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Telle Hailikari

Assessing University Students' Prior Knowledge

Implications for Theory and Practice

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Abstract

The aim of this dissertation was to explore how different types of prior knowledge influence student achievement and how different assessment methods influence the observed effect of prior knowledge. The project was begun by creating a model of prior knowledge, which was then tested in various science disciplines.

Study I explored the contribution of different components of prior knowledge to student achievement in two mathematics courses. The results showed that procedural knowledge which requires higher-order cognitive skills, predicted the final grades best and was also closely related to previous study success. Feedback from the prior knowledge test did not influence student performance. The same pattern regarding the influence of prior knowledge was also seen in Study III, which was a longitudinal study of the accumulation of prior knowledge in the context of pharmacy. The study analysed how prior knowledge from previous courses was related to student achievement in the target course. The results implied that students who possessed deeper-level prior knowledge, that is, procedural knowledge, from previous courses also obtained higher grades in the more advanced target course. This result provided further support for the results of Study I in that prior knowledge consisting of facts did not contribute to student achievement.

Study IV explored the impact of different types of prior knowledge on students' readiness to drop out of the course, on the pace of completing the course and on the final grade. The study was conducted in the context of chemistry. The results revealed again that students who had good prior procedural knowledge were also likely to complete the course in the pre-scheduled time and get higher final grades. On the other hand, students whose performance was weak in the procedural prior knowledge tasks were more likely to drop out or take a longer time to complete the course.

Study II explored the issue of prior knowledge from another perspective. Study II aimed to analyse the interrelations between academic self-beliefs, prior knowledge and student achievement in the context of mathematics. The results revealed that prior knowledge was more predictive of student achievement than were other variables included in the study. Self-beliefs were also strongly related to student achievement, but the predictive power of prior knowledge overruled the influence of self-beliefs when they were included in the same model. There was also a strong correlation between academic self-beliefs and prior knowledge performance.

The results of all four studies were consistent with each other, indicating that the model of prior knowledge may be used as a potential tool for prior knowledge assessment. It is useful to make a distinction between different types of prior knowledge in assessment since the type of prior knowledge students possess appears to have a significance. The results implied that there indeed is variation between students' prior knowledge and academic self-beliefs. This variation influences student achievement and should be taken into account in instruction.

HELSINGIN YLIOPISTO
Kasvatustieteen laitoksen tutkimuksia 227

Telle Hailikari

Yliopisto-opiskelijoiden ennakkotietoa arvioimassa
Teoreettinen malli ja sen käytännön sovellukset

Tiivistelmä

Tämän väitöskirjatutkimuksen tarkoituksena oli tutkia, millä tavalla opiskelijoiden ennakkotieto heijastuu oppimistuloksiin eri tieteenaloilla ja mitkä ovat ennakkotiedon arviointiin soveltuvat keinot ja menetelmät. Tutkimuksessa kehitettiin malli ennakkotiedosta, jonka toimivuutta testattiin kolmella eri luonnontieteellisellä alalla. Tutkimuksen keskeisenä tavoitteena oli tarkastella, miten yliopisto-opiskelijoiden korkeatasoista oppimista voidaan tukea ennakkotiedon arvioinnin avulla.

Ensimmäinen osatutkimus analysoi, miten mallissa eroteltu laadultaan erilainen ennakkotieto ennustaa oppimistuloksia. Tutkimuksen tulokset osoittivat, että opiskelijat, jotka pystyivät ratkomaan suhteuttavan tai soveltavan tiedon tasoisia tehtäviä jo kurssin alussa, menestyivät paremmin kurssilla. Sen sijaan pinnallisella faktatiedolla tai kuvailevalla tiedolla ei ollut vaikutusta oppimistulokseen. Myöskään omasta suorituksesta saadulla palautteella ei ollut vaikutusta oppimistuloksiin. Kolmannen osatutkimuksen tulokset olivat samansuuntaisia. Osatutkimus III oli pitkittäistutkimus, jossa tutkittiin, miten ennakkotiedon tason vaikutukset kumuloituvat kurssilta toiselle siirryttäessä. Tutkimus tehtiin farmasian alalla. Tulokset osoittivat jälleen, että opiskelijat, joilla oli suhteuttavan tai soveltavan tason ennakkotietoa aiemmilta kursseilta, saivat myös parempia kurssiarvosanoja kohdekurssilla. Faktatiedolla ei ollut tässäkään tutkimuksessa yhteyttä opintomenestykseen. Tulokset siis osoittivat ennakkotiedon tason kasaantuvan ja heijastuvan opintomenestykseen myös pidemmällä aikavälillä.

Osatutkimus IV analysoi, miten ennakkotiedon taso on yhteydessä kurssin keskeyttämiseen, suorittamisnopeuteen ja loppuarvosanaan. Tutkimus suoritettiin kemian alalla. Tulokset osoittivat jälleen, että opiskelijat, joilla oli soveltavan tason ennakkotietoa, suorittivat kurssin ajallaan ja saivat korkeampia kurssiarvosanoja. Toisaalta taas opiskelijat, joilla oli heikko ennakkotiedon taso, jättivät todennäköisemmin kurssin kesken tai suorittivat kurssin hitaammin uusintakokeiden avulla.

Osatutkimus II tutki ennakkotiedon merkitystä toisesta näkökulmasta. Tavoitteena oli tutkia opiskelijoiden pystyvyysuskomusten, ennakkotiedon, aiemman opintomenestyksen ja kurssimenestyksen välisiä yhteyksiä rakenneyhtälö-mallinnuksen avulla. Tulokset osoittivat, että ennakkotieto oli paras opintomenestyksen ennustaja mukana olleista muuttujista. Muutkin muuttujat olivat vahvasti yhteydessä opintomenestykseen, mutta ennakkotiedon vaikutus nousi yli muiden. Lisäksi pystyvyysuskomusten ja ennakkotiedon välillä oli vahva yhteys.

Kaikkien neljän osatutkimuksen tulokset olivat yhteneväisiä keskenään ja osoittivat, että ennakkotiedon malli vaikutti toimivan johdonmukaisesti ja sitä voidaan käyttää ennakkotiedon arvioinnin välineenä. Tulokset osoittivat, että on hyödyllistä erotella laadultaan erilainen ennakkotieto toisistaan. Opiskelijoiden ennakkotieto voi olla laadullisesti hyvin erilaista ja täten johtaa myös laadullisesti erilaiseen oppimiseen. Yliopisto-opiskelijoiden ennakkotiedon taso ja pystyvyysuskomukset vaihtelevat suuresti ja tämä tulisi ottaa huomioon opetuksessa.

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Helsinki, November 17, 2009

Telle Hailikari

To Tuure and "Pikkuveikka"

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I Hailikari, T., Nevgi, A. & Lindblom-Ylänne, S. (2007). Exploring alternative ways of assessing prior knowledge, its components and their relation to student achievement: A mathematics-based case study. Studies *in Educational Evaluation*, *33,* 320–337.

II Hailikari, T., Nevgi, A. & Komulainen, E. (2008). Academic self-beliefs and prior knowledge as predictors of student achievement in mathematics: A structural model. *Educational Psychology, 28*(1), 59–71.

III Hailikari, T., Katajavuori, N. & Lindblom-Ylänne, S. (2008). The relevance of prior knowledge in learning and instructional design. *American Journal of Pharmaceutical Education, 72*(5), Article 113.

IV Hailikari, T. & Nevgi, A. (in press). How to diagnose at-risk students in chemistry: The case of prior knowledge assessment. *International Journal of Science Education*. http://www.informaworld.com/ijse

1 Introduction

Students enter the university with diverse skills and prior knowledge. This diversity causes heterogeneity that poses challenges for university education, as differences in prior knowledge have been shown to influence the quality of learning and student achievement in a significant manner (Dochy, 1996). Ultimately, the aim of higher education is to promote high-quality learning which can serve as a sound basis for individuals to build on later in life. High-quality learning and the factors contributing to it have been explored from various perspectives and theoretical standpoints over the years. It is generally agreed that learning outcome is determined by many factors interacting with each other.

While there is probably not general agreement on which concepts to include in a framework of influences on the quality of learning (e.g. Entwistle, McCune & Hounsell, 2003), few would dispute the powerful impact of prior knowledge on learning (Dochy, De Ridjt & Dyck, 2002). Since the 1990s the quality of learning and teaching in higher education has begun to receive more attention due to a considerable increase in research on the subject. However, the effectiveness is still a problem in education. This is revealed in high drop-out rates or slow progress through the study programmes (Dochy, Moerkerke & Martens, 1996). For example, less than half of the students complete their Master's degree in the Faculty of Science at the University of Helsinki (Ms. Anne Palo-Kauppi of the Faculty of Science, personal communication 2009).

Research efforts addressing the impact of different factors on learning outcomes can be readily framed within Biggs's (1993) 3P model, which conceptualises the learning process as an interacting system of three sets of variables. These may be divided into three different points in time: the learning environment and student characteristics (presage); students' approaches to learning (process); and learning outcomes (product). Presage factors are the factors that exist prior to the time of learning and are of two kinds: student-based (e.g. prior knowledge, student ability, motivation) and teaching context-based (e.g. objectives, methods, assessment). Collectively, these background factors determine the cognitive processes the students are likely to use which, in turn, influence the learning outcomes. The model proposes that, firstly, student and teaching presage factors jointly motivate a student to adopt a particular approach to learning which, in turn, influences the types of learning outcomes achieved. Secondly, the model proposes that the presage factors may also directly influence learning outcomes. The present study focuses primarily on these student-based presage factors, or more precisely, on prior knowledge and self-beliefs and their assessment, even though the author is well aware of the interactive system as a whole. The reason for this more limited focus is that student based-presage factors have not been explored as extensively as, for example, teaching methods or students' approaches to learning. Yet, these deserve their own thorough investigation.

Prior knowledge and its impact on learning and performance has been a focus of several studies in recent years. Interest in the influence of prior knowledge is closely related to the constructivist approach to learning, which has become dominant in recent decades. Constructivism sees learning as cognitive activity in which students actively construct knowledge by interpreting new information in the light of their prior knowledge and existing beliefs (e.g. Bruner, 1966; Oxford, 1997; Vygotsky, 1978). Hence, prior knowledge plays an important role in learning. Indeed, almost all studies on prior knowledge conducted during the past decades have undisputedly shown that prior knowledge is a significant variable influencing student achievement (for a review, see Dochy et al., 2002). As Glaser & De Corte (1992) state: "a key to developing an integrated and generative knowledge base is to build upon the learner's prior knowledge" (Dochy, 1992, p. 1). Dochy (1996) has stated that individual differences in the prior knowledge base are a primary source of differences in student achievement. Therefore, the influence of prior knowledge and the methods for assessing it should be a concern for educators promoting high-quality learning. Prior knowledge interacts with many phases of learning, such as the way students are able to construct new knowledge (De Corte, 1990; Vosniadou & Brewer, 1987), the learning approach they adopt (Biggs, 2003), perceptions of the learning environment (Lizzia, Wilson & Simons, 2002), cognitive load (Amadieu, van Gog, Paas, Tricot & Mariné, 2009; Verhoeven, Schnotz & Paas, 2009) and the learning strategies they use (Alexander, Pate, Kulikowich, Farrell & Wright, 1989; Willoughby, Wood & Khan, 1994). Furthermore, a student with scant prior knowledge is unlikely to adopt a deep approach to learning, which has been found to be related to higher quality learning (Biggs, 1979; Entwistle & Ramsden, 1983; Lindblom-Ylänne, 1999; Trigwell & Prosser, 1991a, 1991b). In addition, difficulties caused by individual differences in the prior knowledge base may result in difficulties in completing courses or degrees.

An awareness of constructivist theories of learning has increased the use of new assessment methods as well. Assessment has an important role in determining what and how students learn. Assessment is a central issue to consider in education because it strongly guides student learning (Biggs, 1999; Brown, Bull & Pendlebury, 1997; Gibbs 1992). As Brown et al. (1997, p. 7) put it: "If you want to change student learning then change the methods of assessment." Indeed, there has been a shift in focus during the past decades. Currently, the view of assessment is represented by the notion of assessment as a tool for learning. In the past, assessment has been seen "as a means to determine measures and certification," whereas currently the integration of learning and assessment has received more attention (Dochy & McDowell, 1997). Assessment of prior knowledge shifts the focus from the end of the learning process to the beginning of it in order to enable better instructional support. Taking prior knowledge into account not only provides opportunities to enhance the learning process, but also may lead to better designing of individualised instructional support. Therefore, prior knowledge assessment has been introduced as a potential tool for instructional support (e.g., Dochy & McDowell, 1997; Dochy, Moerkerke, & Martens, 1996; Martens & Dochy, 1997).

However, there are many issues to consider in prior-knowledge assessment. The focus should be on both *what* to assess and *how* to assess it. Such questions are not just theoretically interesting, but also significant in practice for university educators seeking to understand the impact of prior knowledge on learning.

It may be assumed that not all types of prior knowledge have similar relevance in relation to student achievement. Furthermore, the assessment methods influence the observed effect of prior knowledge on performance. As Dochy, Segers & Buehl (1999) argue, it is important to consider the way prior knowledge is assessed as well as what kind of prior knowledge is being activated by the task.

The present study emerged from the need to create a practical prior-knowledge assessment instrument for university teachers, which would take into account the different aspects involved in prior knowledge assessment. The practical aim of the study is to develop a prior knowledge assessment instrument that distinguishes between different types of knowledge and combines different assessment methods. The theoretical aim is to gain a deeper understanding of how different kinds of prior knowledge influence student achievement and how various assessment methods influence the observed effect of prior knowledge.

Firstly, I will elaborate on the concept of prior knowledge and provide an overview of research on prior knowledge. Secondly, I will discuss the change in the assessment culture, its relation to prior knowledge assessment and what kind of implications the structure of knowledge poses on prior knowledge assessment. Finally, I will present the perspective adopted in this research.

1.1 The concept of prior knowledge

In this chapter the concept of knowledge and, more specifically, prior knowledge will be discussed in more detail. Everyone is familiar with the term knowledge. Yet, knowledge may appear in various forms and this has important implications for its operationalisation in educational research.

Knowledge and its multifaceted nature have received considerable attention in educational and psychological literature. Alexander, Schallert & Hare (1991) argue that it is almost impossible to describe any type of cognitive operation or learning process without referring to some aspect of an individual's knowledge. According to them, knowledge may be defined as "an individual's personal stock of information, skills, experiences, beliefs and memories" (p. 317). Knowledge research literature is vast, and includes many related concepts. One such knowledge construct is prior knowledge. Prior knowledge research belongs to the family of knowledge research. However, it deserves its own consideration because it is temporally located prior to the learning process; this gives it a unique character in learning research.

Prior knowledge may be defined as knowledge that:

- comprises both declarative and procedural knowledge;
- is present before the implementation of a particular learning task;
- is available or able to be recalled or reconstructed;
- is relevant for the achievement of the objectives of the learning task;
- is organised in structured schemata;
- is to a certain degree transferable or applicable to other learning tasks;
- is dynamic in nature (Dochy, Moerkerke & Segers, 1999).

Therefore, prior knowledge may be defined as a combination of knowledge and skills. Furthermore, it should be noted that knowledge is fluid and dynamic in nature. Different forms of knowledge may vary between individuals but also within individuals. They may also vary in terms of specialization, position or size (Alexander et al., 1991). Several theorists regard knowledge as hierarchically organised (Ausubel, 1968; Mayer 1979; Reigeluth & Stein, 1983).

In their review, Alexander et al. (1991) analysed the various types of knowledge terminology. They noticed that the use of knowledge terminology often lacks precision. Similarly, Dochy and Alexander (1995) raised the same pervasive problem in prior knowledge research. After an exhaustive review of prior knowledge research, they conclude that there is an abundance of terminology used by researchers to refer to what seems to be the same construct. For example, they provide a list of terms that have been used to refer to prior knowledge; these include: "prestorage", "permanent stored knowledge", background knowledge" and "pre-existing knowledge" etc. (for a review, see Dochy & Alexander, 1995).

The same problem exists with the subcategories or forms of prior knowledge (such as domain-specific prior knowledge): researchers use the same term to refer to different constructs. Furthermore, there is a lack of proper definitions of prior knowledge. Dochy & Alexander (1995) argue that there is general vagueness or lack of precision in the definitions. They go on to state that "if there is a lack of precision in the way that researchers articulate the knowledge construct under study, there is the potential for lack of precision in the way that these researchers operationalise those constructs by means of the questions they ask, the measures they develop, or the analyses they perform" (p. 227). Therefore, it is important to develop a precise definition of prior knowledge as a framework for discussion among researchers and, moreover, to explore the different ways to assess prior knowledge. Dochy & Alexander (1995) addressed this issue by providing a detailed map of prior knowledge.

The map was further modified in Dochy's (1996) research. It makes a distinction between *conceptual knowledge*, which is further divided into content knowledge, subject-matter knowledge, domain knowledge and discipline knowledge, and *metacognitive* knowledge, which includes self or person knowledge, task knowledge and strategy knowledge. Further, he distinguishes between key dimensions of prior knowledge and elaborates on concepts that play a central role in the discussion of prior knowledge terminology. The resulting map is an illustration of the terminology involved in prior knowledge research and the interrelations between the terms. The map aims at providing a theoretical framework that presents all dimensions involved in research on prior knowledge (Figure 1). Dochy & Alexander (1995) note that the map is very detailed and fine-grained distinctions are used, and not all of them will be useful for all researchers in all areas. Rather, it is provided as a framework that presents all dimensions and allows certain groups of researchers to utilise it according to their own interests.

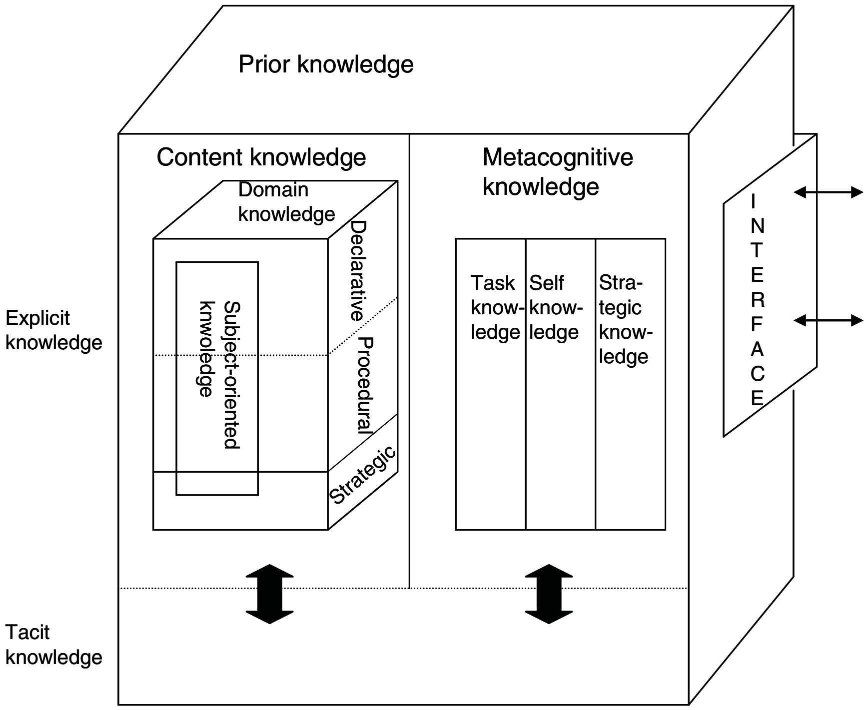


Figure 1. A conceptual map of prior knowledge (Dochy, 1996)

1.2 An overview of research on prior knowledge

1.2.1 A history of research on prior knowledge

Factors influencing student achievement have been the central interest of many educational psychologists over the past decades. These studies have identified a range of factors connected with student performance, but prior knowledge stands out as a key variable affecting student achievement (Ausubel, 1968; 2000; Dochy, De Ridjt, & Dyck, 2002; Harackiewicz, Barron, Tauer, & Elliot, 2002; Portier & Wagemans, 1995; Thompson & Zamboanga, 2004; Tobias, 1994). Among the earliest scholars to emphasise the importance of prior knowledge was Bloom (1956). He stated that student learning is mainly determined by students' cognitive entry behaviours, the term he used to refer to prior knowledge, and affirmed that prior knowledge may account for one-half of the variance of student learning outcomes. Another central scholar who emphasised the importance of prior knowledge was Ausubel (1968). In his book on educational psychology, he stated: "If I had to reduce all of educational psychology to just one principle, I would say this: The most important single factor influencing learning is what the learner knows already. Ascertain this and teach…accordingly" (Ausubel, Novak & Hanesian, 1978; iv). His assimilation theory incorporated the notion of prior knowledge as a foundation for learning. These views on the essence of prior knowledge were rather ground-breaking in an era when the behaviouristic tradition was dominant. In 1976, Glaser created a model of teaching that also acknowledged the important role of prior knowledge. He called for a careful assessment of the learners' initial state to determine the proper type of and level of instruction for each student. In addition, studies conducted by Bransford and his colleagues (Bransford, 1979; Bransford & Franks, 1971; Bransford & Johnson, 1972) were influential in drawing attention to the importance of prior knowledge. These studies demonstrated that learning is a function of the relationship between the things to be learned and the learner's prior knowledge. If the necessary prior knowledge is lacking or fails to be activated, learning is impaired.

Subsequently, prior knowledge has been explored rather extensively and almost all educational studies conducted later acknowledge the importance of prior knowledge in learning and performance (e.g., Alexander, Pate, Kulikowich, Farrell, & Wright, 1989; Anderson, Spiro, & Anderson, 1978; Ausubel, 1968; Chi, Glaser, & Farr, 1988; Dochy, 1992, 1994; Dochy & Alexander, 1995; Ethington, 1990; Glaser, 1984; Portier & Wagemans, 1995; Thompson & Zamboanga, 2003; Shapiro, 2004). Vosniadou & Brewer (1987) argue that the acknowledgement of the important role of prior knowledge in learning was partly a consequence of the breakthrough of the information-processing approach in research and education (see also Shuell, 1986). In their review on prior knowledge research, Dochy et al. (2002) concluded that there is subsequent evidence that Bloom's original statement is even better supported today. In their study, Dochy, Segers & Buehl (1999) showed that 95 % of all studies concerning prior knowledge demonstrated that prior knowledge is strongly and positively associated with learning outcomes. Similarly, in a more recent study, Shapiro (2004) emphasises how important it is to include a measure of prior knowledge in learning research because the failure to account for its effect may compromise the validity of learning outcomes research.

The quality and impact of prior knowledge has been a major issue in research at the university level as well. In the context of higher education, domain-specific prior knowledge has been explored in a variety of academic content fields, including economics (Dochy, 1992), psychology (Thompson & Zamboanga, 2003; Verkoeijen, Rikers, & Schmidt, 2005; Wylie & McGuinness, 2004), social sciences (Portier & Wagemans, 1995), ecology (Wratten & Hodge, 1999), and mathematics (Weinert, 1989). In addition, the influence of prior knowledge on recalling factual information from texts has been explored rather extensively both with child and adult subjects (Clifton & Slowiaczek, 1981; McNamara, Kintsch, Songer & Kintsch, 1996; Willoughby, Waller, Wood & MacKinnon, 1993).

Several extensive reviews of prior knowledge research are available (Dochy, 1992; Dochy et al., 1999b; Dochy et al., 2002; Shapiro, 2004). Moreover, researchers have created psychological models of educational performance (for an overview, see Haertel, Walberg & Weinstein, 1983; De Landsheere, 1988) or used causal modelling techniques (for an overview, see Dochy, 1992) to explore educational performance. The most important finding to emerge from these studies is the superior role of prior knowledge as an explanatory variable. In his study, Dochy (1992) found that prior knowledge may explain up to 42% of the variance in post-test scores. Similar amounts have been found by other researchers depending on the research environment (see Tobias, 1994). However, De Corte (1990) adds that most of these experiments lack ecological validity.

Over the years, there has been debate about the relationship between intelligence and general thinking skills versus domain-specific prior knowledge (see e.g. Alexander & Judy, 1988; Weinert, Schrader & Helmke, 1990). For example, Weinert (1989) found that prior knowledge overrules the effects of intelligence. Similarly, Minnaert & Janssen (1996) found that domain-specific prior knowledge was superior to the influence of general thinking skills. In his study on genetics, Blurton (1985) found that prior genetics knowledge, but not reasoning ability, predicted performance on a genetics post-test (Blurton, 1985). Many researchers have expressed scepticism about exploring the impact of general thinking skills without taking into consideration domain-specific prior knowledge (e.g. Alexander & Judy, 1988; Minnaert & Janssen, 1996; Weinert, Schrader & Helmke, 1990; Shapiro, 2004). Currently, there is general awareness of the pitfalls of not taking prior knowledge into account in learning research (e.g. Shapiro, 2004).

1.2.2 Direct and indirect influences of prior knowledge on learning

The studies reviewed here provide compelling evidence that prior knowledge is a significant predictor of student achievement. However, it is important to explore how prior knowledge affects learning in order to be able to develop implications for instruction. Dochy & Alexander (1995) organize the effects of prior knowledge in three categories: 1) a direct influence of prior knowledge in facilitating learning, 2) the influence of the inherent qualities of prior knowledge (for example, the incompleteness, misconceptions, accessibility, amount, availability and structure of prior knowledge) and 3) interaction effects between the inherent qualities and the facilitating effect. These three effects are illustrated in Figure 2. The inherent qualities of prior knowledge can influence the way prior knowledge impacts on learning. Similarly, Vosniadou (1996, p. 102) has stated that "in the context of cognitive psychology, the construct that seems capable of providing an explanation of phenomena such as inert knowledge and misconceptions is that of prior knowledge. The structure of the acquired knowledge can be said to constrain the acquisition of new information, particularly when the latter is radically different from the former."

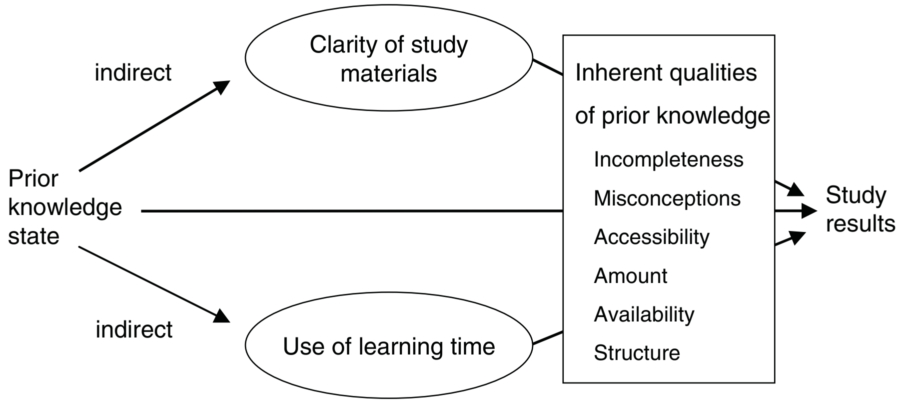


Figure 2. Interaction effects involving inherent qualities and the facilitating effect (adapted and modified from Dochy 1992, p. 28)

Many other studies have also addressed the issue of the influence of the inherent qualities of prior knowledge. For example, in her studies Lipson (1983) has shown that inaccurate prior knowledge may interfere with learning. She found that misconceptions about text content resulted in recall errors. Similarly, Thompson & Zamboanga (2003) address this issue in the context of psychology. Students enrolling in psychology courses usually possess prior knowledge that is derived from many sources because of the widespread interest in psychological concepts in everyday life. These misleading lay-conceptions may be potentially harmful for learning and impair student understanding.

In addition, many other studies have shown that different types of information are available for students with high or low prior knowledge. McNamara et al. (1996) found an interaction between text structure and prior knowledge level. Students with high prior knowledge scored better when presented with texts that were minimally detailed whereas the opposite was true for the low prior knowledge group. Studies on expertise reversal effect (Kalyuga, Ayres, Chandler & Sweller, 2003; Kalyuga, 2005; Tobias, 1989) reveal that designs and techniques (for example concept maps) that are effective with low-knowledge individuals can lose their effectiveness and may even hamper learning for more proficient learners (see also Amadieu et al., 2009). Similar effect was found in study by Van Gog, Paas & Van Merriënboer (2008) which concentrated on the use of worked examples. The results suggest that the worked examples should be adapted according to one's knowledge level in order for effective instructional support to take place. Furthermore, hypertext studies have shown that for low prior knowledge learners the representation of a well-organized structure may support deep comprehension (de Jong & van der Hulst, 2002; Shapiro, 1999). Therefore, it seems that optimal learning depends on whether the format of instruction matches with aptitudes of the learner. Chen, Fan & Macredie (2006) also provide a review of how students with high levels of prior knowledge apply deeper processing strategies, require less instructional support and produce better learning outcomes when learning with hypermedia. Jonassen & Grabowski (1993) conclude that the more prior knowledge there is the less the need for instructional support. Furthermore, Dochy et al. (1996) provide an extensive overview of how prior knowledge may influence study results both directly and indirectly. This overview reveals that prior knowledge influences such study behaviours as study skills, speed and accuracy of study behaviour, study time, the effort required, the use of learning strategies and the effectiveness of instructional methods. Similarly, Hegarty-Hazel & Prosser (1991a, 1991b) found that prior knowledge led to adoption of more effective study strategies, and, consequently, to better achievement in college physics and biology classes. Prior knowledge has also been found to guide information selection, whereby students with high prior knowledge are better able to identify their knowledge needs and make their selections accordingly (Gall & Hannafin, 1994; Lawless & Kulikowich, 1996).

1.2.3 Cognitive processes and prior knowledge

A number of theories have attempted to explain how prior knowledge influences new knowledge acquisition. Dochy et al. (2002) identify eight theories that attempt to explain the effect of prior knowledge on learning. Although these theories differ in their approaches, they lean heavily on each other or overlap to some degree. They are all concerned with different phases of information processing. These theories offer a variety of interpretations of how prior knowledge influences learning through various processes:

1) in the process of learning, prior knowledge serves as a "category label" which influences the way the new information is organized and added to the existing knowledge structures (*the restructuring approach*);
2) prior knowledge serves as an assimilative context in which the new material is related to, and, consequently, knowledge is enhanced and more easily retrieved by the process of elaboration (*the elaboration approach*);
3) the activation of prior knowledge increases access to that knowledge during the learning process (*the accessibility approach*);
4) prior knowledge influences learning through selective attention so that relevant information receives more attention (*the selective attention approach*);
5) prior knowledge influences learning through cueing: the more prior knowledge there is, the more knowledge there is available in one's memory (*the availability approach*);
6) the activation of prior knowledge when learning new materials promotes the recall and retrieval of information from the memory (*the retrieval approach*);
7) prior knowledge is structured in modifiable schemata, which influences the interpretation and understanding of a new situation (*the schema-transfer approach*) and finally;
8) more prior knowledge leads to a more rapid processing of information (*representation-saving approach*).

Similarly, in her review, Shapiro (2004) recognises three of theories which are very similar but broader in their approaches. The first, the *construction-integration* model, is a combination of the different approaches listed by Dochy et al. (2002). The model proposes that learned information is linked together to form macrostructures that serve to both organize and reduce complex information. Therefore, prior knowledge provides an organizational foundation for incoming information and contextualizes and elaborates this new information. This is also similar to Ausubel's (1968) view of learning, according to which learning depends on the availability of the cognitive structure in which new material is assimilated. The second model, the *schema theory*, is the same as Dochy's schema-transfer approach: schemata allow learners to contextualize new information and thus facilitate understanding. The third and last approach by Shapiro is the developmental approach originally developed by Alexander (1997). This model offers a different view of the influence of prior knowledge by proposing that as the learner's knowledge increases, his or her interest and strategies change, resulting in more meaningful learning. This model suggests that prior knowledge influences learning strategies and proposes that learning is a three-stage process where learners move from beginner status (as acclimated learners), to intermediate status (as competent learners) to expert status (as proficient learners). Movement between stages is mediated by the knowledge level.

These different models illustrate the different processes by which prior knowledge influences new knowledge acquisition and learning. Dochy et al. (2002) conclude that the most important contribution of these theories is that they serve as interpretations of experimental results. In sum, whether prior knowledge interacts with other variables or works alone to increase knowledge acquisition, the positive relationship between prior knowledge and learning outcomes is clear.

1.3 The change in the assessment culture

The role of assessment has been a central interest of many researchers, probably ever since the earliest approaches to formal education. Birenbaum (1996) distinguishes between two cultures in the measurement of achievement: the testing culture and the assessment culture. In the traditional testing culture, assessment and instruction have been considered as separate activities. Assessment in the traditional testing culture has mainly consisted of testing the basic skills that the students acquire through memorizing the content the teacher communicated and by reproducing it in the assessment situation. This approach to assessment is based on the behaviouristic theory of learning. Nowadays the approach has changed and resulted in the so-called *assessment culture* which emphasizes the integration of assessment and instruction. This assessment culture is compatible with the constructivist approach to education, in which learning is viewed as a process through which the learner actively creates meaning. According to this view, effective instruction requires a change in teachers' role whereby the teacher becomes a mentor who provides opportunities for the learners to use the knowledge and skills they have in order to understand new information.

Appropriately used assessment practices may be used to improve instruction (Birenbaum & Dochy, 1996). For example, prior-knowledge assessment may be used to make instructional decisions that are supported by the assessment (Dochy & McDowell, 1997; Nitko, 1993). *Placement decisions* are one type of instructional decision, in which assessment is used to decide at what level a student should begin studies. For example, prior knowledge assessment may be for a) determining the degree to which the student possesses the prerequisite knowledge and skills, b) determining the mastery of course objectives and c) placing students into alternative instructional modes.

Diagnostic decisions are another type of decision supported by prior- knowledge assessment. There assessment is used to provide specific information on students learning deficiencies or erroneous prior learning. Properly used prior knowledge assessment may provide this information in order to regulate learning processes. Prior-knowledge tests may be used as a basis for planning group instruction or individualised instruction (Nitko, 1993). They are most useful in situations where the teacher knows very little about the students in advance, or when large variations in prior knowledge are expected. Nitko (1993) points out that there is little need to pre-test individuals if it is already known that all students lack the important prerequisites to the same degree, or if the instructional situation does not allow adaptation to individual needs.

The question of how to assess students' prior knowledge for instructional support purposes will be discussed next.

1.3.1 Assessing prior knowledge

Thompson and Zamboanga (2003) argue that both students and teachers can benefit from prior-knowledge assessment in multiple ways. It gives instructors valuable information, and the possibility of refining and adjusting their teaching according to students' needs. Students benefit from the assessment because the test can provide a means of self-assessment by helping them become aware of their prior knowledge and orient them towards course content by mobilising their pre-existing knowledge (Martens & Dochy, 1997; Wratten & Hodge, 1999).

Two main questions should be considered in prior knowledge assessment: *how* to assess prior knowledge, and *what* to assess. These two issues have been raised by Dochy et al. (1999b), Valencia, Stallman, Commeyras, Pearson, and Hartman (1991) and Shapiro (2004).

Firstly, the way that prior knowledge is measured may alter the outcomes of studies. Dochy et al. (1999b) raised this issue in their research and emphasised that more attention should be paid to the methods applied in assessment. They argued that the type of assessment method researchers use determine what they know about a person's prior knowledge. Different assessment measures activate different kinds of prior knowledge. For example, Valencia, Stallman, Commeyras, Pearson, and Hartman (1991) conducted a study using four different types of methods to assess students' knowledge. They noticed that the different methods produced different types of information about the students' prior knowledge. They argued that decisions on the content of prior knowledge tests ultimately determine the nature of the relationship between prior knowledge and other research variables.

Similarly, Dochy et al. (1999b) concluded that the assessment method influences the observed effect of prior knowledge on performance. For example, in his work Dochy (1996) used content characteristics of the assessment methods to distinguish between various types of prior knowledge. Dochy et al. (1999b) identified six types of assessment methods used in previous studies: multiple-choice tests, open questions/completion tests, association tests, recognition tests, free recall and self-assessment. Dochy et al. (1999b) criticised self-assessment and experimenter judgement as methods of assessing knowledge because they do not provide effective assessments of prior knowledge. Furthermore, free recall tests are so heavily influenced by the subjects' verbal abilities that they may be considered as "weak assessment methods". Alternatively, the other methods, such as multiple choice tests, open questions/completion tests, association tests, recognition and matching tests were fairly valid and accurate ways of assessing knowledge.

It appears that the assessment method researchers use delimits what they know of students' prior knowledge. Thus, knowledge representations differ in respect to the assessment techniques. Valencia et al. (1991) argued that multiple forms of assessment should be used in order to capture the phenomenon of prior knowledge more completely. Furthermore, they pointed out that more research is needed both to explore how different types of prior knowledge contribute to understanding and to determine which type of measurement best predicts comprehension.

Secondly, less attention has been paid to *what* should be assessed in prior knowledge assessment. Nonetheless, the content of prior knowledge assessment is as crucial as its format. Shapiro (2004) draws attention to the quality and breadth of prior knowledge. She argues that incorrect or inaccurate prior knowledge may hinder learning or negatively interfere with it. By breadth of knowledge she refers to the distinction between topic and domain knowledge. By topic knowledge she means knowledge that is more specific to a given topic, such as organic chemistry. Domain knowledge is defined as "the broad, general knowledge of a formal field of study" (p. 163). She argues that it is important to discriminate between topic and domain knowledge because they interact differently with learning.

A similar distinction has been made by Alexander, Kulikowich and Schulze (1994) and Dochy and Alexander (1995). Dochy and Alexander (1995) divided conceptual knowledge into four different hierarchical subcategories: content knowledge, subject-matter knowledge, domain knowledge and discipline knowledge. Content knowledge refers to knowledge of one's physical, social, or cognitive world, which can be formally or informally acquired (see Alexander et al., 1991). Subject-matter knowledge is that dimension of content knowledge that is acquired through formal instruction. Domain-specific prior knowledge is a substructure of subject-matter knowledge that refers to a particular field of study, such as mathematics or chemistry (Glaser, 1984). Discipline knowledge is an even more specialized form of subject-matter knowledge, such as organic chemistry.

Therefore, the relationship between content, subject-matter domain and discipline knowledge is hierarchical and is based on the degree of specialisation (Alexander et al., 1991). There is considerable evidence that domain-specific prior knowledge is the type of prior knowledge that mainly affects learning outcomes, even though it is generally agreed that both forms are essential in learning (Alexander & Judy, 1988; Glaser, 1987; De Corte, 1990; Dochy, 1992; Shuell, 1986). For example, Weinert (1989) found that domain-specific prior knowledge is a crucial factor for good mathematics achievement. Similarly, Shapiro (2004) concluded that domain knowledge aids learners even when a topic itself is completely unfamiliar.

Furthermore, and most importantly, it is necessary to make not only a distinction in broad terms of content but also in terms of the type of prior knowledge to which it refers. These different types play an important role in prior knowledge assessment. The structure of knowledge paradigm has received a great deal of attention in learning research. Following is an outline of some essential models regarding the classification of knowledge and understanding, and further, the implications of these classifications on assessment. Indeed, these models were selected because in their theories they combine two aspects relevant to the present study:

1) identifying the structure of knowledge and forms of understanding
2) determining how these relate to assessment.

1.4 Structure of knowledge and forms of understanding: implications for assessment

The issue of the structure of knowledge and understanding has been explored in a variety of different theoretical disciplines: cognitive psychology, educational psychology, artificial intelligence and instructional psychology (Dochy, 1996). Many theorists have created taxonomies of learning that provide broad classifications, sometimes hierarchies, of skills and capabilities which are useful for creating assessment tasks. These taxonomies describe different levels of cognitive activity in relation to assessment. Knowledge of content is often said to be structured (Schallert, 1987). Several theorists regard knowledge as being hierarchically organised (Ausubel, 1968; Mayer, 1979; Reigeluth & Stein, 1983). Dochy (1996) suggests that a structure-of-knowledge paradigm should be investigated from a more pragmatic point of view, that is, an instructional-psychological viewpoint, in order to find ways for instructional support.

Bloom (1956) was one of the first to create a model of educational objectives. His intent was to create a method for classification of thinking behaviours that were believed to be important in learning. The model describes three types of domains that are important in learning: cognitive, affective and psychomotor. He stated that since the majority of objectives at the higher education level fall into the cognitive domain, the development of the taxonomy for the cognitive domain should be given top priority. That is the focus of attention here as well. Bloom's taxonomy is a complex model of classifying thinking according to six cognitive levels of complexity: *knowledge, comprehension, application, analysis, synthesis* and *evaluation*. The lowest three levels are commonly recognised in educational practice by other theorists as well (see De Landsheere, 1988). The taxonomy is considered to be hierarchical; in other words, each level is subsumed by the higher level.

Subsequently, the taxonomy has been revised and a Revised Bloom's Taxonomy (RBT) created (Anderson & Krathwohl, 2001). The most obvious change in the revised taxonomy concerns changes in terminology. Bloom's six categories were changed from nouns to verb forms. In the revised taxonomy, the six levels are: *remembering, understanding, applying, analysing, evaluating* and *creating*. Furthermore, Bloom's original taxonomy was one-dimensional whereas the revised taxonomy is in the form of a two-dimensional table consisting of the "knowledge dimension" and a "cognitive process dimension". In the original taxonomy, the categories embodied both noun and verb aspects (Krathwohl, 2002). Therefore, the revised taxonomy presents both the desired product of learning, that is, the kind of knowledge to be learned, and the cognitive process along which the knowledge can differ. The revised taxonomy reinforces the perspective of the authors of the original taxonomy that different types of objectives require different types of assessment (Airasian & Miranda, 2002).

Another more recent type of taxonomy of educational objectives is Biggs's (2003) SOLO-taxonomy (Structure of the Observed Learning Outcome). SOLO taxonomy describes how students' understanding and knowledge grow in structural complexity when they master many academic tasks. Thus, the structure and complexity of knowledge is revealed in the tasks that the student is able to perform. Biggs distinguishes between two major changes: qualitative and quantitative. Quantitative changes occur when the amount of detail in students' knowledge base increases, while qualitative changes take place when these details become integrated into a structure.

Biggs identifies five levels of cognitive performance: *prestructural*, when the student simply lacks understanding and misses the point; *unistructural,* when the student concentrates on only one aspect of the task of the complex whole; *multistructural,* when several aspects of the task are addressed but are still a disorganized collection of items and treated separately. Biggs also calls this "understanding as knowing about". At the *relational* level a qualitative shift in understanding occurs as the components are integrated into a coherent whole: the student understands the relationships between different aspects. At the highest level, *extended abstract*, the student goes beyond what is given and applies the integrated knowledge to a new area.

Yet another approach to seeing learning and learning outcomes is provided by Marton, Watkins & Tang (1997). Learning may be illustrated in a two-dimensional outcome space where the distinction is made between ways of experiencing learning (the temporal facet) and the depth of that experience. They found that while talking about their experiences, the students kept alternating between different temporal facets. These conceptions of learning may be categorised according to different temporal aspects of learning: acquiring knowledge, knowing or making use of that knowledge. The second dimension may be seen in terms of the depth of learning, which ranges from committing to memory (reproduction) to learning as understanding (being able to do something; relating). These two dimensions form an outcome space which describes how learning may vary from rather superficial reproduction of knowledge the teacher transmits to the student to understanding and making use of that knowledge in novel situations.

The most recent and ambitious development in the area of prior knowledge research is Dochy's (1992; 1996; see also Dochy et al., 2002) study on prior knowledge. In his work, he makes a distinction between the different dimensions of prior knowledge, components of prior knowledge and the parameters of these components. Each dimension, consisting of several parameters, represents an approach to the structure of knowledge. By the term main dimensions he refers to four main types of dimensions along which the knowledge state is structured: the content dimension; the cognitive-psychological dimension; the educational-psychological dimension and the item-characteristics dimension. These dimensions are further divided into sub-dimensions, numbering thirteen, which are finally operationalised as certain parameters to measure each dimension. He provides a view of several different dimensions on which prior knowledge profiles can be based. The aim is to identify the different dimensions that together make up a students' prior knowledge profile. Constructing a profile along each set of dimensions results in multiple knowledge profiles, namely *profile analysis*, which may be used to identify learning deficits that need to be treated. Dochy's research on the power of different dimensions to detect inter-individual differences in the prior knowledge state provides a model of how prior knowledge of students could be analysed. Dochy's studies suggest that it may be profitable to analyse the structure of prior knowledge in more detail.

Regarding the structure of knowledge, the most general distinction made by many cognitivists is the dichotomy between declarative and procedural knowledge (e.g. Anderson, 1976, 1995). Any form of knowledge, such as topic or domain knowledge, can contain declarative and procedural knowledge. The importance of both declarative and procedural knowledge has already been stressed by other researchers (Anderson, 1982; Dochy, 1992; Dochy & Alexander, 1995; Weinert, 1987). This same distinction may be seen in the models presented above. The distinction between declarative and procedural knowledge illustrates how knowledge may differ qualitatively. Dochy (1992) defines declarative knowledge as the accumulation of facts and concepts that come to the surface by recognition or reproduction. Anderson (1995) refers to declarative knowledge as "knowing that". Procedural knowledge, on the other hand, is referred to as "knowing how" and comes to the surface in assessment through production or application. It may also be referred to as "practical knowledge". The much used distinction between declarative and procedural knowledge is also closely related to the tri-partiate classification: 1) *to know* 2) *to understand* and 3) *to apply,* as proposed by several theorists such as Bloom, De Corte, Guilford and De Block (see De Landsheere, 1988). It could also be proposed that this classification corresponds to the generally acknowledged distinction in cognitive research between recognition, reproduction and production. For example, De Corte (1973) divides cognition into seven categories according to the receiving-reproducing-producing classification (in De Landsheere, 1988). This division makes it possible to define cognitive objectives of education.

In sum, although these models differ in their approaches and do not directly deal with the structure of prior knowledge, but rather with educational objectives and learning outcomes, they still have a great deal to contribute to prior knowledge research. They illustrate how knowledge and understanding are intertwined and what implications they have for assessment. Taking into account how students' prior knowledge may differ qualitatively in terms of the type of prior knowledge they possess, it may be argued that different assessment methods should be used to assess different types of knowledge. Therefore, using assessment methods such as association tests or recognition tests may reveal that the student is able to recognise or reproduce information, but do not demonstrate whether the student is able to use his/her prior knowledge productively in novel situations. The same principles apply whether the aim is to assess knowledge and understanding prior to the process of learning or the resulting learning outcomes. These models indicate how to identify the level and depth of knowledge and understanding in assessment.

1.4.1 Types of prior knowledge tests

Dochy (1992) and Portier & Wagemans (1995) introduced a variety of prior knowledge tests that have a slightly different focus. According to them, the construction of the prior-knowledge test should begin with determining which type of test is required and what function the assessment serves. This decision is dependent on which type of course is in question; for example, basic or advanced. Dochy (1992) argued that there was a need to develop different types of prior knowledge tests because this issue had not been given much consideration before. He started the development process by asking content experts to determine the types of prior knowledge that influence learning outcomes. This resulted in various prior knowledge tests that will be briefly discussed next.

Optimal-requisite prior knowledge state tests measure knowledge and skills that are minimally required before a student can start a course. This type of prior knowledge is what "the student must possess if he is to start the course under optimal circumstances" (Dochy, 1992, p. 110). The test focuses on knowledge from previous courses (Portier & Wagemans, 1995). For example, it may focus on assessing students' knowledge of basic chemistry before they enter a more advanced course.

Subject-oriented prior knowledge state tests measure knowledge and skills regarding the subject the student is about to study (Portier & Wagemans, 1995), and focuses therefore, on the mastery level of the forthcoming course.

Domain-specific prior knowledge state tests are based on the supposition that the learning process is also influenced by broader prior knowledge than subject-oriented prior knowledge (Dochy, 1992). They may be a collection of many subject-oriented tests that are related to the forthcoming course. For example, in the study of pharmacy, prerequisite knowledge of subject-areas such as mathematics and chemistry is needed. In these cases, domain-specific tests may be used.

1.5 Prior knowledge in science disciplines

The relevance of prior knowledge may vary across disciplines. This chapter focuses on reflecting on the differences and classifications of various disciplines and how these differences are related to prior knowledge research.

The differences between disciplines have been broadly explored in educational research (for example, Becher & Trowler, 2001; Biglan, 1973; Donald, 2002; Paulsen

& Wells, 1998; Ylijoki, 1998; 2000). Major differences between disciplines exist regarding teaching, learning, educational beliefs and research practices (Neumann, 2001; Neumann, Parry & Becher, 2002). Furthermore, it has been shown that there is disciplinary variation in students' approaches to learning (e.g., Entwistle & Ramsden, 1983; Lonka & Lindblom-Ylänne, 1996; Smith & Miller, 2005). Students in the sciences and applied sciences, for example, are more inclined to adopt a surface approach to learning, while students in humanities and social sciences are more inclined to adopt a deep approach to learning. Disciplinary differences also exist regarding the nature of knowledge and how it reflects on the structure of the curriculum. In the hard sciences the cumulative nature of knowledge has implications for both learning and teaching, as well as the curriculum (see Donald, 2002). Furthermore, disciplines have their own categories of thought, and thus members of the same academic fields share the concepts of theories, methods, techniques, problems and norms which are tacitly learned during the university years (Parry, 1998; Ylijoki, 2000). Therefore, the discipline-specific context and its influence should be considered in educational research.

In the present study, we use the grouping of disciplines modified by Becher (1989) from the work of Biglan (1973a; 1973b) and Kolb (1981). He classified the disciplines under broad headings such as *hard-pure, soft-pure, hard-applied* and *soft-applied*. *Hard pure knowledge* (for example chemistry and physics) is characterised as having a cumulative, atomistic structure, concerned with simplification and a quantitative emphasis. *Soft pure knowledge* (for example, history and anthropology), on the contrary, is holistic, concerned with particulars and having a qualitative emphasis. In the hard pure sciences there are clear criteria for knowledge verification, whereas in the soft pure sciences there is dispute over criteria for knowledge verification. *Hard applied knowledge* (such as engineering, pharmacy) is based on know-how from the hard pure sciences. It is pragmatic in nature and concerned with mastery of the physical environment. Finally, *soft applied knowledge* (such as education or law), on the other hand, is dependent on soft pure knowledge and is concerned with the enhancement of professional practice and the aim to produce protocols and procedures.

Because of the variation between different disciplines it may also be assumed that the meaning of prior knowledge differs across various disciplines. In the hard sciences, where knowledge is cumulative in nature, it is all the more necessary that students develop an integrated knowledge base from the start of their studies. Courses are usually tightly structured and the curriculum is constructed as "linear and hierarchical, building up brick by brick towards contemporary knowledge" (Neumann et al., 2002, p. 407). Neumann et al. (2002) go on to state that content in hard pure disciplines is characteristically fixed, cumulative and quantitatively measured. Deep-level understanding in basic courses is important in promoting good quality learning because these courses usually form an important foundation for future learning. Inadequate learning in basic courses may have long-term effects that inhibit learning later on. Prior knowledge plays an important role, especially as the studies proceed. By assessing prior knowledge, it is possible to identify students who are struggling to keep up with their studies.

1.6 Other relevant constructs: academic self-beliefs and previous study success

1.6.1 Academic self-beliefs

Although the importance of prior knowledge as a prerequisite for learning is well established, differences in prior knowledge are not the only valuable explanatory factors in academic achievement. There are obviously other important variables that interact with the impact of prior knowledge. It is not merely knowledge that influences learning outcomes but also beliefs and affective factors. One such variable is academic self-beliefs. For example, Bandura (1997) suggests that people's beliefs about their capabilities predict their behaviour better than do the skills and knowledge they actually have, for these beliefs determine what individuals do with the knowledge and skills they possess. One longstanding view among social-cognitive researchers is that the academic beliefs students have about themselves are a key determinant of academic success (e.g., Bandura, 1997; Schunk, 1991). Alexander et al. (1991) place these beliefs under metacognitive knowledge, and more specifically, self-knowledge. The social-cognitive theory suggests that self-beliefs are causal agents in human behaviour and learning and, therefore, predict student performance over and above prior knowledge (Bandura, 1997; Pajares & Miller, 1994). Research has shown that positive expectations facilitate academic performance, increased motivation and persistence (Armor & Taylor, 1998). Self-beliefs are consistently related to students' academic persistence decisions (e.g., Dixon Rayle, Arredondo & Robinson Kurpius, 2005). Murtonen, Olkinuora, Tynjälä & Lehtinen (2008) argue that students' self-beliefs are not necessarily related to difficulties they experience in learning of mathematical subjects but rather it is their self-beliefs that do not support the learning of them. Therefore, academic self-beliefs also play a key role in predicting academic success. The status of these two constructs as prerequisites contributing to academic achievement has been well documented (Bandura, 1997; Dochy et al., 2002) and is supported by substantive evidence. The present study focuses on the academic context; hence the focus is on the academic aspect of human behaviour, namely academic self-beliefs.

Academic self-beliefs are an individual's beliefs about his or her attributes and abilities as a learner (Valentine, DuBois, & Cooper, 2004). Self-beliefs (in a broad sense) have received attention in educational psychology because research suggests that individuals who have more positive beliefs about their abilities tend to show higher levels of achievement (Alfassi, 2003; House, 1995). In the present study, we define academic self-beliefs as consisting of three types of constructs: self-efficacy, expectation of success, and self-perception of ability in a specific domain. There exist a number of different kinds of self-beliefs (for a review, see Valentine et al., 2004) and, consequently, there are many theories and concepts regarding self-beliefs. However, in the present study the choice was made to focus on self-belief constructs that Pintrich (2003) calls "expectancy constructs". These are primarily concerned with expectations regarding performance capabilities and, consequently, are closely related to prior knowledge and learning. Furthermore, these expectancy constructs also exist prior to the learning process and may be regarded as presage factors (see Biggs 1993). Therefore, they fit well with the framework adopted in this research.

The most common type of self-belief pertaining to the academic domain is self-efficacy (Graham & Weiner, 1996; McKenzie & Schweitzer, 2001; Zimmerman, 2000). Self-efficacy is a context-specific assessment and reflects prospective confidence about performing a task successfully. In an academic context, self-efficacy has received attention because it refers to students' beliefs in their cognitive capability to learn or to perform actions to achieve intended results (Bandura, 1997). Self-efficacy involves specific and situational judgements which research suggests are closely related to student engagement and motivation (Linnenbrick & Pintrich, 2003). Therefore, self-efficacy beliefs serve as a useful motivational measure in an academic context (Zimmerman, 2000). Self-efficacy as a construct is theoretically distinct from self-concept and self-esteem (Valentine et al., 2004). Self-efficacy, with goals and capabilities, is concerned with executing specific tasks, whereas self-concept and self-esteem are more concerned with personal qualities and emotional reactions to actual accomplishments (Pajares & Miller, 1994).

Closely related to self-efficacy, yet theoretically distinct, is expectation of success. Although expectation of success can be considered to be a part of self-efficacy, Pintrich and Ruohotie (2000) emphasise that it is a distinct construct (see also Schunk, 1991). An individual may have great confidence in his or her cognitive capabilities, but still not expect to succeed because of other reasons. Previous research has indicated that students' expectations of success influence their achievement behaviour (Niemi, Nevgi, & Virtanen, 2003; Zimmerman, 2000). Students who expect to succeed generally show higher levels of persistence and do their best to achieve their learning goals (Pintrich & Ruohotie, 2000). Although expectation of success and self-efficacy are different constructs, a common attitude probably lies behind them (Niemi et al., 2003). Students who expect to succeed also commonly have confidence in their own abilities to perform well. Ultimately, both of these constructs are concerned with one's beliefs in one's ability to perform a task successfully (Pintrich & Ruohotie, 2000).

In addition to these two types of self-belief, which take a prospective view of future performance, there is a third type of self-belief construct that also influences performance: self-perception of ability in a specific domain. Although this self-perception is probably associated with both self-efficacy and the expectation of success, it remains a distinct construct. Such self-perception focuses on past performance rather than on prospective performance (Lent, Brown, & Gore, 1997). Self-perception is concerned with how students perceive themselves and their capabilities in particular areas, such as mathematics, on a general level. Students who believe they are not good at something, such as mathematics, may not want to commit themselves and, consequently, experience difficulties in their studies. In the context of mathematics, for example, research indicates that self-ratings of mathematics ability significantly correlate with mathematics course grades (House, 1995). For this reason, this measure of self-perception also deserves consideration.

1.6.2 Previous study success

Students' prior knowledge, outcome expectations and related academic achievement can also be explained by their previous study success. Harackiewicz et al. (2002) found prior academic performance to be a positive predictor of student achievement. Previous study success is related to both prior knowledge and academic self-beliefs. It is quite evident that prior academic achievement and prior knowledge are strongly correlated constructs. However, previous studies have found that prior academic achievement also makes a direct and independent contribution to student achievement, separately from its mediating effects through prior knowledge (e.g., Carstens & Beck, 1986; Dochy et al., 1999; Griggs & Jackson, 1988). This may be related to a distinction some researchers make between domain-specific and domain-transcending knowledge, and conclude that both forms are essential in learning (Dochy, 1992; Shuell, 1986). Therefore, in the present study a separate measure of previous study success is used alongside prior knowledge measures. A strong belief guiding the present study is that previous study success cannot be used as an indicator of students' prior knowledge as in some studies (e.g. Yenilmez, Sungur & Tekkaya, 2006; for an overview see Dochy et al., 1999a). This is due to the assumption that Grade Point Average (GPA) is not capable of providing an approximate measure of students' prior knowledge at a specific time. GPA is usually a combination of sub-scores that do not differentiate between different capabilities or knowledge. Furthermore, other characteristics, such as persistence, goal-orientation and commitment to succeed, are strongly reflected in GPA and therefore it is not a reliable measure of the knowledge one possesses. Thus, it may not be used for instructional support purposes because it fails to capture and characterize the prior knowledge that is a snapshot of students' knowledge at a particular time. This is in line with previous studies, which have shown that it is not possible to detect relevant and valid indicators of prior knowledge (e.g. Dochy, 1992; Powell, Conway & Ross, 1990). Thus, GPA is treated as a separate measure that has its own direct influence on student achievement.

Previous study success influences students' academic self-beliefs because self-beliefs are formed by interpretations of past experience (Bandura, 1997). However, some researchers discourage the use of measures of past performance (such as ACT or GPA scores) simultaneously with self-belief measures when predicting performance (Dew, Galassi, & Galassi, 1984; Hackett & Betz, 1989; Randhawa, Beamer & Lundberg, 1993). Their assumption is that self-belief measures already encompass and are influenced by interpretations of past performance and therefore such scores do not contribute significantly to predictions of performance. However, Pajares and Miller (1994) suggest that ability measures should be included when testing the role of self beliefs in order to gain a deeper understanding of the issue. We agree with Pajares and Miller (1994): to explore fully the theoretical relation between these constructs, it is necessary to include them all in the model. Although they are highly correlated constructs, they nevertheless remain distinct, with unique features contributing to student achievement.

1.7 Summary: The perspective adopted

In the above introduction, I have pointed out that prior knowledge research has somewhat suffered from vagueness of concepts and operationalisations. Furthermore, more research is needed on both *how* to assess prior knowledge and *what* should be assessed. In order to explicate the stance taken here, I will next provide a summary of the conceptual perspective the present work is grounded on.

In this study, prior knowledge is defined as knowledge that comprises both declarative and procedural knowledge; it is present before the implementation of a particular learning task; it is available or able to be recalled or reconstructed; it is relevant for the achievement of the objectives of the learning task; it is organised in structured schemata; it is to a certain degree transferable or applicable to other learning tasks; and it is dynamic in nature (Dochy, 1992; Dochy, Moerkerke & Segers, 1999). The present research views prior knowledge as comprising various types of knowledge that differ qualitatively and have different relevance in relation to student achievement. Therefore, this theoretical framework has aimed at identifying diverse ways of viewing the structure of prior knowledge. An important implication derived from the structure of knowledge research is that the research helps to identify the cognitive process along which the knowledge can differ. This is significant for assessment: Different assessment methods should be used to assess different types of prior knowledge. For example, a traditional way of assessing knowledge, measuring factual recall, is not enough when the interest is in capturing the depth of student understanding at the beginning of a course. Furthermore, assessment methods influence the observed effect of prior knowledge on performance. It is therefore useful to combine multiple assessment methods in order to capture a students' prior knowledge more thoroughly (Valencia et al., 1991).

This study focuses on the "content knowledge" aspect of prior knowledge as defined in Dochy's (1996) map of prior knowledge, and largely leaves aside the metacognitive aspect of prior knowledge, except for academic self-beliefs. This choice was based on the aim of the study, which is to create a practical prior knowledge assessment instrument that mainly focuses on the knowledge students possess prior to a course.

2 The aims of the studies

As already stated in the theoretical framework, even though there is a vast amount of research focusing on prior knowledge, little has been said about *what* should be assessed and *how* prior knowledge should be assessed (Dochy et al., 1999b; Shapiro, 2004; Valencia et al., 1991). Previous researchers (Dochy et al., 1999b; Valencia et al., 1991) have stated that the assessment method the researcher uses delimits the observed effect of prior knowledge on learning. Since there was a need to explore the impact of both different types of prior knowledge and the influence of different assessment measures, the present study aimed at creating a theoretical model of prior knowledge that distinguishes between these different types of knowledge and assessment methods. The aim was to create a prior knowledge assessment instrument that could be used for diagnostic assessment and student support in higher education. Subsequently, the model was tested in various science contexts and research settings in order to explore how different types of prior knowledge are related to student achievement. The focus is on the hard sciences (as defined in the introduction) because it was hypothesised that prior knowledge may play an especially important role in the context of hard science due to its cumulative nature. Furthermore, implications about the results are clearer when the focus is restricted to disciplines of the hard sciences that share a similar academic context.

As stated in the introduction, the more general aim of the present work is to understand the contribution of different types of prior knowledge components and prior knowledge assessment measures to student achievement. In accordance with the conceptual and theoretical framework outlined above, the following general research questions were outlined:

1. What is the specific contribution of different a) types of prior knowledge components and b) prior knowledge assessment measures to student achievement in various science disciplines?
2. How does prior knowledge and its components relate to a) previous study success, b) academic self-beliefs, c) prior knowledge from previous courses and d) study pace?

To be more precise, Study I aimed to test the model in the context of mathematics. The study analysed the relation between prior knowledge and student achievement in two university mathematics courses and, particularly, how each type of prior knowledge contributed to student achievement. In addition, previous studies indicate that feedback about one's own performance is a crucial element in learning and assessment because it provides a means for students to improve their performance and correct errors (Martens & Dochy, 1997). Therefore, the aim was to explore whether giving feedback about the prior knowledge test influenced student achievement.

Since it is clear that prior knowledge is not the only factor influencing student achievement, and previous research has shown that another influential factor is students' beliefs about themselves and capacities to perform (Bandura, 1997;

Pajares & Miller, 1994), Study II aimed to analyse the interrelations between academic self-beliefs, prior knowledge and student achievement. The aim was to explore how these variables are related to one another when they are included in the same model. Study II was also conducted in the context of mathematics.

In Study III the interest was in knowing more about how prior knowledge is formed: how is it connected to prior knowledge from previous courses, does the influence of inadequate prior knowledge accumulate over a period of five courses and what happens to knowledge during this period? The aim arose from the concern pharmacy teachers had about a laboratory course in pharmaceutical chemistry. They had noticed that students often lacked the basic skills in mathematics and chemistry when they entered the course. Therefore, a longitudinal setting was applied to explore the impact of prior knowledge from previous courses on student achievement in the target course.

Study IV arose from the interest to explore the influence of prior knowledge on student achievement from another perspective and in the context of yet another discipline of science: chemistry. The aim was to explore whether the impact of prior knowledge is reflected in the students' readiness to drop out of the course and whether prior knowledge is reflected in the pace of completing the course. Again, each type of prior knowledge was analysed separately.

2.1 Summary of the aims

To sum up, all studies (except for Study II) explored the influence of prior knowledge on student achievement by exploring the contribution of each type of prior knowledge separately and in various science contexts. Study I investigated the influence of different types of prior knowledge on student achievement was explored in mathematics. Study IV examined the influence of different types of prior knowledge on student achievement, study pace and the tendency to drop out. Study III applied a longitudinal setting to explore the influence of different types of prior knowledge over a longer period of time and in the context of pharmacy. The setting of Study II was slightly different; the aim was to explore the interrelations between prior knowledge, academic self-beliefs and student achievement.

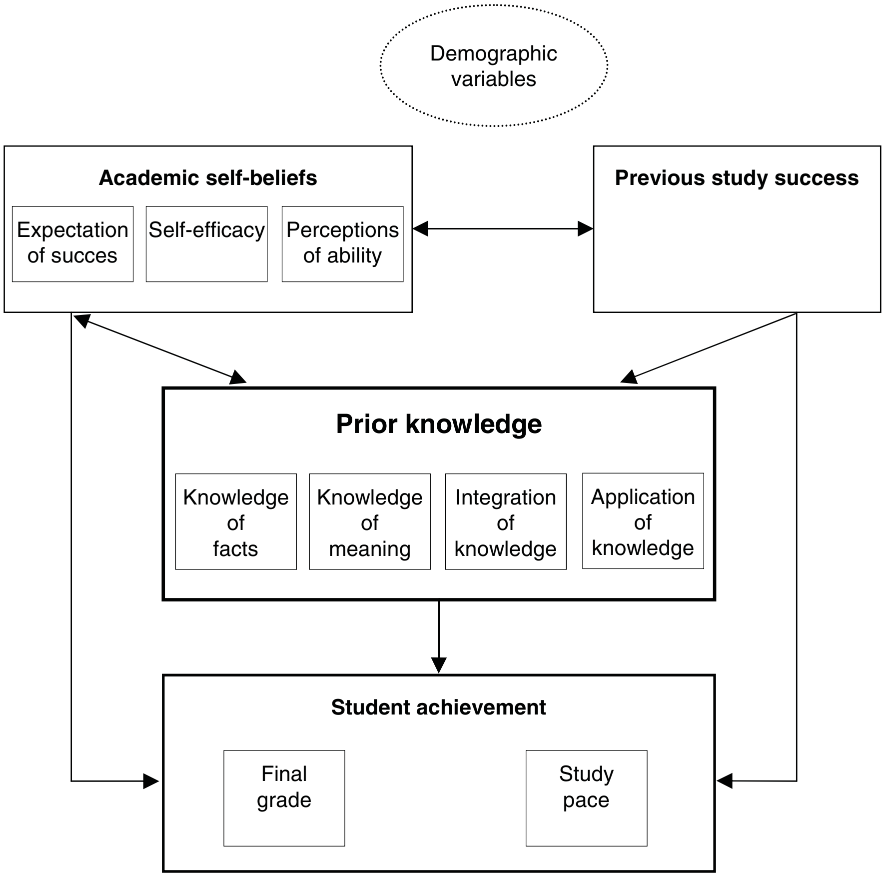


Figure 3. An overview of the research setting

3 Method

3.1 Constructing the model of prior knowledge

The research project started by creating the model of prior knowledge. The first step was to become acquainted with a variety of knowledge taxonomies and models of knowledge (Anderson & Krathwohl, 2001; Biggs, 2003; Bloom, 1956; 1976; Dochy, 1992; Marton, Watkins & Tang, 1997). The model of prior knowledge was influenced by all of the above mentioned models and taxonomies (see chapter 1.4 for details). This helped to identify what types of knowledge prior knowledge may contain. The process produced two basic ideas upon which the model was built: firstly, prior knowledge may vary in terms of its nature and depth, and the relevance of these various types of prior knowledge differ in relation to student achievement. Secondly, different types of prior knowledge should be assessed by applying different assessment methods. The aim, thus, was to create a model of prior knowledge that differentiates between the varieties of prior knowledge and combines different assessment methods to assess them.

The model (Figure 4) recognises that acquiring knowledge and skills is not the same as an ability to integrate and apply them. A distinction is made between declarative and procedural knowledge and their subcomponents. This distinction is often used in educational practice to differentiate between different types of knowledge (see, for example, Alexander et al., 1991; Anderson, 1982; Dochy, 1992). In the model the authors used the same operationalisation that Dochy has used in his research (Dochy 1992). The components referring to the *recognition* and *reproduction* of information were viewed as declarative. The components referring to the *production* or *application* were viewed as procedural. This distinction was made in order to illuminate the nature of prior knowledge components. As may be seen, the model focuses on the three basic taxonomic levels identified in research (e.g., Bloom, 1976; Dochy, 1992): (1) to know, (2) to understand and (3) to apply, because it is assumed that for the purpose of prior knowledge assessment these first three levels are sufficient.

Different tasks were intended to measure different forms of knowledge. Both declarative and procedural knowledge are divided into two subcomponents to describe the growth of understanding. Declarative knowledge is divided into *Knowledge of facts* and *Knowledge of meaning*. The lower level of declarative knowledge is at a very low level of abstraction and can be probed with simple recognition or reproduction tasks, such as enumerating essential concepts. The second level (knowledge of meaning) goes a step deeper and requires an ability to understand the meaning of the concept by, for example, giving it a correct definition. These tasks can be solved with a surface reproductive approach, that is, understanding as "knowing about" (cf. Biggs, 1993).

Procedural knowledge is divided into *Integration of knowledge and Application of knowledge*. This type of knowledge is revealed in production or application tasks. The lower level of procedural knowledge is revealed in the ability to see interrelations between concepts and how different phenomena are linked to each other. The higher level requires a demonstration of the ability to apply knowledge and to perform a problem-solving task.

The question of terminology arose during construction of the model: what would be an appropriate term to refer to different types of prior knowledge. In previous research, the term *dimension* had been used in a much broader sense; examples include the cognitive-psychological dimension or educational psychological dimension (see, for example, Dochy, 1992). Furthermore, the term *level* did not seem suitable either since the model with its subsets (that is, different types of prior knowledge) was primarily seen as a multi-dimensional entity; the focus was not on placing students on different competence levels. Rather, the aim was to provide a diagnostic support tool that would illustrate one's strengths and weaknesses in prior knowledge and assess the varieties of this prior knowledge. The idea was to provide a visualisation of a profile, in which each subset would be interrelated and represents a specific type of prior knowledge as a part of one's whole prior knowledge state. Since the previous research focusing on constructing prior knowledge profiles (Dochy, 1992; Falmagne, 1989; Portier & Wagemans, 1995) had used the term *component* to refer to qualitatively different types of prior knowledge, the decision was made to use that term in the prior knowledge model (see also Letteri, 1980; Wolf et al., 1991).

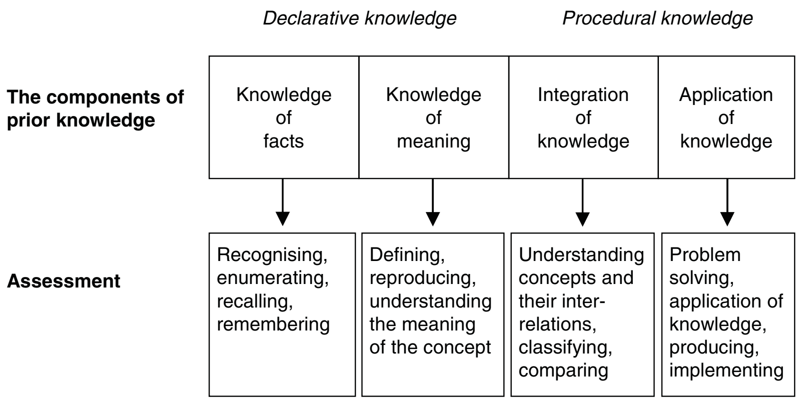
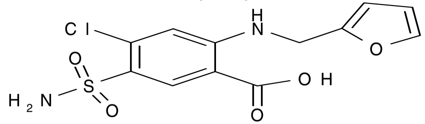
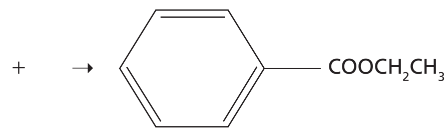


Figure 4. The initial model of prior knowledge components and their assessment

The principal idea in creating the content for the prior knowledge assessment instrument was that the content would be developed in cooperation with the course teachers. The instrument always included at least four tasks, each of which measured different components of prior knowledge (knowledge of facts, knowledge of meaning, integration of knowledge and application of knowledge). The number of tasks varied from one study to another. The model of prior knowledge and the nature of different prior knowledge components were explained in detail to the teachers. These sessions were organised in order to ensure that the teachers understood that the components represented different types of knowledge and understanding, and that they knew what type of tasks could be used to assess different types of knowledge in their respective disciplines. After these discussions the teachers created the tasks and subsequently the tasks were discussed once again. These tasks were based on teachers' conceptions of course-relevant prior knowledge.

Table 1. Examples of the operationalisations of different types of prior knowledge in various disciplines

The type of prior knowledge	**Examples of the operationalisations in different disciplines**		
	Mathematics	**Pharmacy**	**Chemistry**
Knowledge of facts	List as many concepts related to differential and integral calculus as you can remember. (Try to recall the course differential and integral calculus I.1 and what you learned at school.) (Study II)	The functional groups of the molecular structure of furosemide (structure below/vide infra) are: a) amino, ester and halogen b) amino, carboxyl and ether c) thiol, halogen and ether d) amino, ketone and hydroxy 	In which class of organic compounds does each of the following belong: a) $CH_3CH_2CH_2–O–CH_2CH_2CH_3$ b) $CH_3CH_2CH_2NH_2$ c) $CH_3C(=O)—OCH_2CH_2$
Knowledge of meaning	Define the meaning of $\lim_{x \to a} f(x) = A$ (Study II)	What happens in the following reaction? $Ag^+ (aq) + Cl^- (aq) \rightarrow AgCl (s)$ a) solvatation b) precipitation c) an acid-base reaction d) an oxidation-reduction reaction	Describe briefly the following chemical bond types: a) Ionic bond b) Hydrogen bond c) Covalent bond
Integration of knowledge	What separates the set {a,b,c} from the sequence (a,b,c)? What do they have in common? (Study I)	A typical degradation reaction of vanillin, a flavouring agent in drug preparations, is the oxidation of its aldehyde group. In which of the following reactions does the oxidation of an aldehyde take place? a) R-CHO → R-COOH b) R-CHO → R-CH_3 c) R-CHO → R-CH=CH(OH) d) R-CHO → R-CH_2OH	Set the following compounds in ascending order of acidity: acetic acid, ethanol, sulfuric acid and ammonia.
Application of knowledge	Find supremum *A*, when set *A* consists of the numbers 1/3, 2/4, 3/5 … (Study I)	Draw the structural formula of the main product in the reaction below. 	The reaction product (ethylbentsoate) on the right side of the chemical equation can be prepared by esterification. Draw the starting compounds of the reaction and give the essential reaction conditions/catalysts. 

3.2 Participants

The participants were mathematics (N = 202), pharmacy (N = 115) and chemistry (N = 193) students from the University of Helsinki. Thus, all the students represented different science disciplines. The students were mainly first-year students. They were all participating in courses with a high drop-out rate.

In *Study I* the sample consisted of 202 mathematics students from two different courses, Course A (n = 140) and Course B (n = 62). In Course A most of the students (67%) were first-year students and the majority (70%) had mathematics as their major. Students in Course B were more heterogeneous. They consisted of an equal percentage of first-, second- or third-year students and the majority (75%) were mathematics majors. Of the whole sample, 105 (52%) were men and 97 (48%) were women. Courses A and B were different in nature. Course A was the latter part of an obligatory mathematics course comprising two parts over two terms. Course B was optional and more advanced in nature.

In *Study II* the sample consisted of the participants of Course A (N=139) in Study I, who had filled in both the prior knowledge test and a questionnaire of academic self-beliefs. Most of them had mathematics as their major; other majors were physics (9%), computer science (9%), and chemistry (4%). The sample consisted of nearly equal percentages of women (49%) and men (51%).

In *Study III* the sample consisted of pharmacy students (N=115) enrolled in a pharmaceutical chemistry laboratory course. The majority of the students (95%) were first-year students. The rest were second- or third-year students who for some reason had not completed the course during their first study year. The majority of the students were female (79%). Ninety-seven percent of the participants were pharmacy students. The remaining 3% consisted of biochemistry and chemistry students. The sample also included four instructors of the courses who were interviewed about their experiences with the prior-knowledge test.

In *Study IV* the sample consisted of a total of 193 students enrolled in an introductory chemistry course of which 83 students studied chemistry and seven students studied biochemistry as their major. Of the whole sample, 103 students studied chemistry as their minor. Other majors were theoretical physics, biosciences, geology, dentistry, physics, veterinary medicine, environmental science, medicine, computer science, mathematics teacher training, cultural anthropology, craft science, geology and palaeontology, plant biology, food technology, biotechnology, pharmacy, cognitive science, psychology and political science. It was a very heterogeneous group, and the majority of the students were female (67.9%).

3.3 Measures

The principle was the same in all studies: prior knowledge test was used to assess students' prior knowledge and the content of the questionnaire was developed in cooperation with the teachers of the courses (see section 3.1 above: "Constructing the model of prior knowledge). The final grade of the course was used as a measure of student achievement in all four studies. Demographic background questions were included in the first part of the test (Name/student number, gender, major and the year of starting their university studies).

3.3.1 Study I

In *Study I*, the prior knowledge test comprised a total of 14 tasks in both courses: one measuring *knowledge of facts*, one measuring *knowledge of meaning*, six questions measuring *integration of knowledge* and six questions measuring *application of knowledge*. Half of the students received feedback on their performance in the prior knowledge test. The sample was randomly selected. The feedback comprised three elements: corrected test paper, model answers and a short questionnaire encouraging students to compare their performance with the model answers. Student achievement was measured by the final grade of the course. The final grade consisted of two mid-term exams, active participation in tutorials and the final exam. Together they formed the final grade. Previous study success was measured by means of grades obtained from previously completed courses. These data were gathered retrospectively from the university's student register.

3.3.2 Study II

In *Study II*, the data were the same as in Study I and hence prior knowledge was measured with the same six mathematical problem-solving tasks from the prior knowledge test of Course A. These problem-solving tasks were chosen from the questionnaire because *Study I* revealed that they were the best predictors of the final grade. Additionally, academic self-beliefs were measured with a questionnaire. The questionnaire is explained in more detail in the following section.

Academic self-beliefs. Academic self-beliefs were measured with a total of twelve statements. However, after conducting a factor analysis, the number of original statements was reduced to nine because of the low communalities of three statements. Therefore, the final number of statements used in the analyses was nine (see Table 2), seven of which were adapted from an instrument originally developed by Niemi, Nevgi & Virtanen (2003); two additional statements were created by the authors. The original instrument was developed to support learners in virtual learning environments to become more aware of their own learning processes (see Niemi et al., 2003). The original instrument included many different parts that were based on Pintrich's & Ruohotie's Motivational Components, developed for the context of Finnish vocational education (Pintrich & Ruohotie, 2000; see also Pintrich, Smith, Garcia & McKeachie, 1993; Pintrich, 1995, 1999). The items used in the present study were applied from the component called *Forethought* and, more specifically, from its two subscales measuring *expectation of success* and *self-efficacy*.

Table 2. Items measuring academic self-beliefs and its subscales

Items measuring Expectation of success (Niemi et al., 2003)	
1.	I believe that I will achieve excellent grades in this course.
2.	I know that I will learn well the topics taught in this course.
3.	I am certain that I will be successful in this course.
Items measuring Self-efficacy (Niemi et al., 2003)	
4.	I trust that I can understand even the most difficult issues in my studies if I only work hard enough.
5.	I trust that I can learn even the most difficult theoretical issue in this course.
6.	The forthcoming course will not cause me unbearable efforts (modified by Hailikari & Nevgi for the study II).
7.	I know I can achieve the goals that are set for me.
Items measuring Self-perceptions of mathematics ability (created by Hailikari & Nevgi for Study II)	
8.	I believe that I am good at math.
9.	Math has always been easy for me at school.

The adapted statements assessed the students' level of confidence about achieving success in the forthcoming course and beliefs about his/her abilities to perform in terms of two underlying factors: expectation of success (items 1–3) and self-efficacy (items 4–7). The two items created by the authors (items 8 and 9) measured self-perceptions of mathematics ability. Participants rated their confidence on a five-point Likert scale from 1 ("Completely disagree") to 5 ("Completely agree").

The intention was to group the items together to form two dimensions – the same two dimensions that underlie the items we adopted from Niemi et al. (2003). As stated earlier, we adopted the items from factors called "expectation of success" and "self-efficacy", and we sought to explore whether the same dimensions could be identified in our study. We estimated the internal consistency of the groups by using Cronbach's coefficient alpha measures. Indeed, analysis suggested that these two empirically distinguishable, yet strongly related, dimensions could be identified. The analyses yielded the following reliabilities: expectation of success (ES) had a Cronbach's coefficient α of .90 while self-efficacy (SE) yielded a Cronbach's coefficient α of .74. We formed a third group consisting of the additional two items measuring self-perception of mathematics ability (SPM); this yielded a Cronbach's coefficient α of .65. Thus, the reliability was acceptable for all sum scales. These three dimensions are viewed as measures of an underlying feature called academic self-beliefs. Grade point average (GPA) was used to measure previous study success.

3.3.3 Study III

In *Study III* data were gathered from five different courses over a half-year period (see Figure 5). The target course of the study was the pharmaceutical chemistry course because the course teachers had noticed that students often lacked prior knowledge from the basic science courses (mathematics, chemistry and organic chemistry) that preceded the target course.

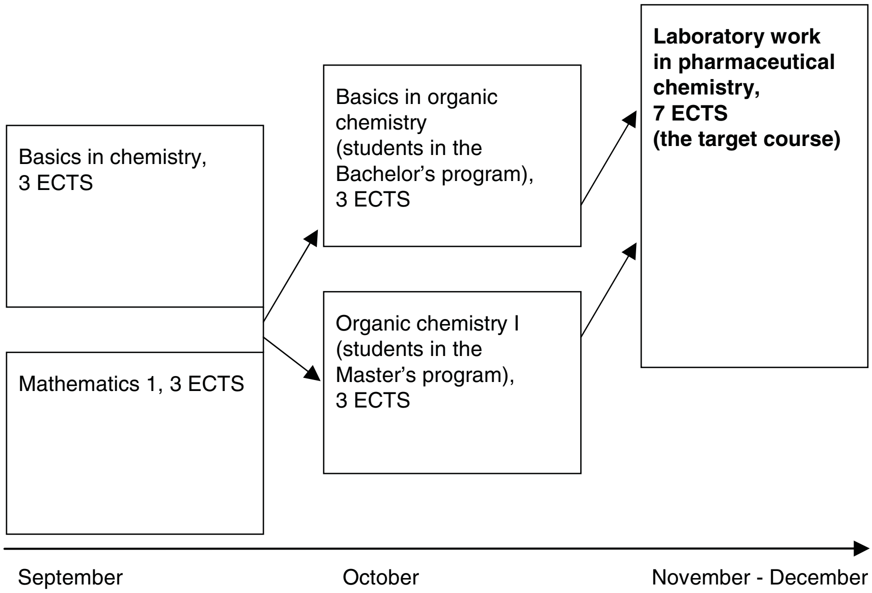


Figure 5. The structure of the first term of the curriculum

The students completed the prior knowledge tests at the beginning of each course. The prior-knowledge test for the pharmaceutical chemistry course included one task from each of the prior knowledge tests of the preceding courses in addition to the tasks regarding the content of the course. The test comprised altogether eight tasks: four tasks on the content of the pharmaceutical chemistry course content and one task repeated from each of the previous courses. We chose tasks from the preceding prior-knowledge tests that measured the two highest levels of prior knowledge, that is, the *integration of knowledge* and the *application of knowledge* components. The reason for this was that these types of tasks require high-quality learning and understanding and are assumed to subsume lower levels of knowledge. The purpose of these repeated tasks was to explore how their mastery is related to success in the target course and whether knowledge from previous courses was retained and whether there were changes in performance between the first and second measurement.

The interview. In addition, four instructors of the courses were interviewed in order to explore their experiences regarding the usefulness of the prior-knowledge test as an instructional design tool. Recorded interviews were conducted after the courses. In the interviews, the instructors were asked how they had used the prior-knowledge assessment tool, how it had impact on their teaching, what were their opinions were about the tool, and how useful it was. The open-ended questions allowed the teachers to talk freely about their experiences. The interviewer asked the teachers to clarify their responses in more detail if something remained unclear to the interviewer. Furthermore, students were given space in the tests to comment on their experiences with the prior-knowledge assessment test. This was voluntary and the comments were gathered during the fall term.

3.3.4 Study IV

In *Study IV,* the prior knowledge questionnaire included four tasks. Each prior knowledge component (knowledge of facts, knowledge of meaning, integration of knowledge and application of knowledge) was measured by one task. Additionally, the demographic background variables (major, age and gender) and information regarding drop-outs and students' pace of completing the course were retrieved from the university's student register.

Table 3. A summary of the operationalisation of different components of knowledge and the number of tasks per study

The component of knowledge	Operationalisation	The number of tasks per study			
		Study I	Study II	Study III	Study IV
Knowledge of facts	Free recall; enumeration; recognition	Course A: 1 Course B: 1	–	1 (target course)	1
Knowledge of meaning	Defining; understanding (as reproduction)	Course A: 1 Course B: 2	–	1 (target course)	1
Integration of knowledge	Understanding inter-relations; classifying; comparing	Course A: 6 Course B: 6	–	2 (one from target course, one from previous course)	1
Application of knowledge	Problem-solving	Course A: 6 Course B: 6	6	4 (one from target course, three from previous courses)	1

3.4 Statistical procedures

3.4.1 Study I

The course teachers corrected the test papers. Course A and Course B students' answers to the questions measuring *Knowledge of facts* and *Knowledge of meaning* were coded differently because of the different nature of the questions. In Course A, the answers were coded as 0 for an incorrect answer, 0.5 for a partly correct answer, and 1 for a correct answer. In Course B, the indicator for *Knowledge of facts* was the total number of the recalled concepts, and for *Knowledge of meaning* the total number of correct definitions. Questions concerning *Integration of knowledge* and *Application of knowledge* were treated similarly in both courses. The answers to these questions were coded as 0 for no answer or the wrong answer, 0.5 for a partly correct answer, and 1 for a correct answer.

Overall prior knowledge achievement was measured by calculating the sum variable *Overall prior knowledge* (range *Course A*: 0.5–12; *Course B* 4–43). Then, since there were many items measuring the components Integration of knowledge and Application of knowledge, the sum variables were calculated for each component in both courses and their reliability was evaluated by Cronbach's Alpha. For the Integration of knowledge the Cronbach's Alpha value was .64 for Course A and .66 for Course B. For the Application of knowledge the Cronbach's Alpha value was .64 for Course A and .72 for Course B. The reliabilities for all the sum variables were acceptable.

Pearson correlation coefficients were used to calculate correlations between different types of prior knowledge and the final grade. An independent samples t-test was used to explore whether there were differences between the feedback and non-feedback groups' performance. One-way ANOVA design or independent sample t-test (in the case of comparing two means) were used to explore the relation between overall performance in the prior knowledge test and different background variables. Games-Howell's post-hoc procedures were used in situations where sample sizes were unequal. Regression analyses were carried out to analyse which types of prior knowledge predicted student achievement. The forced entry method was used for initial analyses (Field, 2000).

3.4.2 Study II

Study II analysed the interrelations between academic self-beliefs, prior knowledge, previous study success and student achievement. The data were firstly analysed to explore the descriptive statistics for each variable. The means and standard deviations were calculated for each variable in the study and the Pearson correlation coefficient was used to explore their interrelations. Then structural equation modelling was used to test the adequacy of the hypothesised model. Path analysis techniques were used to examine direct and indirect effects between variables. We chose structural equation modelling over multiple regression because it has the potential to explore complex directional relationships and answer more substantive questions (Hair, Black, Babin, Anderson & Tatham, 2006; Kline, 2005; Tabachnik & Fidell, 2007).

Then, indicators for the variable academic self-beliefs were created. In structural equation modelling, one should bear in mind that the greater the number of variables and indicators per variable, the more complicated and statistically strenuous the model being tested becomes. Taking into consideration the small sample size of the study and these statistical considerations, the aim was to create a limited number of strong indicators for the latent variables. Therefore, reliable composite indicators for the latent variable of academic self-beliefs were constructed based on theoretical assumptions (see the construction in more detail in section "Measures"). The composite indicators of academic self-beliefs were expectation of success, self-efficacy and self-perception of mathematics ability. Lambda coefficients, which indicate the relationship between measured indicators and latent constructs, were significant in the model, suggesting that the indicators were closely related, and therefore adequate for testing the theoretical model.

For the latent variable prior knowledge, a method of random assignment of items to doublets was used (e.g., Kline, 2005). Calculating a small set of multiple indicators from a larger pool of items ensures the requirements of a normal distribution and a higher reliability of indicators. Prior knowledge was indicated by three doublets called P1, P2, and P3.

There were 21 missing data in the variable final grade. In order to keep as many subjects as possible in the analysis, the missing values were imputed in several ways so as to control any possible effect. First, the Missing Value Analysis (MVA) module of the SPSS program allows one to use an EM algorithm for estimation. MVA also gives information about the nature of missingness (Hill, 1997). It was concluded that it was safe to assume the missingness to be random (MAR). Second, AMOS has an option for imputation using the same algorithm. Finally, much development has been done in multiple imputation (MI). Two programs (Mplus4, and Norm Version 2.03 for Windows) were used to produce multiple imputed data (data augmentation; Schafer, 1999). A comparison revealed that the results were essentially the same for all these methods. Multiple imputation produces estimates that are consistent, asymptotically efficient, and asymptotically normal when data are MAR (cf. Allison, 2002; Collins, Schafer, & Kam, 2001; Schafer & Graham, 2002; Steiger, 1990).

Several goodness-of-fit indices were used to determine model fit: the chi-square (χ^2) goodness-of-fit test, which assesses the overall fit of the hypothesised model to the data obtained, the comparative fit index (Bentler, 1990), the goodness-of-fit index adjusted for degrees of freedom, and the Root Mean Squared Error of Approximation (RMSEA). To suggest model adequacy, χ^2 should be non-significant, whereas CFI and GFI/AGFI should be greater than .90 to be acceptable. RMSEA values in the range 0–.08 reflect acceptable error (Browne & Cudeck, 1993). In Study *II*, β coefficients and R^2 were used as indicators of the effect size. These are both measures of the magnitude of relationships (Cohen et al., 2002) and they are reported in connection with *p* values.

3.4.3 Study III

Study III analysed how prior knowledge from previous courses was related to student achievement in the target course and whether knowledge learned in previous courses is retained as the studies proceed. The course instructors also scored the prior-knowledge tests for their respective courses. In each course, the tasks were scored from 1 to 6, with 1 being the minimum and 6 being the maximum number of points. One point was given if some elements in the answer were correct but the final answer was incorrect. Three points were given if about half of the answer was correct. Six points were awarded for a correct answer. After the instructors' scoring, the authors double-checked the scores. Then, correlation analysis was used to explore the interrelations between different types of prior knowledge. Regression analysis (enter) was carried out to explore which types of prior knowledge predicted student achievement in the pharmaceutical chemistry course. Paired samples t-test was used to explore the changes in performance between the first and second measurement. The instructors' interviews and students' written comments were analysed by qualitative content analysis (see Patton, 1990; Flick, 2002). The interviews were read and analysed in order to capture and describe variation in the comments. The text was read through repeatedly in order to distinguish different categories. Through this process the initial categories were identified. After that, the second author read through the responses independently and some of the initial categories were unified to form the final categories. The unit of analysis was the whole sentence.

3.4.4 Study IV

Study IV analysed how different types of prior knowledge were related to students' tendency to drop out of the course, to the pace of completing the course and to the study success measured as the final grade. In addition, the study explored which background variables were related to students' prior knowledge at the beginning of the course.

Firstly, the professors graded the prior knowledge tasks on a scale from 0 to 3 (0 = failed, 1 = poor knowledge, 2 = average knowledge, 3 = excellent knowledge). Overall prior knowledge achievement was measured by calculating the sum variable Prior Knowledge task sum score (range 0–12; Cronbach's alpha .78), which consisted of the four prior knowledge components. The descriptive values (mean, standard deviation, minimum and maximum values) were calculated in order to examine students' overall achievement in the prior knowledge test and in the four components of prior knowledge. Students with majors in chemistry or biochemistry were classified as *chemistry as major* students (N = 90) and students with majors other than chemistry were classified as c*hemistry as minor* students (N = 103). Students were grouped into three study-pace groups: 1) successful students (n = 106; 54.9 %), 2) re-takers (n = 16; 8.3 %), and 3) drop-outs (n = 79; 36.8 %). The first student group (successful students) included students who studied according to the pre-scheduled study plan and passed the final exam during the first two exam dates. The second student group (re-takers) included students who did not complete the course according to the pre-scheduled plan and passed the final exam during the additional exam dates. The third group (drop-outs) consisted of students who had participated in the first lecture of the course but had not passed the final exam approximately one year after the course had ended.

An independent samples t-test was applied in order to compare the means of the two different groups (chemistry as major or minor, and gender) with performance in the prior knowledge test and study success measured as the final grade. Correlation analysis was conducted in order to explore relationships between age, performance in the prior knowledge test and the final grade. The crosstabs procedure was applied to measure the association between the study-pace groups and different types of prior knowledge and gender as well as between different major groups. Finally, regression analyses were carried out to analyse which prior knowledge components predicted study success. The forced entry method was applied for initial analyses.

3.5 Summary of the studies

A summary of the four different studies and their settings is illustrated in Table 4.

Table 4. Descriptive characteristics of studies I–IV

Characteristic	Study I	Study II	Study III	Study IV
Discipline and sample	Mathematics N = 202	Mathematics N = 139	Pharmacy N = 115	Chemistry N = 193
Prior knowledge in relation to	previous study success and final grade	academic self-beliefs, previous study success and final grade	its origins from previous courses and their co-influence on the final grade	study pace, drop-put and final grade
Materials	Prior knowledge test	Prior knowledge test and academic self-beliefs questionnaire	Prior knowledge test and interview	Prior knowledge test
Statistical analysis	Descriptive statistics, one-way ANOVA, regression analysis	Descriptive statistics, crrelation analysis, structural equation modeling	Correlation analysis, regression analyses, paired samples t-test, content analysis	Descriptive statistics, t-test, correlation analysis, cross-tabulation, regression analyses

4 Results

The most valuable findings are presented below. The results are described in more detail in the journal articles.

4.1 The model of prior knowledge and the influence of different components of prior knowledge on student achievement (Study I)

In *Study I,* the model of prior knowledge was modified and the third level "process" was added to the model (Figure 6). The model of prior knowledge has three levels: knowledge components, their indicators and their classification on the continuum from knowing to understanding to applying. The first level presents different components of prior knowledge. The second level, "Indicator", demonstrates the levels of understanding these components represent by using verbs that describe the cognitive process along which the knowledge components differ. The second level also serves as an indicator of what types of assessment measures may be applied to assess distinct types of prior knowledge. The third level demonstrates the range of understanding from knowing to applying knowledge. It is important to understand the essence of application of knowledge -component. In the model, the term application refers to novel problems that require an adaptation of a learned solution procedure (i.e., transfer) and, furthermore, requires understanding as its base. To sum up, the first level tells what the content of each component is and the next two levels indicate what type of understanding each component represents and how they can be assessed.

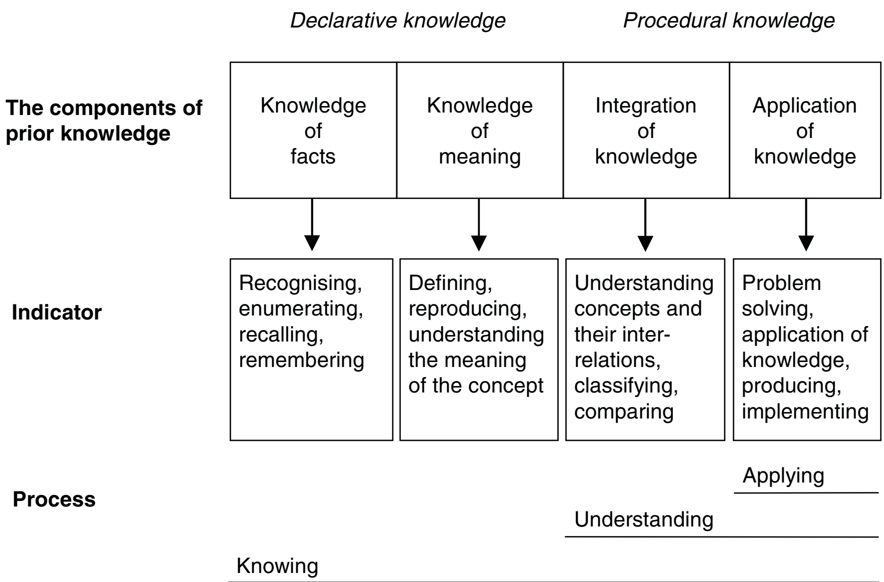


Figure 6. The model of prior knowledge

After the model was created, it was tested in different science disciplines. *Study I* started by exploring the influence of the overall prior knowledge test score on student achievement in two different mathematics courses. In both courses there was a positive correlation between the overall performance in the prior knowledge test and the final grade (Course A $r = .49$; $p = .00$; Course B $r = .32$; $p = .00$). Next, the contribution of each component was explored. In both courses the procedural knowledge components (i.e., *Integration of knowledge* and *Application of knowledge*) were most strongly correlated with the final grade. This indicates that students who performed well in the procedural knowledge tasks were also likely to get better final grades. In Course A, the declarative knowledge component *Knowledge of meaning* also correlated with the final grade whereas in Course B the correlation was non-significant. In both courses the procedural knowledge components correlated strongly with each other. In both courses there was a trend in results: There was always a positive correlation between the knowledge components that followed each other in the model, but not necessarily with any other knowledge component. Further, in both courses *Application of knowledge* had the strongest correlation with the other procedural knowledge component, *Integration of knowledge*, and its correlations with other knowledge components were either weak or lacking (Table 5).

Table 5. Intercorrelations between prior knowledge types and final grade

Prior knowledge type		1	2	3	4	5
Course A (n = 140)						
1	Final grade	-	-.07	.26**	.40**	.47**
2	Knowledge of facts		-	.17*	.14	-.09
3	Knowledge of meaning			-	.35**	.30**
4	Integration of knowledge				-	.41**
5	Application of knowledge					-
Course B (n = 62)						
1	Final grade	-	.20	.24	.43**	.31*
2	Knowledge of facts		-	.65**	.45**	.01
3	Knowledge of meaning			-	.56**	.12
4	Integration of knowledge				-	.42**
5	Application of knowledge					-

Note. $p < 0.01$**, $p < 0.05$ *

Next, an analysis was made to explore whether students' prior knowledge level differed in terms of gender, age, number of study credits, the major subject of studies and previous study success. The analysis revealed that there were no significant differences in performance regarding gender, age, number of study credits or the major subject of studies. However, one-way ANOVA design revealed that previous study success was related significantly to the prior knowledge test performance in Course A (Course A: $F(2.137) = 18.94$, $p = .000$). Games-Howell's post-hoc test with its significant difference procedure ($\alpha = 0.05$) was used for comparisons. Students who had high previous study success (from 3.5 to 5) performed significantly better than those with an average (from 2 to 3.5) or low (from 1 to 2) previous study success. In Course B there was a weak relation between previous study success and prior knowledge test performance but it was not statistically significant.

We also explored whether getting feedback from the prior-knowledge test influenced student achievement. The *t*-test revealed that there were no differences between the non-feedback and feedback groups in either course.

Regression analysis was carried out in order to find out how different components of prior knowledge were related to student achievement. The association between the criterion and explanatory variables was moderate (Course A: Multiple $R = 0.53$; Course B: Multiple $R = 0.46$). In both courses, scores on declarative knowledge components (that is, *Knowledge of facts* and *Knowledge of meaning*) were not related to final grade. However, in Course A, scores on both components of procedural knowledge (*Integration of knowledge* and *Application of knowledge*), were positively related to final grade. Together, they accounted for 26% of the variation in final grades (adjusted R^2). The regression coefficient for *Application of knowledge* was 0.33 and for *Integration of knowledge* 0.30 ($F(4.135 = 13.33$, $p = .000$). The standardised regression coefficients showed that *Application of knowledge* was a stronger predictor than *Integration of knowledge*. Both variables, however, were positively and significantly related to the final grade. The regression model for Course B differed from Course A. In Course B, *Integration of knowledge* became the only variable predicting final grades. It accounted for 15% of the variation in final grades. The regression coefficient for *Application of knowledge* was 0.33 ($F(4,57) = 3,73$, $p = .001$).

Since the amount of explained variation remained fairly low, the study explored whether the differences in student achievement derived from some broader differences in the students' (mathematical) ability rather than course-relevant prior knowledge. Indeed, previous study success appeared to be the strongest predictor of final grades. The association between the criterion and explanatory variables was rather high (Course A: Multiple $R = 0.68$; Course B: Multiple $R = 0.59$). In Course A, previous study success and *Application of knowledge* together accounted for 45% of the variation in final grades ($F(2.137) = 57.498$, $p = .00$). In Course B, previous study success and *Integration of knowledge* accounted for 32% of the variance ($F(2.59) = 15.55$, $p = .00$), previous study success being the stronger predictor (Table 6).

Table 6. Summary of regression analyses: Different prior knowledge types and GPA as predictors of student achievement

	Course A (n=140)			Course B (n=62)		
Explanatory variables	**B**	**SEB**	**Beta**	**B**	**SEB**	**Beta**
GPA	0.63	0.08	0.54**	0.59	0.15	0.43**
Application of knowledge	0.23	0.07	0.23**	–	–	–
Integration of knowledge	–	–	–	0.29	0.12	0.27*

Adjusted R^2 Course A= 0.45; Course B= 0.32.
**p<0.01

4.2 Different components of prior knowledge and their relation to study pace and the tendency to drop out (Study IV)

The aim of *Study IV* was to explore how different components of prior knowledge were related to students' tendency to drop out of the course, to the pace of completing the course and to the study success measured as the final grade. Firstly, the study explored the variables related to students' performance in the prior knowledge test. An independent samples t-test revealed that students' major was significantly related to prior knowledge performance. *Chemistry as major* students scored significantly higher in all the components of prior knowledge than *chemistry as minor students* (for more detailed results, please see Study IV). Gender differences remained non-significant.

Secondly, the study explored how the students' performance in the prior knowledge test was related to study pace. One-way ANOVA design was applied in order to determine how the three distinct study-pace groups (successful students, re-takers, and drop-outs) performed in tasks measuring different components of prior knowledge. Successful students scored significantly higher on all components of prior knowledge other than *knowledge of meaning*. Cross-tabulation was used to further explore the relationship between performance in the prior knowledge tasks and study-pace groups. The analysis revealed that the students whose performance was weak in the prior knowledge tasks (score zero) were more likely to belong to the drop-out group whereas students whose performance was excellent (score three) were more likely to belong to the successful students' group and vice versa (Table 7). There were no significant differences between the different study-pace groups in the knowledge-of-meaning task and hence it was omitted from Table 7.

Table 7. Cross-tabulation between performance in different prior knowledge tasks and the study pace group membership

Performance in the task (scale 0–3)		The student group (N = 188)					
		Drop-outs		Re-takers		Successful students	
		n	%	n	%	n	%
0	Facts	20	50*	7	17.5	13	32.5**
	Integration	7	53.8*	3	23.1	3	23.1**
	Application	32	62.7*	6	11.8	13	25.0**
1	Facts	9	52.9	1	5.9	7	41.2
	Integration	2	66.7	1	33.3	0	0.0
	Application	5	35.7	3	21.4	6	42.9
2	Facts	11	37.9	2	6.9	16	55.2
	Integration	15	57.7	0	0	11	42.3
	Application	22	26.5	6	7.2	55	66.3*
3	Facts	29	28.4**	5	4.9	68	66.7*
	Integration	45	30.8**	11	7.5	90	61.6*
	Application	10	25**	0	0**	30	75*

* significantly more students than the expected count
** significantly fewer students than the expected count

The next aim was to explore the relationship between students' study-pace, major and study success. The relationship between students' study pace and the final grade was examined with an independent samples *t*-test, and only those students who had passed the exam were selected for the analysis. *Successful students*' (M = 3.00, SD = 1.32) final grade was significantly higher ($t_{(120)} = -3.27$, $p = 0.001$) than *re-takers*' (M = 1.88, SD = 0.96). An independent samples *t*-test found a significant difference ($t_{(191)} = -3.66$, $p = 0.000$) in study success between *Chemistry as major* (M = 2.28, SD = 1.74) and *Chemistry as minor* (M = 1.39, SD = 1.64) student groups, revealing that *Chemistry as major* students' final grades were significantly higher.

Regression analysis was used to examine how the major and different prior-knowledge components predicted the final grade. Major was included in the regression because the t-test revealed a significant difference between major and minor students. The association between criterion and explanatory variables was rather weak (Multiple R = 0.38). As seen in Table 8 only the *application of knowledge* was positively related to the final grade. The model explained 12 % (Adjusted R^2) of the variation in the final grade. The regression coefficient for application of knowledge was 0.47 and for major 0.43 (F(5, 182) = 6.25, p = .000). The standardised regression coefficient revealed that application of knowledge overruled the effect of major and thus was the only predictor of the final grade.

Table 8. Regression analysis of major and different types of prior knowledge as predictors of the final grade

Explanatory variables	B	SEB	Beta
Major	.43	.28	.12
Knowledge of facts	–.16	.15	–.11
Knowledge of meaning	.17	.14	.09
Integration of knowledge	.16	.17	.08
Application of knowledge	.47	.16	.30**

** $p<.01$

4.3 The accumulation of prior knowledge (Study III)

The aim of *Study III* was to analyse how prior knowledge from previous courses contribute to student achievement in the target course and whether knowledge learned in previous courses is retained as the studies proceed. Correlation analysis of prior-knowledge scores revealed that performance on almost all prior-knowledge tasks correlated with the final grade in the target course (laboratory course in pharmaceutical chemistry), with the exception of tasks that measured knowledge of (pharmaceutical chemistry) facts and the application of basic chemistry knowledge. Students who possessed relevant and deeper-level prior knowledge from previous courses were also likely to get better final grades in the pharmaceutical chemistry course. The strongest correlations were found between performance in organic chemistry tasks and the final grade in the pharmaceutical chemistry course. Furthermore, performance in the organic chemistry application task also strongly correlated with the other tasks (Table 9).

Table 9. Intercorrelations between prior knowledge types and final grade in the pharmaceutical chemistry course

The type of prior knowledge task (N = 115)		2	3	4	5	6	7	8	9
1	Final grade in the pharmaceutical chemistry course (target course)	**.13**	**.31***	**.25***	**.21***	**.19***	**-.07**	**.24***	**.46****
2	Pharmaceutical chemistry (Knowledge of facts) (pc)		.09	.25*	.19*	.09	-.03	.12	.25**
3	Pharmaceutical chemistry (Knowledge of meaning) (pc)			.32**	.20*	.07	.06	.20*	.26**
4	Pharmaceutical chemistry (Integration of knowledge) (pc)				.17	.05	-.03	.17	.40**
5	Pharmaceutical chemistry (Application of knowledge) (pc)					.13	.02	.17	.31**
6	Mathematics (Application of knowledge) (pc)						-.19*	-.05	.05
7	Basics in chemistry (Application of knowledge) (pc)							.01	.05
8	Organic chemistry (Integration of knowledge) (pc)								.33**
9	Organic chemistry (Application of knowledge) (pc)								–

pc = previous course

Regression analysis was conducted in order to determine which type of prior knowledge had the strongest relationship with the final grade in the pharmaceutical chemistry course. Only variables that significantly correlated with the final grade were included in the analysis. The association between the criterion and explanatory variables was moderate (multiple R = 0.53). The only variable that was positively related to the final grade was the application task in organic chemistry, which accounted for 24% of the variation in the final grade (adjusted R^2). The regression coefficient for the organic chemistry application task was 0.22 and the standardized coefficient (β) was 0.36 ($F(6,107 = 6.9$; $p < 0.01$). The other variables were not related to the final grade, although the application task in mathematics and the knowledge of meaning in pharmaceutical chemistry were close to the significance level ($p = 0.06$ for both) (Table 10).

Table 10. Summary of regression analysis: Different types of prior knowledge from previous courses predicting student achievement in the pharmaceutical chemistry course

Criterion variable: Final grade in laboratory course for pharmaceutical chemistry (N=113)			
Explanatory variables	**β**	**SEB**	**Standardized β**
Mathematics (Application of knowledge)	.15	.08	.16
Organic chemistry (Integration of knowledge)	.07	.07	.09
Organic chemistry (Application of knowledge)	.22	.06	.36**
Pharmaceutical chemistry (Knowledge of meaning)	.11	.06	.17
Pharmaceutical chemistry (Integration of knowledge)	.01	.06	.02
Pharmaceutical chemistry (Application of knowledge)	.02	.06	.02

* Adjusted R^2 = .24
** p<0.01

Analysis of prior-knowledge scores indicated that knowledge was retained over the five courses examined. There was a clear and significant increase between the first and second measurement in all tasks included in the follow-up, with the exception of Basics of Chemistry (Table 11). In the mathematics application task, the mean in performance increased from 1.95 to 3.12 ($p < 0.01$). In the organic chemistry task measuring the integration of knowledge, the mean increased from 1.46 to 2.15 ($p = 0.003$). In the organic chemistry task measuring the application of knowledge, the mean increased from 3.08 to 3.78 ($p = 0.008$). However, in the chemistry application task, the mean of the performance decreased from 4.90 to 4.35 ($p = 0.03$). This deviant result may be explained by the nature of the task. When the instructors were scoring the results they noticed that the task was slightly imprecise and there were multiple ways to interpret it. Therefore, the results may also be interpreted as indicating that students' understanding increased and therefore performance in this task decreased because they noticed the impreciseness of the task. The results suggest that the learned knowledge did not disappear but rather increased.

Table 11. Change in performance between the first and second measurement

	First measurement	Second measurement		
Performance	**M/SD.**	**M/SD.**	**t**	**p**
Mathematics (application) (N = 109)	1.95/2.19	3.12/2.60	–4.64	.000
Basics in chemistry (N = 109)	4.90/1.69	4.35/2.35	2.21	.030
Organic chemistry (integration) (N = 89)	1.46/1.76	2.15/2.17	–3.10	.003
Organic chemistry (application) (N = 89)	3.08/2.86	3.78/2.77	–2.70	.008

4.4 The interrelations between prior knowledge, academic self-beliefs and student achievement (Study II)

In Study II, the aim was to explore the interrelations between student achievement, prior knowledge, academic self-beliefs and previous study success. Firstly, the correlation analysis was used to explore the relations between the variables of the study: previous study success, the three academic self-beliefs' sum-scales, three doublet variables of prior knowledge and the final grade (Table 12). With the exception of self-perceptions of mathematics ability, all variables correlated significantly with the final grade. Furthermore, prior knowledge doublets, self-belief constructs, and previous study success were positively inter-correlated. Prior knowledge and previous study success showed the strongest positive correlation with the final grade. Self-belief components were significantly interrelated, suggesting that they measure the same collective property. Expectation of success and self-efficacy strongly correlated; self-perception of mathematics ability did not correlate as strongly with the other two components. Furthermore, the correlation between self-perception of mathematics ability and other variables was generally low. This suggests that self-perceptions of mathematics ability may not be central to the prediction of student achievement. We also explored whether different background variables had an effect on prior knowledge, self-belief judgements, or student achievement. The analysis revealed no statistical differences arising from gender, age, number of study credits, or the major subject of studies.

Table 12. Descriptive statistics and Pearson's product moment correlation matrix for the manifest variables

	Variable	1	2	3	4	5	6	7	8
1	GPA		.46***	.37***	.13	.25**	.26**	.48***	.66***
2	ES			.66***	.38***	.40***	.32***	.43***	.45***
3	SE				.46***	.48***	.26**	.37***	.37***
4	SPM					.33***	.21*	.20*	.10
5	P1						.27***	.34***	.34***
6	P2							.38***	.35***
7	P3								.50***
8	Final grade								–
	M	3.19	2.99	3.85	3.43	.68	.74	1.46	1.56
	SD	1.04	.80	.57	.79	.60	.49	.54	1.10

*** $p < .001$; ** $p < .01$; * $p < .05$; (two-tailed test)

Note. N = 139. GPA= previous study success; ES = Expectation of success; SE = Self-efficacy; SPM = Self-perception of mathematics ability; P1, P2, P3 = Prior knowledge doublets measuring mathematics problem-solving ability.

The structural model served to test the hypotheses. Based on research into the positive influence of prior knowledge, academic self-beliefs, and previous study success on student achievement, it was hypothesised that student achievement would be a function of these factors. It was hypothesised that previous study success would predict not only student achievement, but prior knowledge and self-beliefs as well. And finally, based on research into the impact of self-beliefs on performance, it was hypothesised that self-beliefs would correlate with prior knowledge.

The proposed model was evaluated using AMOS 6.0. Prior to analysis, all raw scores were normalised to ensure that the variables were distributed normally. Evidence was found to support adequate model-to-data fit. Estimation of the proposed theoretical model revealed a non-significant χ^2 value (χ^2 [16,139] = 25.70, $p = .06$), a goodness-of-fit index (GFI) adjusted for degrees of freedom (AGFI) of .89, a comparative fit index (CFI) of .97, and an RMSEA value of .066. Although all indices indicated a reasonable fit to the model, the path between academic self-beliefs and final grade was non-significant and negative. We removed this path from the model, suggesting that academic self-beliefs only indirectly affected student achievement through prior knowledge. This second model also showed a reasonable fit (χ^2[17,139] = 27.09, $p = .06$; CFI = .97; AGFI = .89; RMSEA = .066). The model was also theoretically grounded; consequently, we retained this as a final model. The final model appears in Figure 7.

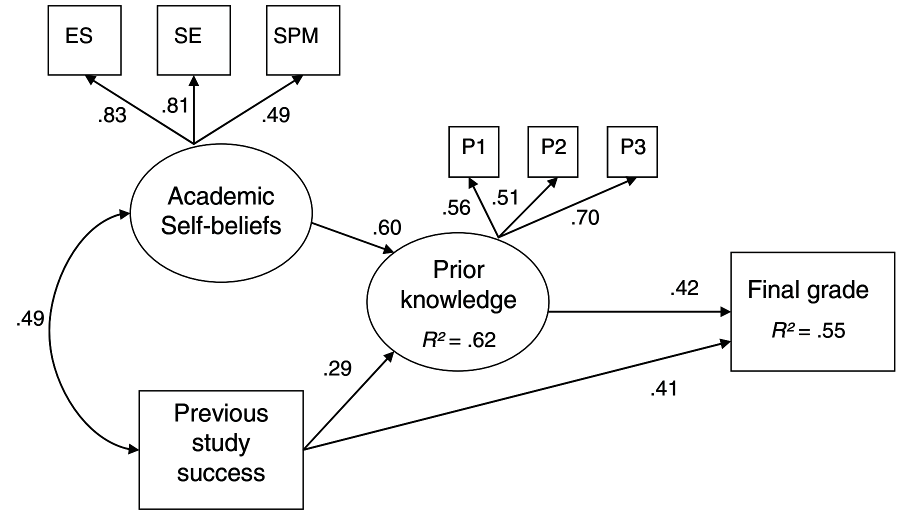


Figure 7. Structural Equation Model of the interplay between previous study success, academic self beliefs, prior knowledge and student achievement. All path coefficients are standardised and statistically significant at p < .001, with the exception of the path from previous study success to prior knowledge at p < .01.

The model's fit was checked using the Mplus4 program's multiple imputation technique developed by Schafer (1997), called data augmentation. The Mplus4 program produced the same result as did AMOS with expectation maximisation (EM), which supported the robustness of the model.

Overall, the predictor variables accounted for 55% of the variance in student achievement. This indicates a strong effect size. The key finding was that prior knowledge predicted student achievement over and above other variables. The effect of prior knowledge on final grade ($\beta = .42$, $p = .002$) was as strong as the effect of previous study success ($\beta = .41$, $p = .000$) on final grade. Previous study success also directly influenced prior knowledge ($\beta = .29$, $p = .010$). Prior knowledge partly mediated the influence of previous study success on the final grade. Moreover, final grade and academic self-beliefs explained 62% of the variance in prior knowledge. One noteworthy finding was that, contrary to expectations, academic self-beliefs did not have a direct effect on the final grade. Rather, the effect was mediated by prior knowledge. As expected, self-beliefs strongly and directly influenced prior knowledge ($\beta = .60$, $p = .000$) and also strongly correlated with previous study success ($r = .49$, $p = .000$).

4.5 Teachers' and students' experiences of the prior knowledge test (Study III)

In *Study III*, teachers' and students' experiences of the prior knowledge test were explored. All four course instructors participated in the post-intervention interviews and provided feedback about the prior knowledge assessments.

The instructors felt that the prior-knowledge tests helped them to recognize the different types of knowledge and to acknowledge the importance of structuring the nature of knowledge in more detail. The model of prior knowledge (Figure 6) and the prior-knowledge test derived from this model were considered as useful and helpful, not only in designing the questions for the prior-knowledge test but also for other examinations. The model helped instructors to reflect on the content of their own examinations. In the present study the instructors did not give feedback to the students on their performance in the prior-knowledge test. However, they considered it important to provide feedback to the students as early as possible during the course. This would enable the prior-knowledge test to enhance students' learning in a more efficient way. The instructors suggested that the test should be conducted before the beginning of the course so that they would have sufficient time to score the answers. They did not apply the results of the test to modify their teaching but they felt that the test helped them to become aware of the nature and level of students' prior knowledge. Two instructors called for guidance in how to use the results in their instruction. They all felt that prior-knowledge assessment could help instructors recognise students with problems. They also felt that the prior-knowledge assessment would be useful, especially in basic courses. Only 48 of the 115 students who completed the prior-knowledge test provided comments about the assessment. Of these comments, 41 were positive and six were negative. The most common positive comment was that the test made students more aware of what they knew and did not know (n = 30). Thus, it served as a means of self-assessment. It also motivated them to think about what they needed to do in order to succeed, such as reviewing course material or asking for help from instructors or fellow students. Six students commented that the prior-knowledge test made them feel that their instructor cared about their learning; they also considered it important for the instructors to know their students' prior-knowledge level. Five students commented that the prior-knowledge test was a good way to review and activate knowledge from previous courses. Negative student comments dealt with negative feelings that arose from taking the test. Two students commented that a prior-knowledge test which is conducted without warning is not a true measure of students' actual knowledge base. These students wished that they had been allowed time to study for the test. Three students commented that the prior-knowledge test made them feel anxious and worried that they did not know enough. One student commented that the test was a "useless waste of time."

4.6 Summary of the main results

The results of all four studies indicate that procedural knowledge components (as defined in this study) are the best predictors of student achievement. In *Study I*, both the application of knowledge and the integration of knowledge components predicted student achievement, but when previous study success was included in the regression, it became the best predictor of student achievement. Similarly, *Study IV* further revealed a significant connection between prior knowledge and students' study-pace. More specifically, the application of a knowledge-component was the best predictor of students successfully completing the course in pre-scheduled time and with higher final grades. On the other hand, low performance in the application of knowledge task was related to leaving the course. S*tudy III* further revealed that students who possessed deeper-level prior knowledge from previous courses (that is, procedural knowledge) were also likely to get better final grades in the target course of pharmaceutical chemistry. And finally, in *Study II* prior knowledge was the best predictor over other variables of the study, that is, academic self-beliefs and previous study success. It is therefore valid to conclude that procedural knowledge components, especially an ability to apply knowledge to problem-solving, appear to influence student achievement in many ways: the influence is reflected in the final grades (all studies), academic self-beliefs (*Study II*) and study pace (*Study III*), and further, the influence seems to *accumulate* over a longer period of time (*Study III*).

The prior knowledge of students appears to vary in terms of previous study success (*Study I*) and major (*Study IV*). Students with better previous study success were also more successful in the prior knowledge test. In addition students with a major other than the subject under study had lower prior knowledge than the major students.

5 Discussion

5.1 The influence of prior knowledge on student achievement

The aim of the present study was to explore how different types of prior knowledge are related to student achievement in various disciplines of science. The study started by creating a model of prior knowledge that distinguished between various types of prior knowledge and used different assessment methods to assess different types of knowledge. Subsequently, the model was tested in several disciplines of science in order to validate its functionality in a variety of science contexts and to gain more insight on the significance of prior knowledge in learning. In addition to confirming most major findings of previous studies on prior knowledge, the present study contributes to the research field by documenting the relationship between different types of prior knowledge and student achievement.

Studies I, III and IV analysed the effect of different types of prior knowledge components on student achievement. The results of all the three studies showed, in general, that prior knowledge that consisted of procedural knowledge was significantly related to student achievement in the course. The results of Study I showed that procedural knowledge which requires higher-order cognitive skills best predicted the final grades and was also highly related to previous study success. This implies that if the student was able to successfully perform these tasks in previous courses, he/she was more likely to possess these skills at the beginning of the new course as well and, consequently, be more successful. However, the relationship differed depending on the course. In Course A, the application of knowledge was the best predictor of student achievement, whereas in Course B, the integration of knowledge was the best predictor. This could be due to the different nature of the courses and the different kind of mathematical pre-understanding these courses require. In both courses, declarative knowledge components were not related to student achievement. This, however, might be a result of methods used to assess declarative knowledge. For example, in Course A knowledge of facts was measured with a free-recall task. Previous studies, however, imply that in general free-recall tasks are not relevant measures of course-relevant prior knowledge, because they might measure something else, such as students' verbal abilities (Dochy et al., 1999b), which might not be a central skill in mathematics. Furthermore, mathematics students might not be familiar with that type of assessment task, although it is frequently used in other disciplines.

In Study I, previous study success was the best predictor of student achievement. This implies that the influence of prior knowledge mainly derived from broader differences in the students' mathematical abilities rather than from course-specific prior knowledge. It should be noted, however, that even when the previous study success was included in the model, procedural knowledge appeared to increase the amount of explained variance; this suggests that content-specific procedural prior knowledge, together with prior educational performance, influences student achievement. We also wanted to determine the relation between previous study success, prior knowledge test performance and final grade.

It appeared that the relation was different in the courses. In Course A, students with higher previous study success scored higher on the prior knowledge test and had better final grades as well. This is in line with previous studies (Carstens & Beck, 1986; Dochy et al., 1999a; Griggs & Jackson, 1988), indicating that previous study success significantly correlates with prior knowledge test scores and the final grade. Interestingly, in Course B the relation was not as straightforward. The influence of previous study success was reflected in the final grades but not in the prior knowledge test performance. The explanation for this might lie in statistical reasons because the number of participants was rather small. However, there might be other explanations as well. Course A was obligatory and was clearly based on previous mathematical knowledge. Course B, on the other hand, was more specific in nature and required a new type of ”bold” mathematical thinking and skills than did previous courses (Dr. Mika Koskenoja of the Faculty of Science, personal communication, 2006). This might have been reflected in the relation between previous study success and prior knowledge test performance; hence, there was no evidence of any significant relation to previous grades. However, the effect of the previous study success was again shown in the final grades. This could be due to other characteristics of the students besides mathematical ability. Those who performed better earlier in the studies might possess characteristics such as persistence, goal-orientation and commitment to succeed, all of which contribute to good performance. These characteristics might also be reflected in the final grades of these courses. Similarly, Dochy et al. (1999) concluded that prior educational performance had both direct and indirect influence on student performance. This result emphasises the importance of inter-individual differences that influence student achievement.

Study I also explored how feedback from the prior-knowledge test influenced student achievement. The hypothesis was that feedback might help students reflect on their prior knowledge and thus lead to changes in their study behaviour, such as effort and rereading (Martens & Dochy, 1997) and that this might be reflected in the final grades. In this study, giving feedback to students about their performance in the prior knowledge test did not have an influence on student achievement. The reason for this might be that feedback was given too late during the course when the students had already lost interest in their prior knowledge test performance. The feedback should be given earlier in the process and it should be detailed enough and informative (for more discussion on the issue, see Martens & Dochy, 1997 and McGinn & Winne, 1994). It may also be that the influence of feedback was reflected on other issues which were not the focus of the study, such as learner engagement and study time as in the study by Martens & Dochy (1997).

The same pattern regarding the influence of prior knowledge was also seen in Study III, which was a longitudinal study of the accumulation of prior knowledge. The study analysed how prior knowledge from previous courses was related to student achievement in the target course. The results implied that students who possessed deeper-level prior knowledge, that is, procedural knowledge, from previous courses also obtained higher grades in the more advanced pharmaceutical chemistry course (the target course). These results complement the results from Study I by implying that procedural knowledge represents deeper-level understanding that is retained and reflected in student achievement also over a longer period of time. However, Study III did not take into account the relation between other types of knowledge from previous courses and their relation to student achievement, but instead focused solely on measuring procedural knowledge components from previous courses. The reason for the exclusion was that the prior-knowledge test could not repeat all the tasks from all the previous courses in addition to the tasks of the target course; otherwise the test would have been too strenuous for the students. Only the tasks regarding deeper-level prior knowledge from previous courses were chosen to be repeated. Thus, it is not possible to make statements about the relevance of lower-level prior knowledge, although this would have brought an interesting addition to the analyses.

However, in regard to the content of the target course, all types of prior knowledge were measured. The analyses revealed that knowledge of facts was not related to student achievement whereas other types of prior knowledge had weak but significant correlations with the final grade. This result provided further support for the results of Study I. Interestingly, the strongest predictor of the final grade was performance in the application of knowledge task in the organic chemistry course that preceded the target course. Good performance in this task was also related to performance in other tasks; this suggests that other courses contributed to good performance in the organic chemistry task, which, in turn, contributed to good performance in the target course. Most importantly, it appears that good performance in the more advanced course originates in the basic courses and therefore prior knowledge is an essential issue to consider. If students drop behind at the beginning of their studies, it is reflected in their performance later on.

5.2 The relationship between prior knowledge components and study pace

The results of Study IV were similar to those of Study I and Study III and again highlighted the importance of the application of knowledge component. The results showed that performance in the application of knowledge task was significantly related to both the students' study pace and final grade. Students who had good procedural prior knowledge, that is, performed well in the application of knowledge task, were also likely to complete the course in pre-scheduled time. On the other hand, students whose performance was weak in the prior knowledge tasks were more likely to belong to the drop-out group or take a longer time to complete the course. This is in line with the findings of Lewis & Lewis (2007) suggesting that low performance in the prior knowledge test was related to dropping out of the course. Furthermore, students who performed well in the application of knowledge task were also likely to get higher final grades, even though the relationship was moderate. There was also a significant relationship between the final grade and the ability to complete the course in pre-scheduled time.

Interestingly, the analysis revealed that the re-takers' performance in the prior knowledge test was even weaker than that of the drop-outs'. Thus, low performance in the prior-knowledge test might have served as a warning sign to which these distinct student groups have responded in different ways. The result may be explained by such factors as student motivation or persistence, which we have not included in our study. Further research is needed on the issue.

The results indicated that there indeed was significant variation in prior knowledge in an introductory chemistry course, implying that inter-individual differences in prior knowledge pose a heterogeneity that should be considered even in an introductory course. Furthermore, the major appears to be a factor that is clearly reflected in prior knowledge performance at the beginning of the studies. Students who had a major other than chemistry scored significantly lower in every prior knowledge task. The students' major was also related to the final grade, but prior knowledge overruled its influence when they were both included in the regression model. This means that the influence of major is only reflected via the differences in the prior knowledge base. Gender did not have a significant influence on prior knowledge test performance.

Moreover, the findings are in line with Study I and Study III, which further affirms to their success. While dropping out of the course may have been a function of prior knowledge, there may have been a variety of other reasons for leaving the course, ranging from personal reasons (see, for example, Mäkinen, Olkinuora & Lonka, 2004) to other aspects such as teaching and curriculum. However, the data do indicate that low performance in the prior knowledge test probably played a role in the decision.

5.3 The relationship between prior knowledge and academic self-beliefs

Study II explored the interplay of the variables that previous research has found to be strongly related to student achievement in mathematics: previous study success, academic self-beliefs and prior knowledge. In Study II, prior knowledge was more predictive of student achievement than were the other variables included in the study. When self-beliefs were included in the model with prior knowledge, the predictive power of prior knowledge overruled the influence of self-beliefs. Contrary to our hypothesis, self-beliefs showed no direct influence on student achievement at the course level. This is in line with the findings of Murtonen and Titterton (2004). However, academic self-beliefs strongly and directly affected prior knowledge test performance. This suggests that academic self-beliefs may have influenced the way in which students responded when they were exposed to the prior knowledge test at the beginning of the course. Students who had greater confidence in their ability to perform well may have persisted longer with the prior knowledge test, which was reflected in their prior knowledge performance. Similarly, low self-beliefs may also have lessened students' engagement in the prior knowledge test. Students are more likely to engage in tasks and achieve when they believe they have the potential to do so (Linnenbrink & Pintrich, 2003). Moreover, students tend to confirm their self-perceptions. Students with positive views of themselves engage in achievement-related behaviours to confirm their positive self-perceptions (Pajares, Britner & Valiante, 2000). It can also be hypothesised that self-beliefs in the past had an influence on achievement behaviour in a similar manner, and that this was reflected in the students' prior knowledge level.

Although self-beliefs seemed to have no direct influence on student achievement, this does not mean that we should be unconcerned about them. Self-beliefs significantly and indirectly influenced student achievement through prior knowledge, and also directly influenced prior knowledge test performance at the beginning of the course. Self-beliefs may influence the way in which students make use of their prior knowledge and how they use such prior knowledge as a base for learning, which thus influences the entire learning process. Negative self-beliefs may reduce levels of motivation and engagement (Randhawa, Beamer, & Lundberg, 1993). Furthermore, studies have found that self-beliefs influence students' enjoyment of the subject (Townsend, Moore, Tuck, & Wilton, 1998), which in turn may influence subsequent achievement behaviour. The effects of self-beliefs on academic achievement have been found to cumulate over time (Valentine et al., 2004). Moreover, the results of study by Murtonen et al. (2008) suggest that self-beliefs are also related to views of future work and motivational factors. Therefore, negative self-beliefs should be addressed and considered in teaching. Discussions concerning the students' self-beliefs may help students become aware of the factors that affect their learning. Students' awareness of their self-beliefs gives them better possibilities to regulate their learning.

Of interest were also the interrelations found between various types of self-belief constructs. Expectation of success and self-efficacy were strongly correlated, whereas self-perception of ability did not correlate as strongly with the other two self-belief measures. Furthermore, self-perception of ability showed no correlation with previous study success or with final grade, and its correlations with the other variables were markedly weak. These results suggest that general self-perceptions of competence, such as "I'm good at mathematics", are not valid predictors of student achievement. This result is consistent with the views of Linnenbrick and Pintrich (2003) and Pajares and Miller (1994).

5.4 Limitations of the study

A central limitation to consider is whether the present study was able to measure what it aimed to measure. Cross-validation between different teachers was used to provide confirmation that the tasks were successful in measuring different types of knowledge and thus assure a certain degree of reliability. Furthermore, the study used different assessment measures to assess different types of knowledge, which brings about a two-layered interpretation of the results: it is not entirely possible to know whether the results are due to different assessment measures or different types of knowledge. Another issue to consider is that in some of the studies only a single item was used to measure each type of prior knowledge. It is worth questioning whether a single item is sufficient for this.

As regards to the academic self-beliefs instrument, the same question pertains: was the instrument able to measure academic self-beliefs? Self-beliefs were measured on a fairly broad level: as confidence ratings of one's abilities to perform well at the course level (cf. Lent et al., 1997). This contrasts with Bandura's (1997) argument that self-beliefs should be measured at a micro-analytic and task-specific level. For example, Pajares and Miller (1994) linked problem-solving self-efficacy to a specific problem-solving task and found it to be a reliable predictor of performance. However, such micro-analytic operationalisations may be unsuitable for educational intervention purposes. The focus in the present study was to explore whether self-belief assessment on a more general level predicts student achievement. Our methodological approach was similar to that of Randhawa et al. (1993) and Lent et al. (1997). This broadness of approach may have influenced the results. Furthermore, there are always some limitations regarding the self-report methods used to analyse beliefs. Students rated their academic self-beliefs fairly positively. This might be due to the social desirability effect which might have affected their answers. Furthermore, theoretically it is easy to distinguish between different constructs of self-beliefs, such as self-efficacy and expectation of success. However, empirically they are quite difficult to distinguish because they are such closely related constructs. Therefore, it is challenging to operationalise these constructs.

Another limitation of the present study was that it was conducted only in the context of science. Therefore, implications can be drawn regarding the context of science but not other disciplines. It may only be assumed that prior knowledge would play a different role in other disciplines because of their different nature but this cannot be verified on the basis on this study.

A further limitation to consider concerns the function of giving feedback. Previous studies indicate that giving feedback from the prior knowledge test influences student achievement in various ways (for an overview, see Martens & Dochy, 1997). The present study did not find any differences between the feedback group and the non-feedback group. This may be because the feedback was given too late, and the students had already lost interest in their performance. Furthermore, the feedback was sent to the students and they were asked to compare their performance with the model answers. Thus, it may be assumed that only highly motivated and self-regulated students took the effort of going through their answers.

It is also self-evident that prior knowledge is not the only factor influencing student achievement; other important factors interfere with the influence of prior knowledge, such as the students' approaches to studying, teaching methods or learning strategies. These factors remained beyond the scope of this study even though they would have brought an interesting addition to the whole picture.

And finally, a central limitation of the present study was that in each study the final grade was used as a measure of student achievement. One may question whether the final grade should be used as an approximate measure of student achievement without knowing exactly what the final grade consists of. It would have been more informative to include the same types of tasks in the final exam for a more well-founded comparison between the types of knowledge and the final grade. In all studies, the teachers were asked what type of knowledge the final exam measured; they answered that the final exam measured procedural knowledge components in each study. However, in addition to these verbal statements, a more thorough analysis of the types of assessment tasks used in the final exam would have added another dimension to the analysis.

5.5 Summary

The findings of all four studies are consistent. In each case the higher-level prior knowledge components, especially the ability to apply knowledge to problem-solving, were the best predictors of student achievement. It is therefore valid to summarize that prior knowledge influences student achievement in a variety of ways: the influence is reflected in the final grades, academic self-beliefs and study pace, and the influence seems to *accumulate* over a longer period of time.

To put it simply, it may be suggested that there might exist a certain "successful student" type. In Study I, students who had higher previous study success also performed better in the prior knowledge test and obtained higher final grades. Similarly, in Study IV students who performed well in the prior knowledge test completed the course in the pre-scheduled time with good final grades. Furthermore, the results of Study II showed that previous study success, academic self-beliefs and prior knowledge are highly related. And finally, the results of Study III imply that study success might be rather stable and accumulative. Therefore, it may be summarized on the basis of all four studies that the higher and the deeper-level prior knowledge, the better the academic self-beliefs and previous study success as well.

6 General discussion

The aim of the present study was twofold. Firstly, it was to create a prior knowledge assessment model that distinguishes between various types of prior knowledge components and uses different assessment measures. It was important to test the functionality of the model. Therefore, the second aim was to test the model in a variety of science disciplines in order to explore what is the contribution of these distinct prior knowledge components to student achievement. The findings of all four studies were rather consistent with each other, indicating that the model may be used as a potential tool for prior knowledge assessment. The relation between prior knowledge and other relevant constructs, such as previous study success, academic self-beliefs and study pace, was also explored. The findings, their interpretation and implications will now be discussed more thoroughly.

6.1 Issues regarding the interpretation of the results

The present study showed that prior knowledge indeed is an important variable influencing student achievement. The results of this study highlight the diversity of students' prior knowledge in different science programmes and underscore the importance of prior knowledge assessment in recognizing this variation between students. Unfortunately, many students have problems in their studies, which is reflected in high drop-out rates, especially in the context of science (Kivinen, 2007; Ms. Anne Palo-Kauppi from the Faculty of Science, personal communication 2009).

The present study showed that students' prior knowledge is related to many different aspects of the learning process: academic self-beliefs, study pace, previous study success and student achievement. Considering the findings, an important issue emerges. The students are unequal in regard to their capabilities and self-beliefs. Students who *do not* belong to the "successful student" -type (who have high prior knowledge, high self-beliefs and whose study success is rather stable), should be identified and provided with further support, preferably early in their studies.

The study implies that it is useful to make a distinction between different types of prior knowledge in assessment since the type of prior knowledge students possess appears to make a difference. The results showed, in general, that higher-level prior knowledge components (integration of knowledge and application of knowledge), which require higher order cognitive skills, appear to be most strongly related to all of the factors mentioned above, whereas the lower level knowledge components (knowledge of facts and knowledge of meaning) either did not predict or were only weakly connected to student achievement. The application of knowledge -component seems to have the most significant relationship with different aspects of student achievement.

These findings on the relevance of different types of prior knowledge provide more insight into the issue addressed by Valencia et al. (1991): exploring how different types of knowledge contribute to understanding. It may be concluded that reproduction level prior knowledge, that is, declarative knowledge does not serve as a basis for further learning. Declarative is not so-called active knowledge, as is procedural knowledge, and therefore does not serve as "a springboard for future learning" as Glaser & De Corte express it (Dochy 1992, p. 1).

Another possible interpretation of the results concerns the assessment methods. Dochy et al. (1999b) raised the question of how prior knowledge influences student achievement when assessed with different assessment methods. They argue that different types of assessment measures influence the observed effect of prior knowledge. The findings of the present study reveal that different measures indeed predict the final grades differently, suggesting the superiority of some measures over others. It may well be that that traditional assessment methods that concentrate on the reproduction of factual knowledge are not able to capture the 'real' level of student understanding and therefore do not discriminate well enough between students' prior knowledge. Therefore, they do not serve as predictors of student achievement. On the other hand, a qualitative shift occurs when production tasks are used to assess students' prior knowledge. It is at this point that the differences in the depth of prior knowledge are exhibited. Therefore, another conclusion to be drawn may be that different measures simply measure different types of knowledge and some knowledge, in this case procedural knowledge, has more relevance in relation to student achievement. In the present study, it is theoretically well founded to assume that the more developed the prior knowledge base, the more significant its impact on student achievement.

It may also be assumed that it is not all about knowledge, but also thinking skills. This was shown in Study I where the *Application of knowledge* -component consistently had the strongest correlation with the other procedural knowledge component, *Integration of knowledge.* However, the correlations with the declarative knowledge components were either weak or lacking. Therefore, it may be assumed that procedural knowledge components measure similar types of thinking skills, which are relevant in relation to student achievement as well.

6.2 The structure of knowledge paradigm revisited

The model of prior knowledge presented in this study has been influenced by many different taxonomies and classifications of knowledge (Anderson & Krathwohl, 2001; Biggs, 2003; Bloom, 1976; Dochy 1992; Marton, Watkins & Tang, 1997). One might raise the question of why the study did not use the available models. The focus of this study was to create a simple and practical prior knowledge assessment tool for university instructors, which is easy to grasp but still takes into account the theoretical issues that have been highlighted in previous research. These include the focus on what type of prior knowledge is assessed and the influence of different assessment methods (Dochy et al., 1999b; Tobias, 1995; Valencia et al., 1991).

Although our model resembles Bloom's revised taxonomy (Anderson & Krathwohl, 2001), it is fundamentally different in some ways. I believe that each knowledge component contains different types of cognitive processing. Thus, once factual knowledge is being processed at a deeper level (for example application of factual knowledge in the revised taxonomy), it also changes its form and can no longer be considered as mere factual knowledge. In our model we attempt to make explicit these shifts between different types of knowledge and thinking. Furthermore, the model has excluded the highest levels identified in many taxonomies, such as analysing evaluating and creating in the revised taxonomy (2001) or the extended abstract in Biggs's SOLO-taxonomy, which refer to skills that are needed in, for example, conducting independent scientific work. Since the model is created primarily for prior knowledge assessment, these skills are beyond the scope of this model. It is neither reasonable nor relevant to assess these skills when the focus is on assessing optimal-requisite prior knowledge at the course level.

The initial idea in creating the model was that prior knowledge is a multidimensional entity and that the different components of prior knowledge are not necessarily hierarchical in relation to one another. The interest was in exploring the contribution of each component separately. However, the results of all the four studies imply that the model should be considered as hierarchical, with procedural knowledge components representing the highest two levels of the model. This finding is in line with previous knowledge studies suggesting that prior knowledge is hierarchical in nature (Ausubel, 1968; Mayer, 1979; Reigeluth & Stein, 1983). Furthermore, as the results of all four studies are consistent, it may be claimed that the model is quite successful in distinguishing between different components of knowledge.

6.3 Discussion of the terminology used in this study

One might criticise the use of the term "component" to refer to different dimensions of prior knowledge. Indeed, the term "component" may evoke an image of something static in nature whereas prior knowledge is viewed as dynamic in nature. The term dimension could have been used as well, but in previous studies it has been used to refer to broader categorisations (see e.g., Dochy, 1996). The reason for making a distinction between different components was to clarify that the person's prior knowledge state may differ qualitatively. Different components comprise different levels of cognitive processing. Thus, there might be differences in prior knowledge both on an interpersonal-level but also on intrapersonal-level, depending on the situation. The measurement of prior knowledge provides only a snapshot of a person's prior knowledge and its components at a certain time (see Dochy et al., 1996; Glaser, 1976). In the present study, the term component is used to represent the qualitative shifts in one's depth of understanding and cognitive processing and, thus, should not be understood in a rigid manner.

Another point of criticism about the study terminology refers to the use of the terms declarative and procedural knowledge. The decision to use these terms was based on the work by Dochy (1992), in which he makes a distinction between declarative and procedural components of prior knowledge based on their operationalisation. The components referring to the *recognition* and *reproduction* of information were viewed as declarative. The components referring to the *production* or *application* were viewed as procedural. This distinction was made in order to illuminate the nature of different prior knowledge components. Retrospectively, this distinction between declarative and procedural knowledge fit well with the initial idea of the model which regarded prior knowledge as a multidimensional entity that involves different types of knowledge and cognitive processing.

However, as the study proceeded and the results revealed that the model is hierarchical in nature, the choice of the terms declarative and procedural no longer seems appropriate, but rather, misleading. In the light of knowledge research (Anderson, 1982; 1995), it is not valid to suggest a continuum between declarative and procedural knowledge, that is, declarative knowledge is not regarded as a springboard for procedural knowledge. To be more specific, the literature does not suggest a hierarchical relationship between these different types of knowledge, that is, declarative knowledge is not regarded only as superficial, reproduction level knowledge and procedural knowledge as higher-level knowledge, which implies a contradiction between the results of the study and the choice of terms. Therefore, it is necessary to alter the choice of terms to the final model of prior knowledge. In the final model of prior knowledge, the terms are replaced with the terms "reproduction" and "production" which describe the difference between the components better (see Figure 8). Furthermore, for teachers using the prior knowledge assessment instrument, these terms might be more informative.

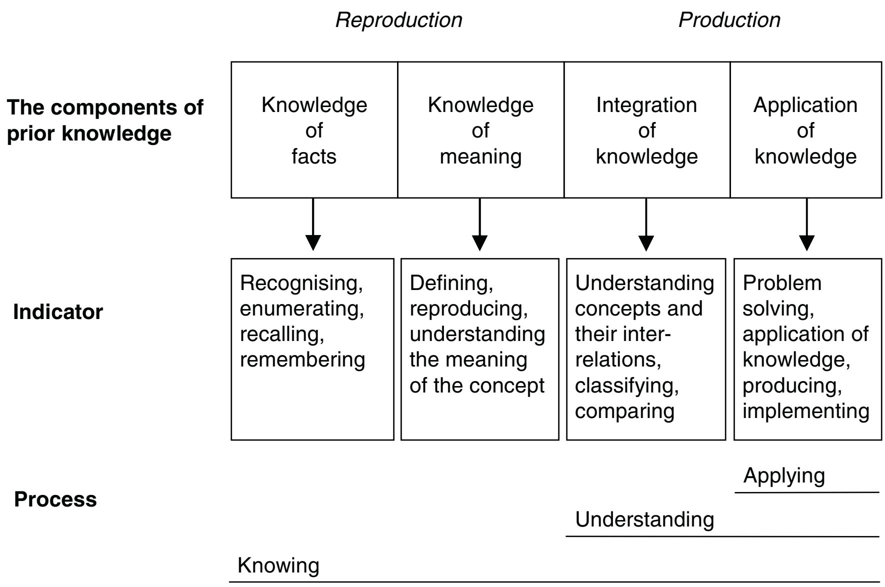


Figure 8. The final model of prior knowledge

6.4 Practical implications

6.4.1 Suggestions concerning the use of the prior knowledge model

Regarding the previous discussion of whether the results should be viewed in light of the contribution of different types of prior knowledge or the assessment measures used or their co-influence, some central issues should be pointed out. The findings reveal that the measures assessing more complex production level knowledge (as defined in this study) which requires a deeper understanding of the content have a better predictive value for student achievement. Although production level knowledge, and the methods used to assess those knowledge components, appears to be the best predictor of student achievement, it does not necessarily mean that the lower levels should not be assessed at all.

I believe that it is advantageous to combine several assessment methods when assessing prior knowledge. Each measure contributes its unique information to the picture as a whole. It provides a more accurate representation of knowledge and thus gives more insight into those knowledge characteristics that may interact with learning. This, in turn, may reduce the constraints of choosing only one assessment method. It is also student-friendly to use different types of tasks, proceeding from easier to more difficult ones. The easier tasks would serve the function of activating relevant knowledge related to the course content (see Dochy et al., 1999b) even if they are not as useful in relation to student achievement.

Another advantage of the prior knowledge model is that it provides an analytical tool for teachers to assess prior knowledge. It helps teachers at grass root level to become aware of what types of methods could be used to assess students' prior knowledge and, most importantly, what type of knowledge is being assessed with different methods.

Measuring different types of prior knowledge is a challenging task. Teachers and professors hold different views of what the core prerequisite knowledge of the course to be taught is and how it could be measured. Operationalising different types of prior knowledge is not easy task and requires a thorough introduction to the model of prior knowledge, as well as to what type of knowledge each component represents. This demands good pedagogical skills on the part of the teacher. However, the interviews of Study III indicated that teachers found the prior knowledge model useful because some of them had never even thought of the relationship between the assessment method and the knowledge being assessed. Some of the teachers commented that it also influenced the way they constructed the final exam. Therefore, the model is not only limited to prior knowledge assessment but to other aspects of assessment as well, and it may help teachers develop a pedagogical awareness of these issues.

It is also evident that assessing students' prior knowledge at the beginning of every course is simply beyond the resources of the teachers. Nor is it always necessary. However, the results of the study imply that it might be more relevant to assess prior knowledge in more advanced courses with clear prerequisites (Study I and Study III). In those courses, the relevance of prior knowledge is more significant. Furthermore, the purpose of prior knowledge assessment should be clarified to the students so that they do not perceive it as a test but as a means of supporting their learning (Study III). The more students become acquainted with the new assessment methods, the more prior knowledge assessment becomes a natural part of the learning process for them.

6.4.2 Implications for instruction

Teaching in higher education should actively aim at helping students reach higher levels of understanding where knowledge is active and functioning; students, however, should not be expected to reach those levels on their own (Biggs, 2003). Academic education involves the increase in knowledge but also the development of thinking skills. The beginning student is not expected to have the same thinking skills as the student at the end of his/her studies. However, it is possible to promote the development of these thinking skills by moving beyond isolated facts towards the integration of knowledge into a whole. This entails, for example, the learning of concepts through studying the interrelations between concepts and their application which promotes deeper understanding and thinking skills. This is possible from the very start of the higher education. The distinction between different levels of understanding is made apparent in the model of prior knowledge, and the results clearly imply that the development of understanding towards integration and application of knowledge provide an important base for future learning. By providing powerful learning environments (De Corte, 1990) where students' prior knowledge and its quality are taken into account in instruction, it is possible to develop students' knowledge base towards deeper understanding. This notion of powerful learning environments is also shared by Bransford, Brown & Corking (1999). They state that paying attention to the prior knowledge and skills the students bring with them helps to create powerful learning environments.

Regarding the power of assessment to steer learning (Biggs, 1999; Brown, Bull & Pendlebury, 1997; Gibbs, 1992), prior knowledge assessment has a potential to shift the focus of learning to the beginning of the learning process and, thus, give students a sign that the teacher cares about their learning process and wants to help them truly understand the content of the course to be studied. Students' comments regarding the prior knowledge test (Study III) were mainly positive because they felt that their learning was taken seriously. This positive perception of the learning environment may have a positive influence on the way students approach their studies (Entwistle & Ramsden, 1983; Parpala, Lindblom-Ylänne, Komulainen, Hirsto & Litmanen, 2009; Vermetten, Lodewijsk & Vermunt, 1999).

Furthermore, it is important to consider prior knowledge assessment in relation to aligned teaching (Biggs 2003), which means that a teacher supports the students' deep approach to learning by aligning teaching and assessment methods with the learning activities stated in the objectives. Assessment of prior knowledge is not something that happens in isolation; it should support the objectives of the teaching-learning process. If prior knowledge assessment is not aligned with, for example, the objectives and teaching methods, negative friction might arise and harm the learning process (see Vermunt & Verloop, 1999).

The results of this study imply that prior-knowledge assessment at the beginning of a course may be an important tool for instructional support. Low prior knowledge was found to be connected with low academic self-beliefs (Study II), the tendency to drop out of the course (Study IV) and lower final grades (all four studies). By assessing prior knowledge, it is possible to identify students who are struggling with their studies. However, both students and teachers can benefit from prior knowledge assessment in multiple ways (Thompson and Zamboanga, 2003). It gives instructors valuable information and the opportunity to refine and adjust their teaching according to students' needs. Students benefit from the assessment because the test can provide a means of self-assessment by helping them become aware of their prior knowledge and it can orient them towards course content by mobilising their pre-existing knowledge (Martens & Dochy, 1997; Wratten & Hodge, 1999). Assessment may also help students find connections between old and new knowledge. However, in order to benefit from prior-knowledge assessment, the students should be provided with feedback on their performance and instructors should be aware of how the assessment results can be used in instructional design. Prior-knowledge assessment results can be used for various purposes:

a) identifying students who are struggling with their studies;
b) finding an appropriate level at which to start the course;
c) providing feedback to students;
d) bridging the gap between instructors' expectations and students' actual knowledge base;
e) grouping students according to their abilities and providing support for students who need it.

Furthermore, the results imply the importance of acknowledging that different types of prior knowledge have different relevance to student achievement and that using multiple assessment methods provides a more thorough representation of students' prior knowledge.

6.1 Future research

Most importantly, future research in this field should help us gain a more profound understanding of the relation between different types of prior knowledge and how they serve as predictors of student achievement. Furthermore, it is equally important to explore how the influence of different types of prior knowledge relates to the assessment methods. In designing studies on the relevance of prior knowledge to learning, it is important to pay particular attention to prior knowledge assessment and its influence on the observed effect of prior knowledge. There is still not enough systematic research addressing this issue and, therefore, particular attention should be given to the assessment of prior knowledge.

It would also be interesting to take the development of the model created in this study a step further, and test its usefulness in teachers' pedagogical courses. It could help us explore teachers' experiences of the model as a practical tool for instructional support as well as their ability to understand the qualitative difference between different types of knowledge and their assessment.

Assessment has an important role in determining what and how students learn. Whereas inappropriate assessment and a heavy workload push students toward surface approaches to learning, the perceptions of good teaching influence students to move toward deep approaches to learning (Lizzio, Wilson & Simons, 2002). Thus, an interesting topic for future research would be to explore the interplay between the assessment of prior knowledge and students' approaches to learning. This would give us a more complete understanding of how the assessment of prior knowledge could act as a part of aligned teaching, which aims to support students' deep approach to learning.

Furthermore, replication of the study with a different sample would enable examination of the generalisability of the findings to other disciplines as well. Testing the model of prior knowledge in soft disciplines would enable us to explore whether the same principles apply. Further research should address these issues.

The present study was not very successful in giving feedback to students about their prior knowledge performance. Future studies should address this issue by improving the feedback function, and exploring how this feedback could be used as a positive way to influence student performance.

And finally, it might be fruitful to connect the present prior knowledge research to conceptual change studies. The term conceptual change is used to characterise the kind of learning required when new information to be learned comes in conflict with a learner's prior knowledge. It might be hypothesised that lower level prior knowledge, which does not form a coherent base for new learning and understanding, might even act as an obstacle for new learning, whereas higher level knowledge might serve as a favourable base for conceptual change as well. This hypothesis could be tested in future research.

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