mere computation.

Research in science education as well as cognitive science has examined how students learn general relational schemes and specific modelling styles. Goldwater and Gentner (2015) have argued that familiarity to particular causal systems as well as comparing relational structures across contexts is required in order to learn general causal schemes. Likewise, Perkins and Grotzer (2005) explicated particular causal models through discussion and by applying them to several contexts. They concluded that explication and comparison of models helped students to learn the concepts better.

The ideas and views developed in article **III** derive from many different sources and an attempt is made to provide a synthesis of these different views based on the idea of the centrality of relational schemes in acquiring advanced scientific knowledge. Article **III** includes theoretical underpinnings of the work reported in this thesis, but at present many ideas put forward there are tentative and have not yet led to practical implementations in science education or science teacher education. However, such implications and applications are envisioned and under development.

6 COMPUTATIONAL MODELLING OF CONCEPT LEARNING

Articles **IV** and **V** present computational modelling and simulations of the concept learning process. Article **IV** reports work based on an earlier study by Koponen and Huttunen (2013) and utilizes a DGM developed therein as the template for the simulations. Putting the mathematics of the simulations aside (reported in detail in articles **IV** and **V** but not of central interest here), article **IV** introduces a connectionist-type model, while in **V** a simplified, complex systems-type model is introduced.

6.1 CONNECTIONIST COMPUTATIONAL MODEL

In the model presented in article **IV**, the basic idea is that a knowledge system is a directed graph consisting of connected nodes which have dynamically evolving strengths. The nodes correspond to the different conceptual elements, and the different activation patterns correspond to different learning outcomes. The learning outcomes can be monitored via the quantities *theoricity* and *separability*, which operationalize the notions of the theory content of the concept and its degree of differentiation, respectively (see the Appendix in article **IV** for details and precise definitions).

6.1.1 THE SIMULATION

In the DGM presented in article **IV**, the concepts consist of sets of attributes (dubbed C constructs) as in the feature-based theories of concepts (see chapter 3.2). Such C constructs can become connected via relational schemes (called D constructs), which not only link the C constructs but also constrain what attribute sets can be applied. In the context of the DC circuit the relevant schemes are Kirchhoff's laws and Ohm's law. In addition, C and D constructs can be parts of models (M constructs), which serve as vehicles for generating explanations (comparably to the explanation models explained in article **I**, see section 5.2). C, D, and M constructs serve as nodes in the graphs and are connected via directed links. Each of the nodes has a dynamically evolving strength, which determines the node's effect (either inhibiting or strengthening) on the nodes to which it is connected.

The evolution of the concept system (i.e. updating node strengths) is driven by comparing the models to evidence, which corresponds to the observations of different DC circuits. The models' *utility* (i.e. the ratio of their complexity and explanatory power) determines which model will be favoured and, thus, how the strengths of the other conceptual elements will evolve. In

simple situations, simple models will provide adequate explanations and, hence, their utility will be high whereas complex models will have low utility. In contrast, in more complex situations, more complex models will be favoured, as the simple models cannot explain the evidence. The models' utility and hence the evolution of the concept system is also affected by learner dependent parameters, namely the ability to use theoretical knowledge and attentiveness to the evidence. Cognitive utility has previously been proposed as a key variable underlying reasoning and decision-making processes in general (Ohlsson, 2009; 2013). Ohlsson (2013) describes utility as usefulness of a given knowledge structure in a certain context.

In the computational model, concept differentiation and ontological change are modelled as changes in the concepts' links to the attributes. Differentiation is measured as the separability of the C constructs, which is a measure of the dissimilarity of the sets of attributes connected to the concepts. Another measure of the state of the system (i.e. the learning outcome) is the theoricity of the concept, which is operationalized as the connectedness of the models and the C constructs (see the Appendix in article **IV** for details).

6.1.2 RESULTS AND DISCUSSION

The main results illuminate the context-dependent dynamics of learning. The learning trajectories resulting from the simulation resemble the learning trajectories to the extent that they can be inferred from empirical data. Examples of the simulated learning trajectories corresponding to different initial conditions (modelling different initial states of students' knowledge) are given in Figure 7.

In the computational model, the utility of students' explanatory models drives the evolution of the concept system, and complete learning of the most complex models appears only in sufficiently rich contexts (i.e. when the models are compared to the most complex circuits)(cf. Ohlsson, 2013). This reflects how during learning certain features, or "misconceptions", appear robust but are fundamentally context dependent.

In the computational model, ontological changes (i.e. changes in the attribute sets connected to the C constructs) and differentiation are driven by the successful application of models. This in turn strengthens certain relational schemes that constrain which attributes are used. So instead of ontological change driving concept learning, the present model implies that it is a consequence more of adopting theoretical structures (i.e. relational schemes). Hence, the models' implications of top-down learning, leaning on relational schemes known to a learner at least partially, stand in contrast to views where learning happens in a more bottom-up fashion (e.g. through changes at the ontological level). According to the systemic view, and how the computational model embodies its main assumptions, ontological shift as a driving mechanism for advanced learning is implausible. Rather, ontological

shift results from improvements in the acquisition and use of relational schemes.

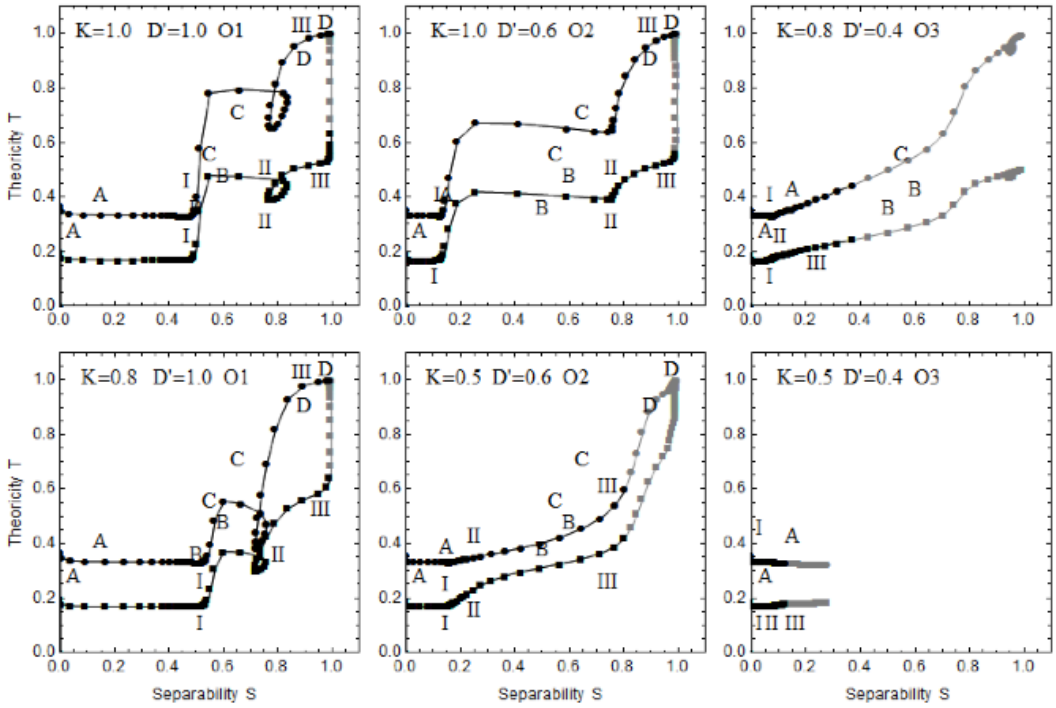


Figure 7 The *theoricity T* and *separability* S of concepts C1 (bullets) and C2 (boxes) in the case of six different learning paths with given parameters K and D' that control the strength of the theoretical guidance. Parameter K is related to the potential of an individual student to make use theoretical knowledge in constructing explanatory models. Parameter D' controls how strongly theoretical knowledge will guide the learning process. The upper row shows cases where K ≥ 0.8 is always relatively high but D' varies from 1.0 to 0.4. In the lower row, K also varies from a high value of 0.8 to a lower value of 0.5. The initial values of the model strengths and strengths of the observations are different in the cases shown in the left, middle and right columns (corresponding model strengths are shown in Figure 6). Left column: Initial values of model strengths favour models M1 and M2' with strengths of 0.5, while other models have a weaker but equal strength of 0.25. The observations of events I-III (corresponding to different DC circuits, for details see article **IV**) are strong (link strengths have a value of 1). Middle column: model strengths as in the left column, but M3, M3' and M4 are reduced to 0.15, observations I-II are strong (1), but III is only moderately strong (0.75). Right column: otherwise similar to the middle column, but the observations in case III are weak (0.10). The training sequence from I to III (end points of each sequence are marked in the figure), with three repetitions for each event are shown by black dots. The training sequence testing the permanence of learning from I to III, then back from III to I, and one random sequence are shown by grey dots. Letters A-D indicate the values of *T* and *S* corresponding to typical DGMs (see article **IV**), which depict students' conceptions (two letters for each are located in the pairs of the lowest estimated and highest estimated values for *T* and *S*). Originally published in article **IV**.

6.2 COMPLEX SYSTEMS MODEL

6.2.1 THE SIMULATION

The DGM represents the concept system as directed graphs and as connected groups of nodes with evolving strengths, which correspond to the conceptual states. The corresponding computational model is necessarily a connectionist model, which is difficult to handle. One disadvantage of such a model is that a parametric description of how the input of the model is connected to the output cannot be produced. Despite all its advantages the connectionist model remains a kind of "black box" model. To gain more transparent insight into how robust learning outcomes might be related to initial states of learning and task structures, a different type of model was developed in the study reported in article **V**. It starts from a simplified DGM, but transforms the dependencies contained in it to a complex system model, in which the DGM is replaced by an abstract continuum representation of the target knowledge. The continuum model is a kind of epistemic landscape (cf. Weisberg & Muldoon 2009), and learning is described as foraging for the best model in that landscape. The resulting model is a probabilistic learning model (PLM), where the learning progression is guided by the epistemic landscape.

The PLM explores the possibility of modelling concept learning in a context which resembles learning a simple theory. The "theory" consists of three concepts and three relational schemes arranged into a three-tiered model space. The learning process in PLM is conceptualized as the foraging of the epistemic landscape, in which a model is selected based on its utility as the evidence unfolds. As in the DGM, utility is a trade-off measure between the model's complexity and its explanatory power.

The components of the epistemic landscape considered here are *proficiency* κ, *evidence* ε, and utility u. Proficiency describes the learner's proficiency in using the model to give an explanation. Evidence refers to the cases (e.g. different circuits) students need to explain although it is taken as a continuous parameter in the model. The utilities of the different models are given as probability distributions, which take proficiency and evidence as parameters. The epistemic landscape thus corresponds to an abstract representation of the likelihood of adopting certain explanation model given the evidence and proficiency. An example of a simplified epistemic landscape is shown in Figure 8. The topography of the landscape corresponds to the utilities while the other coordinates correspond to evidence and proficiency.

Foraging of the epistemic landscape consists of utility-based selection of explanatory models. In practice, κ is given an initial value and ε is increased by 0.01 (which corresponds to unfolding evidence). Then it is decided whether: 1) a model switch happens 2) κ is changed or remains unchanged, and 3) whether the selected model explains the given model or not. For each of the steps 1)-3) each outcome is assigned a discrete probability.

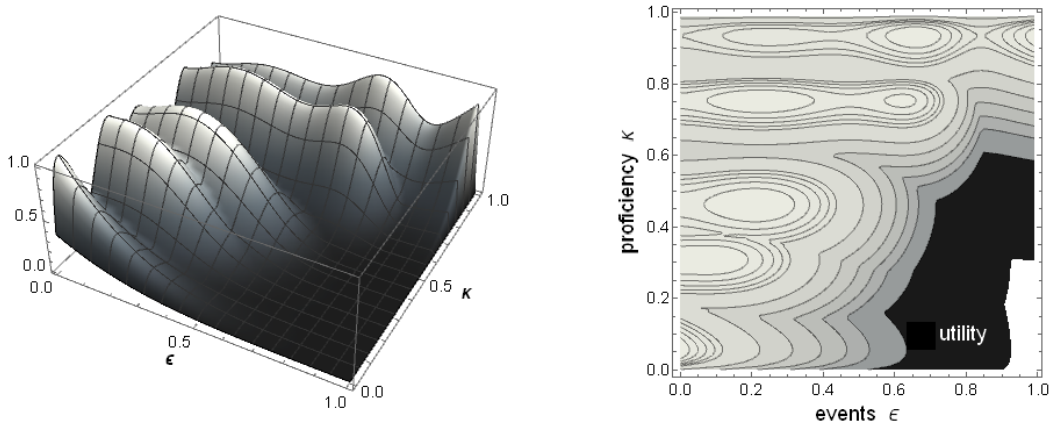


Figure 8 The epistemic landscape illustrating the utilities of five different explanation models as functions of ε and κ. The diagram on the left shows the landscape and the diagram on the right is its representation as a contour plot.

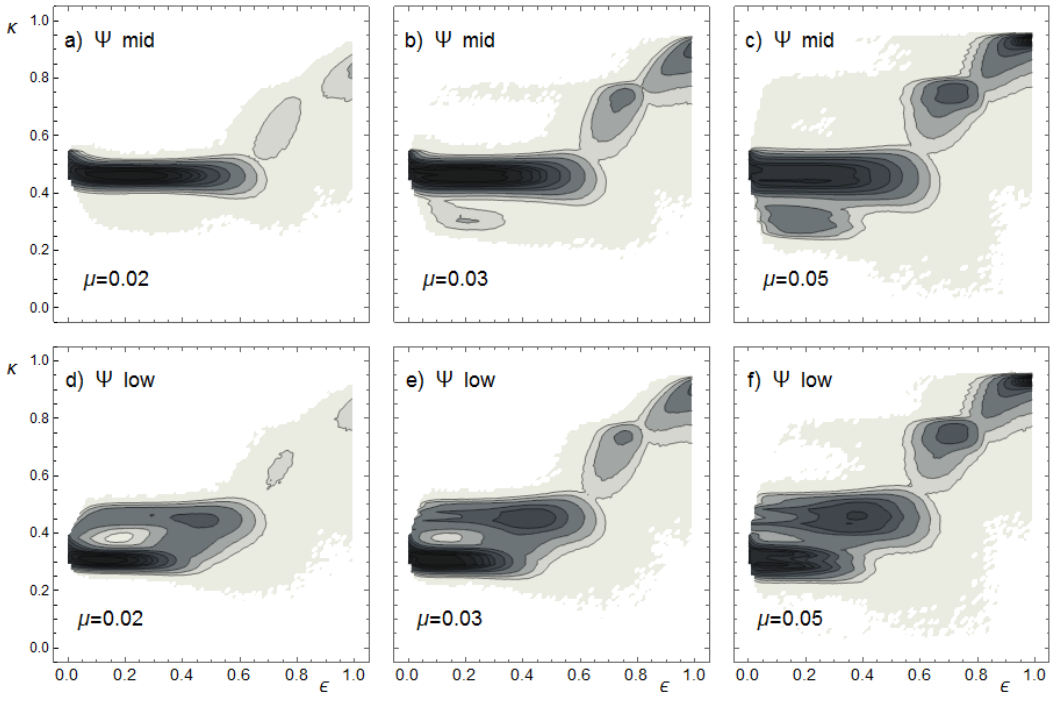


Figure 9 The densities $\Psi_k(\varepsilon, \kappa)$ of selected explanatory models, m_1–m_5 for different memory parameters (see article **V**) μ = 0.02, 0.03 and 0.05. The upper panel shows results for the initial mid-cohort (0.45< κ <0.55) and the lower panel for the low-cohort (0.30< κ <0.40).

6.2.2 RESULTS AND DISCUSSION

The simulations of PLM are carried out as event-based stochastic simulations (for details, see article **V**). The outcome of the simulations is a number density distributions Ψ_k of different explanatory models corresponding to the different stages of learning during the learning task. The interesting behaviour of the simulation is the formation of attractor-type areas to which the learning paths accumulate—that is, regions where the number density of a certain model peaks. Some of such attractor states are shown in Figure 9.

The attractor-type states can be interpreted as robust learning outcomes. The formation of such states can be partly attributed to the confidence and memory parameters and their interplay with the learning design. Such learning outcomes are traditionally the targets of studies regarding students' conceptions, but we suggested that they can arise through the interplay between learning dynamic and task characteristics. So instead of thinking that students enter the learning situation with robust pre-existing misconceptions (or develop them during the course of learning), we could think of them as epiphenomena of the learning dynamics.

7 DISCUSSION AND CONCLUSIONS

In this thesis, it is advocated that research on concept learning benefits from linking views about the cognition of learning with views about the nature of the targeted scientific knowledge. On one hand, as learning is a psychological phenomenon involving the transformation of one's cognitive representations, we need to lean on theories which concern cognitive conceptual representation. On the other hand, in order to assess learning, we need to compare learners' inferences to the benchmark inferences provided by accepted scientific knowledge. While these two perspectives offer a complementary picture of the learning process, it is underscored that they are distinct because scientific knowledge cannot be conceived as the representation of any one individual.

Traditional approaches about concept learning and conceptual change put little emphasis on the level of individual concepts. In this thesis, it is suggested that at the advanced level of learning the relational aspects of concepts are central. This assumption is supported by the notion that cognitive science research has shown that relational representations are central to our higher cognitive competences in general. This is relevant for concept learning in science, as it implies that learning advanced concepts is markedly cognitively different than learning e.g. simple concepts.

The conviction of the centrality of relational concepts in learning science stems partly from analyses of the nature of scientific knowledge, which have pointed out the centrality of different types of relational structures in scientific knowledge. For example, according to the so-called semantic view, scientific knowledge consists of classes of structures, which are identified based on laws or principles. Relational knowledge thus also provides the basis for reinterpretations of model-based learning (MBL) and provides insight why it is so successful. First, the use of analogies in constructing models hinges on mapping the relevant relations between the source and the target. Second, analogical mapping based on relational knowledge enhances learning abstract, general relational schemes. Third, general relational schemes are important in applying and constructing models in novel situations.

The empirical results presented in this thesis reveal that in the context of DC circuits, students at the university level still rely on rather unsophisticated explanation models. In general, they can differentiate the concepts at the attribute level but lack the relevant relations. This suggests that (qualitative) differentiation precedes the learning of relations and learning in the advanced setting can be attributed to greater proficiency in using relational knowledge. Some students taking part in the studies could modify their explanations. Analysis of the changes identified three types of changes: model switch, model refinement and model elaboration.

The results imply that students' ability to apply and modify relational knowledge is vital to the construction of correct explanation models. Moreover, as relational knowledge is central to human cognition on the one hand, and to physics knowledge on the other, it has a key role in learning and understanding physics. Seen this way, the central learning processes are those which relate to revision of the relational structure. This view differs from previous research suggesting simple categorization processes as the main mechanisms behind concept learning (cf. Chi, 2008; 2013; Vosniadou, 1994) and provides a fresh approach on old, still unresolved problems of concept learning and conceptual change.

In this thesis, simulations were also carried to test certain hypotheses and to underscore the role of relational knowledge in guiding concept learning. The results of simulations imply that a major driving force behind concept learning is competition between different explanation models and the utility of the models. Model competition is driven partly by the model's explanatory power and its complexity but also the learner's' proficiency in adopting the model. Importantly, the simulation models imply that robust learning outcomes are the outgrowths of the learning task design and certain parameters describing the learner stemming from the psychology of learning. This is in contrast with traditional approaches where the learners are assumed to enter the learning situation with robust and well-defined preconceptions instead of preconceptions which emerge from context-dependent dynamics and the interaction between the learner and the task at hand.

The literature on concept learning from science education research is here linked with recent cognitive science research about relational concepts as well as with views about the nature and structure of scientific knowledge. The proposed conceptualizations put relational knowledge at the core of learning scientific concepts, where relations are seen as fundamental in constructing the understanding and meaning of concepts. This systemic view of concept learning offers a cognitively well-justified framework for analysing concept learning and its mechanisms. The centrality of relational schemes and structures in both areas—cognition and science—have fundamental implications and repercussions for science education research and practice which are now beginning to emerge.

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