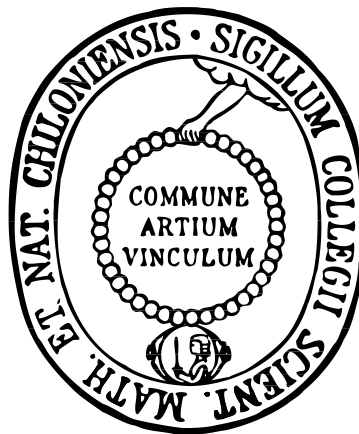


Process Mining Potentials for Technology-Enhanced Learning - Analysis of Computer Usage and Learning Paths Using the Example Geosciences



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Kurzzusammenfassung:

Diese Arbeit handelt von der Übertragung des Process Mining zur automatischen Modell-Generierung auf E-Learning-Prozesse. Hierfür wurde ein Framework für geeignete didaktische Unterstützung von unterschiedlich motivierten und vorgebildeten Studierenden entwickelt, welches in einer Studie untersucht und mit Process Mining unterstützt wurde.

Die Eigenschaften der Studierenden wurden zudem umfassend untersucht. Der Schwerpunkt der Untersuchung waren die Lernvoraussetzungen für das Lernen mit Technologie.

Die vorläufigen Hauptergebnisse sind, dass Process Mining den Erkenntnisprozess von Lehrenden unterstützen kann, um geeignete Maßnahmen zur Verbesserung des Lernprozesses abzuleiten. Weiterhin konnten Studierendencluster identifiziert werden, die die Lernvoraussetzungen für das Lernen mit Technologie in den raumbezogenen Wissenschaften wie Geologie und Geographie aufzeigen. Die Ergebnisse sind als vorläufig zu verstehen und bedürfen der Überprüfung in zusätzlichen, repräsentativeren Studien.

Minimal Abstract:

In this work the method 'Process Mining' which automatically builds process models was applied to technology-enhanced learning processes. A framework was constructed to define applicable didactical

support measured for students who are motivated and skilled to different degrees. With this framework as a basis, a preliminary testing study was conducted using Process Mining.

Additionally the student characteristics were thoroughly analyzed. The analysis focused primarily on the students' preconditions for learning with technology.

The main results are that Process Mining can support instructors who are in charge of improving technology-enhanced learning processes. Another result was the definition of a student typology which supplies a meaningful description of technology-enhanced learning preconditions in geosciences. The results are preliminary due to the small samples and need to be validated in additional, more representative studies.

*I would like to dedicate this thesis to my family, close friends, and
Rafael in particular.*

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Abstract

Within learning scenarios it is crucial to constantly develop innovative strategies in order to improve learning processes. This especially applies to studying content such as geoinformatics for geosciences which represents a topic requiring abstract thinking and is therefore easily perceived as complex.

Process Mining has successfully been applied in different subject areas, e.g. software development, business management and natural sciences. To date Process Mining has not sufficiently been applied to structure complex learning processes in order to facilitate learning success in technology-enhanced learning environments (TELE) and linked to Geoinformation learning. This applies even though the potentials of Process Mining techniques to structure complex processes are already known.

In this work the method *Process Mining* which automatically builds process models was applied to technology-enhanced learning processes. A framework was constructed to define applicable didactical support measured for students who are motivated and skilled to different degrees. With this framework as a basis, a preliminary testing study was conducted using Process Mining.

Additionally the student characteristics were thoroughly analyzed. The analysis focused primarily on the preconditions for learning with technology. The results were the following.

From the geoscience samples evaluated over four semesters a new typology was generated which classifies eight computer literacy types based on empirical data and previous computer literacy and media

usage findings. These new computer literacy types did not correlate with the learning paths analyzed by Process Mining.

The clusters found for the typology can be described consistently and are acceptably separated. Moreover, the results could be used to preliminarily explain student differences in technology-enhanced geoscience learning. A considerable challenge to be addressed according to this study is that instructors are constantly confronted with the high use of entertainment media which affects the available attention in courses. These tend to be increasingly technology-enhanced or more specifically: computer-supported.

The learner support showed a positive effect on the test results of learners who followed the path suited to them according to theoretical assumptions of an ideal learning path. The results show how Process Mining can support the instructor's monitoring of student learning activity.

Further influencing factors of technology-enhanced learning success were the access to motivational elements and intrinsic learning motivation. It was tested whether providing material intended to motivate helped the respective group perform better. The students with access to the motivational elements scored considerably better and the intrinsic motivation of the successful group of learners was higher.

The main results are that Process Mining can support instructors who are in charge of technology-enhanced learning processes: In the study it was found that learners who unintentionally followed the learning path which was theoretically suited best for them scored better than those who did not. Another result was the definition of a student typology which supplies a meaningful description of technology-enhanced learning preconditions in geosciences. These typology led to three general types: Trend or habitual users with low competencies and reserved attitude towards computers with the tendency to remain on this level, high competency users with tendency to remain

on this level and those with high development potential. The results are preliminary due to the small samples and need to be validated in additional, more representative studies.

Zusammenfassung

In raumwissenschaftlichen Lernszenarien, aber auch generell im Bildungswesen, ist es entscheidend, beständig an innovativen Strategien zu arbeiten, um Lernprozesse zu verbessern. Das betrifft insbesondere Lerninhalte, die von hohem Abstraktionsgrad gekennzeichnet sind, wie es für geoinformatische Inhalte charakteristisch ist.

Die Methode des Process Minings ist mittlerweile erfolgreich in verschiedenen Fachgebieten eingesetzt worden. Dazu zählen Bereiche wie Software-Entwicklung, Management und die Naturwissenschaften. Bisher hat jedoch noch keine weitreichende Anwendung auf komplexe Lernprozess-Strukturen stattgefunden, um Lernerfolg am Beispiel des Geoinformations-Lernens gezielt zu fördern, obwohl die Möglichkeit der Strukturierung dieser Prozesse grundsätzlich bekannt ist.

Das übergeordnete Forschungsziel dieser Arbeit ist die Übertragung des Process Mining zur automatischen Modell-Generierung auf E-Learning-Prozesse. Hierfür wurde ein Framework für geeignete didaktische Unterstützung von unterschiedlich motivierten und vorgebildeten Studierenden entwickelt, welches in einer Studie untersucht und mit Process Mining unterstützt wurde.

Die Eigenschaften der Studierenden wurden zudem umfassend untersucht. Der Schwerpunkt der Untersuchung waren die Lernvoraussetzungen für das Lernen mit Technologie. Nachfolgende Ergebnisse wurden erzielt.

Die aus den raumwissenschaftlichen Stichproben von vier Semestern generierte Computerkompetenz-Typologie lieferte acht Typen. Diese

korrelierten jedoch nicht mit den Lernpfaden, die anhand des Process Minings untersucht wurden.

Die Lernunterstützung hatte einen positiven Effekt auf die Lernergebnisse der Lernenden, die einen Pfad wählten, der für sie als geeignet eingestuft wurde. Es wird anhand der Ergebnisse deutlich, wie Lehrende anhand des Process Minings auf Basis didaktischer Prinzipien Lernprozesse der Unterrichteten verbessern können.

Weitere Einflussfaktoren waren der Zugang zu motivationalen Elementen und die vorhandene intrinsische Motivation. Es wurde überprüft, ob die Lernenden mit Zugang zu motivierenden Materialien bessere Ergebnisse erzielten als diejenigen ohne. Die Studierenden mit Zugang zu motivationalen Elementen erzielten bessere Ergebnisse und die intrinsische Motivation der erfolgreicherer Gruppe war höher.

Es war anhand der erhobenen Daten möglich, empirisch und theoretisch begründete Schlüsse zu ziehen und einen Teil der Lernstudienenergebnisse zu erklären. Als eine entscheidende Herausforderung für Lehrende stellte sich heraus, dass der hohe Einsatz von computergestützten Unterhaltungsmedien das Unterrichten, welches zunehmend auf Technologie-Einsatz angewiesen ist, in nicht nur lernförderlicher Weise verändert, sondern auch erschwert, da mehr Ablenkung im Spiel ist.

Zusammengefasst lauten die vorläufigen Hauptergebnisse, dass Process Mining den Erkenntnisprozess von Lehrenden unterstützen kann, um geeignete Maßnahmen abzuleiten: Im vorliegenden Fall zeigte sich, dass Studierende, die sich von selbst gemäß der Vorhersage ihres idealen Lernpfads verhielten bessere Ergebnisse erzielten als die restlichen Lerner. Weiterhin konnten Studierendencluster identifiziert werden, die die Lernvoraussetzungen für das Lernen mit Technologie in den raumbezogenen Wissenschaften wie Geologie und Geographie aussagekräftig beschreiben. Aus den Typologien ließen sich drei Gruppen ableiten: Trend- oder Gewohnheitsnutzer, mit geringen Fähigkeiten

und einer ablehnenden Haltung gegenüber Computern mit der Neigung, dieses Level zu halten, kompetente Nutzer, mit der Tendenz dieses Level zu halten und diejenigen mit hohem Entwicklungspotential. Die Ergebnisse sind als vorläufig zu verstehen und bedürfen der Überprüfung in zusätzlichen, repräsentativeren Studien.

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Chapter 1

Introduction

1.1 Motivation

Within learning scenarios it is decisive to constantly develop new strategies in order to improve learning processes. This is true especially for Geoinformatics as a growing field of interest considering that the amount of data and new technology with spatial component increases. 80% of all information are assumed to dispose of a geospatial component (BKG n.y.).

The ability of handling spatial data in a qualified manner can have a considerable influence on quality and spatial detail provided by the respective data sets. To reach these quality goals technology-enhanced education can play a major role.

This study aims at constructing an innovative approach tackling the challenge of adapting a technology-enhanced lesson to motivational and prior knowledge preconditions by means of Process Mining in a preliminary study sample.

The process analysis method of Process Mining is mainly used to build process models. This can also take place in technology-enhanced learning environments (TELE). The goal is to describe the behaviour contained in the traces produced by information systems usage (DE MEDEIROS & WEIJTERS 2005). The method has to date successfully been implemented in software development (RUBIN ET AL. 2007), business management (VAN DER AALST 2005) and natural sciences (BOSE & VAN DER AALST 2011, MANS ET AL. 2012). According to previous research, it has exhibited considerable potential to improve learning in TELE. Still, this

field has not sufficiently been investigated with empirical methods to ensure its applicability in didactical settings, i.e. especially not in geoinformatics learning. To know which computer literacy types are mainly represented in the courses which university professors teach, offers a wide range of possibilities to improve didactical settings for technology-enhanced learning. Process paths generated by computer supported learning can additionally provide useful information to explain the learning behaviour in question. Until now no work has been conducted yet which combines the analysis of computer literacy types with Process Mining paths. This work tackles this approach and a set of characterizations has been found at last, whereas the focus here lies on geoinformation science.

The following research questions have been defined.

1.2 Research Questions

This research project is concerned with the empirical analysis of a Process Mining application in the geoinformation context with special focus on the requirements of geoinformation didactics. Moreover, the methodical setup of this study provides an approach to systematically monitor learning behaviour in TELE.

To summarize, this work aims at developing a studying support approach in a geoscience lesson which promises to improve the studying success in geoscience learning settings. This effect is assumed when the preconditions of geoscience students for learning with computer support can be considered in a learning environment which adapts to individual learning processes.

The resulting research questions are now introduced.

The first two research questions generally treat technology-enhanced learning and its preconditions. They aim at empirically identifying characteristics of technology-enhanced learning.

Research Question 1: Technology-enhanced learning: How can learning in technology-enhanced learning environments (TELE) be characterized?

This requires a general answer which can be retrieved from the current state-of-the-art in the field.

The rather specific approach tackles the question *how the TELE can be characterized in the case at hand.*

Hypotheses:

- *Learning material employment and interest show considerable differences.*
→ H 1.1
- *The motivational elements: Testimonials of professionals and explanations of the lesson's value-added have a positive effect on the lesson test scores.*
→ H 1.2

For the following two hypotheses, the variables in brackets were grouped according to the conceptual framework introduced in [section 3.1](#).

- *How does the learner respond to the TELE (learner response to the TELE: motivational elements response, usability experience, mood)? correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load) → H 1.3*
- *How does the learner respond to learning with ICT- whereas ICT stands for information and communication technology (learner response to learning with ICT: basic and advanced computer self-efficacy, computer attitude)? correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load)→ H 1.4*

To answer the hypotheses H 1.1 to H 1.4, statistical tests are conducted on questionnaires and lesson test results. The instruments are explained in the method section.

The second research question combined the Process Mining approach with the design of a computer literacy typology from the geoscience sample.

Research Question 2: Computer literacy and learning processes: Can a measurable correlation between the identified learning paths and computer literacy types be detected?

Hypotheses:

- *A computer literacy typology generated from the student data (four semesters geoinformation courses in geology and geography) can be utilized to enhance previous findings of computer usage and technology-enhanced learning. → H 2.1*
- *Measurable correlations between the identified learning paths and the computer literacy types can be detected. → H 2.2*

To create a computer literacy typology as solicited in H 2.1, a brief theoretical analysis of computer and media literacy research is conducted and the student data is evaluated by statistical methods (explained in the methods section) which are suited for creating a typology. The results are related to the Process Mining results by using statistical methods as well (H 2.2).

The third research question tests Process Mining as a methodical instrument regarding its benefits for learning and learning support processes. The Process Mining approach is to test hypotheses which are derived from current learning theories which consider relevant technology-enhanced learning factors.

Research Question 3: Does Process Mining qualify as methodical instrument to test hypotheses derived from current learning theories?

Hypotheses:

- *When learner groups choose elements according to their interest and previous knowledge level derived from current learning theories their test results are more favourable compared to those of the ones that choose a different path. → H 3.1*
- *The use of Process Mining can generate learning support measures which lead to the improvement of learning performance. → H 3.2*

To answer the hypothesis H 3.1, a theory-based framework with four learning support categories for a specific kind of technology-enhanced geoinformatics lesson (database normalization) will be defined. Then an experiment is conducted which is supposed to show differences between those learners that follow a path which is assumed to be favourable and those that choose a different path.

To answer the hypothesis H 3.2 the learning paths represented by Process Mining models are analyzed regarding characteristics which distinguish the successful learners (high lesson test scores) from the less successful learners (low lesson test scores).

Research Design

This work is organized as follows whereas [Figure 1.1](#) gives a graphical overview of the research design:

The theoretical part of this work deals with the basic concepts of the field of investigation. The chapter starts with the explanation of the term *learning environment* which involves a general definition of learning as well. It continues with an introduction into fundamental learning theories which are relevant for technology-enhanced learning.

From the learning theories two particular theoretical concepts are explained in detail, i. e. cognitive load theory and motivational theory which are the major components of the study.

The next section concerning *learning styles*, *learning strategies*, and *studying techniques* lays the theoretical foundations for the studies:

- *evaluation of learning material interest and employment* and
- *general computer usage survey*.

The interest and use of learning materials, especially computers, is assumed to depend on the way learning is habitually exercised by the individual. Similarly to the two studies mentioned, the study *Computer Literacy Cluster Analysis* in section 3.4.3 relates to the section 2.6 (*Computer Literacy and Media Usage*) and the *Technology-Enhanced Learning study* in section 3.4.4 relates to the section 2.8 (*Process Mining for learning processes*).

The study is conducted in a particular discipline, i. e., geoscience and more specifically: geoinformatics. The geoinformatics lesson topic *database normalization* is explained in the methods section where the reason for its special importance is presented as well.

The methods chapter involves two general sections, i. e. the overall conceptual approach and the short description of the data collection procedure. The last section of the methods chapter *learning environment set-up for learning process improvement* only is relevant for the technology-enhanced learning study.

The introduction of the next chapter, i. e. *statistical methods*, about general quality measures of statistical tests refers to all studies. Then four sections follow which introduce the operationalization of the methodical design.

The *results* chapter summarizes the findings of the conducted studies. The *discussion* is carried out in a separate chapter and the *conclusions* chapter represents the final chapter of this work.

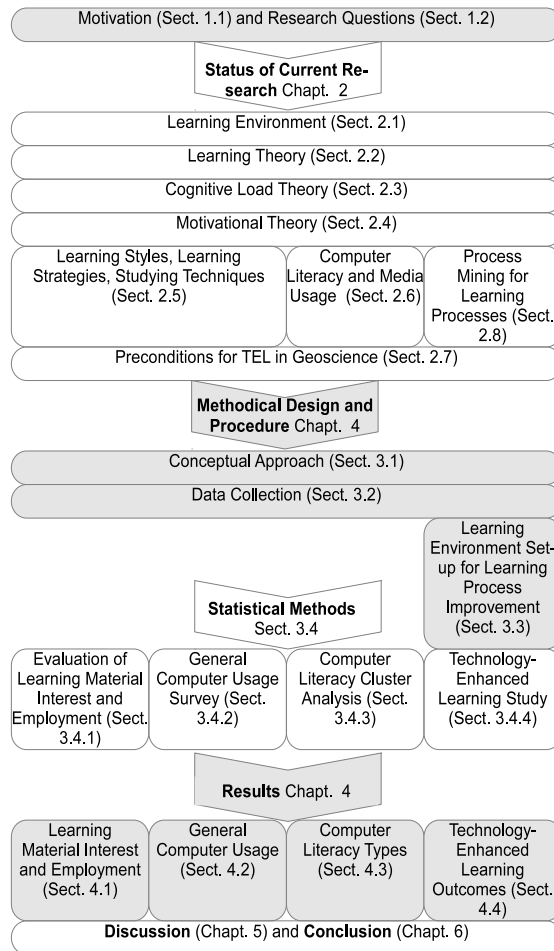


Figure 1.1: Research Design (author's illustration)

Chapter 2

Status of current research

The need to support lifelong education has not just been articulated recently. Technical support, e. g. by technology-enhanced learning environments (TELE) and appropriate didactical methods provide considerable means in this respect (PALMER 2003). GROSCH & GIDION 2011 describe the field of online media as highly dynamic and have identified the necessity to encourage ongoing research to improve technology-enhanced learning support. This support requires the consideration of the general factors which influence technology-enhanced learning.

The term *technology-enhanced learning* involves the use of Information and Communications Technology (ICT) for instructional processes. It is carried out in (technology-enhanced) learning environments which are explained in detail in the first section of this chapter (section 2.1).

A learning environment supports technology-enhanced learning by a variety of content representation forms which are defined and distinguished in section 2.1. A TELE can be more precisely called an Adaptive Educational Hypermedia System (p. 12) as it is capable of adapting these representation to individual learner needs via learner models (p. 13).

How learning and teaching processes are analyzed and supported, is investigated on by researchers constructing and testing different kinds of learning theories (section 2.3). One of these theories, i. e. *cognitivism*, focuses on mental structures leading to a specific learning outcome. It is of special interest for individual learning of clearly defined learning content, unlike e.g. *constructivism*. This theory

focuses on individual use of resources to facilitate learning (cognitive constructivism) or emphasizes the role of learning together with other individuals (social constructivism) as summarized by WINDSCHITL 2002. These assumptions emphasize the discovery characteristic of learning which usually involves less clearly defined learning content.

The cognitivist theoretical approach referred to in this study is the *cognitive load theory* (section 2.3). The basic assumption of cognitive load theory is that working memory, which stores the information humans are conscious of (SWELLER 2002), disposes of limited capacity when dealing with novel information. This leads to numerous principles to follow when constructing and managing TELE (p. 17).

A studying success factor of relevance is the concept of *motivation* (section 2.4). Motivation can be influenced indirectly, especially by applying useful studying techniques which in turn can lead to a certain set of learning strategies or even learning styles. These factors are explained in section 2.5.

Technology-enhanced learning involves the learners' computer literacy as additional studying success factor. The level of computer literacy, i. e. the degree to which computer users possess a certain amount of computer experience and skills combined with a favourable computer attitude, determines to which extent the computer represents an obstacle to studying success (ROZELL & III 2000). These factors are treated in section 2.6

In section 2.7 these general theoretical foundations are related to the particular discipline which was empirically investigated regarding applicable support measures, i. e. geoscience and more specifically: geoinformatics.

In section 2.8 current approaches dealing with Process Mining in general and with its application to technology-enhanced learning are investigated and evaluated regarding existing research gaps of interest for this study.

2.1 Learning Environment

Learning is defined as the process of acquiring new, modifying, or reinforcing existing knowledge, behaviours, skills, values, or preferences, and is likely to involve synthesizing different kinds of information (ISSING 2011, p.20). The learner,

consequently, is the individual who carries out this activity of learning.

ISSING 2011 adds that what we already know is the basis for our learning whereas what we learn is contextual and not compulsory, i. e. learning content depends on the perspective taken and not on a kind of truth behind it.

Learning is viewed as a process, rather than the collection of factual and procedural knowledge (ibid.). Factual knowledge is the outcome of concept learning. The basis of concept learning, i. e. concepts, possess a meaning, and a structure (ECKES 1991). Procedural learning is carried out by exercises and revision accompanied by step by step eliminating mistakes (SEEL 2003).

The changes produced by learning in the organism are relatively permanent (**SCHACTER & WEGNER 2011**, p. 264). That means that changes caused by maturing processes and temporary changes due to fatigue or illness are not defined as learning (**ISSING 2011**, p. 20).

Now the more comprehensive concept of the *learning environment* is treated.

A learning environment corresponds to the instructional setting, i. e. the goals, media, materials, methods, instructors, and learners, including the learning processes and outcomes (REINMANN-ROTHMEIER 2001).

As a part of the learning environment, learning materials can generally be defined as follows:

The learning material consists of that part of the learning environment which includes information, tasks, or prompts which are presented to the learner via different media (GRÄSEL 2006, p. 325).

Technology-enhanced learning entails the use of Information and Communications Technology (ICT) for instructional processes. This describes the concept in general. For a complete definition, the term of technology-enhanced learning as well as related concepts need to be clarified.

REY 2009 defines the concept as teaching and learning by use of different electronic media (p. 15). **SHUTE 1994** and **SEEL 2003** consider the different states, processes and outcomes in their concept of learning. Therefore this definition has been chosen:

Technology-enhanced learning is the term for teaching and learning states, processes and outcomes of individuals and groups supported by electronic media.

The different electronic media can be summarized as *multimedia*. To clarify the term, the following three aspects of multimedia need to be distinguished (WEIDENMANN 2002):

1. technical medium,
2. codification/ mode,
3. and modality.

To distinguish between the relevant terms SCHAUMBURG & ISSING 2004 recommend that the definition of multimedia is classified into these three representation categories:

1. multimedial,
2. multicoded,
3. and multimodal representation of content.

One definition of the term *media*, which is referred to in this study is the following: *Media are resources, technical devices, or configurations employed to communicate or save information. Examples are books, audio players, or computers.* (WEIDENMANN 2011, p. 75)

The different media tend to be integrated into a unique device, e.g. mobile phones or computers. This development is likely to increase in the future. As computers combine the different media easily they deserve special consideration in this work:

From the Information Technology (IT) view technology-enhanced learning is a network-based computer application. The requirements generated by the learners and the different media employed have to be met by the computer and network architecture with priority on the technical functions. The term architecture to this effect corresponds to the structure and functionality of a computer and/ or network system (WUTTKE 2011, p. 48.).

The learning material dimension of a computer is concerned when its function and role for learning are focused. The computer remains a medium for reaching

computer-supported goals but if the way a computer works and affects the user is of equal interest as the content it provides, the learning material characteristic is obvious. [MCATEER ET AL. 1997](#) regards computer-mediated communication as a *learning resource* which is his term for what is referred to in this study as *learning material*.

For geographic content especially the visual aspect is of interest. Therefore media such as maps or satellite images in the context of learning qualify as learning material made accessible by geographic media.

The concepts *multicodal representation* and *multimodal representation* are introduced to distinguish between the different kinds of learning materials treated in the study.

Multicodal representation of learning content is another category when discussing the different dimensions of how learning can be supported by electronic media.

The codification determines the way the learning content is represented ([WEIDENMANN 2002](#)). *The same information can be represented in different ways, e. g. graphics, animations, or texts. This kind of codification needs to be distinguished from the mental representations within human minds* ([REY 2009](#), p. 19).

The next category of representation is as well to be distinguished from the mental representations within human minds.

Multimodal representation of learning content addresses different sensory channels. The term sensory channel corresponds to the sensory organs through which technology-enhanced learning content is perceived, e. g. auditory or visual ([WEIDENMANN 2002](#)).

The following section goes into detail on the adaptive form of learning environments, i. e. Adaptive Educational Hypermedia Systems.

Adaptive Educational Hypermedia Systems (AEHS)

In the context of technology-enhanced learning, the term of Adaptive Educational Hypermedia Systems, which correspond to the adaptive version of learning environments, is of special importance.

Generally speaking, to *adapt* refers to the procedure of adjusting from one situation or condition to another, whereas software programmes as well as persons

are able to adapt (SHUTE & ZAPATA-RIVERA 2007, p. 279).

The term *hypermedia* is a composition of *hypertext* and *multimedia* (SHUTE & ZAPATA-RIVERA 2007, p.286). From these two concepts multimedia has previously been explained. *Hypertext*, however, refers to a networked structure of material. Examples of hypertext applications are electronic encyclopedias or the structure of the Internet (RIEHM & WINGERT 1995).

The following definition summarizes the relevant characteristics of AEHS:

Adaptive Educational Hypermedia Systems are TELE that adjust and personalize studying content, pedagogical models, and interactions between learners and the learning environment (STOYANOV & KIRCHNER 2004).

Studying content, pedagogical models, and interactions in these systems can be formalized by the activity of learner modelling. As this aspect is of considerable importance, the next subsection is dedicated to this topic.

Learner Model

ZUKERMAN & ALBRECHT 2001 describe learner modelling as the procedure of inferring unobservable information about a learner from observable information such actions or utterances. SHUTE & ZAPATA-RIVERA 2007 refer to a learner model as a representation of learners which is managed by AEHS. This kind of model provides the basis for personalization and can consist of both, cognitive and metacognitive information. This information according to KOBASA 1991 includes assumptions about knowledge, misconceptions, goals, plans, preferences, tasks, and abilities. Learner models contain common characteristics of learners regarded as relevant, which can be associated with specific user subgroups of the application system, i.e. referred to as stereotypes. They classify users as constituents of one or more of these subgroups and provide the typical characteristics to the individual learner model. Learner models track learner behaviour (ibid.).

The following sections specify a selection of relevant learning theory aspects which help understand how technology-enhanced learning support can adjust to learning models.

2.2 Learning Theory

Three theories which structure a larger set of educational sub-theories are generally referred to in literature (SCHAUMBURG & ISSING 2004, MEIER 2006): behaviourism, cognitivism, and constructivism.

The basic assumption of the first and oldest of the three relevant learning theories is that learning is an observable change of behaviour as reaction to environmental stimuli. Therefore the organism experiences a certain behaviour as successful. The consequence is that the successful behaviour is preferred (ARNOLD 2005, p. 2).

The behaviouristic approach does not consider metacognitive learning processes which are relevant in the learning process (ARNOLD 2005, p. 2, f.).

Metacognitive learning processes are supposed to improve the reflection of the learner's own thoughts. They additionally include the ability to monitor task handling and to organize learning and thinking processes effectively (SEEL 2003).

Even though this approach does not take metacognition into account and therefore might seem deprecated (REY 2009, p. 32), applications in practice, e. g. vocabulary learning programmes, are still based on behaviouristic principles. The advantages, e. g. adjusting a lesson to one's own speed by use (NIEGEMANN 2008) are still of interest. Adjusting to the learner's speed is carried out by complexity reduction which results from the explained assumptions of the behaviouristic approach.

The next theory takes the processes between stimulus and response into account. In cognitivism, the focus lies on mental structures leading to a specific learning outcome.

The cognitivist theory conceptualizes learning as information processing. This includes processes of perception, thought, memory, problem solving, speech, and speech comprehension (ARNOLD 2005, p. 3).

The theory is of special interest in current educational research discussion (REY 2009, p. 33). The cognitive load theory (section 2.3, p. 16) is an example of a common approach based on cognitivism (ibid.).

The characteristics of learning suggest a number of difficulties when trying to interpret learning outcomes. The more the constructive character of learning is

assumed, the more these difficulties increase. If knowledge is rather *constructed* than *acquired* the overall consistent measurement of performance is not possible. This challenge especially applies to the theory of constructivism. This theory compared to the other two considers social, motivational, and emotional aspects.

LOYENS 2007 (p. 352) perceives learners in the constructive sense as responsible and active agents regarding their knowledge acquisition processes.

The approach is defined differently in educational research. The two main approaches are social and cognitive constructivism (PALINCSAR 1998, PHILLIPS 1997). Cognitive constructivism focuses on individual use of resources to facilitate learning. In contrast, social constructivism emphasizes the role of learning together with other individuals (WINDSCHITL 2002). The benefits of the explained theories for current TELE research and practice can be summarized and consolidated (WOOLFOLK 2011, p. 443):

1. Learners need to recognize the relevance of the learning content (constructivism),
2. learning content needs to be processed and kept in mind (cognitivism) and
3. skills need to be applied and improved by practice (behaviourism).

Constructivism vs. cognitivism

The empirical evidence of the constructivistic approach has been criticized. Complex learning environments tend to overburden the learner in contrast to guided learning as studies have shown (KIRSCHNER ET AL. 2006, MAYER 2004).

On the one hand this observation is often contradicted by promoters of constructivism. The cited studies criticizing constructivism rather concentrate on cognitive effects. In contrast, the cognitivism theory, which is representing this contradicting position, is criticized because social, motivational, and emotional aspects are not considered sufficiently (REY 2009, p. 33, LOYENS & GIJBELS 2008). On the other hand favourable learning performance is not guaranteed in complex learning environments, i. e. the constructivistic option, when compared to the guided alternative, i. e. the cognitivistic option (e. g. WINBERG & HEDMAN 2008).

The cognitive approach has been chosen as theoretical basis in this work because cognitive outcomes are assumed to be represented in a more reliable manner by Process Mining methods than constructivist outcomes. Moreover, the cognitive load theory as a state-of-the art representative of cognitivism has been chosen as additional theoretical basis to explain crucial cognitive effects in a technology-enhanced learning environment. Cognitive load theory is the topic of the next section.

2.3 Cognitive Load Theory

When instruction fails, we must randomly organize information and test the combinations for effectiveness. This is possible with a limited number of elements only. This corresponds to the cognitive load assumption of the limited working memory when dealing with novel information whereas familiar, organized information stored in long-term memory, can in contrast reduce the need for working memory. Consequently instruction can considerably influence the processing of novel information (SWELLER 2010).

It becomes evident that the learning setting organization can profit from cognitive load principles (ibid.). These principles can support learning processes by providing the appropriate amount of control to the learner. The learners' ability to exercise control or carry out discovery are determining factors of an appropriate learning setting, which ideally reduces cognitive overload.

As KIRSCHNER ET AL. 2006, MAYER 2004 and DRON 2007 clearly identify the need for complexity reduction in TELE, this topic qualifies as an educational research topic of interest. Section 2.8 (p. 36) introduces the theoretical foundation of the main field of investigation in this study, i. e. Process Mining. This approach promises to strongly support the goal of complexity reduction.

The need for control in TELE concerns specified kinds of learning processes: Processes which can be considered in its main characteristics without information loss. This abstraction requires a type of process which is not individualized to define a representative process type (HOLZHÜTER ET AL. 2010). These processes exhibit considerable potential for improvement. If paths are effective for similar

learners, this information helps to recommend the respective path for new learners with similar preferences (HOLZHÜTER & FROSCH-WILKE 2012).

Cognitive load theory has emerged to a widely accepted cognitivism-related approach among technology-enhanced learning designers (THOMPSON & MCGILL 2008, GERJETS ET AL. 2009). It is based on the following assumptions and concepts.

1. One of the core assumption is that working memory, which stores the information humans are conscious of (SWELLER 2002), disposes of highly limited capacity when dealing with novel information.
2. The next assumption is that the so-called long-term memory in contrast disposes of a nearly unlimited capacity which stores cognitive schemas (ibid.).
3. These schemas' function is to organize the incoming information for storage in long-term memory. They vary in complexity and automation (SWELLER 2010).

Cognitive load consists of three different types which are explained in detail below (ibid.):

- intrinsic cognitive load, determined by these two factors:
 - the interaction between the elements learned/ to be learned
 - and the previous knowledge of the learner.
- germane cognitive load.
- and extraneous cognitive load,

Germane cognitive load is related to the learning process. Cognitive load theory aims at reducing extraneous cognitive load and at increasing germane cognitive load (SWELLER 2010).

Germane cognitive load is the result of effortful learning resulting in schema construction and their automation. (SWELLER 2010. p 27).

Extraneous cognitive load is the result of inappropriate instructional designs which ignore the limits of working memory (SWELLER 2010 p. 26).

Due to one single cognitive resource which processes the extraneous cognitive load, the resources available to process intrinsic and germane load are reduced. That means, if intrinsic and/or germane load increase (i. e. through difficult problems), it is recommendable to reduce extraneous load in learning materials (GINNS 2006).

Table 2.1 (p. 21) shows effects on extraneous cognitive load which have been empirically found.

The worked example effect (COOPER & SWELLER 1987) has been discovered when comparing studying outcomes of learners who were provided a working example to outcomes of learners without. The learners in the cited study profited considerably from the worked example. The demands on working memory for the search is high and could be eliminated by the working example (SWELLER 2010. p 26).

The split-attention effect (e. g. SWELLER ET AL. 1990) needs to be considered because the mental integration of separate sources of information imposes heavy extraneous cognitive load.

The modality effect (e. g. TINDALL-FORD ET AL. 1997) occurs where only one modality e. g. the visual representation of information requires to split attention. Extraneous cognitive load can be reduced by changing one modality, e. g. to an auditory representation.

The redundancy effect (CHANDLER & SWELLER 1991) corresponds to settings where multiple sources of information exist whereas one source is sufficient to understand the topic. In this case redundant information needs to be eliminated.

The expertise reversal effect (KALYUGA ET AL. 2003) indicates that novice and advanced learners profit differently from instructional support.

SWELLER 1994 classifies vocabulary learning as an activity with little intrinsic cognitive load. That is, because the words can be studied as separate pairs. An increase of intrinsic cognitive load is the construction of syntactically and semantically correct sentences as analogy to transforming mathematical equations.

Figure 2.1 (p. 20) shows a process diagram which indicates the cases in which applying the principles of cognitive load theory is recommended. SWELLER 1994 states that the modification of learning material is useful if a high intrinsic cognitive load has been identified. In contrast to the intrinsic form of cognitive load, extraneous cognitive load is not directly linked to the process of learning itself.

Figure 2.1 (TUOVINEN 2000) presents the following heuristic:

- If the learning content is rather difficult and not enough prior knowledge exists, then cognitive load principles need to be applied. These especially involve considering the presented effects to reduce extraneous cognitive load. Generally, well tested principles which have been developed on the basis of the cognitive load assumptions (see p. 17) are applicable.
- If prior knowledge is high but the instruction format poses on extraneous cognitive load, e.g. by not considering the effects shown in Table 2.1, then cognitive load principles need to be applied with focus on material modification.
- If students have difficulty in applying the content to multiple context, the variability effect principles need to be applied. These principles involve clustering problems according to certain categories instead of randomly sequencing these problems (PAAS ET AL. 2010, p. 349).

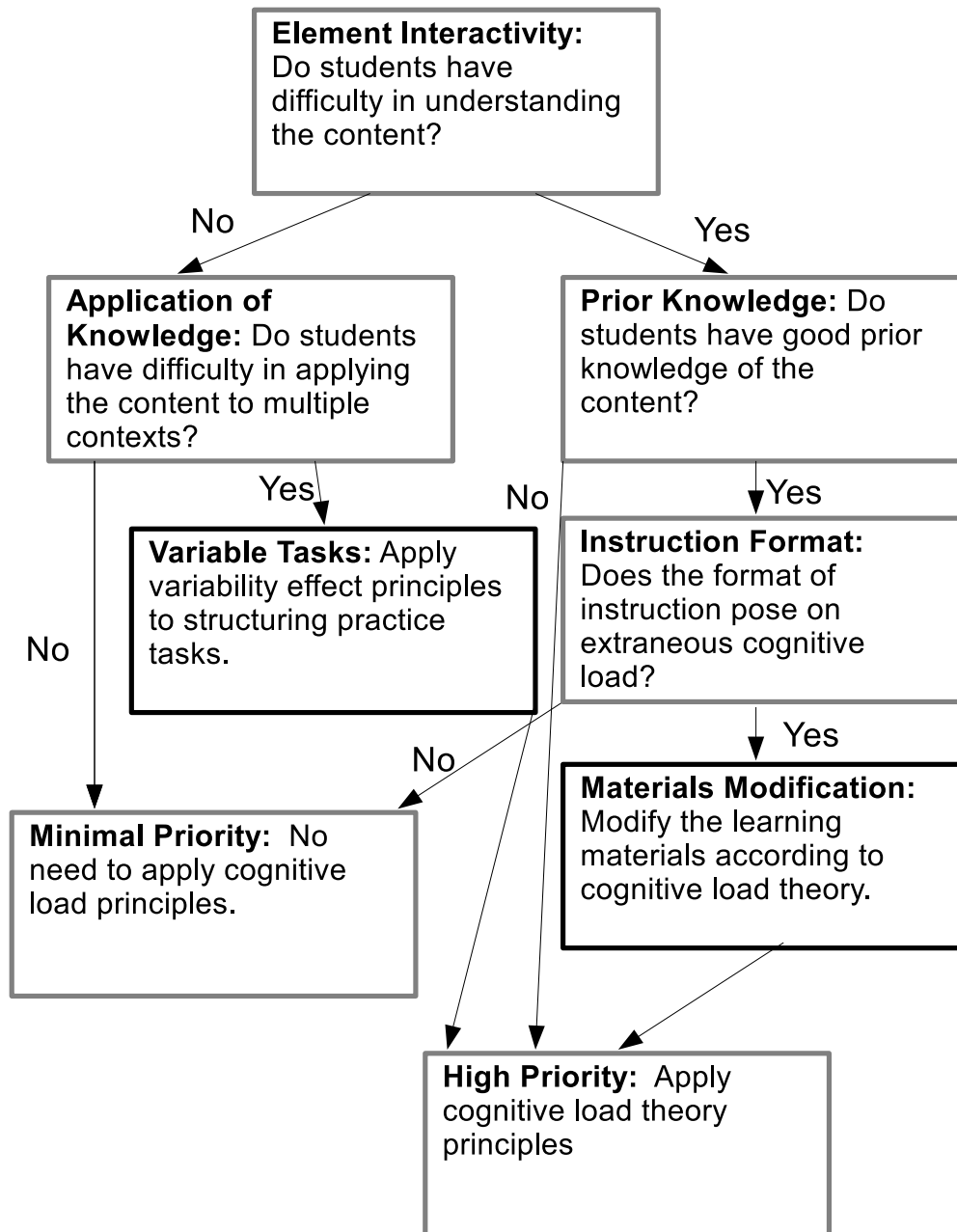


Figure 2.1: Process diagram: How to apply cognitive load principles? (TUOVINEN 2000, p. 239)

Table 2.1: Summary of discovered cognitive load effects applied to TELE (by SWELLER 2010, pp. 26)

EFFECT	DESCRIPTION	EXTRANEOUS COGNITIVE LOAD
Worked Example effect (e.g. COOPER & SWELLER 1987)	Instead of having to solve a problem a worked example is provided.	Focuses attention on problem states and solution steps.
Split-Attention effect (e.g. SWELLER ET AL. 1990)	Multiple sources of visual information, e.g. a geometric diagram and its associated statements must be mentally integrated.	Integrating these multiple sources in the presentation reduces extraneous cognitive load.
Modality effect (e.g. TINDALL-FORD ET AL. 1997)	Similar to previous effect whereas the integration into a single element is not useful.	Presenting verbal material by spoken text reduces extraneous cognitive load by using the visual and the auditory processor of working memory.
Redundancy effect (e.g. CHANDLER & SWELLER 1991)	Multiple sources of information exist whereas a one source is sufficient to allow understanding and learning.	Extraneous cognitive load is reduced by eliminating redundant information.
Expertise reversal effect (e.g. KALYUGA ET AL. 2003)	Formerly explained procedures first lose their advantage when learner expertise increases.	Present diagrams alone as well as statements whereas associated with previously acquired cognitive structures.

2.4 Motivational Theory

Motivational approaches to improve technology-enhanced learning activities have strongly been investigated (KELLER & KOPP 1987).

Motivation can be described as condition of cognitive and emotional arousal leading to conscious choice to take action and initiate a phase of continued intellectual and/ or physical effort, e. g. to achieve a determined goal (BURDEN 1997). It has also been found that enabling students to socially experience relatedness, feel autonomous, and receive competence feedback are primary motivating factors (DECI ET AL. 2001).

Motivation can be intrinsic or extrinsic. The first category, intrinsic motivation, can be described as the tendency to choose those challenges which correspond to personal interests and abilities (DECI & RYAN 1985, DECI & RYAN 2002, REEVE 1996). The second category, extrinsic motivation, is the driver when our interest is not concerned with characteristics of the task itself but rather with the advantages of carrying out the task (WOOLFOLK 2011, p. 452).

Comparing these two types, intrinsic motivation facilitates learning outcomes which tend to last longer (KRUSE 1997). Nevertheless both types of motivation are of importance for studying success (THARENOU 2001).

One of the core presumptions according to HECKHAUSEN & HECKHAUSEN 2008 is: Motivation is influenced by the value of the task for the learner as well as the perceived probability to achieve his or her learning goals. If one factor is not sufficient a learner lacks motivation to perform successfully.

These perspectives suggest that only indirect measures can have an effect on the learner's motivation. Besides preconditions such as a favourable culture of learning (HOCHHOLDINGER ET AL. 2008) or appropriate didactical settings, motivation plays a decisive role for the success of technology-enhanced learning (HOCHHOLDINGER & SCHAPER 2008, p. 17). However, when evaluating the available products, this crucial role does not yet seem sufficiently considered (ibid., WELSH ET AL. 2003).

FRICKE 1991 found that computer usage increases learning motivation of students, reduces studying time up to 30% and improves studying quality. Regard-

ing the motivational effect [WEIDENMANN 2002](#) (p. 61) more precisely stated that real-world situations can be presented to enable different perspectives on studying content. Student interest, flexible thinking, and application knowledge can be increased this way. [KULIK & KULIK 1991](#) found in a meta-analysis that students mostly aim at improving knowledge skills when working with computers and are therefore likely to develop higher studying motivation which usually leads to favourable studying success.

[SUN ET AL. 2008](#) found that learner computer anxiety, the instructor's attitude towards e-learning, e-learning course flexibility, perceived usefulness, perceived ease of use, and diversity in assessments influence the learner's perceived satisfaction. It is assumed that motivation is strongly influenced at least by a set of these factors.

Motivational aspects need to be considered when developing TELE. Nevertheless, it is important to consider the possibilities which learners have to increase their studying motivation and learning success.

Factors which can directly be influenced by the learner when given the opportunity are studying techniques. These can lead to a certain set of learning strategies or even learning styles in the long run. These factors are explained in the following section.

2.5 Learning Styles, Learning Strategies, and Studying Techniques

The topic of learning styles is briefly mentioned for the sake of completeness but is linked rather indirectly to the field of investigation. In contrast, learning strategies and studying techniques have a stronger connection to the field of investigation because they determine the use of learning material which is of special interest in this study.

[GASSER 2005](#) (p. 162) concludes from his findings that the concept of learning styles summarized roughly a set of learning habits, thinking routines and depth of understanding. Moreover, he states that these components can support a didactical common sense. Nevertheless empirical evidence has not yet been found.

A comprehensive discussion of this topic has been conducted by **COFFIELD ET AL. 2004**. They have compared the different approaches regarding learning styles whereas especially the disadvantages of the general concept of learning styles (which is very categorical regarding the learner characteristics) are presented.

GASSER 2005 states that, as a learner, it is useful to know personal learning and thinking habits or preferences especially in examination or stress situations. However, it is of special importance to improve neglected thinking and problem solving behaviour. This rather involves exercising learning strategies (**MANDL & FRIEDRICH 2006**) and studying techniques (**SCHUSTER & DUMPERT 2007**) than primarily reflecting learning styles.

MANDL & FRIEDRICH 2006 (p. 1) define learning strategies as *behaviours and attitudes which activate learners to influence and control their motivation and the process of knowledge acquisition* (author's translation). **DERRY 1989** (as cited by **WOOLFOLK 2011**) characterizes these strategies as a *comprehensive plan*. Learning techniques in contrast are defined as *the particular means which are necessary for the completion of this plan* (ibid.).

To improve studying techniques, decelerated studying situations are helpful. These less stressful settings compared to exams or tests during university lectures enable students to apply not yet fully mastered skills to variable contents and situations (**SCHUSTER & DUMPERT 2007**).

The recent trend that social media encourages multi-tasking while learning (**ROSEN ET AL. 2013**) calls for an additional set of strategies. **ROSEN ET AL. 2013** show that students tend to overestimate their capacity for multi-tasking. They often do not realize that it is not the crucial moment when information is being recalled. An unsuccessful recall of information does not seem to be of relevance but instead the moment where it had to be encoded matters.

This field of investigation is linked to the concept of media usage and computer literacy which is presented in the next section. Media and computer use require a set of strategies to achieve a certain literacy. Even though the strategies are not evaluated in this study, their importance for technology-enhanced learning needs to be considered.

2.6 Computer Literacy and Media Usage

The level of the learners' computer literacy determines to which extent the computer represents an obstacle to studying success (ROZELL & III 2000). According to the model in ROZELL & III 2000 computer self-efficacy is linked to computer related performance. A direct relation is assumed between computer self-efficacy and effort, as well as effort and the initial computer related performance.

In terms of section 2.1 where learning environments and their components were introduced, a computer has the following characteristics:

A computer is a medium employed to communicate or save information (WEIDENMANN 2011). Additionally, a computer represents a resource which can be characterized as learning material. The way a computer works and affects the user can be a focus of learning as well (MCATEER ET AL. 1997).

A large body of research has been dedicated to the examination of computer usage and determining factors. The access of nearly all students to computer and media technology is assumed. The Internet is nearly ubiquitous with tendency to rise among potential users of ages between 10 and 65 and thereby especially among the younger generation and economically active persons according to statistical evidence (DESTATIS 2014, p. 202, ff.).

The ubiquitous access to media technology - highly facilitated by the Internet - results in a high expectation level regarding media supply and standards which universities provide. This development as well entails an intensified use. This use tends to be more sophisticated than the use exercised inside the university apparatus (GROSCH & GIDION 2011, p. 4). Generally it can be stated that media usage, especially the one of computers and online media has become routine in higher education whereas research findings indicate that high computer literacy does not necessarily transform into studying success (SCHULMEISTER 2008, p. 93).

Table 2.2 summarizes the studies introduced in this section and provides a comparison of current state-of-the art computer and media literacy approaches.

HORRIGAN 2007 conducted a survey on American's use of the Internet which showed that 8% of Americans are deep users of the Web and mobile applications,

23% use gadgets to use social networks and be productive at work, 10% highly use mobile devices for voice, texting, or entertainment, another 10% find it a hassle using information gadgets but keep using them and 49% occasionally use modern gadgetry.

EYNON & MALMBERG 2011 identified four profiles of Internet users in Great Britain. The peripherals are the largest group and use the Internet the least frequent, the normatives are the largest group and mostly use the Internet to communicate, entertain themselves and seek for information, the all-rounders have a high and frequent Internet use, and the active participators which represent the smallest group use the Internet the most frequently.

Computer and media literacy studies for users in Germany have been conducted by HEIM & BRANDTZÆG 2007 and BARNES ET AL. 2007. The characteristics of the users in this study have been included in the typology of BRANDTZÆG 2010 which is the result of a meta-analysis of computer and media usage typologies.

Table 2.2: Comparison of studies related to study investigation field *computer literacy and media usage*

PUBLICATION, FOCUS TYPE	INDEPENDENT VARIABLE	DEPENDENT VARIABLE	DESIGN	RESULTS/ FINDINGS	ASPECTS TO CONSIDER
EYNON & MALMBERG 2011, paper	Internet usage typology	Internet user characteristics	Internet usage typology	Survey, N=1000	Internet user types British population
GROSCHE & GIDION 2011, paper	Media usage of students	Student characteristics	Usage frequency, experience, acceptance	Survey, N=1397	More successful free time usage than in university context/ sufficient media literacy Trends in students' media usage
BRANDTZÆG 2010, paper	Media usage studies	Previous media user typologies	Media-User Typology (MUT)	Meta-analysis	8 usage groups Comprehensive typology
KLEIN 2008, PhD	Geo-media literacy and ICT	Learner/ teacher characteristics	Geo-media effects	Survey, N=722	Positive effects of geo-media employment on geographic interest. Geo-media analysis
HORRIGAN 2007, paper	ICT typology	ICT user characteristics	ICT typology	Survey, N=4001	10 user types American population
SENKBEIL 2004, PhD	Computer literacy typology	TELE, computer literacy types, learner characteristics	Computer literacy typology, motivational/ technical abilities	Survey, TELE study, N=629	Typology, unexperienced/ free time users at risk, no disadvantages of females, insufficient media literacy Validated typology

Eight user types have been defined from which the first two are rather passive users. Moreover, all following user types except for the advanced users are characterized by medium use of media. Therefore this characteristic is not mentioned for every following user type.

- The first (Non-User) type exhibits the least media usage activity. The tendency is non-use.
- The second (Sporadics) in contrast is characterized by low usage which is not further specified.
- The Debaters' media use is characterized by a medium variety. They typically use blogs and Social Networking Services (SNS).
- The Entertainment Users are similar to the Debaters in terms of media use. However, they have a different focus. They prefer advanced media use and prefer new media in general.
- The users described as Socializers are even more similar to the Debaters but differ from these in their strong focus on socializing.
- Lurkers are characterized by the low variety of their media use. Their typical activity is rather passive. It can be described as time-killing.
- The Instrumental Users in contrast have a strongly purposeful use whereas entertainment plays a minor role for them.
- The Advanced Users use media on a high level of frequency and variety in more or less all categories.

Table 2.3: Media User Typology (BRANDTZÆG 2010, printed with kind permission from Elsevier Inc.)

USER TYPE	FREQUENCY OF USE	VARIETY OF USE	TYPICAL ACTIVITY	MEDIA PLATFORM
Non-Users	No use	No use	No	All
Sporadics	Low use	Low variety	No particular activity. No contact with electronic government services. The Internet is rarely used for private purposes. Low interest, less experienced.	All
Debaters	Medium use	Medium variety	Discussion and information acquisition and exchange. Purposeful action.	Blogs and SNS.
Entertainment Users	Medium use	Medium variety	Gaming or passively watching videos, also advanced use, such as User Generated Content (UGC), programming, shopping.	New media in general.
Socialisers	Medium use	Medium variety	Socializing, keeping in touch with friends and family, connecting with new acquaintances. Active social life, but less organised and purposeful, more spontaneous and flexible.	SNS
Lurkers	Medium use	Low variety	Lurking, time-killing.	SNS, user-generated sites, shopping, new media in general
Instrumental Users	Medium use	Medium variety	Choose media content for information and civic purposes, utility oriented, often work related, searching for electronic government or public information. Low on entertainment use. When shopping, comparing brands and promotional offers.	New media in general, including Internet, online shopping
Advanced Users	High use	High variety	All (gaming, homepage design, shopping, programming, video, electronic government s., UGC, etc.).	All

The focus of computer typology studies conducted for German users mainly lies on pupils (HEIM & BRANDTZÆG 2007) or on adults in the non-educational context (BARNES ET AL. 2007). A different example is SCHULMEISTER ET AL. 2009. The categorization found here involves the types *technologically*, *culturally*, *realistic*, and *socially oriented* and attributes different studying disciplines to these types. This typology does not specify the technology-enhanced learning aspect explicitly and takes a rather general view.

To develop a computer literacy typology for adults in the educational context, i. e. students, the following former studies are enriched by the theoretical findings of BRANDTZÆG 2010.

The PISA study which is conducted worldwide since the year 2000 has applied the concept of computer literacy types to measuring preconditions for learning with ICT (Information, Communications and Technology). PISA is short for *Programme for International Student Assessment* which is a worldwide study by the Organization for Economic Co-operation and Development (OECD) conducted in member and non-member nations in the years between 2000 and 2010 of 15-year-old school pupils' performance on mathematics, science, and reading in school education including the assessment of ICT skills (HANUSHEK & WOESSMANN 2011).

The study conducted by SENKBEIL 2004 is concerned with the computer literacy typology used during the PISA-study in 2003. The main findings of this work were:

1. The computer literacy types who are at risk regarding their learning development are the unexperienced and free time users.
2. Female learners have no disadvantages compared with male learners.
3. A mainly insufficient media literacy could be observed among the learners.

Four factors were used in the PISA survey to identify computer literacy types. The computer usage is measured as a combination of frequency and duration. The computer self-efficacy comprises standard computer abilities in school and higher education, e. g. working with spreadsheet diagrams or databases. This

typology as well was used for a survey in the geoscience domain by [KLEIN 2008](#). Therefore the use of this typology provides a wide range of comparison possibilities and is therefore considered for this study.

[Table 2.4](#) shows the differences between computer literacy types defined in [SENKBEIL & DRECHSEL 2004](#):

- Enthusiasts,
- Pragmatists,
- Freetime Users,
- and Unexperienced.

These literacy types describe sets of media and computer users. That means, the terms *literacy type* and (*computer or media*) *user* describe the same group but with the slight difference that a *type* is more general and a *user* refers to a more individual level.

Table 2.4: Computer Literacy Types (SENKBEIL & DRECHSEL 2004)

LITERACY DIMENSION	ENTHUSIASTS	PRAGMATISTS	FREETIME USERS	UNEXPERIENCED
Computer usage frequency	often, all kinds	seldom, more often for study purposes	more often freetime use	seldom
Computer self-efficacy	high	low	high	low
Positive attitude towards computers	yes	yes	yes	no

The preceding section had a general focus on learning. The following two sections deal with technology-enhanced learning support in geoscience.

2.7 Preconditions for Technology-Enhanced Learning in Geoscience

The didactics of geoscience is concerned with the teaching and learning processes about geoscience. Geoscience in this case is referred to as a spatial science subject which includes e. g. the subdisciplines geography and geology.

Geography is concerned with capturing, describing and analyzing geospatial phenomena and processes whereas natural and social aspects are focused. Therefore geography has a clear interdisciplinary dimension as a bridge between the natural science and cultural science, economy, and humanities (FALK 2006, p. 27). Geology, in contrast, is the science of the earth with focus on the evolution of the planet, its development, and its function (PRESS ET AL. 2008, p. 1).

Geology as well as geography treat the concept of geospatial information. The specificities of geospatial information are summarized as follows:

- The phenomena are discrete or continuous and may alter along time.
- The geospatial factors (see below), objects (see also below) and data have physical, biotic and anthropogenic components.
- The information needs to be captured, managed, analyzed and presented.

Geospatial factors or geofactors are space-filling and space-categorizing phenomena and effects of the earth's surface and the geosphere. The different kinds of geofactors are: first of all abiotic geofactors, e. g. surface shapes, soil, waters, secondly biotic geofactors of the type flora and fauna and biotic geofactors of the type human beings, society (WEISS & BUHL 2005, KLEIN 2008, p.7). However, spatial objects are described by geoinformation which is defined as information about geospatial phenomena which are directly or indirectly linked to a position related to the earth. (DIN/ISO-19101 2012.)

The information system support for dealing with these topics is carried out by use of Geographic Information System. Therefore in the geoscience disciplines *geology* and *geography* Geographic Information Systems are applied.

A Geographic Information System (GIS) as a medium includes various methods as a prerequisite for successful use.

Regions in their respective borders, networked linear structures, as e. g. roads or single locations, as e. g. meteorological stations can be subject to analyses in GIS. GIS programmes can help capture the respective data in a digital form, process, analyze, present and interpret them (DICKMANN & ZEHNER 2001, DE LANGE 2005, FALK & HOPPE 2004). A GIS according to MUND & SCHÄFER 2001 is composed of:

- the user,
- spatially representable technical data and digital maps,
- GIS software and further software packages for data analysis,
- computer hardware including scanner and colour printer.

A GIS contains pieces of information about the real world which are represented in dots, lines, and areas. These data are characterized in layers. This concept helps combine and contextualize the contained information (SIEGMUND 2001).

The goal of geoinformation processing for knowledge acquisition is to create and apply spatial models in a way that even high levels of abstraction keep the models descriptive and concise (SCHWARZ & ASCHE 2006). This goal can be supported by technology. A categorization of competence levels when working with GIS has been carried out by SIEGMUND ET AL. 2009. Figure 2.2 shows four competence levels starting with the simple level of localizing easy to find pieces of information which meet a single criterion. For data capturing and editing support is needed and the theoretical background consists in the goal to provide an understanding of the basic idea of GIS.

The competence level for gathering information and analyzing it increases when additional criteria are met, e. g. when spatial data are related to a timeline. This level is characterized by stronger independence in capturing and editing data whereas the theoretical background consists in the goal to provide an understanding of visualization possibilities, e. g. how to work with a symbology.

The next level is characterized by typical analysis activities. This level is characterized by advanced data capturing and editing skills whereas different sources

can be handled. The theoretical background consists in the goal to provide a fundamental understanding of GIS analysis functions. An example is the application of logical operators.

The last and highest level of the model increases the complexity of analyses. The theoretical background consists in the goal to provide an advanced understanding of GIS analysis functions. An example is understanding and applying *intersection* to define spatial overlaps.

A general study regarding GIS and TELE has been conducted by [WENG 2008](#) who gives a general overview of how digital learning can work in the GIS context:

- Video, audio and e-learning reduces traditional text teaching and improves the interaction between teachers and students.
- Blended learning, which integrates traditional and digital learning methods, is advantageous to the learning process.
- Open Source software is a major trend to be kept in mind.
- Mobile learning becomes more and more important.
- All these aspects can support the learning with GIS.

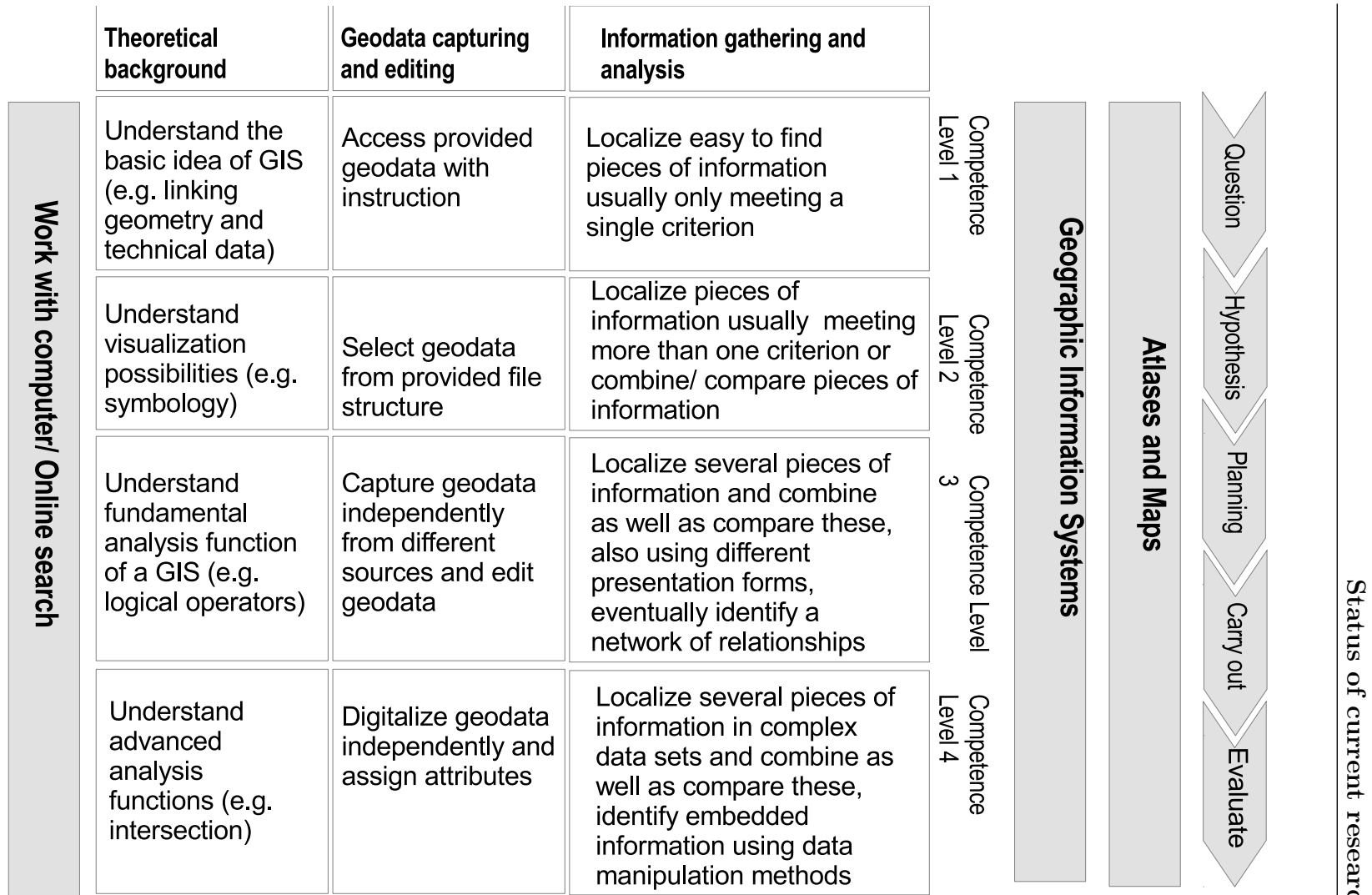


Figure 2.2: Competence model concept SIEGMUND ET AL. 2009 (own translation)

The next section deals with the theoretical foundations of the method used to analyze learning processes. It is applied to the geoscience context in the methodology section.

2.8 Process Mining for Learning Processes

This section introduces Process Mining by explaining its objectives and relevant instruments on a theoretical basis as well as current research approaches with special focus on Process Mining of technology-enhanced learning processes.

Process-oriented knowledge discovery techniques in educational systems are an upcoming field of interest (BERGENTHUM ET AL. 2012, HOLZHÜTER ET AL. 2010). The process-oriented view helps to exceed the mainly isolated view on datasets which dominates in traditional Data Mining. This and additional benefit potentials of process-oriented knowledge discovery techniques have been illustrated by HOLZHÜTER ET AL. 2010, HOLZHÜTER & FROSCH-WILKE 2012, and BERGENTHUM ET AL. 2012.

As the combination of learning technology with Process Mining entails considerable potentials, the term *Learnflow Mining* has been introduced by BERGENTHUM ET AL. 2012 whereas TRČKA ET AL. 2011 and ROMERO & VENTURA 2013 use the term *Educational Process Mining*.

Learnflow Mining or Educational Process Mining explicitly combines Process Mining with technology-enhanced learning environments. A supporting framework for the Learnflow Mining approach is the concept of Learning Design (KOPER & TATTERSALL 2005) which formalizes technology-enhanced learning support tools and methods including Educational Modelling (RAWLINGS ET AL. 2002) - the modelling language for implementing learning and learning support rules.

An overview over the Process Mining instruments applicable to technology-enhanced learning can be found in TRČKA ET AL. 2011. The work shows how visual data exploration, conformance checking, and process discovery can be carried out technically.

Basic Concepts of Process Mining

The process analysis method of Process Mining is used to build process models in order to describe the behaviour contained in the event logs of information systems (DE MEDEIROS & WEIJTERS 2005). These event logs are occurrences which trigger business processes and represent the basic units of the process models. Events have a stage at which they occur and a type. The stage is either the start or end and the type can be e.g. a message or an exception (HAVEY 2005, p. 147). The record of these event logs is the documentation of a workflow (VAN HEE & VAN DER AALST W.M.P. 2004, p. 346), i.e. a fully or partially automated business process.

This so-called log, audit trail, log file, or trace keeps track of the start and completion of process steps combined with related context data (e.g. user roles and resources) of a workflow (VAN HEE & VAN DER AALST W.M.P. 2004, p. 346). The logs are produced by process-aware information systems, e.g. information systems in business companies which can execute processes automatically, i.e. Workflow Management Systems.

The main category of all mining types is Data Mining. Data Mining - and therefore Process Mining in general - involves the nontrivial extraction of implicit, presumably useful but previously unknown information from data (FAYYAD ET AL. 1996, FRAWLEY ET AL. 1991, FRIAS-MARTINEZ ET AL. 2006) and a procedure which identifies potential, valid, useful as well as understandable patterns in databases (FAYYAD ET AL. 1996).

Process Mining as a sub-discipline of Data Mining adds the process-oriented view to the Data Mining procedure. It is a method which is especially used in Business Process Management (VAN DONGEN ET AL. 2005). The resulting process models support different objectives in Business Management (VAN DER AALST 2011) from which a selection is followingly applied to studying scenarios:

- Insight: A process model enables the modeler to view a process from different angles. Applied to a learning scenario this means that the instructor of a technology-enhanced lesson may model a general process. The resulting model embraces all possible paths. A different angle can be the specialist view which focuses on a maximum of details regarding a certain topic.

- **Documentation:** Documenting a process can support beginners in a domain about required procedures. Students who start to work with a GIS can profit from process models on how to carry out fundamental tasks, e. g. to manage spatial data sets.
- **Performance analysis:** Techniques such as simulation support the understanding of influencing factors. Activity times and task performance can be used as dependent variables and the corresponding processes can be analyzed to find reasons for a certain outcome.
- **Animation:** Models can be used to define different scenarios whereas the dynamic perspective is provided by the respective presentation programme. This method can be used by instructors to discuss a certain lesson design with a learning system implementer.

Figure 2.3 shows how Process Mining works (VAN DER AALST 2011, p.9, f.). Four Process Mining procedures can be distinguished: *Discovery*, *conformance*, *enhancement*, and *recommendation*:

1. The first category, discovery, does not use a-priori information, i. e. a former process model (ibid., p.10). A-priori information can be generated from previous logs or may have been designed by process experts.
2. The second category, conformance, requires a process model containing a-priori information. The new model is generated from real world behaviour and can be compared to the a-priori model (ibid., p.10).
3. The third category, enhancement, uses the information generated from the second category. The objective of carrying out the enhancement procedure is to improve the existing a-priori model.
4. KHODABANDELOU ET AL. 2013 add a fourth category to the approach of VAN DER AALST 2011, i. e. recommendation. The approach of MOBASHER ET AL. 2000 involves recommendations based on URL traces and SCHONENBERG ET AL. 2008 found that process performance improves with an appropriate selection of activities.

The approach *Intention Mining* enhances the original idea of Process Mining by considering processes focused on the reasoning behind activities (KHODABANDELOU ET AL. 2013). The four Process Mining procedures *discovery*, *conformance*, *enhancement*, and *recommendation* can be adapted to this approach in the following way (KHODABANDELOU ET AL. 2013, p. 6):

1. The first category, discovery, involves identifying the actors' intentions as well as strategies from the event logs.
2. The second category, conformance, corresponds to the procedure of checking to which degree the prescribed intentional model and the way it is enacted allows measuring the gap between what is prescribed and what is actually done.
3. The third category, enhancement, uses the information generated from the second category. The objective of carrying out the enhancement procedure is to improve the existing model. (It is checked which intentions are not being achieved or which strategies are not put in to action.)
4. The fourth category, recommendation, involves supplying recommendations to actors in an information system based on the assumed reasoning behind their activities.

Process Mining Notations

A complete introduction to the large existing number of process modelling notations for Process Mining results representation is not within the scope of this work. A systematic comparison has been carried out within the Workflow Patterns Initiative (WPH 2010, VAN DER AALST ET AL. 2003).

KHODABANDELOU ET AL. 2013 refer to Petri Nets and the Business Process Model and Notation (BPMN) as the ones which are used most in Process Mining. These two are introduced in the following.

A Petri net consists of places, transitions, and arcs. A place represents a system state (circle) and transitions (squares or bars) represent events whereas the

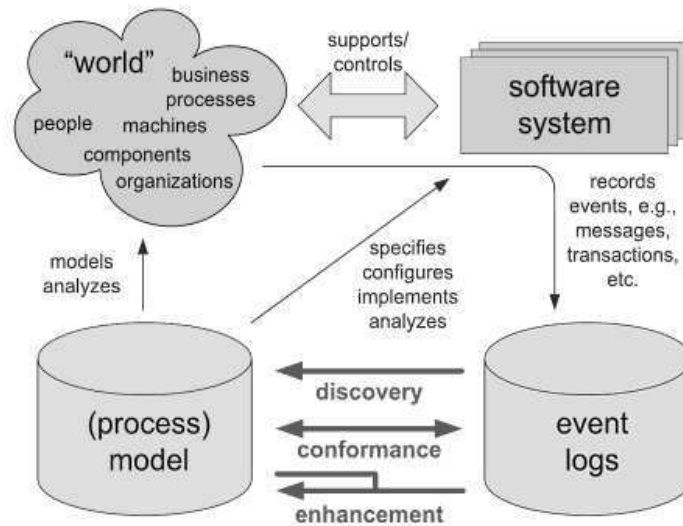


Figure 2.3: Process Mining scheme (VAN DER AALST 2011, p. 9), printed with kind permission from Springer-Verlag GmbH

arcs relate places to transitions. The aim of Petri nets is to model system behaviour by providing a visual communication support (W. VAN DER AALST 2011). Regarding the educational context, PECHENIZKIY ET AL. 2009 identify typical constraints defined in the academic curriculum and use the Petri net language *Colored Petri nets* (CPNs) to encode the constraints as patterns which give for the study rules.

The graphical notation *BPMN* depicts the different steps of a business process. The target of the models are business users who can analyze complex processes and as well map the models to other languages, e. g. to make the process models executable (PECHENIZKIY ET AL. 2009).

Process Mining Application

Aiming to enlarge the research and practitioners' community, the ProM framework qualifies as a Process Mining framework providing tools which represent the state of the art (VAN DONGEN ET AL. 2005). Although not the complete variety of tools is available in the framework, the user disposes of tools applicable to educational processes.

For converting log files from different systems to the necessary format the ProMImport Framework can be used. This framework allows developers to extract information and convert the files into the MXML format, i. e. a markup language for Process Mining (RUBIN ET AL. 2007, p.177). It is shown in an example in the methods section.

A comprehensive overview of the entire set of available algorithms is not in the scope of this work. The focus lies on a selection of algorithms which address the main issues in Process Mining. The first algorithm which is shortly mentioned is the α -algorithm. It can be characterized as a basic Process Mining algorithm because it illustrates a number of the general ideas used by Process Mining algorithms (VAN DER AALST 2011, p.125). In addition to the rather basic α -algorithm the *Heuristic Miner* is introduced more detailed to show how Process Mining can deal with problems the α -algorithm is confronted with.

The α -algorithm rebuilds process models from existent relations in the event log. A revised version of the algorithm, i. e. $\alpha++$ has been developed by VAN DER

AALST ET AL. 2004.

However, the α -algorithm does not manage to deal with noise and incompleteness. This is the focus of more advanced process discovery techniques. An overview over the most relevant approaches in Process Mining research is given by VAN DER AALST 2011 (p. 157 ff.).

(Event) logs mostly contain noise. Noise is the kind of logged information that derives from flawed activities which were not intended to be carried out in that specific way, e. g. because of a technical defect. Therefore algorithms have been developed which deal with incompleteness or noise (WEIJTERS ET AL. 2006) .

The Heuristic Miner algorithm (WEIJTERS ET AL. 2006) considers the frequency of traces in the log in contrast to previously developed algorithms (LANG 2008), such as the alpha-algorithms, i. e. alpha and alpha++ (VAN DER AALST ET AL. 2004).

The metric for mining the sequences is the following: $a \Rightarrow_w b = \left(\frac{|a >_w b| - |b >_w a|}{|a >_w b| + |b >_w a| + 1} \right)$

To calculate the frequency model these process elements are considered:

1. How often does step b follow step a ($a >_w b$)?
2. In contrast: How often does step a follow step b ($b >_w a$)? These occurrences are subtracted.
3. The denominator consists in the whole of the occurrences ($|a >_w b| + |b >_w a|$),
4. The value „1“ is needed to obtain valid frequencies for the model. The letter w belongs to the notation and has no specific meaning itself.

It is not always clear whether a certain trace was caused by noise or is a low frequent pattern. Therefore dependency thresholds are available in the Heuristic Miner which allow to accept or exclude the observed behaviour in question:

1. *The dependency threshold,*
2. *the positive observations threshold,*
3. *and the relative to best threshold.*

These thresholds allow the Process Mining user to also accept relations between activities which have:

1. *a dependency measure above the dependency threshold value (WEIJTERS ET AL. 2006, p. 8),*
2. *a frequency higher than the positive observations threshold value (ibid.),*
3. *and a dependency measure for which the difference regarding the best dependency measure is below the relative to best threshold value (WEIJTERS ET AL. 2006, p. 8, f.).*

Procedure:

1. A dependency measure above the dependency threshold value of 0.4 is accepted to also mine low frequent behaviour in the small sample. A strict model contains a threshold close to 1. WEIJTERS ET AL. 2006 (p. 9) use the value of 0.45 in their example.
2. A frequency higher than the positive observations threshold value 1 does not mine very low frequent activities as assumed in this study. Therefore the value 1 is chosen. This value is chosen as well in the example of WEIJTERS ET AL. 2006.
3. The activities for which the difference regarding the *best* dependency measure is below the relative to best threshold value 0.4 are accepted. This value corresponds to the example in WEIJTERS ET AL. 2006.

Process Mining for Technology-Enhanced Learning Processes

The domain to which Process Mining for technology-enhanced learning processes belongs is called *Educational Data Mining* (EDM). EDM aims at the development, research, and application of computerized methods for pattern detection in large collections of data from the educational context which would otherwise be difficult or impossible to analyze because of the enormous volume of data within which they are stored (ROMERO ET AL. 2011). EDM can be generally be understood as the application of the formerly explained Data Mining (p. 37) to

the specific type of dataset that comes from learning environments to address educational questions of special importance (ROMERO & VENTURA 2007 ROMERO & VENTURA 2010).

ROMERO & VENTURA 2007 particularly name the objectives of getting a better understanding of learning processes, generating recommendations and advices for students, or improve the management of learning objects which are used to modularize learning material and are intended to support reusability of studying content (KNOLMAYER 2013). Tables 2.5 to 2.7 summarize recent studies of interest whereas Table 2.7 includes the crucial parameters of the conducted study of this work. Relating the studies allows a comparison of current state-of-the-art approaches dealing with Process Mining of technology-enhanced learning processes.

A general overview of works indicating an increase of interest in Process Mining support for educational processes has been given in the introduction of this section (p.36). This subsection zooms in from the rather general perspective to particular challenges in technology-enhanced learning which can be tackled by Process Mining support. First of all, a set of technology-enhanced learning studies are of interest which do not primarily employ Process Mining but offer a considerable potential for combined use.

The first study summarized in Table 2.5 has been conducted by ROMERO ET AL. 2013. They demonstrate how Educational Data Mining approaches can be applied in TELE in order to predict the student grades in the final exams. The study can be related to this research regarding the attempt to analyze student behaviour leading to different learning outcomes.

The second study of PECKHAM & McCALLA 2012 applies a mining approach on patterns of student behaviour in reading comprehension. The framework used for strategy pattern classification may not be uncontested (PAUL & WILLSEN 1993). However, it was found that cognitive strategies could be recognized in the TELE. A missing link remained the significant detection of skill differentiation. The study can be related to this research because the difficulty of skill differentiation becomes obvious and cannot be treated as simple task.

The study of KRÜGER ET AL. 2010 was conducted by applying a data model in

a TELE and presenting mandatory as well as optional exercises to the learners. The main contribution of this work was that the model supported the organization of data which is very often scattered and therefore difficult to manage in TELE. Moreover it was found that voluntary task solving decreases towards end of semester and those who keep solving them reach slightly better marks. The study can be related to this research as the voluntary solving of tasks plays a major role for success. In the Process Mining study students are supposed to find a matching way of working through the lesson. Those who take the path which is assumed to be adapted to their skills score better.

Student behaviour is explored similarly to Process Mining approaches regarding student behaviour exploration (KRÜGER ET AL. 2010, p.132). Still, Process Mining is not limited to the association of events to define IF-THEN-relations but additionally creates comprehensive process models as explained previously. Nevertheless, the Data Mining approach offers potential to be used together with the Process Mining approach which can produce analysis results for behaviour prediction.

JEONG ET AL. 2010 finds that Process Mining is useful for detailed analysis of processes. They argue that metacognitive tasks increase cognitive overload whereas following a given path supports its reduction.

Table 2.5: Comparison of studies related to the investigation field *Process Mining in TELE I*

PUBLICA- TION, TYPE	FOCUS	INDEPEN- DENT VARIABLE	DEPENDENT VARIABLE	DESIGN	RESULTS/ FINDINGS	ASPECTS TO CON- SIDER
ROMERO ET AL. 2013, paper	Analysis of clustering approaches in TEL	Participation in online discussion forum	Final performance	N=114	Use of data from the middle of the course allows early prediction	Further investigations needed for generalization
PECKHAM & MC- CALLA 2012, paper	Patterns of student behaviour in reading comprehension	Texts and comprehension tasks in TELE	Strategies	TELE-study, adult English course, N:1st condition=17, 2nd condition=11	Cognitive strategies could be recognized automatically	Further studies needed to detect significant skill differentiation, use of controversial strategy framework according to Bloom (PAUL & WILLSSEN 1993)
KRÜGER ET AL. 2010, paper	Data model for EDM	Mandatory/optional exercises	Dependencies between exercise attempts, exam	TELE-study, N=65	Model to organize data, usually scattered in TELE; voluntary task solving decreases towards end of semester, those who keep solving them reach slightly better marks	Similar to Process Mining approach of PECHENIZKIY ET AL. 2009 (see Table 2.7) regarding student behaviour exploration (KRÜGER ET AL. 2010, p. 132)
JEONG ET AL. 2010, paper	Mining approach without Process Mining	Groups of different performance levels	(Mathematical) model path deviations	6298 learners, 50 learning modules, 10 independent workplace training courses	Process Mining is useful for detailed analysis of paths	Conclusion: metacognitive tasks increase cognitive overload, following path supports its reduction

Table 2.6: Comparison of studies related to the investigation field *Process Mining in TELE II*

PUBLICA- TION, TYPE	FOCUS	INDEPEN- DENT VARIABLE	DEPENDENT VARIABLE	DESIGN	RESULTS/ FINDINGS	ASPECTS TO CON- SIDER
REIMANN ET AL. 2014, paper	Contribution of Process Mining to e-Research, learning theory	Process Mining	Explanational power	Process models for successful and less success- ful learners, 38 individ- ual learning sessions	Successfull students: Reading is con- nected with monitoring and elaboration, less success- ful students: reading is strongly con- nected with repeating and monitoring	Not the amount of data but how rich and deep they happen to be mat- ters, difference between open and closed sys- tems
FERNÁNDEZ- GALLEGO ET AL. 2013, paper	Process Mining approach for virtual worlds	3D teach- ing scenar- ios	Learning activities	Avatars are tracked by their event logs	Methodical approach can be used to identify real-world learning behaviour	Framework can be used for learning analytics studies
KINNEBREW & BISWAS 2012, paper	Learning behaviour analysis via sequence mining	Student perfor- mance	Learning patterns	N=40	Different patterns, i.e. Successful students ex- hibit a more systematic reading behaviour	More detailed analysis of sequences than when using Process Mining where sequences are not yet defined

Table 2.6 shows the studies of interest which investigate Process Mining in TELE as well:

REIMANN ET AL. 2014 discusses the use of sequence and Process Mining for e-Research and learning theory by carrying out a conceptual discussion and citing an empirical study. The results can be related to this research because the principle which REIMANN ET AL. 2014 plead for, i.e. *not the amount of data but how deep and rich they are counts*, is followed in the interpretation of the Process Mining data.

FERNÁNDEZ-GALLEGO ET AL. 2013 have generated a 3D Process Mining framework to analyze learning behaviour in virtual worlds. This approach is closely linked to the gamification scenario and aims at generating knowledge about unstructured learning behaviour. This study treats an aspect which can be used in combination with the approach followed here.

KINNEBREW & BISWAS 2012 analyze learning behaviour by use of sequential mining. They are able to detect patterns of successful and not successful readers. Sequential mining in contrast to Process Mining is based on the assumption that a sequence is a subsequence of another sequence (VAN DER AALST 2011). This method can be compared to Process Mining whereas there are clear similarities. The focus of sequence mining lies on already predefined step orders and not on the discovery of new processes.

DOMINIC ET AL. 2015 (Table 2.7) have designed a framework which can be used to implement adaptivity in TELE. They also work with learning paths but they do not use the learning paths in the TELE to generate a model of process paths as in the Process Mining approach. Instead they use a database which contains a set of learning paths which students have went through or calculate new paths from the existing data. That means that process logs remain unused. There is no learning effect which the learning analyst benefits from regarding the paths which students go through anyway.

BOGARÍN ET AL. 2014 in Table 2.7 have combined clustering methods and Process Mining in TELE. Their focus is to determine whether you can predict that students are going to pass or fail exams. This approach is similar to the approach in this study where the learning paths are clustered as well. But BOGARÍN ET AL.

2014 use Process Mining clustering methods. Here the learners are classified in advance and their learning paths are analyzed according to a theoretical framework.

HOWARD ET AL. 2010 analyze process models along the inquiry cycle. This cycle is characterized by differently accessible resources. A set of these resources can be accessed anytime (discretionary) and others require learner actions by prompts. The study provided preliminary results to adequately support learner control. This approach could also be combined with Process Mining.

The works of PECHENIZKIY ET AL. 2009 and BERGENTHUM ET AL. 2008 both treat the topic of Process Mining in TELE whereas BERGENTHUM ET AL. 2008 focus on collaborative learning processes. They conduct technical analyses whereas the mining environments are different. ProM as described previously is used by the majority of Process Mining practitioners and researchers (VAN DONGEN ET AL. 2005) and is used in the current study as well.

To summarize the findings of this entire chapter and relate them to the current study (see Table 2.7), it can be stated that a large body of research has been conducted on computer literacy typologies and a small amount on Process Mining of non-collaborative technology-enhanced learning processes. However, these approaches have not yet been combined. The combination of these two approaches offers potential to investigate on how computer literacy types and learning path types possibly correlate. This question is being investigated on by choosing the example of geoinformatics for geosciences which represents a topic requiring abstract thinking and is therefore easily perceived as complex.

The methodological procedure which is explained in detail in the next chapter is based on a generic support framework which can be applied to other disciplines as well. Moreover it enables the exploration of influencing factors and outcomes of technology-enhanced learning processes. The results are intended to preliminarily define reasonable support measures which can be validated in future studies.

Table 2.7: Comparison of studies from the investigation field *Process Mining in TELE III*

PUBLICATION, FOCUS TYPE	FOCUS	INDEPENDENT VARIABLE	DEPENDENT VARIABLE	DESIGN	RESULTS/ FINDINGS	ASPECTS TO CONSIDER
DOMINIC ET AL. 2015, paper	Adaptivity in LMS	Learner characteristics	Learning path, feedback, performance	Use of case based reasoning, simplex method	no data	Approach does not generate reusable learning path models
BOGARÍN ET AL. 2014, paper	Clustering and Process Mining	Online learning activities	Scores	Process Mining of clustered data (84 students)	Method can be used to predict that students will fail a course	Tools: ProM and WEKA (WITTEN & FRANK 2005)
HOWARD ET AL. 2010, paper	Inquiry cycle	Differently accessible resources (prompted, discretionary) in TELE	Process Models of inquiry behaviour	50 online learning modules, N=5617 deliveries	Preliminary results support learner control	Further investigations needed
PECHENIZKIY ET AL. 2009, paper	Educational data	-	-	Technical analysis	Concept application, necessity of process steps can be identified	Use of ProM-Tool
BERGENTHUM ET AL. 2008, paper	Educational data	-	-	Technical analysis	Concept application, assumed benefit potentials for collaborative learning	Technical implementation independent of ProM
Current study	Process Mining in geoinformation lesson	Motivational/explanatory support, learner characteristics	Learner characteristics, learning material experience	N: surveys=439, TELE-study=28	Effects of support measures	Findings show tendencies to be verified in further studies

Chapter 3

Methodical Design and Procedure

3.1 Conceptual Approach

The objective of finding appropriate TELE support strategies not only requires an experimental setting for testing a defined set of strategies, but also a contextualization of the conducted learning experiment. The precondition of learners can also be considered as an own field of investigation.

This precondition of the learners in question is expected to determine a set of measures for increasing ICT learning benefits in higher-education learning. **CLARK & FELDON 2010** (p. 105) review approaches that help adapt learning environments according to cognitive or learning styles, individual differences, intelligence, motivational goal orientations, and prior knowledge. From these, intelligence, individual differences, motivational goal orientations, and prior knowledge have exhibited significant effects.

One major focus of this study is the prior knowledge of the learner. Prior knowledge, according to **CLARK & FELDON 2010**, offers great promise for the customization of technology-enhanced learning. This is a common view in the educational psychology community, as **AUSUBEL ET AL. 1968** (p. 4) stated decades ago:

If I had to reduce all educational psychology to just one principle, I would say

this: The most important single factor influencing learning is what the learner already knows. Ascertain this and teach him accordingly.

Study Variables

The following section deals with the study variables used to operationalize the methodical framework.

The concept of intelligence is beyond the scope of this study. This needs to be considered when interpreting the empirical results, especially of the technology-enhanced learning tests. The other three concepts, i. e. individual differences, motivational goal orientations, and prior knowledge are considered in this study. The individual differences are analyzed with a focus on learning preconditions for technology-enhanced learning of geoscience topics.

All in all, motivational goal orientations, such as intrinsic motivation and interest regarding the evaluated task, mood, and prior knowledge were treated as influence factors.

The elements of the whole study are:

1. Comparison of employed and therefore experienced learning material to evaluate general computer learning preconditions ([subsection 3.4.1](#))
2. Evaluation of general computer usage in geoscience samples to analyse the *computer usage factors* which are assumed to support learning processes ([subsection 3.4.2](#))
3. Computer literacy study to define new computer literacy clusters for geoscience students and to compare the students of the subjects geology and geography ([subsection 3.4.3](#))
4. Technology-enhanced learning study or TELE study ([subsection 3.4.4](#)):
 - (a) Instruction of the participants
 - (b) Paper-based survey evaluating:
 - the the intrinsic motivation regarding technology-enhanced learning topic

- the task interest regarding technology-enhanced learning topic
 - the current mood status
 - computer literacy
- (c) e-lesson part Ia: Pretest without explanations
- (d) e-lesson part Ib: Self-estimated interest in e-lesson task
- (e) e-lesson part II: Introductory explanations, optional information elements (task-unrelated practical information and technical sub-item) and control task
- (f) Paper-based survey evaluating:
- the perceived usability of the TELE
 - the students' cognitive load
 - the appropriateness of the motivational elements
- (g) e-lesson part IIIa: Second normal form explanation and control task
- (h) e-lesson part IIIb: Third normal form explanation and control task

Theoretical Framework

The learning support approach of this work is based on cognitive, motivational and computer literacy theories. The learning support framework proposed in this study enables technology-enhanced learning instructors to systematically adapt structured learning environments to the motivational and cognitive category of the students. In the following, the term *technology-enhanced learning environment* is shortened to *learning environment* or *TELE* for readability reasons.

The theoretical assumptions can be summarized in the conceptual framework in [Figure 3.1](#). This framework was adapted on the basis of the theoretical framework of [NIEGEMANN 2011](#) (p. 135), which represents an extended version of the framework in [NIEGEMANN 2008](#) (p. 303).

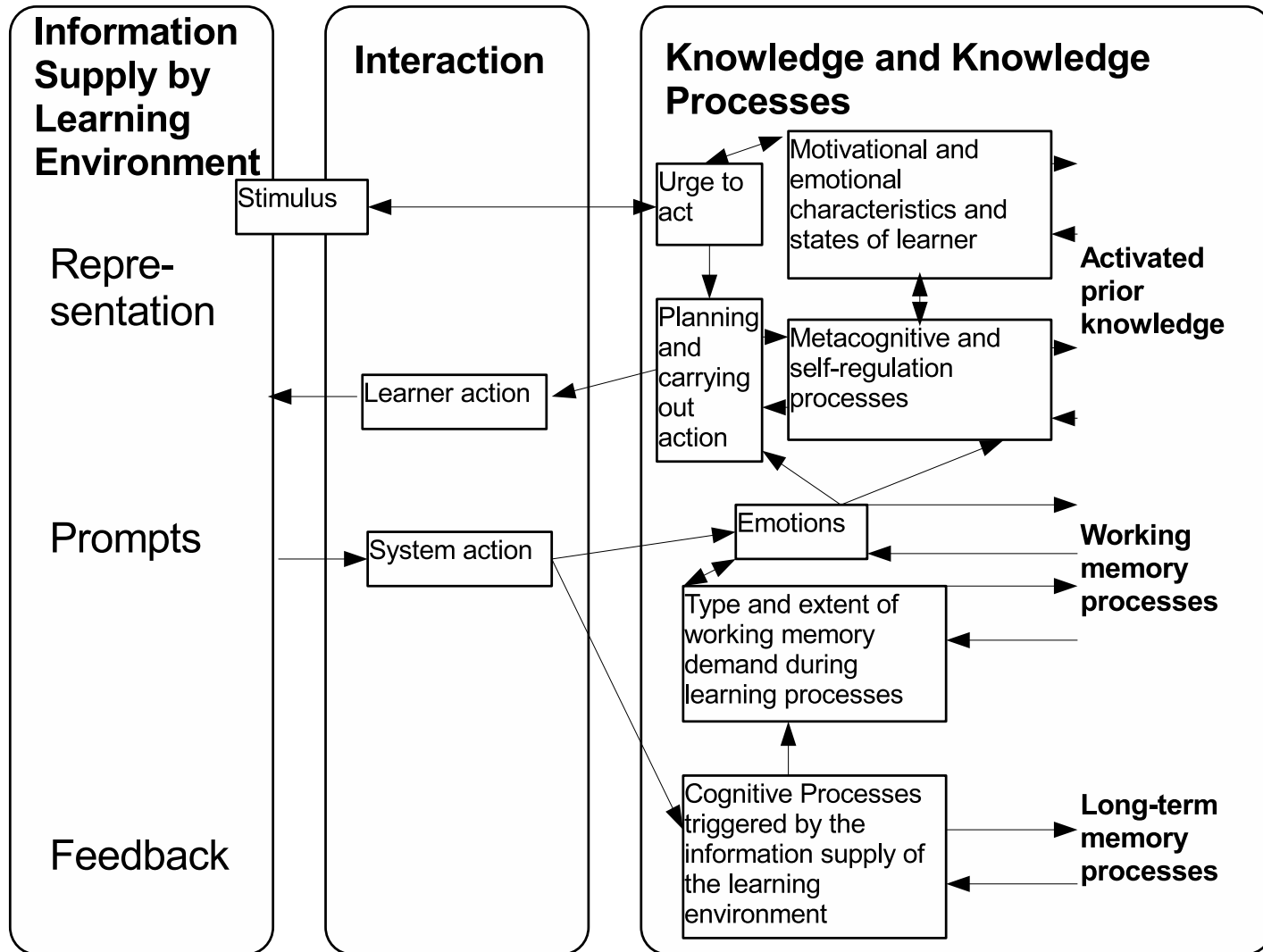


Figure 3.1: Model of interactive learning adapted according to NIEGEMANN 2011, p. 135

The theoretical framework is called NDH model, referring to the authors Niegemann, Domagk and Hessel (NIEGEMANN 2008). For structuring reasons, Figure 3.1 shows the three separate dimensions *information supply by learning environment*, *interaction*, and *knowledge and knowledge processes*. This structure is important not only for the representation of the methodical concept, especially in Figure 3.2, but also for summarizing the study results in the conclusions.

In the following sections the framework is described in detail.

The *information supply by the learning environment*, creates a stimulus, which is intended to cause an interaction with the learner. The stimulus can consist of a representation, prompts, or feedback. The representation refers to all aspects explained in the theory section (p. 9), i. e. multimedia, multicode, and multimodal representation of content, whereas the mental representation is not included. The multimedia aspect is affected when the content can be represented by e. g. smartphones as well as notebooks. The multicode representation determines in which way content is shown, i. e. coded as graphic, text or other. The multimodal representation aspect determines whether learning content is designed to be perceived audibly or visually, or both.

The prompts are designed to convey the instructional messages according to learner response and calculated needs. Their form of representation depends on whatever category explained above qualifies as appropriate.

Feedback is generally the instructional reaction to the result of the learner assessment. It can result in prompts, which have just been explained, and is represented with regard to learner requirements analogous to the prompts.

The urge to act, which is caused by the respective stimulus, not only depends on the motivational and emotional characteristics and states, as well as the activated prior knowledge of the learner, but also influences these (RHEINBERG 2006). Main factors that trigger an urge to act can be curiosity or expecting the consequences of an action (NIEGEMANN 2011, p. 134).

Additionally, mood, as a specific emotional characteristic that depends highly on the situation, can influence learning processes. SCHWARZ & BLESS 1991 found that a lower mood level improves learning performance where focus is of importance, whereas the opposite applies to creative tasks.

Depending on the metacognitive skills, the learner plans and carries out actions by applying the amount of self-regulation he or she is capable of. These actions, e.g., a mouse click or text input, result in information processing in the learning environment system. The system then acts in a way that the information supply is changed and adapted to the cognitive and emotional states of the learner. This ideally causes desirable change of cognitive operations and knowledge structures in the learner's long-term memory. The field of cognitive operations and knowledge structures requires more research to describe the affected processes in further detail (ibid.).

The working memory is highly responsible for the effectivity of learning processes. The way the learning environment is built up strongly influences how these working-memory processes operate (ibid.). One approach of relevance in this aspect is the cognitive load theory, which has been discussed in the theory section (p. 16).

The following section goes into detail about how the framework of this study was constructed based on the previous considerations.

Methodical Framework

The research questions were solved by applying the methodical design illustrated in [Figure 3.2](#) (p. 57). This methodical design was derived from the previously introduced framework ([Figure 3.1](#)) and is supposed to identify core influence factors that support technology-enhanced learning.

Regarding knowledge and knowledge processes, the study focuses on the following elements:

- Motivational and emotional states,
- the computer literacy type,
- cognitive load, and
- (prior) knowledge regarding the e-lesson topic were evaluated.

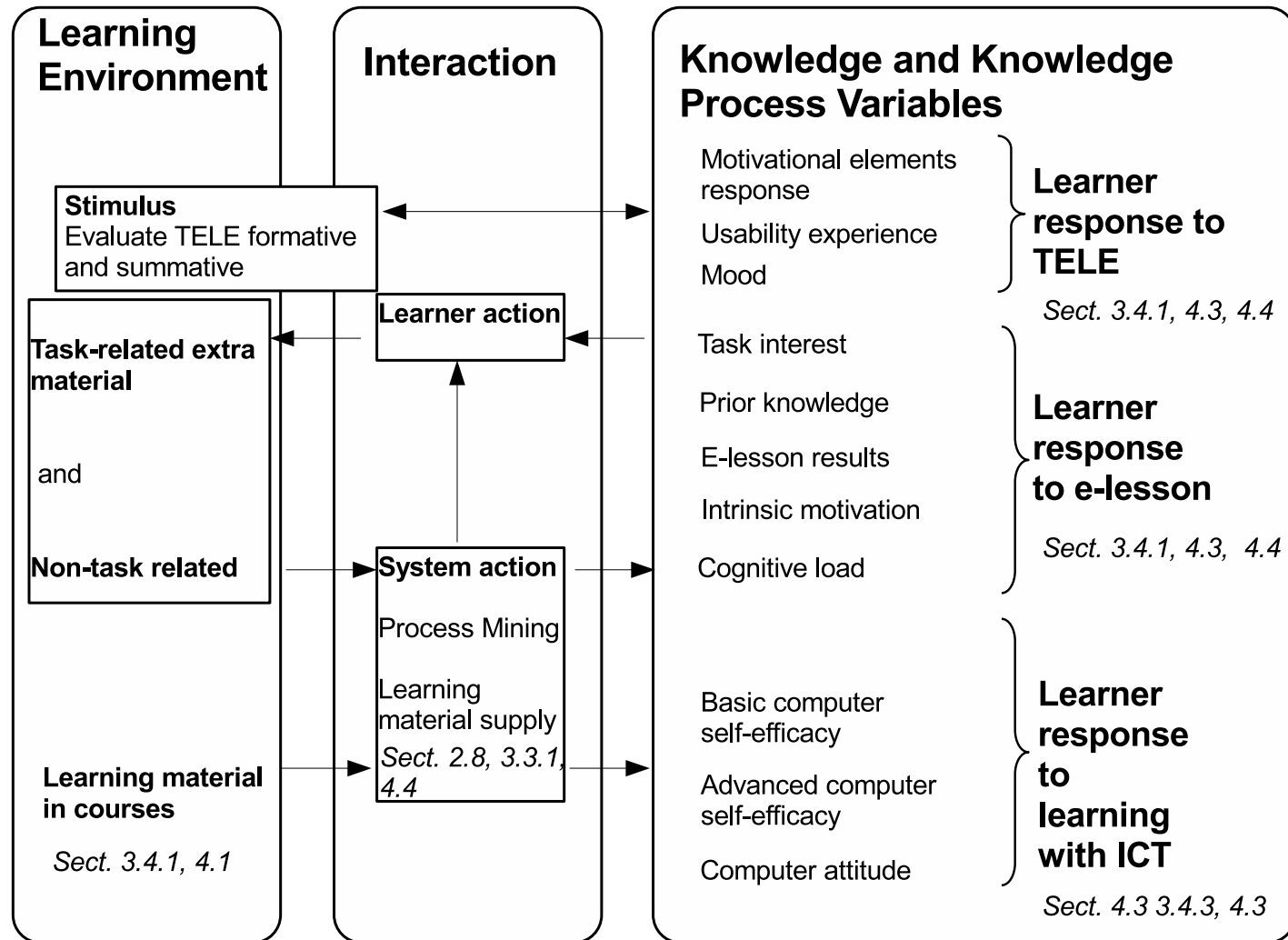


Figure 3.2: Conceptual framework (author's illustration according to NIEGEMANN 2011, p. 135)

The variables concerned were further categorized according to the four dimensions: *learning environment*, *learner response to TELE*, *learner response to e-lesson* and *learner response to learning with ICT*.

The first dimension of the NDH model is the *learning environment*, containing a general and two specific categories, i. e. the learner is exposed to these categories, which work with at least one of these methods: representation, prompts or feedback. The other three dimensions (*learner response to TELE*, *learner response to e-lesson* and *learner response to learning with ICT*) are linked to knowledge or knowledge processes of the learner.

The interaction between the NDH dimensions, i. e. the interaction of the learner with the TELE including the presented e-lesson, is visualized by *Process Mining* and indirectly evaluated by questionnaires as well as tests that measure constructs related to interaction. These constructs are *usability*, *cognitive load*, and *studying success (e-lesson task results)*. They were measured after the treatment (lesson part II of the TELE study).

The framework does not embrace studying activities which do not require interaction with a learning environment, i. e. the use of learning material such as texts, animations or images which can be viewed without learner interaction tracked by the TELE. It needs to be considered that these actions affect the lesson results but are not transparent to the evaluator.

The testing of the framework required a lesson topic which would produce measurable results. Therefore the topic of database normalization was chosen. The exact reasons are explained in detail in the following section.

Lesson Topic

The lesson topic needed to be chosen in the context of GIS, which was the course all study participants had in common. The reason for choosing GIS is that the topic experiences increasing interest, not only in university teaching, but especially in the different sectors (private and public) where today's students are going to be employed in the future.

From the discipline of GIS, as shown in the following excerpt (p. 59), the learning goal (*Relational Database Management Systems ((R)DBMS)*) belongs to the core

units of the GIS&T Body of Knowledge (DIBIASE ET AL. 2006).

Data Modelling as core GIS learning unit (excerpt from DIBIASE ET AL. 2006)

Knowledge Area DM. Data Modelling

Unit DM1 Basic storage and retrieval structures

Unit DM2 Database Management Systems (lesson topic of this study)

Unit DM3 Tessellation data models

Unit DM4 Vector and object data models

Unit DM5 Modelling 3D, temporal, and uncertain phenomena

The bold topics are referred to as *core units*, i. e. all graduates of a GIS degree or certificate programme should be able to *demonstrate some level of mastery* (ibid. p. 116).

In search of study topics which address procedural knowledge skills database normalization qualified as the most suitable. The relevant concepts of this topic are explained in [subsection 3.3.2](#) (p. 70).

The GIS&T Body of Knowledge is a comprehensive inventory of the intellectual content defining the field of Geographic Information Science and Technology (DIBIASE ET AL. 2006). It is designed for curriculum planners and evaluators, as well as for certification and accreditation bodies, and further, for current and prospective students, as well as geospatial professionals in government, industry and academia (ibid.).

Studying the principle of database normalization can be compared to applying a mathematical formula set to a specific mathematical problem. This requires the ability of abstract thinking to apply a model or assumptions to a real world setting or a designed issue.

Therefore, knowledge about database normalization has the following advantages for a short learning unit:

- Database normalization is a relevant topic which is required in the stage of managing geoinformation objects. It is necessary to define a useful data structure. This is crucial to the work with geoinformation systems.

- The fundamentals can be easily summarized, which makes it easier to detect lack of prior knowledge regarding the topic (normal forms and normalization rules in contrast to mathematical skills and knowledge about the different coordinate systems with their different scales).
- It is easier to present advantages of a learning topic, which standing for itself can already lead to a considerable value-added for the learner. (Deductive reasoning can be improved: the topic is not only relevant for a specific context such as GIS, but also when generally dealing with information systems.)

The following section shows how these theoretical considerations have been put into practice, i. e. have been operationalized.

Operationalization

The considerations regarding the lesson topic are kept in mind while additional methodological procedures are carried out. The methodological procedure is based on the matrix of support measures shown in [Table 3.1](#), which can be applied to other disciplines as well. It enables the exploration of major influencing factors and outcomes of technology-enhanced learning processes.

The matrix of support measures was designed of selected cognitive and motivational theory elements to develop a method to apply theoretical learning principles to technology-enhanced learning environments systematically while gaining knowledge about procedural learning, which is carried out by exercises and revisions, accompanied by eliminating mistakes step by step ([SEEL 2003](#)). The results are intended to preliminarily define reasonable support measures that can be validated in future studies.

The Process Mining procedure, which includes the activity *discovery*, *conformance*, *enhancement*, and *recommendation* presented in the theoretical section (p. 38), is applied in the following way:

1. The first activity, discovery, which does not use a former process model (a priori information), has been carried out by constructing the matrix of support measures ([Table 3.1](#)) from educational theory.

2. The second activity, conformance check, requires a process model containing a priori information. The matrix of support measures provides the necessary reference model. The new model is generated from the learner behaviour in the TELE study and can be compared to this a priori model.
3. The third activity, enhancement, uses the information generated from the second category. The objective of carrying out the enhancement procedure is to improve the existing a priori model. That means, the comparison of the learner behaviour with the assumed paths can exhibit weaknesses of the theoretically designed matrix of support measures. Based on that, it is possible that the former model needs to be adapted.
4. The fourth activity, recommendation, is carried out by analyzing the results with the objective to improve subsequent learner behaviour by recommending certain paths. Those who use the TELE in the future are therefore assumed to benefit from the learning steps that have worked for previous learners and can thus avoid unfavourable steps. This strongly requires considering the relevant context of the learning situation in order to assume a principle behind effects along the learning path.

These activities are explained in the following paragraphs.

The first activity (discovery) involves the construction of the support measures matrix.

As illustrated in the introduction, CLARK & FELDON 2010 found considerable effects of TELE adapting to intelligence, individual differences, motivational goal orientations, and prior knowledge. For developing the support strategy, interest as representative of motivational goal orientations and prior knowledge are considered. These variables can be assessed easily and, as said, are highly influential for learning processes. Precisely speaking:

1. The variables support a viable learner classification in terms of reliability and operationalization aspects.
2. Even though not the whole complexity of learner characteristics can be captured by these two variables, combined with additional statistical and

process analysis methods, new appropriate support and monitoring strategies can be defined.

To build up the support framework, which will be represented by a matrix of four categories, a set of assumptions that have been validated in former studies is synthesized. These underlying assumptions for the experiments conducted on this theoretical basis are the following:

1. Less prior knowledge leads to higher cognitive load, because working memory has a restricted capacity when dealing with new information (see p. 16). Additional technical sub-items are favourable for learners with higher prior knowledge.
2. Interest conserving material only has a favourable effect and does not cause cognitive overload if a basic interest already exists. This assumption derives from the autonomous learning requirement in the motivational theory of [DECI ET AL. 2001](#).

The matrix of support categories illustrated in [Table 3.1](#) (p. 62) is based on these main assumptions.

Table 3.1: Matrix of Support Measures
Studying support for different categories

Factors	Less prior knowledge	More prior knowledge
More interest of learner in task	Category 1: Supply interest conserving material, reduce cognitive overload by offering less optional technical sub-items	Category 4: Supply interest conserving material, adapt to level of knowledge by providing more technical sub-items
Less interest of learner in task	Category 2: Adapt to interest (less material), reduce cognitive overload by offering less optional technical sub-items	Category 3: Adapt to interest (less material), adapt to level of knowledge by providing more technical sub-items

The supply of motivational material requires a minimum level of motivation represented by a certain task-related interest. For instructors, it is not possible to actively increase intrinsic motivation as argued in [Section 2.4](#), (p. 22). Especially,

the motivational theory of [DECI ET AL. 2001](#) postulates autonomous learning activities to gain or preserve motivation.

When the prior knowledge level is low, it requires more mental effort to study a topic than when the level is higher. In case of higher prior knowledge, the risk of cognitive overload is reduced. Therefore additional task-related information supports knowledge gains without the necessity of overcharging the learner.

The prior knowledge is tested in a question that involves two items about the first normal form of database normalization. The motivational level is assessed by a three scale questionnaire asking the learner how interested he or she is in studying the topic at hand.

The reason for evaluating the learner's interest to define the motivational support measures is the following: [KRAPP 1999](#) identifies a connection between interest and intrinsic motivation; [KRAPP 1993](#) and [SCHIEFELE 1996](#) assume that intrinsic motivation results from the connection between the learning-task and the learner's objects of interest ([KRAPP 1999](#), p. 27). In this case, the related learning goal leads to the realization of interest, which is accompanied by intrinsic motivation. The material provided according to the learner's interest level can therefore be called motivational.

The framework applied in a specific learning context (spatial sciences) is applicable to other subjects as well. That is, because the matrix of support measures is generalized.

The detailed description of the lesson, including methodological considerations, follows in [subsection 3.4.4](#). The overview given at this point is intended to relate the procedure of this work to the *Process Mining* activity of checking conformance of real world behaviour regarding an a priori model.

The second activity (conformance check) involves the adjustment of the support measures matrix.

The four categories of [Table 3.1](#) were operationalized as follows in order to set up an experimental environment that allows the comparison of learner behaviour to the a priori model:

1. The interest and prior knowledge were assessed to classify the learners into the four categories of [Table 3.1](#).

2. The descriptions in [Table 3.1](#) represent the elements of the paths that need to be accessed by the classified learners in order for them to qualify as what is supposed to be called *followers*. That means, that if they behave the way their ideal behaviour is assumed according to the matrix, then they *follow* the a priori model. Analogously, those who deviate from the elements assumed as appropriate for the classified learner, are called *non-followers*.

The last two activities (*enhancement* and *recommendation*) are mentioned in short in this method section and are treated in greater detail in the results section. After Process Mining has been carried out in the TELE, the results of the model comparison are used to improve the existing a priori model. Additionally, recommendations are carried out by analyzing the results with the objective to improve subsequent learner behaviour by recommending certain paths.

Process Mining as explained in [section 2.8](#) was combined with statistical tests to examine the different states the learners start from and change to throughout the lesson ([section 3.4](#) (p. 77)). In that way, their learning processes could partly be observed and explained by the different influencing factors.

Aside from correlation and effect size tests, group comparison methods, and especially cluster analyzes that describe learner characteristics in sufficient detail were conducted. To assure the quality of the empirical study, a set of standards was used. The next chapter refers to the detailed representation of these standards in the appendix. Additionally, the data collection process is explained.

3.2 Data Collection

The data collection was carried out with the students' consent whereas all data was anonymized. The students were assured that the data was going to be used for scientific purposes and that no personal information was collected. The students agreed to the conditions by signing a form.

The empirical standards according to [BORTZ & DÖRING 2009](#) were considered as shown in the appendix (p. 272).

Study samples

Instead of a random sample, a convenience sample was used for the study settings: A total of 369 valid computer literacy and learning material questionnaires were filled out by geoscience students at Kiel University in four semesters between summer semester 2011 and winter semester 2012/13.

Total of 38 university students from a GIS course in the semester 2012/13 participated in the database normalization e-lesson. The pretest of the study was conducted with 10 students. 28 students were evaluated in the main study.

For conducting a preliminary study these kind of samples are acceptable. [Figure 3.3](#) shows the variables assessed within the different samples. The questions answered by this study set-up were presented in section [1.2](#) (p. 2).

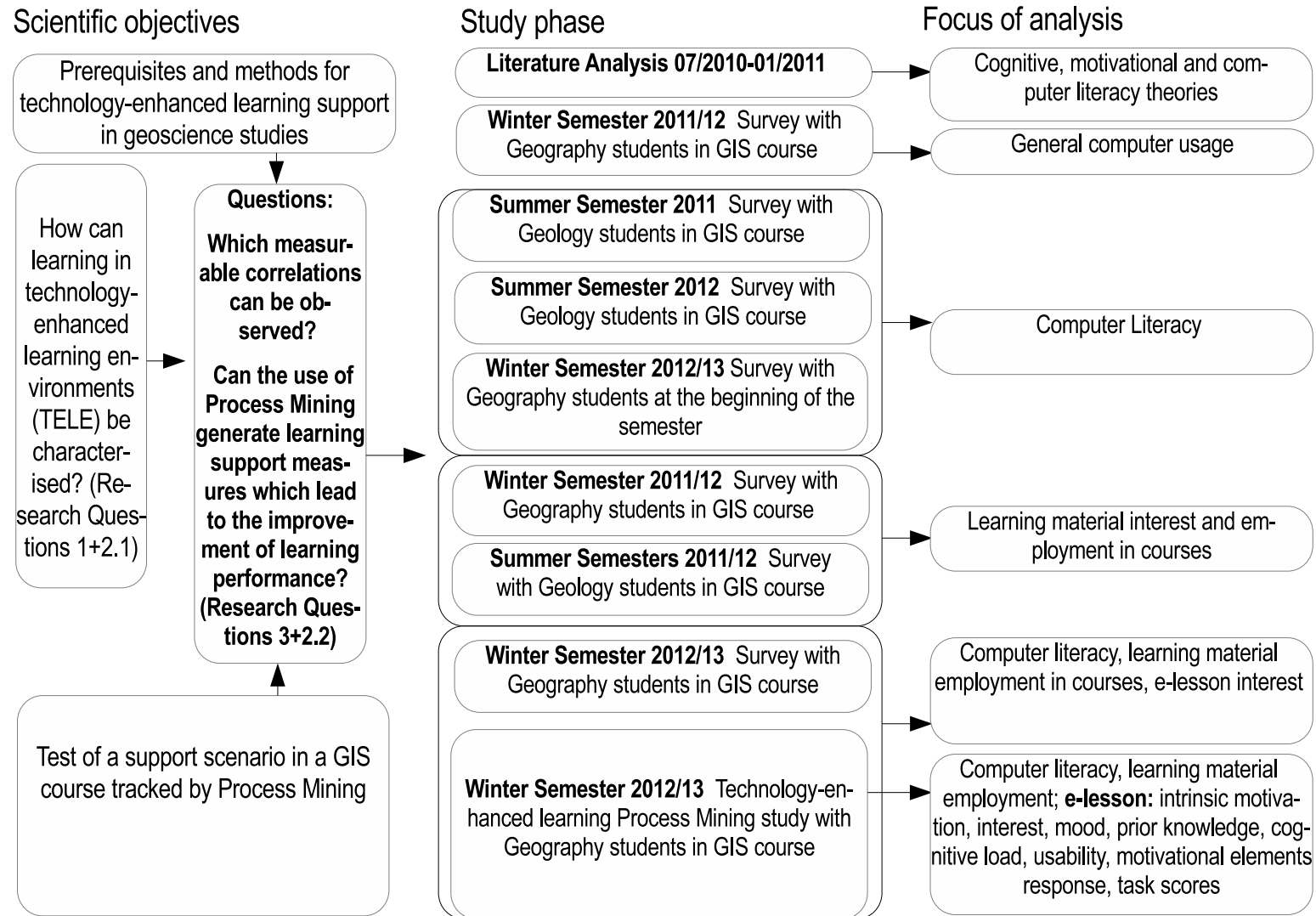


Figure 3.3: Assessed variables per sample

The representativity of a study sample can be ensured globally or specifically regarding a set of characteristics and ideally requires a randomization (BORTZ & DÖRING 2009). A randomized sample was not provided, therefore the general representativity of the sample is restricted. Nevertheless, it was possible to find useful interpretations of the results regarding a set of relevant characteristics because the specific representativity was given. A comparison of the sample with the population via chi-square test (p. 98) provided an additional basis for finding useful interpretations of the results (BORTZ & DÖRING 2009, p. 137 ff.). Additionally the homogeneity of the sample enabled comparisons among the datasets at hand.

3.3 Learning Environment Set-up for Learning Process Improvement

This chapter points out what is needed to carry out Process Mining in a specific scenario (subsection 3.3.1) and sketches the didactical settings which come in to play in the TELE study (subsection 3.3.2). The basis for geoinformatics studies is laid in geography lessons at school if university is not preceded by an apprenticeship in a related field.

3.3.1 Process Mining Scenario for Geoinformation Learning

For constructing a valid model, it is crucial to identify learner variables, which help to anticipate the appropriate learning paths that support learning best.

A generalized learning activities improvement scenario is the following: Frequently prior knowledge in a new study topic does not correspond to the knowledge level required to solve the respective task without any support. An example could be the topic of projection: Map projections allow transferring the spherical earth onto a two-dimensional surface. That involves errors regarding the spatial data, whereas the character of the errors varies, depending on the projection method (HEYWOOD ET AL. 2011, p. 44., f.). Necessary prior knowledge

here is e.g. the understanding of the reference ellipsoid concept: The earth is approximately representable by a mathematically defined rotating ellipsoid. Different reference ellipsoids exist, e.g., WGS84 (World Geodetic System 1984) (see [HAKE ET AL. 2002](#), p. 39, f.). A prior knowledge test which evaluates whether the learner understands the basic concepts of projection can be conducted easily in a TELE.

The support can be supplied by comparing the learner's precondition to those of similar learners in order to recommend a learning path, or even automatically adjust his or her path in a way previous learners were helped successfully before. Process Mining requires the following data categories: First, process instances, i.e. learning processes that have been executed need to be identified. It is useful to enrich these process instances with informational elements, i.e. process characteristics. The Process Mining algorithms can be fed with these data and the actual values can be compared to the respective thresholds to predict success or failure of the process execution.

In order to assess and generate rules, it is necessary to analyze the correlations between the following process characteristics:

- process owner = learning session
- process object = learner
- process object characteristic (e.g., learning path categories *basic*, *advanced*, and *interested*)
- process context characteristic = timely conditions

[Figure 3.4](#) shows: A learner needs to solve a task after his or her prior knowledge has been assessed. The purpose of the conducted assessment is to avoid an ineffective learning process execution. In case of the necessity to modify the process flow, an instructor is able to reconfigure the manipulable process attributes, e.g. when a student has not participated in technology-enhanced learning settings yet and former students had exhibited difficulties with the task in previous situations, then recommending a guided tour through the programme might qualify

as appropriate. After the learner finishes the guided tour, the lesson starts, e. g., a data management online tutorial for geographical research topics.

The data storage differs for the operational data and the data for planning purposes. For operational data Content Management Systems (CMS), administrative data bases and Workflow Management Systems (WFM) can be used. CMS are used for the creation and organisation of content (BAUMGARTNER ET AL. 2004), administrative databases are used for handling the different information systems tasks and WFMS are used to manage workflow specific tasks, whereas a workflow can be defined as an automated process (WFMC 1999), see also previous explanations (p. 37).

For planning purposes a Data Warehouse System can be used. It is defined as *subject-oriented, integrated, timevarying, non-volatile data storage* (INMON 2005). Data which comes from these storage systems are analyzed by a Process Mining expert and used to enhance the rule-based model. This model can then be used to generate the different matching learning paths.

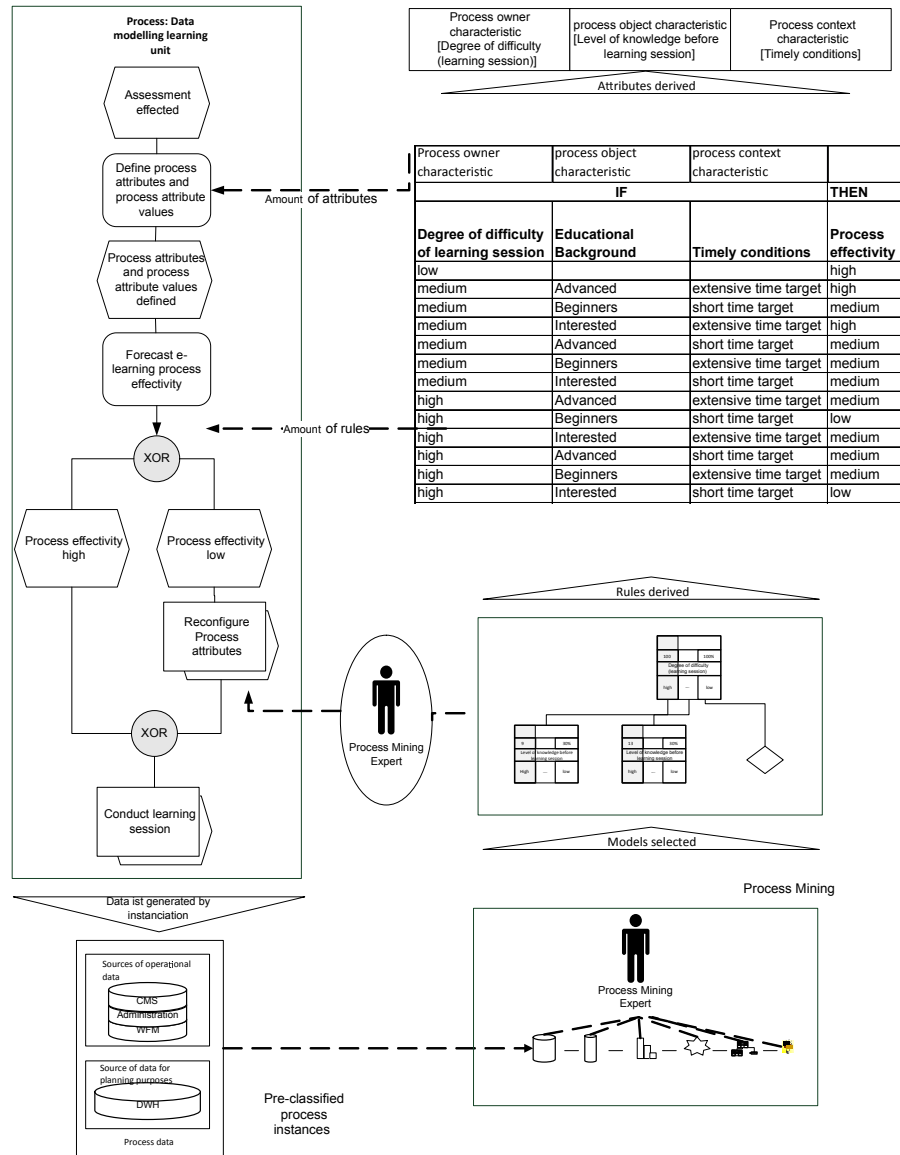


Figure 3.4: Process Mining model (HOLZHÜTER ET AL. 2010)

3.3.2 Database Normalization Learning Environment

This section introduces the test instruments and the studying material used to conduct the technology-enhanced learning study. The described content was used to teach the GIS students an important concept of Geoinformation Systems modelling.

The concept of database normalization is part of the relational model. The basic terms relevant for the technology-enhanced learning task are introduced in the following and in [Figure 3.5](#) (p. 72). This table was part of the participants' handout that was allowed for use after the pretest section.

The relational model goes back to Edgar F. Codd. Data in a database are divided into relations. That is, a relation corresponds to the content or the objects of a database table. The heading of a database table corresponds to the term of the relation scheme, i. e. *customer* in our example. The objects in a relation belong to the same category, e. g., they may all be customers. Customers are defined by characteristics, such as their name and address. These characteristics are gathered in the table columns. The column headings, such as *Name* or *Country*, are the attributes, whereas the column content, such as *Meier* and *D* for *Deutschland* (*Germany*), are the attribute values. Each object has a unique identifier, i. e. the primary key (*ID*).

First normal form

The relation has a primary key ([CODD 1970](#)).

The attribute values comply to the requirement of atomicity, that is composed values such as shown by the example of the address in the *customer* table are not admitted ([ZIMMERMANN 2012](#), p. 73).

Second normal form

The first normal form is provided.

No non-prime attribute in the table is

functionally dependent on a proper subset of any candidate key ([CODD 1971](#)):

Attributes which do not belong to the primary keys only depend on the primary key's attributes in the table or the table needs to be split up.

Third normal form

The second normal form is provided.

Every non-prime attribute in the table

is non-transitively dependent on every candidate key in the table ([CODD 1971](#)), that is attributes which are not a primary key do not - not even indirectly - depend on other non-prime attributes or the table needs to be split up.

Example:

Customer

ID	First Name	Name	Address	Country	City
1	Hans	Meier	Holm 5	D	Kiel
2	Heinz	Müller	Holm 1	D	Kiel

Explanations:

Table	Relational database
Table heading (->"Customer")	Relation scheme
Content of table	Relation
Column heading (->"Name")	Attribute
Content of column (->"Meier" "Müller")	Attribute values
Content of a cell (->"Meier")	Attribute value
Row (->"1Hans Meier Holm 5 D Kiel")	Data set or tuple

Figure 3.5: Basic terms of relational databases (author's illustration according to HEYWOOD 2011)

Edgar F. Codd introduced the first normal form in **CODD 1970** and the second and third normal form in **CODD 1971**. The main goal of database normalization is to avoid redundancy of data sets in databases. As a consequence, data sets are modified more efficiently by only having to change, delete or add data in a single table, whereas these modifications are valid for the whole database due to the relationships defined.

The primary key choice, therefore, is crucial for the model. It is required to be unique as well as minimal. Postal codes, for example, might appear appropriate at first sight but are not unique as soon as a certain regional restriction is excluded,

i. e. a national border is passed. [Figure 3.5](#) (p. 72) shows the illustrating table as the only additional learning content help handed out as a paper handout.

As described before in the *Conceptual Approach* chapter about the chosen lesson topic (p. 58), *Database Normalization* is one of the core topics in Geoinformation Learning. The possibility to isolate the content well, i. e. separate it from related topics, enabled the author to evaluate the gained knowledge in the learning test in clear response to the test instruments.

For the complete lesson documentation in the original language (German) see appendix 8 (p. 227). Briefly summarized the lesson was designed in the following way according to the results of the work of [ROSENSHINE 1987](#) as cited by [WOOLFOLK 2011](#). Note that this work only refers to a part of the procedure recommended by [ROSENSHINE 1987](#) because this conducted study took place once and not several times in the course of a longer period.

- *Review of previous work* corresponds to the prior knowledge test.
- *Introduction of new materials* took place everytime it could not be assumed that the learner already has a specific knowledge.
- *Exercises with instructions* where provided.
- *Give feedback and correct* was followed as well.
- *Exercises to practice independently* where used in the lesson.

More detail about lesson elements, e. g. messages and specific sequences can be found in [subsection 3.4.4](#) which deals with the operationalization of the learning study concepts.

The TELE used is based on Moodle, short for modular object-oriented dynamic learning environment, which is a free software platform ([MOODLE 2013a](#)). On server-side, Moodle is based on the script programming language *hypertext pre-processor* (PHP). On client-side, it uses JavaScript and Cascading Style Sheets. MySQL and PostgreSQL are the database technologies.

The approach in this study used PHP, MySQL, and the open source programme *xampp*, which is a web server simulation environment that does not require an

additional server installation (XAMPP 2012). This was sufficient for the test environment. However, the server space for the e-lesson was on a separate server, because student data was entered via the learning platform.

Figure 3.6 shows an extended illustration of how the approach was technically implemented (see also HOLZHÜTER ET AL. 2010, HOLZHÜTER ET AL. 2013). The learning objects and metadata are not used in the study but integrated into the scheme for the sake of completeness. The glossary can be consulted for explanations. Workflows, instead, are a potential application field for the framework of the study. Therefore, only the term *workflow* is explained in this section.

Workflows and workflow management systems have previously been described (p. 37). In the context of the Process Mining approach as shown in Figure 3.6, workflows are defined and triggered by the rules of the rule management system. In Moodle, it is possible to implement the workflows using the OU Workflow System (MOODLE 2013b).

The implementation scheme shown in Figure 3.6 is intended to be generic. Therefore, the specific technologies used are not included but are additionally named: The Process Mining environment used was *ProM*, which has been introduced in section 2.8 (p. 41). The file was generated by a PHP script (see appendix Appendix 6) in the browser, connected to the MySQL database, and generated the Process Mining file from the Moodle data.

This mandatory information in the entries of the log file in the TELE was necessary to be able to create a file in Mining extended Markup Language (MXML) format (see the example below). This is the basis to generate process models from, i. e.:

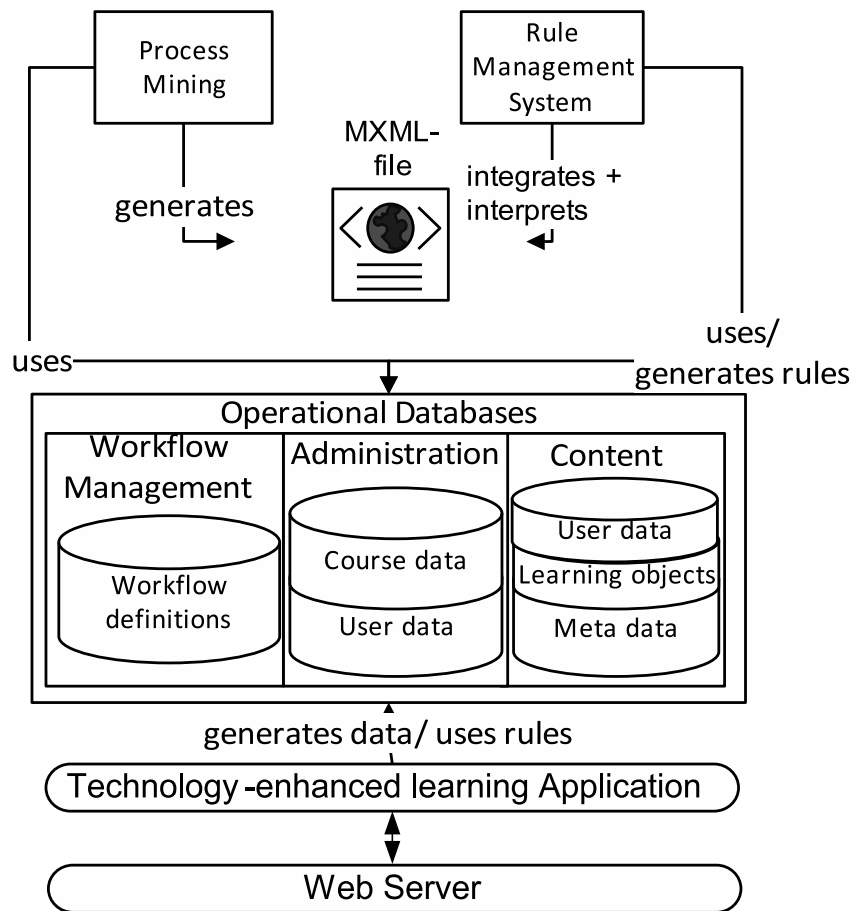


Figure 3.6: Technical implementation of the Process Mining approach in a TELE (HOLZHÜTER ET AL. 2010)

- The name of an event (e.g. a task),
- the start of an event,
- the end of an event (optional because the end of the preceding event marks the start of the next one automatically),
- the timestamp,
- the originator, e.g. the system or a specified user, in the example identified by a user identification number.

MXML (Mining extended Markup Language) example

```
<Process id="UNIFIED" description="Unified single process">
  <ProcessInstance id="0" description="Simulated process
    instance">
    <AuditTrailEntry>
      <WorkflowModelElement>
        login
      </WorkflowModelElement>
      <EventType>
        start
      </EventType>
      <Timestamp>
        2012-01T11:03:00.000
      </Timestamp>
      <Originator>
        Student
      </Originator>
    </AuditTrailEntry>
  </ProcessInstance>
</Process>
```

3.4 Statistical Methods

This section explains the statistical fundamentals and methods used for the empirical studies.

Quality of statistical tests

According to the Standards for Educational and Psychological Testing, the following criteria for the quality of a test are defined (AERA 2004, see also SCHNELL ET AL. 2011): Validity and reliability. Validity is referred to as the degree to which the applied measurements correspond to real world settings (AERA 2004, p. 9 ff.). Reliability is referred to as consistency of measurements throughout the testing procedure which is assumed to be repeated among different populations of individuals or groups (AERA 2004, p. 25 ff.).

The validity indicators chosen for this study are external criteria. An external criterion is the estimation of a person variable already to be held valid, e. g., a formerly validated study or a real world context. The studies described in SENKBEIL & DRECHSEL 2004 have employed the computer self-efficacy questionnaire items within a representative sample and have obtained indicators for sufficient validity of the results. This applies as well to the learning material questionnaire items regarding the study of KLEIN 2008. Further, the e-lesson took place in a nearly real life setting in the computer laboratory where they usually attend their GIS lessons.

The reliability of test items can be measured using the Cronbachs- α coefficient (BORTZ & DÖRING 2009, p. 198 f., LIENERT & RAATZ 1998). Cronbachs- α checks whether all items of an itemset or test measures the same characteristic.

Cronbach's- α is defined as

$$\alpha = \frac{K}{K-1} \cdot \left(1 - \frac{\sum_{i=1}^K s_{item(i)}^2}{s_{test\ value}^2} \right) \quad (\text{BORTZ \& DÖRING 2009, p. 199})$$

where K is the number of test items or scales and s^2 is the average correlation between the items. Further explanations regarding the basic statistical terms are summarized in the appendix (p. 276). The Cronbachs- α values range between minus one and plus one. According to GEORGE 2006 (p. 231) the following interpretation of Cronbachs- α is valid:

- $a \geq 0.9$ excellent
- $0.7 \leq a < 0.9$ good
- $0.6 \leq a < 0.7$ acceptable
- $0.5 \leq a < 0.6$ poor
- $a < 0.5$ unacceptable

For psychological constructs a value of 0.7 and greater is sufficient (GEORGE 2003).

Regarding knowledge tests, a lower value is accepted as well, because this kind of tests is characterized by temporal variability (BORTZ & DÖRING 2009, p. 199). Temporal variability, according to LIENERT & RAATZ 1998, (p. 201), applies to characteristics changing their denotation in the course of test repetition. Values up to at least 0.45 are accepted in analogy to former works, e.g. ECKHARDT 2010.

Comparing the two itemsets:

- *Please name the capital cities in Europe.* (measures knowledge)
- and *How interested are you in the following geomedias?* (measures psychological construct, i. e. interest).

The item values answering the first question have a stronger tendency to vary when tested, even in a similar sample. The second question is likely to produce more homogeneous answer values when asking test persons with similar characteristics.

Requirements for Statistical Tests

Whether data is normally distributed or not defines the set of analysis methods that can be used. In this study, the Kolmogorow-Smirnow test (JANSSEN & LAATZ 2013) was used for measuring the normality distribution in the samples larger than $N=50$.

The Shapiro-Wilk test (SHAPIRO & WILK 1965) can be applied to samples smaller than $N=50$. This test is applied to the learning test results ($N < 50$) for more

robust results. A negative result (data is not normally distributed) for descriptive analysis implies the use of the median or percentages instead of mean values for interval scaled data (ibid.). The result also affects the selection of statistical tests of dependencies or hypotheses.

The median corresponds to the value greater than 50% of the sample, i. e. half the sample is smaller and half the sample is greater than the median (BORTZ & SCHUSTER 2010, p. 46).

Moreover, the general effect of the instructional treatment was examined by a Wilcoxon-Mann-Whitney test for small samples and not normally distributed populations (BORTZ & SCHUSTER 2010, p. 133 f.). The sample comparison regarding their computer literacy was as well carried out with this test. This test measures the effect as a significant difference between control and treatment group or between two groups to be compared without treatment.

For very small samples measuring the effect size, Cohen's d , Bravais-Pearson correlation r are acceptable as well (SEDLMEIER 1996).

The effect size is a measure for the power of statistical tests. This power is not directly measurable. To be precise, the power of a statistical test corresponds to the degree to which an experiment can actually disclose a certain effect (BORTZ & SCHUSTER 2010) (p. 108).

The effect size according to Cohen is calculated as $d = \frac{\bar{x}_1 - \bar{x}_2}{s}$.

It is calculated as the two means which are for standardization reasons divided by the standard deviation (see the appendix on page 276 for additional explanations).

Control variable effects were measured by correlation tests, which allow to assess the interaction of two variables in detail (BORTZ & SCHUSTER 2010).

To calculate significant differences, the Wilcoxon-Mann-Whitney test explained previously can be used for two sample comparisons. For more than two samples, the Kruskal-Wallis test can be used (e. g. DANCEY & REIDY 2010).

3.4.1 Evaluation of Learning Material Interest and Employment

A paper-based standardized questionnaire was used to investigate how often learning materials are employed in the participants' courses and how interested they are in the different resources. However, in previous studies, there are different perspectives on what is referred to in this study as learning material:

The selection which [KLEIN 2008](#) refers to as *geo-media* is referred to by [HEMMER & HEMMER 2002](#) as *studying methods*, whereas [KLEIN 2008](#) also included GIS in her selection. The perspective taken by [HEMMER & HEMMER 2002](#) focuses on the aspect of study support. In contrast, [KLEIN 2008](#) focuses on the representation of study content by media.

As defined in [section 2.1](#), the focus of the media is on communicating and saving information. This focus is too narrow for this study, and therefore the term *learning material* is used instead of *geo-media*.

The definition introduced in [section 2.1](#) can be applied to the selection, which is explained in [subsection 3.4.1](#) (p.80): [GRÄSEL 2006](#) (p.325) views learning material as that part of the learning environment, which includes information, tasks, or prompts, which are presented to the learner via different media.

Learning material such as a GIS includes information, tasks, or prompts, which are, for example, presented to the learner via the medium *computer*. A GIS in the context of learning is viewed as a resource for learning and therefore is attributed to the category of learning materials.

The items in [Tables 3.2](#) and [3.3](#) according to [KLEIN 2008](#) qualify as learning materials assuming that they are applied during university lectures. In these settings, multimedia use involves information, tasks, or prompts for teaching purposes. This characteristic complies with the definition of learning material by [GRÄSEL 2006](#), p. 325.

Learning materials can be employed in university learning settings but can also be of private use. Learning materials of practically no private use are listed in [Table 3.2](#). Learning materials that are assumed to often involve private use are listed in [Table 3.3](#).

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Table 3.2: Learning materials of hardly private use (author's illustration)

LEARNING MATERIAL	FUNCTION
Specialised book/syllabus	Knowledge transfer
Presentations	Knowledge transfer, point out practical relevance
Statistics or tables	Knowledge transfer
Drawings or figures	Knowledge transfer by visualisation
Geographic Information Systems	Capture, analyse, manage and represent geograhic phenomena
Computer-based learning programmes	Gain procedural knowledge

Table 3.3: Learning materials of also private use (author's illustration)

LEARNING MATERIAL	FUNCTION
Computers in general	Undefined concerning specific use, all named tasks applicable; without Internet access only offline tasks can be carried out
Photographs or images	Knowledge transfer by visualisation, also concerning everyday life phenomena, entertainment
Aerial or satellite images	Representation of geographic phenomena
Atlas or maps	Representation of geographic phenomena
Animations or animated illustrations	Knowlegde transfer using animated pictures, outside the university context: entertainment and knowledge transfer
(Press-clippings of) magazines in their current issue	point out practical relevance, also concerning everyday life phenomena, entertainments
Schemes or MindMaps	Knowlegde transfer, also concerning everyday life phenomena, entertainment
Internet	undefined concerning specific use, all named tasks applicable
Original objects	Point out practical relevance; outside the university context: objects from everyday life of considerable importance, especially: objects of spatial interest, e. g. monuments or buildings
Essays based on personal experience or field reports	Point out practical relevance; outside the university context: planning of journeys
Films	Limited knowlegde transfer using animated pictures, outside the university context: mainly entertainment

The analysis of the previously mentioned references was the basis for identifying various forms of learning material crucial to geoinformation learning success. A questionnaire, which disposed of the items and scales shown in the appendix (p. 258), was used to identify the interest of the geoinformation students and the employment of the different learning materials in the respective lessons.

In order to generally analyze computer usage activities of geoscience students the following survey was conducted.

3.4.2 General Computer Usage Survey

Not only learning materials envisaged by instructors are elements of learning for geoscience students. Moreover, the ubiquitous availability of learning material especially provided by the Internet (see also p. 25) needs to be considered to answer the question of how technology-enhanced learning is facilitated.

It can be assumed that the large choice of learning materials strongly influences how TELEs are viewed as a useful learning instrument by students, as, e.g., STERN & WILLITS 2011 have pointed out. As in the study of STERN & WILLITS 2011, it is assumed that similar tendencies of high social media use can be found in the data at hand.

The research design (Figure 1.1) indicates that especially section 2.5 is of relevance for this part of the study dealing with the general computer usage behaviour of geoscience students. In section 2.5 the importance of the students' general habits in the context of learning is stressed.

The survey conducted on the general computer usage behaviour of geoscience students aims at providing a comprehensive picture, which is supposed to support the more specific evaluations of computer literacy (subsection 3.4.3) and technology-enhanced learning (subsection 3.4.4). The items for this evaluation according to OECD 2009 are shown in detail in the appendix (p. 252).

The following two sections and the next chapter zoom in from the more general view to the specific focus of learning with computers.

3.4.3 Computer Literacy Cluster Analysis

In [section 2.6](#), two typologies of interest were introduced. The aim of this empirical evaluation is the combination of the following user types:

- Typology of BRANDTZÆG 2010
 - Non-user
 - Sporadics
 - Debaters
 - Entertainment users
 - Socializers
 - Lurkers
 - Instrumental users
 - Advanced users
- Typology of SENKBEIL & DRECHSEL 2004
 - Enthusiasts,
 - Pragmatists,
 - Free time users, and
 - Unexperienced users.

The computer literacy evaluation according to OECD 2003 comprises the students' study and free time computer usage, their basic and advanced computer self-efficacy, as well as their computer attitude. The exact item text and scales, which are presented here in a summarized version, are shown in the appendix (p. 181).

These variables were measured and used to define different clusters. The cluster description was enhanced by including more recent results regarding media/computer usage typologies.

The R statistics programme (<http://www.r-project.org/>) offers a variety of clustering methods with different capabilities. After having analyzed different clustering methods, the method PAM has qualified as best fit. The disadvantages, or at least the similar advantages, of core methods as discussed in literature are summarized in the following.

From the two categories of clustering methods, the hierarchical methods have the disadvantage that an object which has been assigned to a cluster cannot be reassigned afterwards (BORTZ & SCHUSTER 2010, p. 459). That is why at least a combination of hierarchical and partitioning methods is recommended. The hierarchical methods can especially be used to define a starting partition (ibid.). In this study the partitioning methods were sufficient to answer the research questions related to the computer literacy clusters. Four core methods are:

- PAM: Partitioning Around Medoids
- K-means
- CLARA: Clustering Large Applications
- FANNY: Fuzzy Analysis Clustering

Learner clusters could be identified using the Partitioning Around Medoids (PAM) clustering method. This clustering method searches for partitions around representative objects, i. e. medoids. These are objects from which the average distance to all other elements is smaller than the average distance of any other object of the same cluster to any other object of the same group. In other words: In a group of objects all objects have a smaller distance to each other than the medoid has to any object in the group. When a number of representative objects has been found, all other objects are attributed to the next medoid (HELLBRÜCK 2011, p. 220).

The method CLARA supports the classification of a huge number of objects. A disadvantage of CLARA is that the sample size can influence the results (KAUFMAN & ROUSSEEUW 2009). It was developed during a time where computing capacity was limited and these kind of methods enabled more possibilities whereas PAM has proven to provide the same functionality nowadays (HELLBRÜCK 2011, p. 218).

The k-means method is the basis for clustering methods such as PAM. It has the disadvantage that the classification result can depend on the first automatic ordering of the objects in the data matrix (KAUFMAN & ROUSSEEUW 2009,

p. 114). Additionally it is known as less robust than a method like PAM (MIRKES 2011). Therefore this method did not qualify as first choice method.

FANNY is similar to PAM regarding its way of dealing with missing or accepted data formats. To decide between these alternatives, it is necessary to ask especially the following question: Do I expect clusters with very small clustering values, i. e. is it possible that many objects cannot be attributed to a representative object very well? Then FANNY is an appropriate method, because it focuses on the degree to which objects can be attributed to a cluster.

This scenario did not apply to the data at hand. That is, since in case the application of PAM would have resulted in clusters with very small clustering values, it would have been advisable to use the FANNY method. As the clustering values were high enough to interpret the results as acceptably separated (clustering values >0.5), using FANNY would not have led to considerable advantages compared to PAM. Therefore, the clustering method *FANNY* did not qualify as a more appropriate method than PAM.

The meta-analysis of BRANDTZÆG 2010 has been theoretically introduced before. The resulting typology is used to describe the resulting clusters in further detail. That means, if two clusters would have been attributed to a single cluster according to the clusters used by SENKBEIL & DRECHSEL 2004, similarities to BRANDTZÆG 2010's clusters are identified and in case of congruence used to refine the description.

The items to evaluate the students' computer literacy are presented in detail in the appendix (pp. 255 ff.)

The dichotomization of variables was carried out theory-based. That means, the separating values that are decisive to attribute 1 or 0 are not empirically defined by a certain mean or other metric derived from dividing the evaluated sample, but were identified as separating the groups from a theoretical perspective:

- The dichotomizing value for computer utilization in free time was considered „8“, i. e. a combination of a use once to twice a week for more than 4 hours or 3 to 4 times a week for 2 to 4 hours is considered the medium usage. It does not necessarily take place on a daily basis but in case of use, it is a considerable time span. All values which equal 8 or which are

above belonged to learners with a higher item mean for the corresponding question. The value 1 is assigned to these data sets. The others receive a 0

- The dichotomizing value for computer self-efficacy was considered „3“ (I can do that with the help of someone else), i. e. all values above „3“ (4= I can do that on my own) belonged to learners with a higher item mean for the corresponding question. „3“ is the second highest rank on the scale and a corresponding mean requires all answers to be at least on this level or at least one level higher when at the same time one lower value has been selected. The students who at least manage to carry out a certain task with the help of someone are considered more proficient than someone who only knows how to do so on a theoretical level.
- The dichotomizing value for the computer attitude was considered „3“, i. e. all answers need to be „3“, (I rather agree) or answering with „2“ (I rather do not agree) needs to be compensated by giving answer „4“ (I fully agree) once. The answers are assumed to correspond to a rather positive attitude towards computers. Answer „2“, which is „I do not agree“, implies a rather reserved attitude.

Table 3.4 shows all used values.

The variable to dichotomize the computer utilization data is a combination of the two single but related items *utilisation frequency* and *duration*. This is not advisable for multiple item questions but does not lead to information loss for these single items, which belong to the same context.

If answer values are nearly constant, then the information contained in this variable is limited for the cluster analysis. This variable needs to be mentioned but may not be included to find a cluster solution with acceptably separated cluster groups. From the questions referring to study and free time computer use, only the second question was used. The study use did not show a considerable difference between the students.

Table 3.4: Variable dichotomization for cluster analysis

VARIABLE	SCALE	0 (AS-SIGNED TO LOWER VAL-UES)	1 (AS-SIGNED TO HIGHER VAL-UES)
Computer utilisation in free time	Frequency 1 = not at all t, 2 = not regularly, 3 = one to twice a week, 4 = three to four times a week, 5 = daily AND duration 1 = up to half an hour, 2 = up to an hour, 3 = one to two hours, 4 = two to four hours., 5 = more than five hours	<8	>=8
Self-estimated computer self-efficacy (basic (p.181, ff., items 4.1, 4.4, 4.5, 4.6) and advanced (p.181, ff., items 4.2, 4.3, 4.7))	4 = I can do that all by myself., 3 = I can do that with the help of someone else., 2 = I know what that means but I cannot do that. 1 = I don't know what that means.	<=3	>3
Computer attitude	1 = I do not agree at all. 2 = I rather do not agree. 3 = I rather agree., 4 = I fully agree.	<=3	>3

3.4.4 Technology-Enhanced Learning Study

The following section goes into detail about methodological aspects of the operationalization of the technology-enhanced learning study. The study was conducted once, i.e. the students only had access during a defined time span of about an hour.

The lesson structure for the four support measures categories, *less prior knowledge/more interest (1)*, *less prior knowledge/less interest (2)*, *more prior knowledge/less interest (3)*, and *more prior knowledge/ more interest (4)*, is shown in [Table 3.6](#). The first part of the technology-enhanced lesson about database normalization was identical for all students. If learners answered the question *How interested are you in the lesson?* (Short explanation was provided) with *I have little interest.*, the value of the lesson for the learner was classified as low. The pretest included two question items about the first normal form without further explanations.

The use of a single item for assessing the task interest, or two items for assessing prior knowledge, is methodically vulnerable. The results of this classification were therefore not used to describe the learners in a valid manner but to preliminarily attribute them to the four learning path groups shown theoretically in [3.1](#). The learning path analysis carried out is supposed to detect behavioural principles of the learner groups who are at first classified according to a tendency. For this purpose, this kind of classification offered a sufficient and viable operationalization.

In lesson part II, the learners were supposed to chose their preferred elements. These choices determined whether their learning path conformed to their assessed preconditions (N=8) or whether it did not (N=20). Their knowledge was examined. This variable consisted of the complete score gained throughout the lesson, from which the prior knowledge test results were subtracted.

For lesson part III, the effect of the motivational elements on task scores representing a learning performance component was examined. However, [VISSER & KELLER 1990](#) found the following characteristics of motivational messages, which have been implemented as shown in the right column of [Table 3.5](#). The additional motivational element (short jokes from science, which belong to the motivational

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category of humour) is not a message in the traditional sense and therefore does not need to conform to the rules explained formerly, while still having the potential to improve motivational preconditions (ECONOMIDES 2005).

Table 3.5: Recommended structure of motivational messages (adapted from ECONOMIDES 2005)

MESSAGE CHARACTERISTIC	IMPLEMENTATION IN STUDY
Constant motivation	The messages (motivating quotes) encourage studying the topic by showing practical general advantages.
Systematic distribution	The messages are consistently offered to the learner when seeming appropriate (see next characteristic for further detail).
The message arrives at the right moment.	Offering an optional motivational quote seemed appropriate when the learner was in an introductory phase of a lesson unit and did not need to concentrate on solving a task yet, i.e., the learner had the following options when a new topic (e.g. second normal form etc.) started: Information about the studying goals, proceed directly to the task of the unit or view the motivational quote
The message is informative and motivational at the same time.	The informational character of the messages consists in the practical relevance of the statement. Furthermore the affirmative tone of the statements indicates a positive emotion of the originators and is therefore assessed as a motivational element.

Table 3.6: Support measures for learner categories

LESSON ELEMENT	High value + low understanding (of task)	Low value + low understanding (of task)	Low value + high understanding (of task)	High value + High understanding (of task)
Lesson part I:				
Prior knowledge test - no explanation or results feedback	yes	yes	yes	yes
Interest self-evaluation	yes	yes	yes	yes
Lesson part II (evaluation: score of followers compared to non-followers):				
Introductory testimonial of geoscientists or other professionals	yes	no	no	yes
Goals of database normalisation in Geoinformation Systems	no	no	yes	yes
General value-added of lesson	yes	no	no	yes
First normal form explanation	yes	yes	yes	yes
First normal form task	yes	yes	yes	yes
Postal code explanation	no	no	yes	yes
Lesson part III (evaluation: score and motivational access effect):				
Second normal form explanation	yes	yes	yes	yes
Second normal form task	yes	yes	yes	yes
Second normal form (detailed)	yes	yes	no	no
Short scientific jokes	no	yes	yes	no
(optional:) Testimonial of geoscientist or other professionals	no	yes	yes	no
Third normal form explanation	yes	yes	yes	yes
Third normal form task	yes	yes	yes	yes

The methodical framework for evaluating learner variables was introduced in [section 3.1](#). The generic support framework that proposes the support measures in [Table 3.1](#) is supposed to be applied in an experimental setting. This evaluation requires to especially analyze certain general factors that influence technology-enhanced learning.

The following items have been used and are presented in detail in the appendix.

1. Intrinsic motivation according to [ZIMMERMANN 1994](#)(p. [267](#))
2. Mood according to [VON ZERSSEN & PETERMANN 2011](#)(p. [200](#))
3. Cognitive load according to [URHAHNE 2002](#) (p. [269](#))
4. Usability according to [LEWIS 2002](#) (p. [268](#))
5. Appropriateness of the motivational elements, i. e., the participants' response (p. [271](#))

Chapter 4

Results

How can TELE be characterized by the results of this study? First of all the students' use of technology-enhanced learning environments needs to be mentioned. A clear tendency can be observed regarding first-year students and Technology-Enhanced Learning Environments (TELE): In the survey periods 2011 and 2012 (summer semester), the geology students replied having used a TELE at 74% (77% male and 72% female students). The survey in the winter semesters 2011/12 and 2012/13 with geography students resulted in the students having used a TELE at 81% (80% male and 81% female students).

At the beginning of their studies, the geography students had used a TELE at 35% (the same value for both male and female students). In the middle of the semester, the use had risen to 99% (98% male and 100% female students). The majority of students have thence been observed to get in contact with technology-enhanced learning from the first semester on.

4.1 Learning Material Interest and Employment

The following chapter deals with the students' interest in learning materials in contrast to the current learning material employment. This learning material employment influences the students' experience with technology-enhanced learning. This kind of learning depends on the instructors' priority to introduce their students to modern technology in learning as opposed to traditional learning

material.

These following findings answer the hypothesis H 1.1: *Learning material employment and interest show considerable differences.*

The questions regarding the learning material employed in the university courses were: *How often do your professors employ the following learning materials?* and *How interested are you in the the following learning materials?*

The items were introduced in the learning material section in the methodical part (3.4.1, p. 80).

To point out once more the difference between geography and geology explained in section 2.7 (p. 32): Geography is a spatial science, which also focuses on social aspects (FALK 2006, p. 27), whereas geology exclusively focuses on topics related to the evolution of the planet, its development, and its function (PRESS ET AL. 2008, p. 1).

Figures 4.1 and 4.2 show the results of the learning material survey.

As explained in the methods section, the median is chosen over the mean value as measure of central tendency in case of not normally distributed data.

In the geologists sample the following tendency was found: From the learning materials where hardly private use is assumed, presentations, specialized books/syllabuses and GIS are employed more often than the students are interested in the use. *Statistics and tables* as well as *Drawings and figures* are used as much as the students are interested in their use. *Computer-based learning programmes* are used much less than students would want them to be used.

The learning materials for which also private use is assumed are all employed less than the students are interested in their use. Two exceptions are *computers in general* where the use clearly differs from the interest and *Photographs or images* where the interest corresponds to the employment.

In the geographer's sample the following tendency was found: From the learning materials where hardly private use is assumed, presentations, specialized books/syllabuses and statistics or tables are employed more often than the students are interested in the use. *GIS* as well as *Drawings and figures* are used as much as the students are interested in their use. *Computer-based learning programmes* are used less than students would want them to be used

The learning materials for which also private use is assumed are all employed less than the students are interested in their use. The exceptions are *Computers in general* where the use clearly differs from the interest and *Photographs or images* and *Schemes or MindMaps* where the interest corresponds to the employment.

This discrepancy allows the assumption that these programmes in the respective samples could be employed more often according to the students' preferences. The preferences are represented by their interest regarding the respective learning material.

For blended learning settings where e-learning and traditional learning are combined, these results can lead to setting up a mixture of learning materials which the students are interested in. Many learning materials can also be used as a computerized version so there is not much effort required to provide the learning material which is supposed to be used.

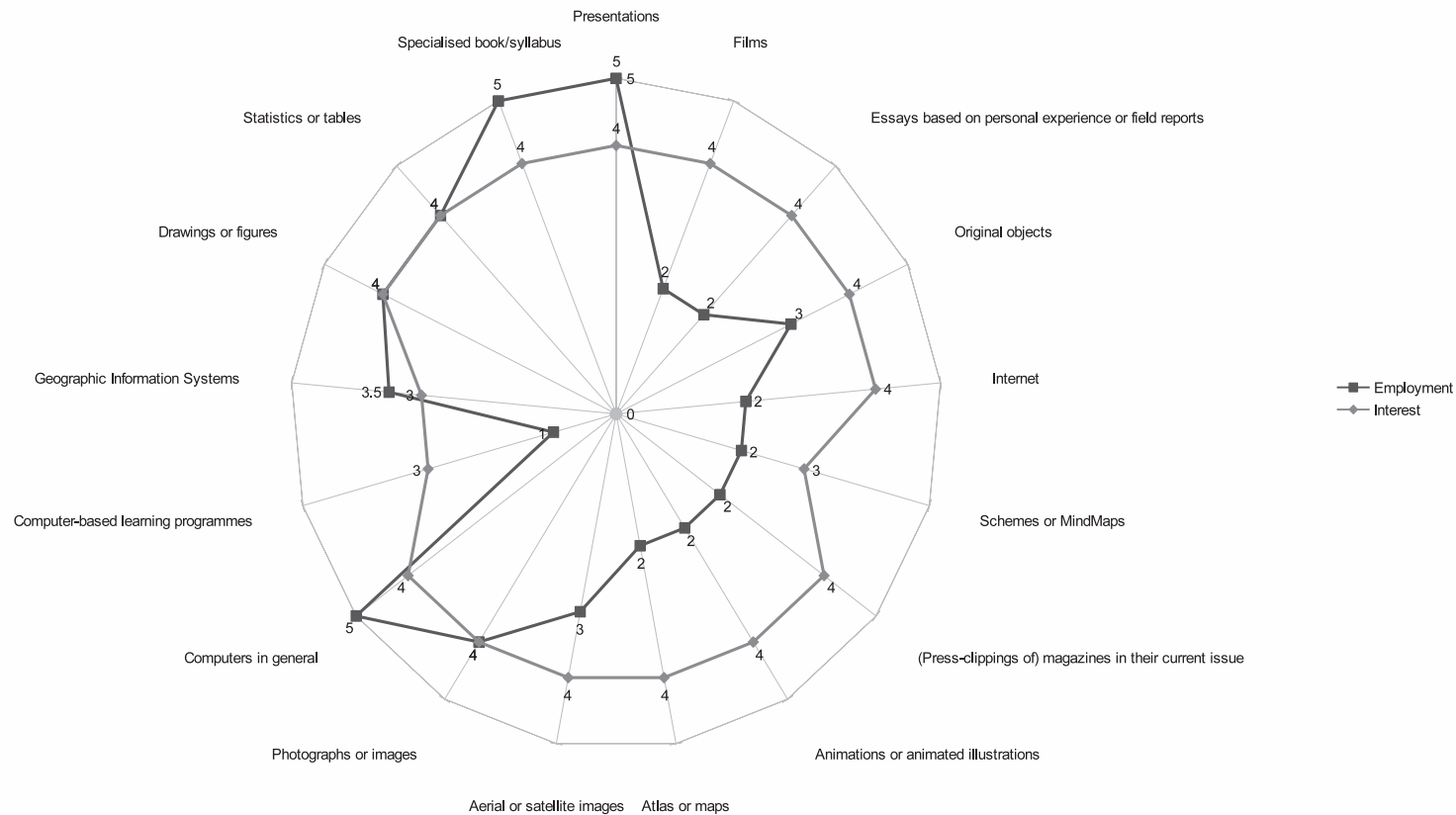


Figure 4.1: Radar chart showing learning material interest and employment: Geology sample results to question *How often do your professors employ the following learning materials?* (0=term unknown, 1=never, to 5=every lecture) (N=148) and *How interested are you in the the following learning materials?* (0=term unknown, 1=I have no interest to 5=It interests me very much)(N=144)

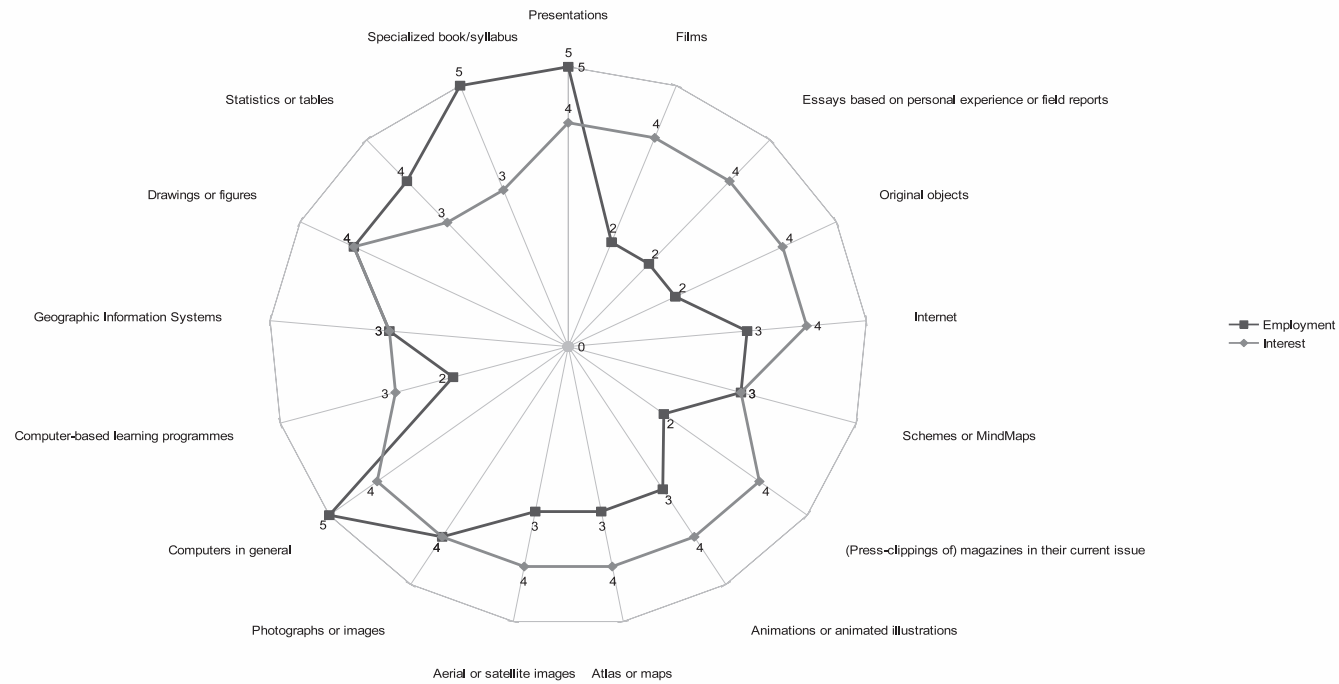


Figure 4.2: Radar chart showing learning material interest and employment: Geography sample results to question *How often do your professors employ the following learning materials?* (0=term unknown, 1=never, to 5=every lecture) (N=65) and *How interested are you in the the following learning materials?* (0=term unknown, 1=I have no interest to 5=It interests me very much)(N=67)

4.2 General Computer Usage

The preconditions for technology-enhanced learning and the different learning material of importance in geoscience have been described in the theory section. Now, a closer look needs to be taken at the specific kind of computer usage, which is fundamental for technology-enhanced learning. Aside from evaluating the different kinds of use, the computer literacy values are as well analyzed in detail.

KLEIN 2008 (p. 197 ff.) found that the perceived learning success is higher the more a specific learning material is employed. Aside from the employment frequency, the kind of use, e. g., comparing different specialized geoscience subjects such as geology and geography, needs to be considered to determine the success factors of technology-enhanced learning in geoscience.

The questionnaire shown in detail in the appendix (p. 252) was used for the PISA studies in 2009 (**OECD 2009**).

Table 4.1 shows the computer usage activity preferences of geography students at Kiel University in the winter semester of 2011/12. The sample was compared to the student population regarding the distribution of male/female as well as the age groups 17-20, 21-24 and 25 and older. A chi-square test indicated a dependency to a p-value of .1 between population and sample, i. e. a highly significant dependency. Therefore, the sample represented its population regarding the respective characteristics to an acceptable degree. The population values are shown in detail in the appendix (Tables 1 and 2, pp. 209 and 210). The questionnaire, shown in detail in the appendix (p. 252), was used for the PISA studies in 2003 (**SENKBEIL & DRECHSEL 2004**). The questionnaires from 2009 and 2003 do not differ considerably regarding the items of interest, i. e. using the new questionnaire items would not have led to a different methodical procedure. In addition, the study conducted to examine computer literacy in the geoscience context by **KLEIN 2008** is based on this questionnaire, and therefore the items have proven to have sufficient external validity, from which this study profits considerably, i. e., an additional prior study to test the questionnaire items in the geoscience context is not needed.

A chi-square test for the samples from the semester of 2012/13 indicated a depen-

Table 4.1: Computer-supported activity (author's illustration)

COMPUTER-SUPPORTED ELEMENT	ACTIVITY FREETIME OR STUDY USAGE	MEDIAN (N=72)
E-mail in general	Freetime usage	4*
Surf the Internet for entertainment (e. g. watch videos on YouTube)	Freetime usage	4
Take part in social networks (e. g. Facebook) or online virtual worlds (e. g. Second Life)	Freetime usage	4
View announcements on university website (e. g. absence of (assistant) professors)	Study usage	3
Chat online	Freetime usage	3
Work on course tasks	Study usage	3
Surf the Internet to work on course tasks	Study usage	3
E-mail to communicate with classmates about course tasks	Study usage	3
Download (e. g. lecture plan or exercise material) from the university website or upload documents or other material	Study usage	3
E-mail to communicate with (assistant) professors about course tasks	Study usage	3
Group work using a university computer with other students	Study usage	2
Download music, films, games and software from the Internet	Freetime usage	2
One-player games	Freetime usage	1
Work with computer simulations	Freetime or study usage	1
Collaborative online games	Freetime usage	1
Publish and attend to own website or blog	Freetime or study usage	1

Cronbachs- α =.67; *1= never or almost never, 2 = once or twice a month, 3 = once or twice a week, 4 = every day or almost every day

dependency to a p-value of .25 between population and sample, i. e. a not significant dependency.

χ^2 is the measure for the differences between the observed and the expected values (BORTZ & SCHUSTER 2010 (p.138)). Therefore, the sample, representing its population regarding the respective characteristics, does not satisfy this criterion. This needs to be considered when drawing conclusions about the population. The values are shown in detail in the appendix (Tables 1 and 2, pp. 209 and 210).

As stated formerly, Cronbach's α is not considered for isolated items; this applies to the frequency and the duration of computer usage (Tables 7, 8, 9, and 10 in the appendix pp. 215) and the use of a learning platform (answer possibilities are yes and no). It is exclusively of interest how often and how long students use their computer for study or free time purposes.

The geologists were only evaluated via questionnaires and only at one point of time in the semester. The geographers, in contrast, on whom this study is focused, were evaluated additionally in a study at the beginning of the semester and in the TELE study. As geography students could have participated in more than one study from these three, the samples need to be treated separately and cannot be perceived as independent.

The computer usage of geographers is similar to the usage of geologists in mid-semester. It takes place daily for free time purposes for one to two hours and three to four times a week at the beginning of the semester and during mid-semester daily for study purposes for half an hour to one hour at the start of the semester and one to two hours during mid-semester (Tables 7- 10 in the appendix). As explained in the methods section, the requirements of test items regarding the reliability of knowledge are less strict than regarding test items measuring psychological constructs. Therefore, the reliability values between .40 and .70 are acceptable. The values are summarized in the appendix (Table 6, p. 225).

Table 22 in the appendix shows the computer self-efficacy of the tested samples. These question items were used to evaluate basic computer self-efficacy. Table 12 in the appendix summarized the reliability values and adds the values of the TELE-study. The answers to the question *What do you prefer doing with the*

computer in your free time? are shown in Tables 13, 14, 15, and 16 in the appendix from page 217 on. Multiple answers were possible.

The mostly pursued computer usage activities (Table 4.1) evaluated in a general survey with geographers in the winter semester of 2011/12 were

- e-mail in general,
- surfing the Internet for entertainment,
- and taking part in social networks or virtual worlds.

These activities all belong to the free time usage category, i. e., less time is spent on study activities with the computer. Productive computer free time usage activities, e. g., attending to own website or blog or working with computer simulations all are on the last ranks.

The computer-supported free time activities preferred most were *searching for information* and *communication* (Tables 13 (p. 217) and 14 (p. 218)). Game-playing and downloading are chosen least (Tables 15 (p. 218) and 16 (p. 219)). Game-playing is chosen rather by male students. Regarding the free text field: Most activities preferred are entertainment activities (Table 17, p. 220).

The computer usage for study purposes (Table 7 (p. 215) and Table 9 (p. 216)) increases towards mid-semester in the geography sample. The use by the geologists during mid-semester corresponds to the use by the geographers at the start of the semester, i. e., the computer is not used daily for study purposes in those two samples. The increase applies as well to the usage duration, whereas the geologists and the geographers evaluated in the middle of the semester use the computer for study reasons for the same duration span. The free time use frequency and duration is the same for all samples (Tables 8 (p. 215) and 10 (p. 216)): It takes place daily one to two hours.

These evaluated preconditions confront instructors with the challenge that high use of entertaining learning material, such as computers with free internet access, also affects the available attention in courses. Therefore, a certain focus on learning material selection is crucial when having in mind that the potential of learning material use is especially made use of by application and practice.

4.3 Computer Literacy Types

This section presents the findings which answer hypothesis H 2.1:

A computer literacy typology generated from the student data (four semesters geoinformation courses in geology and geography) can be utilized to enhance previous findings of computer usage and technology-enhanced learning.

First, the terms *clusters* and *types* need to be distinguished: The term *cluster* refers to a set of objects resulting from the cluster analysis. The ordering and description of these clusters results in a *typology*. If the typology has been defined, the term *type* is used for the study objects assigned to the typology. That means, the term *cluster* always refers to the result of the cluster analysis and is not used when speaking of an element of the typology.

The typologies explained in the theory section have been combined and elaborated for this study to define computer literacy types for geoscience learning settings. Totals in [Table 4.2](#) may not equal 100% because of rounding off. The exact values in those cases are presented in the appendix ([Table 3](#), p. 211).

As explained in the method [subsection 3.4.3](#) (p. 83), the clustering method PAM was used for defining the clusters.

[Table 4.4](#) shows the combination of the Media User Typology (MUT) introduced by [BRANDTZÆG 2010](#) with the computer literacy types used by [SENKBEIL & DRECHSEL 2004](#) and [KLEIN 2008](#). The identified new types were found by clustering the students from the three samples (one geography sample (start and mid-semester) and two geology mid-semester samples): The *sporadic enthusiast*, *sporadic pragmatist*, *sporadic unexperienced*, *free time pragmatist*, *lurker*, *instrumental user*, *enthusiast*, and *advanced pragmatist*.

The clustering variables were used to describe the clusters and the MUT elements were used to differentiate between mainly similar clusters that only differed regarding one variable. The former typology by [SENKBEIL & DRECHSEL 2004](#) does not distinguish between advanced user types. The results of this study and the typology of [BRANDTZÆG 2010](#) allow the definition of reasonable types. The types result from the cluster analysis in case the clusters can be categorized in a typology. The procedure of categorizing the clusters in a computer literacy typology

could be carried out in this study.

The clustering variables are explained in further detail in [Table 4.3](#). How often the new types appeared in the different samples is shown in [Table 4.2](#).

[SENKBEIL & DRECHSEL 2004](#) identified four literacy types. [BRANDTZÆG 2010](#), in contrast, distinguished a larger number. Assumed that four clusters are not sufficient to describe the student variety in the sample at hand, a larger number than found by [SENKBEIL & DRECHSEL 2004](#) is acceptable. The typology of [SENKBEIL & DRECHSEL 2004](#) is extended by the typology of [BRANDTZÆG 2010](#) as follows:

- *Enthusiasts* have high values in all computer literacy categories. These characteristics are similar to those of the *advanced user* ([BRANDTZÆG 2010](#)). In the matrix of the two typologies, the combination of the *enthusiast* and the *advanced user* results in the cluster type *enthusiast*.
- If the free time computer usage and computer attitude values are low, the high self-efficacy values are still characteristic for the *enthusiast*. The *sporadic user* is described as hardly interested and experienced. The combination of these two types was found in the student data. The cluster is called *sporadic enthusiast*.
- *Pragmatists* have low values in computer self-efficacy, as they use the computer rather seldom for free time purposes. They have high computer attitude values.
 - These characteristics mainly correspond to those of the *sporadic user*. The resulting cluster is called *sporadic pragmatist*.
 - In case of high values in the free time usage category, the cluster is called *free time pragmatist*.
 - The cluster with the same values as the *free time pragmatist* except for low computer attitude values is called *lurker*. These users tend to use the computer in their free time, in contrast to the *sporadic user*, for example.

- In case of high values except in free time usage, the *pragmatist* characteristics are extended by higher computer self-efficacy. This cluster is called *advanced pragmatist*.
- *Unexperienced users* have low values in the four categories *free time usage*, *computer attitude*, *basic computer self-efficacy*, and *advanced computer self-efficacy*.
 - These characteristics correspond to those of the *sporadic user*, but the low computer self-efficacy especially characterized the *unexperienced user*. The resulting cluster is called *sporadic unexperienced*.
 - In case of higher basic computer self-efficacy, the *unexperienced user* has similarities with the *instrumental user*, who has a low free time use as well, but has a utility-oriented computer use. This cluster is called *instrumental user*.

Table 4.2: Computer Literacy Clusters in study samples (author's illustration)

SAMPLE	ENTHU- SIAST	SPORADIC ENTHUSI- AST	ADVANCED PRAGMA- TIST	FREE TIME PRAGMA- TIST	SPORADIC PRAGMA- TIST	LURKER	INSTRU- MENTAL	SPORADIC UNEXPE- RIENCED
Geologists 2011/2012 (N=140)	11%	11%	21%	-	30%	-	-	27%
Geographers 2012/13, start (N=137)	8%	9 %	7%	20%	21%	-	-	34%
Geographers 2012/13, mid- semester (N=90)	16%	4%	11%	12%	13%	7%	28%	9%
Geographers 2012/13, TELE study (N=28)	21%	-	71%	-	7%	-	-	-

From the questionnaires the students had to fill up during the survey, the clusters shown in [Table 4.3](#) were identified. The cluster silhouettes are all above 0.5, i. e. their clustering values are acceptable ([ADVGUIDE 2013](#)), whereas high clustering values correspond to well-defined clusters.

The variable that described the computer usage for studying reasons was excluded from the clustering variables. Nearly none of the datasets reached the dichotomizing value in this category. Therefore, the use for study purposes can be characterized as low compared to the free time usage.

Referring to the types and explanations in [Table 4.4](#), the following considerations can be drawn whereas three groups could be defined. The sporadic enthusiast, the sporadic unexperienced type, the instrumental user and the lurker have in common that their combinations of characteristics do not necessarily lead to behavioural change. The sporadic enthusiast already has a high computer but a reserved attitude towards computers. The lurker, the instrumental user and the sporadic unexperienced type have low values in almost all categories. The literacy types can be described as *Trend users or habitual users with low competencies or reserved computer attitude with tendency to remain on this level* (group 1).

The enthusiast and the the advanced pragmatist type have in common that their combinations of characteristics do not necessarily lead to behavioural change. They have high values and can be classified as learners who can be satisfied with the level they have reached. The literacy types can be described as possessing *High competencies or a positive computer attitude with tendency to remain on this level* (group 2).

The sporadic pragmatist and the free time pragmatist have partly low values but all have a motivation to improve their skills. The sporadic pragmatist and free time pragmatist are focussed on computers. The literacy types can be described as possessing more *Development potential* than other types (group 3).

Table 4.3: Computer Literacy Clusters (author's illustration)

LITERACY DIMENSION	ENTHUSIAST	SPORADIC ENTHUSIAST	ADVANCED PRAGMATIST	FREE TIME PRAGMATIST	SPORADIC PRAGMATIST	LURKER	INSTRUMENTAL	SPORADIC UNEXPERIENCED
Freetime computer usage	high	low	low	high	low	high	low	low
Basic computer self-efficacy	high	high	high	high	high	high	high	low
Advanced computer self-efficacy	high	high	high	low	low	low	low	low
Computer attitude	positive	reserved	positive	positive	positive	reserved	reserved	reserved

Table 4.4: Computer Literacy Typology (author's illustration)

MEDIA USER TYPE	ENTHUSIASTS	PRAGMATISTS	UNEXPERIENCED
Sporadics	High computer literacy but reserved computer attitude and low use → Sporadic Enthusiast Type	High basic, low advanced computer literacy, low/ sporadic free-time use, focus on computers → Sporadic Pragmatist Type	Low values in all categories, low use (type: sporadics) rather than no use (type: Non-User) is assumed → Sporadic Unexperienced Type
Entertainment user		High basic, low advanced computer literacy, high free time use leading to entertainment use rather than advanced use, focus on computers → Free Time Pragmatist Type	
Lurker		High values in freetime usage and basic computer self-efficacy (others: low), prerequisites for time-killing (behaviour of a lurker) given → Lurker Type	
Instrumental user			See Sporadic Unexperienced Type but basic computer literacy is high, prerequisites for instrumental use given → Instrumental User Type
Advanced user	High free time use, high computer literacy, focus on computers, corresponding to advanced user characteristics → Enthusiast Type	Low free time use, high computer literacy, positive computer attitude, prerequisites for advanced use given → Advanced Pragmatist Type	

Learning Material Experience of Computer Literacy Clusters

This section deals with the current learning material employment perceived in terms of the different computer literacy types.

The result of a Kruskal-Wallis group comparison test identified a significant difference between the computer literacy clusters regarding their task interest. The exact values are presented in the appendix (Table 18).

Advanced pragmatists and *free time pragmatists* have the highest task interest. Their mean values all reach >4 , which is the middle value on the seven level scale. The academic interests and studying priorities of the participants strongly influence the set of optional modules that they choose. These sets of modules may lead to differences in experienced learning materials.

However, it is assumed that their learning material experiences characterize them temporarily. In addition, different computer literacy types are assumed to have different learning material experiences in their study, whereas a causal relationship is not tested in this study.

The result of the Kruskal-Wallis group comparison test is that one element distinguishes the groups significantly, i. e. *animations or animated illustrations* and one element distinguishes with marginal significance, i. e. *magazines*. The exact values are presented in the appendix (Tables 19 to 21 in the appendix).

When comparing the experience of the cluster types regarding computer-based learning programmes (Table 21), it becomes clear that those types that were also found in the TELE-study experienced medium-low employment of these programmes in their courses. The mean values of these groups were all slightly below 2, whereas 1 corresponds to *never* and 2 corresponds to *seldom*. The *sporadic enthusiasts* and *sporadic pragmatists* were not represented in the TELE-study and had higher mean values (2.67 and 2.71), whereas 3 corresponds to *sometimes*.

The three clusters that were as well not represented in the TELE-study, i. e. *lurkers*, *free time pragmatists*, and *instrumental users*, had even lower values than the TELE-study clusters. On the one hand, these cluster types possess a considerable basic self-efficacy, and on the other hand, their computer attitude values are low or only assumed high for free time usage, see *free time pragmatists*. As opposed to the *sporadic unexperienced* type, the users who belong to these two

clusters might not perceive the need to improve their computer skills as strongly as the unexperienced users.

The radar chart in [Figure 4.3](#) summarizes all differences of the computer literacy types regarding their task interest and learning material experience. As indicated previously, the learning material employed by their professors which distinguished between the computer literacy types were the *animations or animated illustrations* as well as the *magazines*.

The highest employment of *animations or animated illustrations* was perceived by the sporadic pragmatists who at the same time had a task interest above the mean value of the sample. All other literacy types experienced the employment in a range between 3 (*sometimes*) and 1 (*never*).

The highest employment of *magazines* was perceived by the Enthusiasts who at the same time had a task interest above the mean value of the sample. All other literacy types experienced the employment in a range below 3 (*sometimes*) but above 2 (*seldom*).

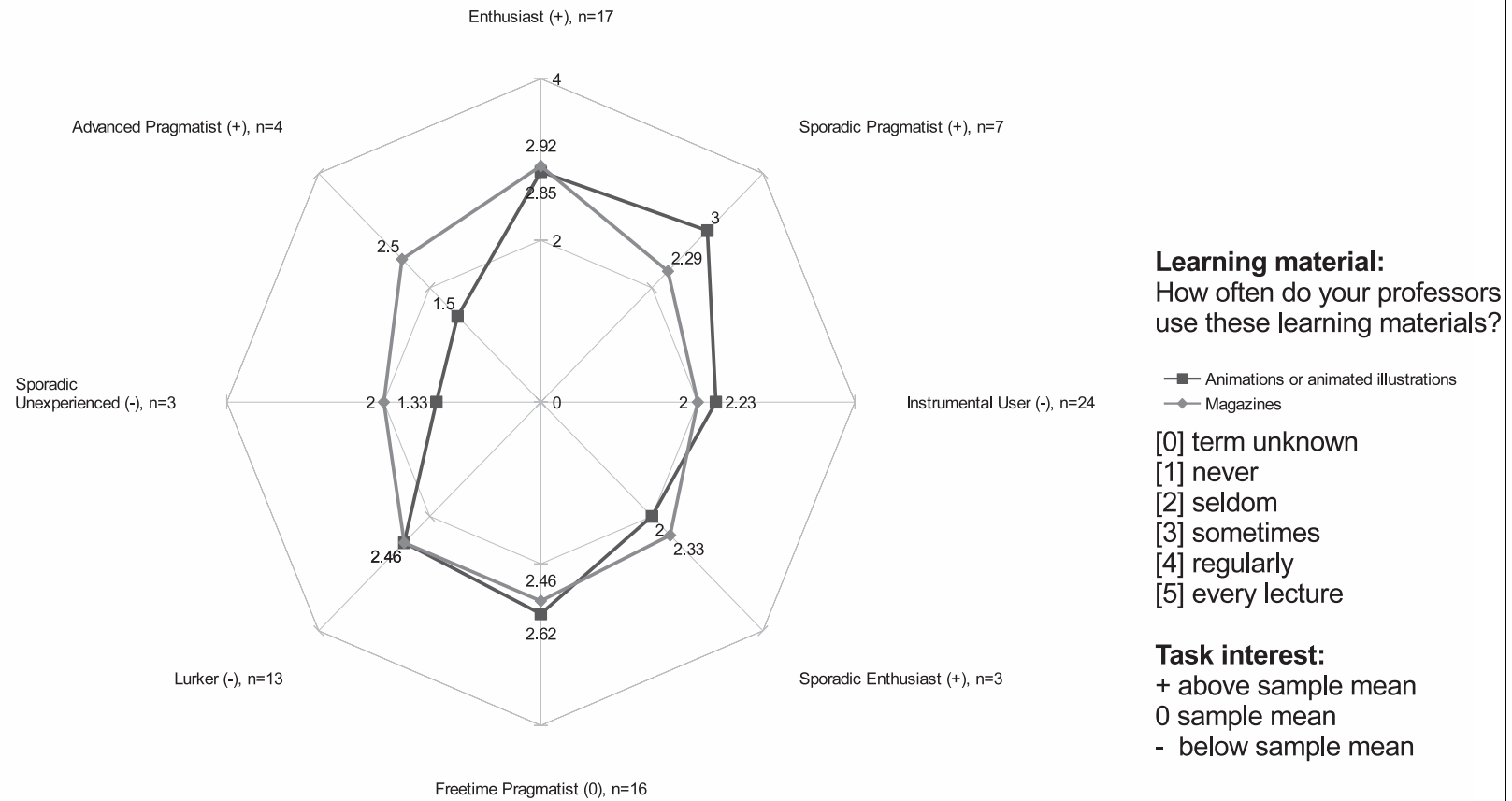


Figure 4.3: Learning material which distinguishes between computer literacy types (Magazines and animations) who are differently interested in the TELE-task (sample mean: + above, 0 equal, - below)

The employment of *animations or animated illustrations* is of considerable interest because they qualify as learning material especially suited for geoinformation topics such as operating a particular GIS. This potential has been pointed out by [SCHWARZ & ASCHE 2006](#) and applied in an empirical study e. g. by [FOURNIER-VIGER ET AL. 2008](#).

When comparing the experience of the cluster types regarding *animations or animated illustrations*, it becomes clear that those types that were also found in the TELE-study experienced low employment of these learning materials in their courses, except for the enthusiast. The mean values of the sporadic unexperienced and advanced pragmatists were all below 2, whereas 1 corresponds to *never* and 2 corresponds to *seldom*. These values are the lowest in the sample.

Technology-Enhanced Learning of Computer Literacy Groups

The following findings answer the hypothesis H 2.2: *Measurable correlations between the identified learning paths and the computer literacy types can be detected*. [Table 4.5](#) shows the differences of the identified clusters regarding their technology-enhanced learning paths ([Table 4.6](#)), which answers the hypothesis 2.2. [Table 4.5](#) points out that the three cluster groups (enthusiast, advanced pragmatist and sporadic unexperienced) followed the learning paths presented in [Table 4.6](#) without possible assignment to recurring learning path per cluster.

- The studying support matrix category 1 (Existing interest requires interest conserving material, low prior knowledge needs cognitive overload reduction) was classified for the enthusiast type and the advanced pragmatist type. Only one learner (advanced pragmatist type) also followed the path 1.
- The studying support matrix category 2 (Less interest requires less motivational material, low prior knowledge needs cognitive overload reduction) was classified for the enthusiast type and the advanced pragmatist type. Only one learner (advanced pragmatist type) also followed the path 2.
- The studying support matrix category 3 (Less interest requires less motivational material, high prior knowledge allows providing more technical

sub-items) was classified for the enthusiast type and the advanced pragmatist type. Only one learner (enthusiast type) also followed the path 3.

- The studying support matrix category 4 (Existing interest requires interest conserving material, high prior knowledge allows providing more technical sub-items) was classified for all three types. The enthusiast type and the advanced pragmatist type followed the path 4 in two cases. The rest deviated from this path.

Table 4.5: Cluster groups paths matching from TELE-study results (author’s illustration)

MEDIA USER TYPE	ENTHUSIAST TYPE	ADVANCED PRAGMATIST TYPE	SPORADIC UNEXPERIENCED TYPE
Type description	High free time use, high computer literacy, focus on computers, corresponding to advanced user characteristics	Low free time use, high computer literacy, positive computer attitude, prerequisites for advanced use given	Low values in all categories, low use (type: Sporadics) rather than no use (type: Non-User) is assumed
Learning process type	3 , 2 → 4 , 1 → 4 , 3 → 1 , 3 → 4 , 4 → 3	1 , 2 , 4 , 4 → 3 , 1 → 3 , 4 → 2 , 2 → 4 , 3 → 2 , 2 → 1	4 , 4 → 1

Legend: **1,2,3 or 4**: Classified process type, →: deviation from classified process type
 1,2,3 or 4: Process type followed instead of classified process type

Table 4.6: Matrix of Learners
 Studying support for different categories (author’s illustration)

Factors	Less prior knowledge	More prior knowledge
More interest of learner in task	Category 1: Existing interest requires interest conserving material, low prior knowledge needs cognitive overload reduction	Category 4: Existing interest requires interest conserving material, high prior knowledge allows providing more technical sub-items
Less interest of learner in task	Category 2: Less interest requires less motivational material,, low prior knowledge needs cognitive overload reduction	Category 3: Less interest requires less motivational material, high prior knowledge allows providing more technical sub-items

A test for dependency between the learning paths and a certain computer literacy type would have been conducted if a minimum correlation could have been assumed. As the first analysis did not lead to any patterns that would have provided useful material for a dependency test, the result of this part of the study is that hypothesis H 2.2 could not be confirmed.

Correlations such as the tendency of *enthusiasts* to belong to category 4, or the *sporadic unexperienced* type to belong to category 4, could not be observed. The reason might be that the sample of 28 learners is too small to draw valid conclusions from the data in this regard.

The main differences between the literacy types are shown by the boxplots in Figures 4.5 to 4.7.

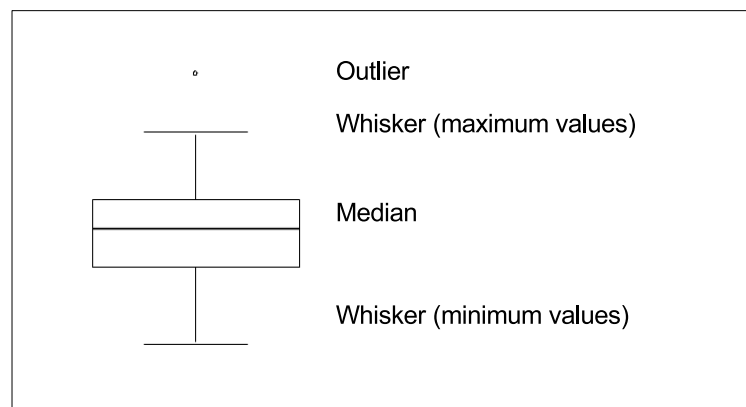


Figure 4.4: Boxplot legend

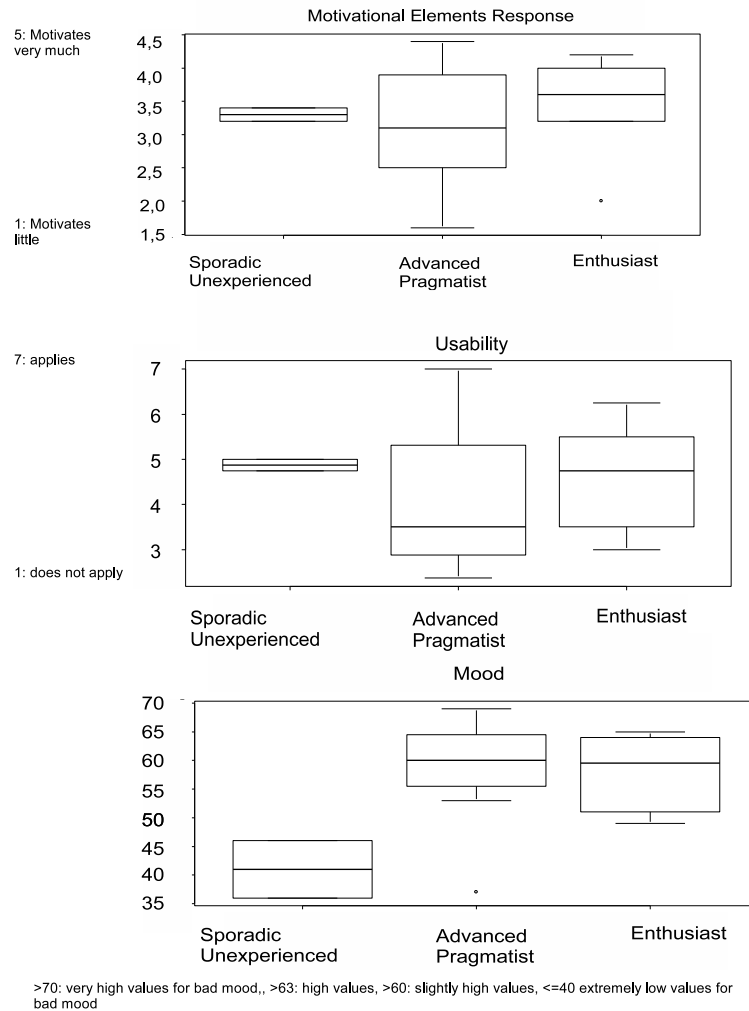


Figure 4.5: Response of computer literacy types to TELE - emotional and behavioural, N=28

The Shapiro-Wilk test (p. 79) conducted on the TELE study data provided positive results, i.e. the data is normally distributed. A t-test is used for normally distributed data, but the group sample sizes should ideally be equal (BORTZ & SCHUSTER 2010, p. 122). As this is not the case, the Kruskal-Wallis test is used to detect group differences (p. 79).

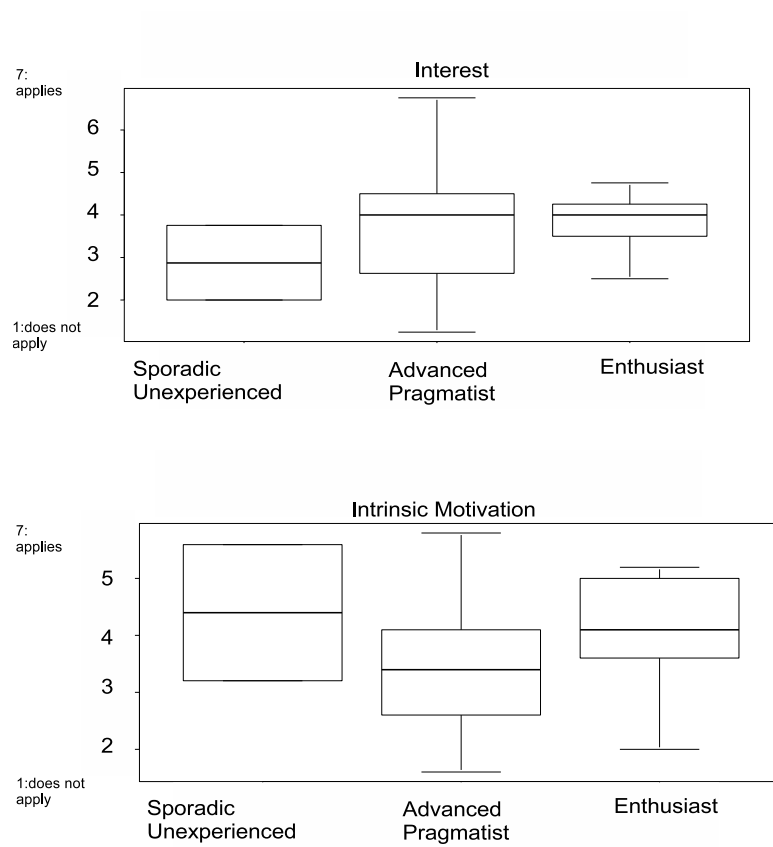


Figure 4.6: Cognitive or emotional response of computer literacy types to e-lesson - motivational, N=28

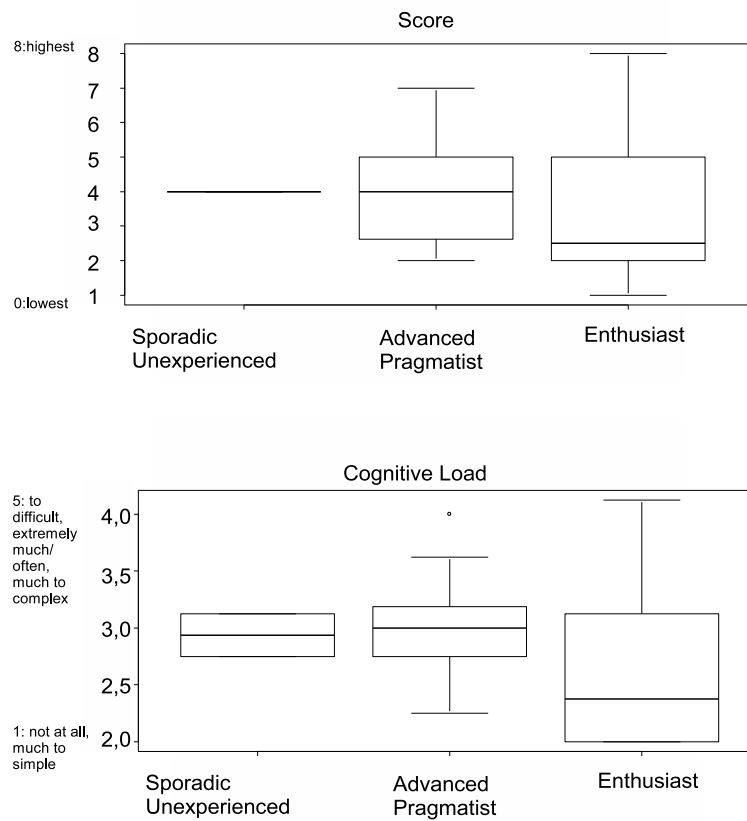


Figure 4.7: Response of computer literacy types to e-lesson - cognitive response, N=28

The test did not find significant group differences. The only slight group difference that can be observed concerns the mood variable with a p-level of $\leq .10$ (.07213, one-sided). Therefore, the following observations can only be interpreted as descriptive results. The group difference regarding the mood level may indicate a considerable tendency. The significance level of $p \leq .05$ has not been met, but as recommended by FISHER 1926, $p \leq .10$ is acceptable as marginal significance level.

The results of the boxplot analysis of Figures 4.5 to 4.7 are:

- The *enthusiast* group has cognitive load and score values, which can be assumed for advanced TELE users. The cognitive load values are low and the score values are high (Figure 4.7).
- The *advanced pragmatist* group has the slightly highest perceived cognitive load (3.03).
- The *sporadic unexperienced* type has the highest scores. (For solving the task 0.5 to 1 point were given for correct answers. There were no minus points given.)
- The *enthusiast* group has the highest motivational elements response (Figure 4.5).

The following section is concerned with the technology-enhanced learning paths. The conceptual basis is the support measures matrix (Table 3.1 (p. 62)).

4.4 Technology-Enhanced Learning Outcomes

In this chapter, the conducted learning experiment is treated in detail. The reliabilities of the variables are shown in Table 4.7, with the following exception: The reliability of the test items for measuring the mood level in the reference sample (VON ZERSSEN & PETERMANN 2011, p. 21 f.) is determining for this specific sample, as the complete set of items has been used for the survey.

The reliability of the computer literacy variables are shown in an extra table, because these variables have been measured in different samples (see [Table 12](#) (p. 217)).

Table 4.7: Reliability of question item sets (author’s illustration)

VARIABLE	RELIABILITY
E-lesson test	0.57
Prior knowledge test	0.57
Learning material experience	0.72
TELE task interest	0.9
Usability experience	0.88
Cognitive load	0.7
Motivational elements response	0.71
Intrinsic motivation	0.81
Mood	0.93→reference sample

These following findings answer the hypothesis H 1.3: *How does the learner respond to the TELE (learner response to the TELE: motivational elements response, usability experience, mood)? correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load)*

Table 4.8: Correlations (author's illustration)

VA- RIABLE N=28	Lear- ning material exp.	Task In- terest	Usabili- ty	Cog- nitive load	Mot. elem- ents re- sponse	Intrinsic motiva- tion	Com- puter attitude	Bas. com. self- effica- cy
Usability	+ns	++***	/	/	/	/	/	/
Cognitive load	-ns	+ns	+++***	/	/	/	/	/
Mot. elements response	0	+++ ***	+++***	+++***	/	/	/	/
Intrinsic motiva- tion	0	+++ ***	+++***	+++***	0	/	/	/
Computer attitude	+*	0	++***	+++***	0	+*	/	/
Bas.com. self- efficacy	0	0	++**	+**	+*	+ns	+ns	/
Ad. com. self- efficacy	0	+ns	+++***	+++***	++***	++**	+*	+**

0: no correlation, +/- small correlation, ++/- medium correlation, +++/- high correlation
ns: not significant, *:significant, .05, **:very significant, .01, ***:extremely significant .001

Table 4.8 shows the correlations between the variables that were evaluated in the TELE study. The exact values can be found in the appendix in Table 6 (p. 214). Variables which correlate highly and with several other variables are *usability*, *cognitive load*, and *advanced computer self-efficacy*. Those variables that do not correlate significantly with other variables at all are not shown in the table. The e-lesson and pretest results are not included in Table 4.8 but show significant correlations, which are treated separately in this section. The reason for a separate representation of variables correlating with these respective variables is the

particular role of the task results.

Usability correlates with the task interest. It is probable that the easier the environment can be used by the learner, the higher his interest in the task at hand. But as the causal relationship has not been measured reliably, it is also possible that learners with a high task interest perceive the environment as easy to use and vice versa. This applies to the cognitive load, the motivational elements response and the intrinsic motivation as well.

The motivational elements response correlates with the task interest and the cognitive load. It can be assumed that a high motivational elements response increases the task interest but also the cognitive load. The opposite direction is possible, too, because the task interest or high cognitive load is likely to affect the motivational elements response.

These following findings answer the hypothesis H 1.4: *How the learner responds to learning with ICT (learner response to learning with ICT: basic and advanced computer self-efficacy, computer attitude) correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load)*

The computer attitude correlates with the cognitive load values. This could be caused by high engagement with computers leading to a high perceived cognitive load. The other direction is not likely because computer attitude is a more general construct. This also applies to the basic and advanced computer self-efficacy.

The computer attitude also correlates with the intrinsic motivation. It is probable that a positive computer attitude leads to a higher intrinsic motivation. The other direction is improbable because the computer attitude is a more general construct. This also applies to the advanced computer self-efficacy.

Additional correlations are presented in the following section. The findings partly correspond to previous findings (see, e. g., ROZELL & III 2000 and CELIK & YESILYURT 2013): ROZELL & III 2000 found a major relationship between computer experience and computer attitude. Transferred to the geoscience context, this relationship could be assumed to apply to learning material experience and computer attitude. In the e-lesson study sample (N=28), and as well in the semester sample (N=90), a slight correlation with an acceptable small error rate (0.05 in

the e-lesson study and 0.001 in the semester sample) was found.

Further, [ROZELL & III 2000](#) and [CELIK & YESILYURT 2013](#) found a considerable relationship between the computer attitude of the test persons and their computer self-efficacy. This correlation could as well be found in the dataset at hand:

- The correlation between advanced computer self-efficacy and computer attitude could be found to a small but significant extent (significance level: 0.05) in the e-lesson study and to a medium and therefore considerable extent with a significance level of 0.001 in the semester sample study.
- The correlation between basic computer self-efficacy and computer attitude could be found to a small but highly significant extent (significance level: 0.001) in the semester sample study.

Comparing Learning Paths

To compare the learning paths the data is analyzed by the already introduced methods *Process Mining* and *effect size tests*. To carry out the Process Mining approach, the relevant process model is introduced. This model has been technically implemented as presented in the methods section. However, the lesson content has not been presented in detail.

[Table 4.9](#) gives an overview of the lesson content elements in the process model. The starting element (question 1) represents the prior knowledge test without any explanations regarding the task or the test result. A confirmation follows so that the participants needed to carry out to reduce the risk of guessing the answer in the first try.

The element *less/more interest* showed the answer result and presented the question regarding the learner's task interest. The answer of the student was marked in the database and therefore is shown in the model as *less* or *more interest*.

The next elements are optional and present

- an explanation of the value-added of the lesson (*Value added of lesson topic*) and
- short testimonials of persons having applied the concept of

- database normalization (*motivating statements*).

The next element (*first normal form*) is mandatory for all participants and explains the first normal form. It is followed by two optional elements: *question 1*, in contrast, is mandatory, as well as *Wrong/correct answer to question 1*, where this answer and explanation are shown to the student. The following line indicates an optional element (*return to question 1*), which offers the possibility to get back to the explanation without changing the answer.

As explained previously, the effect size test is an accepted method to analyze correlations and effects in small samples. Therefore, this part of the methodical design is operationalized by effect size tests for the experiment analysis.

Table 4.9: Explanation of Model Elements (author's illustration)

ELEMENT	EXPLANATION
Question 1	Prior knowledge test without explanations given, test result hidden
Question about interest	(1) Answer result, (2) Question about e-lesson topic-specific interest
Answer: less/more interest	Answer result database entry (hidden to student)
Lesson topic value added	Option: Explanation about value-added of e-lesson
Motivational statements	short testimonials of persons having applied the concept of database normalisation
First normal form	First normal form
Lesson topic goals	Option: Explanation of RDBMS goals
Additional material postal code explanation	Optional explanation treating the issue of postal codes as unique identifiers in practice
Question 1	Repetition of starting question, this time with preceding explanation and showing of test result
Wrong/correct answer to question 1	Answer result and explanation shown to student
Return to question 1	Possibility to get back to the explanation without changing the answer

It is of special interest how these results can be refined to define ideal support processes. Table 4.10 shows the results of the first effect size test, which answers the hypothesis 3.1:

When learner groups, homogeneous regarding the object of investigation, choose elements according to their interest and previous knowledge level, their test results are more favourable than those who choose a different path.

The students with a learning path that matches their interest and prior knowledge level scored considerably higher than those who chose at least one deviating element (medium effect size). This hypothesis has therefore been confirmed.

Table 4.10: Score comparison of group treated with measures to control group (author's illustration)

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 8	3	1.24
Non-follower: 20	2.054	1.24
Cohens d=.8, r=.338		

For the effect size calculation, both the groups' mean values and standard deviations are necessary. The mean corresponds to the average of the respective values, the standard deviation is the square root of the variance. It is of special importance as it possesses the same unit as the measured data. (BORTZ & SCHUSTER 2010 p. 31.). The variance is the sum of the squared deviations of all measured arithmetic means divided by n-1. (JACOBS 1994).

For different group sizes, GLASS 1976 recommends using the standard deviation of the control group for calculating the effect size. A value of d=0.2 (r=0.1) is considered a small, 0.5 (r=0.3) a medium and 0.8 (r=0.5) a great effect size (COHEN 1988).

Small effect sizes and therefore not considerable differences have been measured between the two groups regarding:

- prior knowledge,
- computer literacy (self-efficacy and computer attitude),
- task interest,

- usability experience,
- cognitive load,
- motivational elements response, and
- mood.

Table 4.11 shows the first distinguishing variable values between control and follower group, i. e. learning material experience in their university courses. The follower group had been exposed less to different learning material than the control group (large effect size).

Table 4.11: Learning material experience comparison of control and follower group (author’s illustration)

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 8	2.8	0.31
Non-follower: 20	3.11	0.31
Cohens d=1.19, r=0.474		

Table 4.12 shows the second distinguishing variable values between control and follower group, i. e. the intrinsic learning motivation regarding the task. The follower group revealed a higher intrinsic motivation (large effect size).

Table 4.12: Intrinsic motivation comparison of control and follower group (author’s illustration)

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 8	4.19	1.29
Non-follower: 20	3.49	1.29
Cohens d=1.04, r=0.4245		

Table 4.13 shows the results of the first effect size test, which answers the hypothesis 1.2:

The motivational elements have a positive effect on the task scores. The motivational elements had a positive effect on the participants’ learning performance as shown in Table 4.13. Those who had access to the motivational elements independent of explicit need revealed higher improvement values comparing pretest to subsequent test results.

Table 4.13: Motivational elements effect on performance (test result) (author's illustration)

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 14	3.57	1.74
Non-follower: 14	2.14	1.83
Cohens $d=0.83$, $r=0.3837$		

Follower and Non-Follower Group Comparison for Motivated Beginners

Figure 4.8 allows the comparison of the follower and control group model for the category 1 of the support matrix. This group is characterized by high interest and low prior knowledge, they can be called motivated beginners. They are best supported with additional non-task-related information, which has the potential to increase interest, but which also requires a minimum level of interest. Their prior knowledge requires to reduce cognitive overload by omitting extra task-related information.

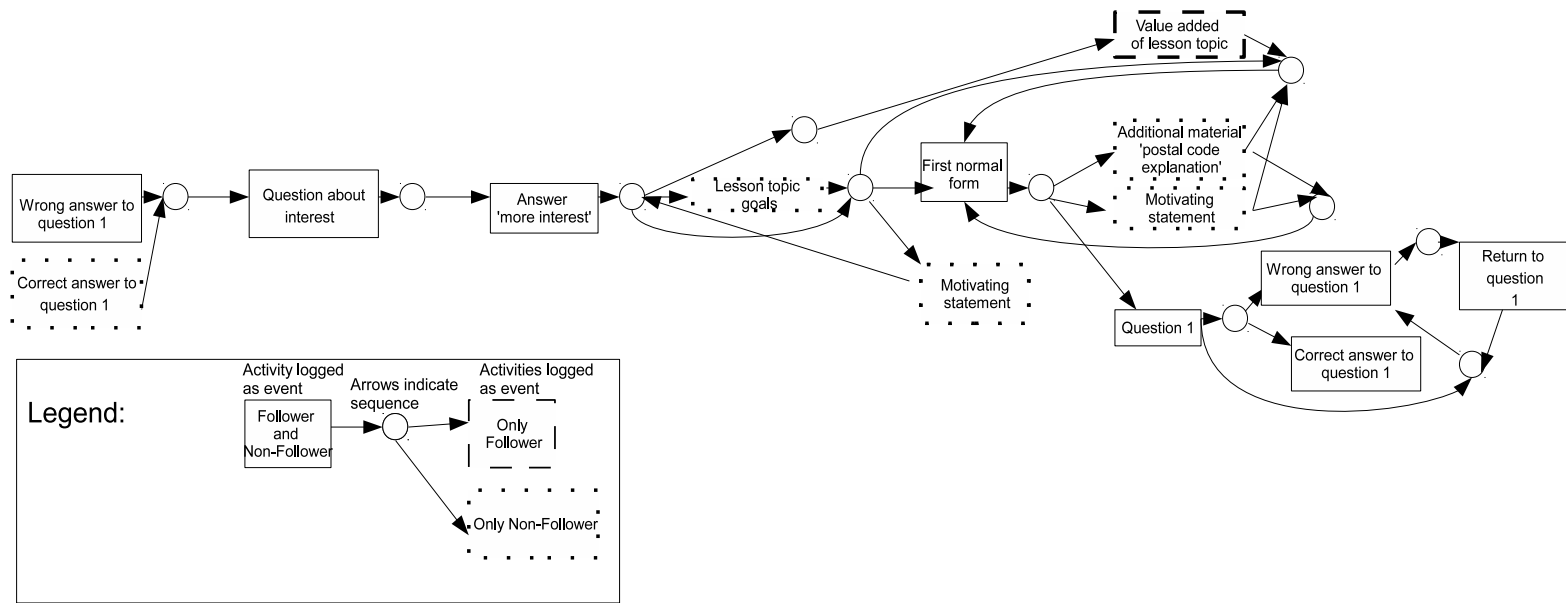


Figure 4.8: Group 1 classified with 'high interest, low prior knowledge', Follower, N=1, Non-follower, N=6, Motivated Beginners (author's illustration)

It is possible that objects of different groups have steps in common. Therefore there can be more than one path which derive from a knot.

As the follower group followed the appropriate process, the models are characterized rather briefly. They correspond to the process descriptions in the methodical section. The information value of the models is highly non-exhaustive considering the small samples in the filtered models. Still, the results can be related to the methodical concept of the study, which has been validated for the complete sample.

The control group produced a process with traces indicating high activity regarding all kinds of elements, in contrast to a the linear model of the follower group.

Follower and Non-Follower Group Comparison for Low Performers

Figure 4.9 belongs to category 2 of the support matrix. This group is characterized by low interest and low prior knowledge. They are best supported by reducing additional non-task-related information, which has the potential to increase interest, but also requires a minimum level of interest. Their prior knowledge requires reducing cognitive overload by omitting extra task-related information.

The control group produced a process with traces indicating high activity regarding all kinds of elements, even in contrast to the first control group. The treatment group revealed a rather linear behaviour and jumped back to the task after giving a wrong answer.

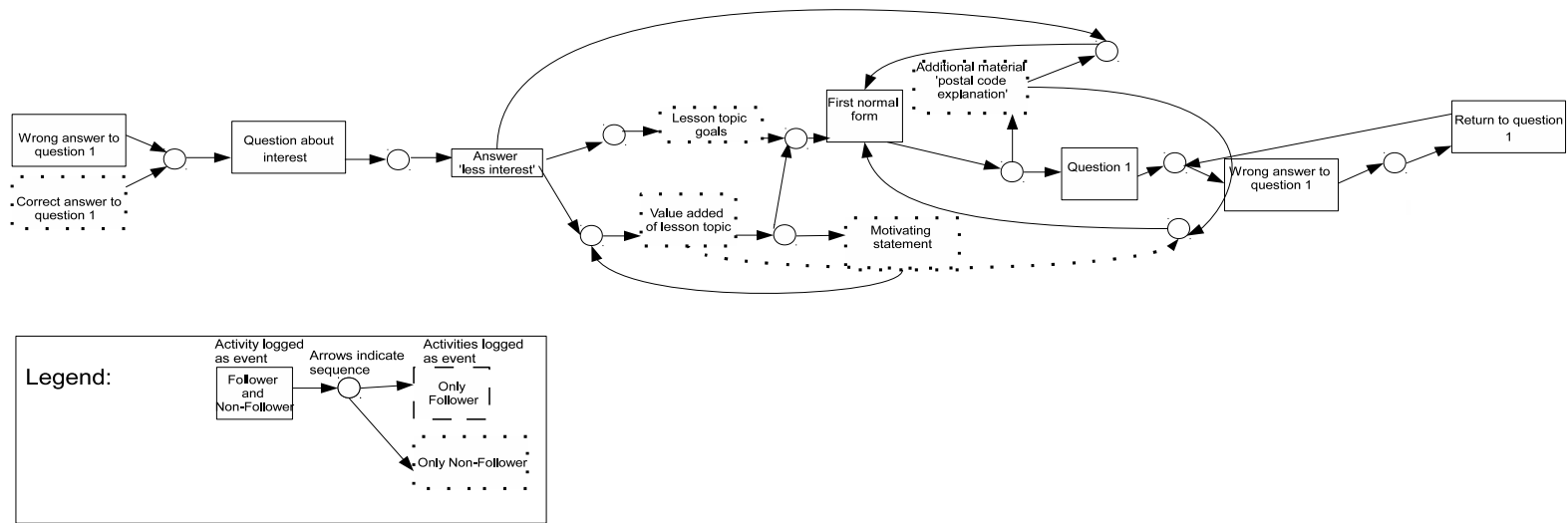


Figure 4.9: Group 2 classified with 'low interest, low prior knowledge', Follower, N=3, Non-follower, N=8, Low Performers (author's illustration)

The group supported by the measures in category 2 of Table 3.1 (p. 62) plays a significant role in this study. As the focus lies on appropriate support measures, it is of interest to especially evaluate the group with the low interest as well as prior knowledge. These characteristics are exhibited by the learner group 2 which can be called *Low Performers*. Therefore, this group is specifically analyzed by effect size tests. The results need to be viewed as preliminary, due to the very small sample.

Table 4.14 shows the distinguishing variable *score* values between control and follower group in the second support group. The follower group revealed higher scores (large effect size).

Table 4.14: Score comparison for support measures category 2 (control and follower group (author’s illustration))

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 3	3	1.125
Non-follower: 8	1.875	1.125
Cohens d=1.11, r=0.4417		

Table 4.15 shows the distinguishing variable *basic self-efficacy* values between control and follower group in the second support group. The control group had a higher basic self-efficacy (large effect size).

Table 4.15: Basic self-efficacy comparison for support measures category 2 (control and follower group (author’s illustration))

GROUP SIZE	GROUP MEAN	STANDARD DEVIATION
Follower: 3	3.42	0.28
Non-follower: 8	3.72	0.28
Cohens d=1.18, r=0.4666		

The results indicate a contradicting effect regarding the basic self-efficacy, whereas the advanced self-efficacy values did not distinguish between the groups. Opposed to these results, the follower group had higher scores than the control group. This effect direction was assumed.

Follower and Non-Follower Group Comparison for Unmotivated Performers

Figure 4.10 belongs to category 3 of the support matrix. This group is characterized by low interest and high prior knowledge. They are best supported by reducing additional non-task related information, which has the potential to increase interest, but which also requires a minimum level of interest. Their prior knowledge allows access to extra task-related information with less risk of cognitive overload. They can be called *Unmotivated Performers*.

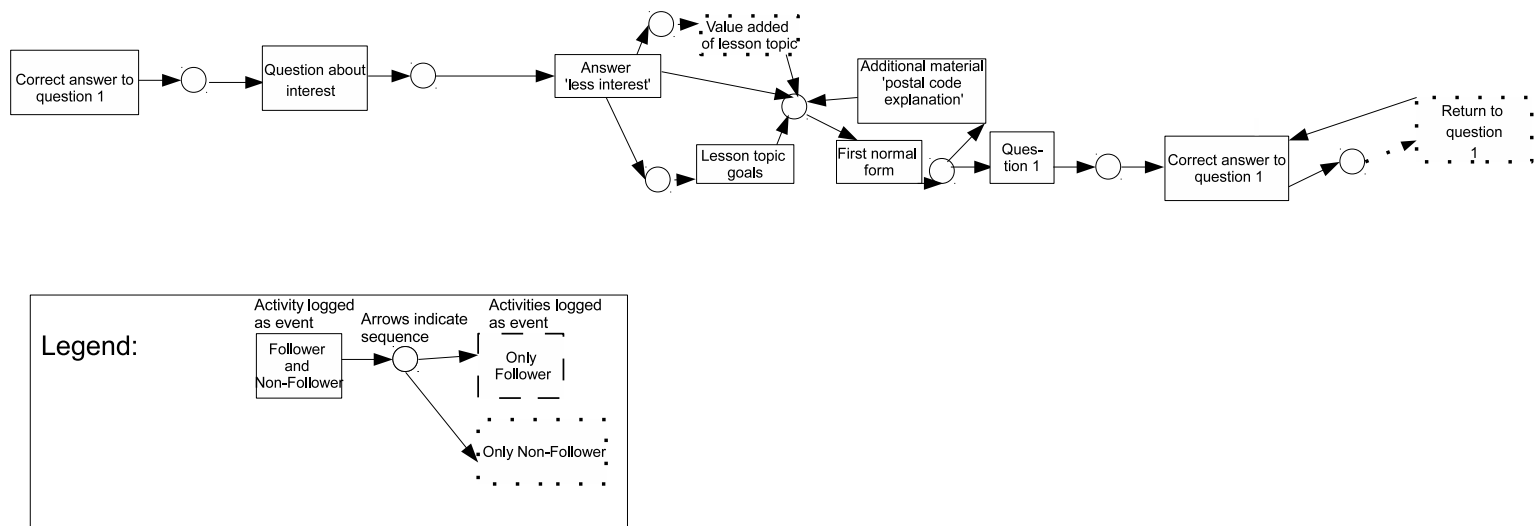


Figure 4.10: Group 3 classified with 'low interest, high prior knowledge', Follower, N=2, Non-follower, N=4, Unmotivated Performers (author's illustration)

The control group produced a rather linear process and only indicated additional activity regarding an interest increasing element and the task description after having received the result (correct answer). The treatment group revealed a behaviour that corresponded strongly to the path assumed appropriate for this learner. Two additional task-related elements were accessed.

Follower and Non-Follower Group Comparison for High Performers

Figure 4.11 belongs to the category 4 of the support matrix. This group is characterized by high interest and high prior knowledge. They are best supported by additional non-task-related information, which has the potential to increase interest, but which also requires a minimum level of interest. Their prior knowledge allows access to extra task-related information with less risk of cognitive overload. They can be called *High Performers*.

Non-follower and follower group models are similar, except for the follower group accessing a non-task-related information additionally to the extra task related information.

Referring to section 2.4, the indirect measures to increase learning motivation is to let the learner develop intrinsic motivation in case it is not existent. Moreover, section 2.3 and section 2.5 laid the theoretical basis for the implication that learning material is supposed to be adapted to the attention and cognitive capacity of the learner.

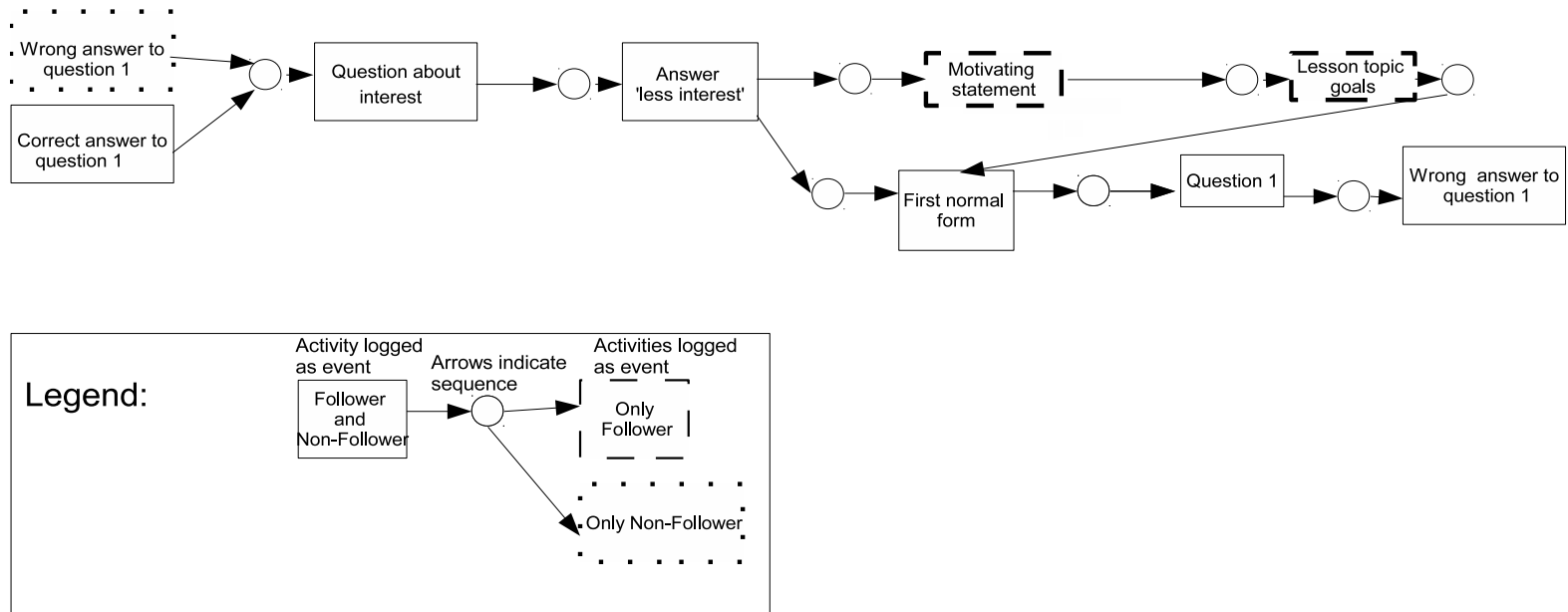


Figure 4.11: Group 4 classified with 'high interest, high prior knowledge', Follower, N=1, Non-Follower, N=3, High Performers (author's illustration)

The preliminary workflow recommendations deduced from these results are:

1. For learners with less prior knowledge, extra material that is not directly related to the task may not be provided before the end of a subunit in the e-lesson.
2. For learners with high prior knowledge, extra material that is not directly related to the task may also be provided before the end of a subunit in the e-lesson.

A framework has been developed, which visualizes the knowledge and knowledge process variables of learners in geoscience via technology-enhanced learning support. This framework can be used to develop empirically tested technology-enhanced lessons in a systematic way.

Chapter 5

Discussion

5.1 Research Questions and Hypotheses Overview

Technology-enhanced learning: How can learning in technology-enhanced learning environments (TELE) be characterized?

A characterization of learning in TELE can be described on a theoretical basis as follows:

A stimulus is created which causes an interaction with the learner (e.g. a representation, prompts, or feedback). The urge to act, which is caused by the respective stimulus, not only depends on the motivational and emotional characteristics and states, as well as the activated prior knowledge of the learner, but also influences these (RHEINBERG 2006). Main factors that trigger an urge to act can be curiosity or expecting the consequences of an action (NIEGEMANN 2011, p. 134).

Depending on the metacognitive skills, the learner plans and carries out actions by applying the amount of self-regulation he or she is capable of. These actions, e.g., a mouse click or text input, result in information processing in the learning environment system. The system then acts in a way that the information supply is changed and adapted to the cognitive and emotional states of the learner. This ideally causes desirable change of cognitive operations and knowledge structures in the learner's long-term memory.

The working memory is highly responsible for the effectivity of learning processes. The way the learning environment is built up strongly influences how these working-memory processes operate (ibid.).

The motivational approach of [DECI ET AL. 2001](#) and cognitive load theory referred to in this work were integrated into a support measures framework for learning processes reducing cognitive overload and facilitating intrinsic motivation in order to improve learning performance.

A characterization of the TELE in this study on the empirical basis can be described as follows: *H 1.1: Learning material employment and interest show considerable differences.*

This hypothesis was preliminarily confirmed: A considerable difference was found. The main results in detail are the following: In the geologists sample presentations, specialized books/ syllabuses and GIS (from the hardly in private used learning materials) are employed more often than the students are interested in the use. Statistics and tables as well as drawings and figures are used according to their interest. Computer-based learning programmes are used much less than they would want them to be used. In the geography sample similar results were found - except for the statistics and tables which are employed more often than the geography students are interested in this learning material.

From the other learning materials which are also being used privately almost all materials are used less than the students are interested in their use. In both groups the use of photographs and images corresponds to their interest. In the geographer's sample schemes and MindMaps are used as much as the students are interested in their use. In both groups computers are used more than the students are interested in their use. It is assumed that computers are used but not computer-based learning programmes.

The results show a discrepancy between interest and employment which might be caused by the equipment of the university in combination with the course curriculum. Even if there might be a certain fit, it could be beneficial to increase the use of learning material which interests most students. Especially the use of computer-based learning programmes could increase student motivation and skills (see e. g. [FRICKE 1991](#), p. 22 in this work).

H 1.2: The motivational elements: Testimonials of professionals and explanations of the lesson's value-added have a positive effect on the lesson test scores.

The motivational elements had a positive effect on the participants' learning performance. Those who had access to the motivational elements independent of explicit need revealed higher improvement values comparing the pretest to subsequent test results.

H 1.3: How does the learner respond to the TELE (learner response to the TELE: motivational elements response, usability experience, mood)? correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load)

This hypothesis was confirmed for the following variables: Usability correlates with the task interest. It is probable that the easier the environment can be used by the learner, the higher his or her interest in the task at hand. But as the causal relationship has not been measured reliably, it is also possible that learners with a high task interest perceive the environment as easy to use and vice versa. This applies to the cognitive load, the motivational elements response and the intrinsic motivation as well.

The motivational elements response correlates with the task interest and the cognitive load. It can be assumed that a high motivational elements response increases the task interest but also the cognitive load. The opposite direction is possible, too, because the task interest or high cognitive load can affect the motivational elements response.

H 1.4 How does the learner respond to learning with ICT (learner response to learning with ICT: basic and advanced computer self-efficacy, computer attitude)? correlates with the way he or she participates in an e-lesson (learner response to e-lesson: task interest, prior knowledge, e-lesson results, intrinsic motivation, cognitive load)

This hypothesis was confirmed for the following variables: The computer attitude correlates with the cognitive load values. This could be caused by high engagement with computers leading to a high perceived cognitive load. The other direction is not likely because computer attitude is a more general construct. This also applies to the basic and advanced computer self-efficacy. The advanced com-

puter self-efficacy correlates negatively with the prior knowledge test results. The prior knowledge test results might be impeded by a too advanced level, because the need to invest attention and effort might not be perceived as high as when starting from a beginner's level.

The computer attitude also correlates with the intrinsic motivation. It is probable that a positive computer attitude leads to a higher intrinsic motivation. The other direction is improbable because the computer attitude is a more general construct. This also applies to the advanced computer self-efficacy.

It needs to be considered for the cognitive load results what REY 2009 (p. 48) points out. The problem of cognitive load measures is that they do not yet distinguish in a reliable manner between the different types of cognitive load. This needs to be considered regarding the cognitive load variable.

Can a measurable correlation between the identified learning paths and computer literacy types be detected?

H 2.1: A computer literacy typology generated from the student data (four semesters geoinformation courses in geology and geography) can be utilized to enhance previous findings of computer usage and technology-enhanced learning.

This hypothesis was preliminarily confirmed: A solution with acceptably separated clusters was found. The exact values are summarized in the appendix (Tables 4 and 5 (p. 212), f.).

H 2.2: Measurable correlations between the learning paths and the computer literacy types can be detected.

This hypothesis was not confirmed in this study: The computer literacy clusters did not correlate with the learning paths.

The computer literacy types did not correlate with the learner process types analyzed by Process Mining. Nevertheless, the clusters found for the typology can be described consistently and are acceptably separated. Therefore, they provide comprehensive, explorative material for further validating studies.

Unfortunately the sample size for the study was beneath the recommended level: For future studies, the following considerations are of importance: The ideal

sample size for a geoscience learning study, with a confidence level of 95%, i. e. an error rate of 5%, is 313 geography students. The population of the winter semesters 2011/12 and 2012/13 is 1686. The geology sample would require 236 students. The population of the summer semesters 2011 and 2012 is 608.

Does Process Mining qualify as methodical instrument to test hypotheses derived from current learning theories?

H 3.1: When learner groups choose elements according to their interest and previous knowledge level derived from current learning theories their test results are more favourable compared to those of the ones that choose a different path.

Adjusting learning paths according to the support measures matrix leads to favourable task scores. An additional influence factor of importance was the intrinsic motivation. This variable had a large positive effect on higher test results. The access to motivational elements had a large positive effect on the test results as well. The combination of these two factors appears favourable for learning processes.

When analyzing one specific group of interest (low interest, prior knowledge), the results indicate a contradicting effect regarding the basic self-efficacy, whereas the advanced self-efficacy values did not distinguish between the groups. Opposed to these results, the follower group had higher scores than the control group.

H 3.2: The use of Process Mining can generate learning support measures which lead to the improvement of learning performance.

The support measures matrix was combined with Process Mining. This approach led to preliminary conclusions about effective technology-enhanced learning, which can be validated in further studies.

5.2 Research Contributions

All in all it can be stated from the results that a valid preliminary model has been designed and tested. The empirical findings are now summarized and transformed into contributions to the body of research.

These results were crucial:

A contribution of the study to the body of research findings was inter alia a computer literacy typology, which can be generated from the student data (four semesters geoinformation courses in geology and geography). It comprises these types:

sporadic enthusiast, sporadic pragmatist, sporadic unexperienced, free time pragmatist, lurker, instrumental user, enthusiast, advanced pragmatist.

This typology has been developed by empirical studies in different geoscience samples. It has further been extended from former works (SENKBEIL & DRECHSEL 2004, KLEIN 2008, meta-analysis of BRANDTZÆG 2010) to allow a more comprehensive classification.

Regarding the types found in the geology sample, it needs to be mentioned that the Chi-Square test provided the result of a dependency between the sample and the population. The results need to be stressed because they can be (carefully) used to make a general statement about the literacy types in the population of geologists at Kiel University.

The types identified in this sample are the *enthusiast, sporadic enthusiast, advanced pragmatist, sporadic pragmatist, sporadic unexperienced.*

The computer literacy types did not correlate with the learner process types analyzed by Process Mining. Nevertheless, the clusters found for the typology can be described consistently and are acceptably separated. Therefore, they provide comprehensive, explorative material for further validating studies. These may possibly not operate with a convenience sample that was required in this study, due to organizational restrictions.

The computer literacy types can be categorized into three groups:

1. Trend users or habitual users with low competencies or reserved computer attitude with tendency to remain on level (sporadic enthusiast type, sporadic unexperienced type, lurker, instrumental user type)
2. High competency with tendency to remain on level (enthusiast type, advanced pragmatist type)
3. Development potential (sporadic pragmatist type, free time pragmatist type)

Taking into account the different characteristics of the literacy types, these groups could be identified. The classification allows to draw conclusions about how to support geoinformation learners best. The group of learners with development potential is the one which can be taken into focus by e-learning technicians. E-learning material needs to exhibit a clear purpose of the studying procedure. And regarding the trend users it is helpful to motivate students who are rather contented with their level to search for practical applications of their computer knowledge.

These results did not correlate with the Process Mining results which were generated in the TELE study. Nevertheless, the TELE study led to these valid recommendations: When learner groups, homogeneous regarding the object of investigation, choose elements according to their interest and previous knowledge level, their test results are more favourable than those who choose a path not corresponding to their support measures category.

Additional technical sub-items are favourable for learners with higher prior knowledge, and interest conserving materials only have a favourable effect if a basic interest already exists. The reason for this is avoiding cognitive overload.

When given the choice, considerably more learners chose a path deviating from the one appropriate to their interests and prior knowledge. The implementation of TELE processes, which considers these assumptions, is likely to produce higher learning performance than otherwise. However, the results are limited to the restrictions of the study, which, on one hand, are caused by a small sample size and, on the other hand, by referring to a single discipline.

The analysis of the specific *low interest, prior knowledge* group exhibited a contradicting effect regarding the basic self-efficacy, whereas the advanced self-efficacy values did not distinguish between the groups. The follower group scored better, but at the same time had lower basic self-efficacy values.

The four categories and the computer literacy types can be used in subsequent e-learning studies with more study participants to investigate the link between learning paths and more or less permanent learner characteristics such as the computer literacy types.

For a future Process Mining study, additional mining algorithms can be tested,

which involve larger sets of users who produce the mining logs. These are assumed to result in additional models, which can be transformed into technology-enhanced learning workflows, which control the learning paths, especially of beginners. Considering crucial learning success factors, the high influence of the intrinsic motivation for learning success is one of the major findings. Future studies might include additional variables such as intelligence to define other influences on the learning result. However, finding influencing factors for technology-enhanced learning in general was not the main objective of this study. If this were the case, state-of-the-art methods for causal relationships would have been eligible, e. g., structural equation modelling as used in a comprehensive study by [LAU & WOODS 2008](#).

The limitations of Information Technology - especially in learning - need to be considered while taking advantage of its wide-ranging potentials. Especially the support of structured learning can be implemented with the highest cost-benefit ratio in technology-enhanced learning environments. The challenge is to find an underlying structure in learning topics. The presented method of Process Mining offers a wide range of exploratory methods to comply with this task.

Chapter 6

Conclusions

One major aim of this study was to provide a methodology to structure technology-enhanced learning processes. The underlying support approach was preliminarily validated. On the basis of these results and of the current state-of-the-art in technology-enhanced learning research, a generic support framework and analysis procedure were generated. It can be altered or refined for use in other didactical domains.

Another objective of this study was the application of Process Mining to technology-enhanced learning processes. This focus required a set of conceptual, statistical and technological instruments which have been investigated and applied in a preliminary study. For this purpose the methodological set and sample size have been sufficient.

This work tackled the challenge of combining knowledge about computer literacy types with learning path analysis via Process Mining by focusing on geoinformation learning. In the empirical studies a set of correlations could be discovered. The correlations implied that the easier the environment can be used, the higher the interest in the task at hand. Additionally it can be assumed that a high motivational elements response increases the task interest but also the cognitive load.

Furthermore it was found that high engagement with computers led to a high cognitive load. Additionally advanced computer self-efficacy correlated negatively with the prior test results. A valid assumption is that prior test results might be impeded by a too advanced level because the need to invest attention and effort

might not be perceived as high as when starting from a beginner's level. The correlation between the computer attitude and the intrinsic motivation can be explained by the probability that a positive computer attitude leads to a higher intrinsic motivation.

The contradicting result in the TELE-study that the follower group scored better but at the same time had lower basic self-efficacy values can be related to the computer literacy findings: The literacy types *lurker* and *instrumental user* have high basic computer self-efficacy and low advanced computer self-efficacy, whereas their computer attitude is reserved. This set of characteristics suggests that a sufficient basic literacy leads to a decreasing ambition to participate in an e-learning study as the one described because the benefit is not attractive enough. This can be the reason for these two literacy types not being represented in the TELE study. However, learners who have similar characteristics appear to be at disadvantage compared to learners who especially differ in the basic self-efficacy from these literacy types.

As presented in the discussion, three groups could be formed for the computer literacy types found in this study (*Trend users or habitual users with low competencies with tendency to remain on level; High competency with tendency to remain on level and Development potential*). The recommendations generated for these groups (p. 142) need to be refined in future studies.

The Process Mining results which did not correlate with the mentioned computer literacy types can be used in the following way: The guidance of meta-cognitive learning strategies can be carried out by visualizing learning paths and discussing learning outcome from the perspective of how the student carried out the necessary learning steps. These can be reflected assuming the theory of the support measures matrix.

For example, a learner was supported by the measures from category 2 (Low Performer, less material to increase interest and less optional technical sub-items to facilitate studying focus). Then the process model that was generated can be used to track the learner's personal progress. These questions can support the learning path reflection:

- What was the reason for using optional materials? (The task is boring? The material was interesting?)
- Which material would have helped best to focus on the task?
- Did the interest in the task increase or diminish?
 - If the interest has diminished: Is there a way to improve the e-lesson or are there specific learning obstacles for the learner which need to be resolved first such as inefficient time management or lack of useful learning goals?
 - If the interest increased: Would it be an option to continue working on this topic in the future?

After review of the findings of this study, what appears to be necessary are educational computer-supported learning sessions, which focus on learning process monitoring and learning material efficacy. The presented method supports these goals by combining the Process Mining method with learner and learning material evaluations.

Considering the need to focus on useful and easy-to-implement studying support principles, the support measures framework offers a practical classification scheme for instructional strategies. As the principles can be transformed into IF-THEN learning rules, they can easily be implemented in technology-enhanced learning environments, where process analysis techniques help generate learning models and therefore supply further material for to improve learning.

An approach as in [DOMINIC ET AL. 2015](#) could benefit from the Process Mining method instead of the case based reasoning and simplex method to match learning paths. Process Mining enables the author to model the learning path while it is being used and not afterwards. Additionally, the Process Mining approach works without collecting to many confidential data.

Future studies should focus on learners' tendency to overestimate the human capacity for multi-tasking ([ROSEN ET AL. 2013](#)). Especially the high usage of entertainment media found in this study suggests the importance of this perspec-

tive. Instructors are constantly confronted with the challenge that high use of entertainment media also affects the available attention in courses.

In accordance with [ROSEN ET AL. 2013](#), [LAU & WOODS 2008](#) found that classroom attentiveness together with group participation were positive predictors of deep learning. Therefore, a core objective might be the learning support to deliberately draw attention to what matters in the current learning situation - ideally based on individual (i.e. intrinsic) motivation. Further studies based on the proposed framework are necessary to consider the *attentiveness* factor as related to the learning performance, and especially to the learner's meta-cognitive processes.

The findings of this study are assumed to support social learning in geoscience as well. The following considerations relate the aspect of *attentiveness* to the social component in learning.

[SCHULMEISTER 2012](#) identifies the following success factor for technology-enhanced learning: *It is of importance not only to draw our self-confidence from our social relations.* Not to focus primarily on social relations while learning consequently supplies additional resources for deep learning. But social relations tend to dominate in times of learning with modern communication. [JOHNSON ET AL. 2013](#) identified major learning trends that do not involve less but rather more online communication and mobile access to learning content.

[ADAMEK 2011](#) (p. 303) additionally hypothesizes that the widely accepted urge of being online constantly could be the main problem of what he calls the *Facebook trap*. He refers to [FOUCAULT 1984](#) (p. 31) who already stated that humans are not capable of being with company when it is impossible for them to be alone.

[ADAMEK 2011](#) argues that this applies to the modern society who is not able to keep track of this tendency, because it is so strongly individualized. Paying attention to learning processes appears to be impeded by the availability of constant distraction whereas a considerable part of society perceives this distraction as *normal*.

As shown in Chapter 4.2 the main usage categories of computer-supported media are information, communication, and basic entertainment, but little intensive entertainment use, as e.g. online games. Further, the usage examined is char-

acterized by little productive usage, represented by website or blog activity or working with computer simulations. At the same time, geoscientists are supposed to be able to use media to encourage discourse to better understand areas of deeper knowledge, i.e. spaces, identities, power contained within performance of media form or representation (LUKINBEAL & CRAINE 2009, p. 5).

However, instructors need to be aware of the need for manifold and didactically appropriate learning material employment. This is usually facilitated by the respective practical experience not necessarily with learning material such as computer-supported alternatives.

Geo-media usage can expose issues beyond its narrative content, a richer engagement with geo-media is likely to increase geo-media literacy (LUKINBEAL & CRAINE 2009, p. 5), whereas films, computers, internet, photographs and images in general are clearly preferred and regarded useful for geoscience learning (KLEIN 2008, p. 168 ff.).

The manifold options of technology-enhanced learning can be especially made use of by computer support. The computer literacy analyzed in this study can be a key to general competencies in media usage. That is, because the focus lies on the methodology of learning with media.

As argued before, BRADLOW ET AL. 2002 found that students tend to overestimate their knowledge about computer functions but at the same time underestimate their technical abilities. This tendency might be facilitated by the wide range of learning materials introduced by educational institutions. To focus on the functional aspects of media rather than the novelty effect may lead to higher competency levels without sparing the advantages of the wide range of new materials.

These new materials may often promise to solve more problems that cannot be solved without them. Instead, it may not be proven that previous learning material does not cover the respective needs. As has been argued before in the section about motivational aspects in TELE (p. 22), the didactical needs and available learning support do not necessarily coincide (HOCHHOLDINGER & SCHAPER 2008, p. 17, WELSH ET AL. 2003).

Announcements, such as to be found on GML 2015 provide food for thought when

speaking of a *increase of flexibility regarding learning spaces and time, concepts and support of self-determined learning*, which are needed.

The acronym GML² stands for *Fundamental questions of multimedia teaching and learning (German: Grundfragen Multimedialen Lehrens und Lernens)*, a conference which is held yearly since 2003. The GML² conferences encourage discussions about current technology-enhanced learning issues and trends among experts and other interested parties.

Additionally [STROHMEIER ET AL. 2015](#) provide insight into current Human Resource trends regarding analytics. They explicitly point out that TELE environments can be a useful source of information when applying Real Time Analytics to LMS logs.

The trends that were named suggest that technology-enhanced learning support needs to be scalable while based on valid educational principles. The approach presented in this work provides a preliminary basis that guides into this direction. In practical terms: The four categories of support measures can be implemented by the scheme used in [RACHBAUER 2009](#), [SAUERSTEIN 2007](#), which could be a future project of interest.

As [DOWNS & DE SOUZA 2006](#) take into consideration, the need for increased scientific and technological literacy in the workforce and everyday life is given. Starting in school, graduates need to be equipped with skills that will enable them to think spatially and as well apply tools and technologies such as GIS for supporting spatial thinking (*ibid.*, p. 13). In contribution to this, one of the main goals of the Open Geospatial Consortium Inc. ([OGC 2013](#)) is to standardize GIS technology to involve a larger user community in the development process of GIS technology.

The demand for qualified use of technology appears to be of special interest in the geoscience discipline. The analyses of this study have shown that the potential of geoscience students to develop expertise in the field of geoinformation technology is given, but needs to be transformed into the ability of practical application. This remains a field of further research - ideally in interdisciplinary and multimethod analysis settings.

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Appendix 1 - Abbreviations

EDM

Educational Data Mining

ICT

Information and Communications Technology

Moodle

Modular Object-Oriented Dynamic Learning Environment

MUT

Media Usage Typology or Media Usage Types

RDBMS

Relational Database Management Systems

Appendix 2 - Glossary

Cognitive Load (p. 16)

Theory assumes that working memory disposes of limited capacity when dealing with novel information whereas long-term memory disposes of nearly unlimited capacity.

Concept learning (p. 10)

Has factual knowledge as outcome. The basis of concept learning, i. e. concepts, possess a meaning, and a structure.

Computer Literacy Types (p. 25)

Classification of computer and media user behaviours into meaningful categories.

Data Mining (p. 37)

Nontrivial extraction of implicit, presumably useful but previously unknown information from data and a procedure which identifies potential, valid, useful as well as understandable patterns in databases.

Effect Size (p. 79)

Measure for the power of statistical tests whereas this power is not directly measurable i.e.: the power of a statistical test corresponds to the degree to which an experiment can actually disclose a certain effect.

Educational Data Mining (p. 43)

Aims at the development, research, and application of computerised methods for pattern detection in large collections of data from the educational context which would otherwise be difficult or impossible to analyse because of the enormous volume of data within which they are stored.

Event log (p. 37)

Occurrence which triggers a business process and represents the basic unit of a Process Mining model (stages off occurrence: e.g. start or end, a type, e.g. message, exception). The record is the documentation of a workflow, i.e. a fully or partially automated business process.

Geoinformation learning (p. 33)

The goal of geoinformation processing for knowledge acquisition is to create and apply spatial models in a way that even high levels of abstraction keep the models descriptive and concise (SCHWARZ & ASCHE 2006). This goal can be supported by technology.

Learner (p. 9)

Individual who carries out the activity of learning, i.e. the process of acquiring new, modifying, or reinforcing existing knowledge, behaviours, skills, values, or preferences, and is likely to involve synthesising different kinds of information.

Learning material (p. 10)

Corresponds to the instructional setting, i.e. the goals, media, materials, methods, instructors, and learners, including the learning processes and outcomes.

Learning material (p. 10)

Consists of that part of the learning environment which includes information, tasks, or prompts which are presented to the learner via different media.

Learning objects

Modularise learning material and are intended to support reusability of studying content (KNOLMAYER 2013).

Media (p. 11)

Resources, technical devices, or configurations employed to communicate or save information. Examples are books, audio players, or computers.

Meta data

Describe objects which are processed by information technology (EICKER 2012).

Motivation (p. 22)

Condition of cognitive and emotional arousal leading to conscious choice to take action and initiate a phase of continued intellectual and/ or physical effort, e. g. to achieve a determined goal; enabling students to socially experience relatedness, feel autonomous, and receive competence feedback are primary motivating factors.

Motivational elements (p. 22)

Elements employed to promote motivational reaction

NDH model (p. 55)

Model of interactive learning named after the authors Niegemann, Domagk, and Hessel

Typology (p. 102)

Result of the cluster analyses in this study. Set of objects resulting from the cluster analysis: cluster. Element of the typology: type.

Procedural learning (p. 10)

Carried out by exercises and revision accompanied by step by step eliminating mistakes.

Process Mining (p. 1)

Method to build process models by use of event logs (see p. 173) in order to describe the behaviour contained in the traces produced by information systems usage.

Appendix 3 - Questionnaire 1

Fragebogen Studie zu Lernwegen in elektronischen Lernumgebungen

Dieser Fragebogen dient einer wissenschaftlichen Erhebung zu Lernwegen in elektronischen Lernumgebungen.

Bitte unterstützen Sie dieses Vorhaben, indem Sie diesen Fragebogen vollständig und korrekt (bitte nur mit einem Kreuz (außer bei Frage 2)) bei Ankreuzfragen) ausfüllen. Es werden keine personenbezogenen Informationen abgefragt.

1. Allgemeine Fragen:

1.1 Geschlecht weiblich männlich

1.2 Alter

1.3 In welchem Semester befinden Sie sich? Semesteranzahl:

1.4 Welche/s Fach/ Fächer studieren Sie?

Hauptfach:

Nebenfach:

2. Wie oft verwenden Sie den Computer oder ein mobiles Gerät für folgende Aktivitäten?

2.1 Spiele im Einzelspieler-Modus

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.2 Online-Spiele für mehrere Spieler

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.3 E-Mails zur Kommunikation mit Dozent(inn)en über auf das Studium bezogene Aufgaben benutzen

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.4 Einen Rechner in der Universität für Gruppenarbeiten und zur Kommunikation mit anderen Studierenden verwenden

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.5 E-Mail generell

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag 2.6 Online-chatten (z.B. mit Skype©)

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.7 Zur Unterhaltung im Internet surfen (wie etwa zum Videoschauen, z.B. auf

YouTube™)

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag 2.8 Musik, Filme, Spiele oder Software aus dem Internet herunterladen

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

jeden Tag oder fast jeden Tag

2.9 Eine eigene Website/Internetseite, Blog veröffentlichen und betreuen

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.10 An Online-Foren oder virtuellen Welten teilnehmen (z.B. Second Life©oder Facebook™)

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

jeden Tag oder fast jeden Tag

2.11 Aufgaben aus den Vorlesungen oder bungen bearbeiten

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.12 Zur Bearbeitung von Aufgaben im Rahmen des Studiums im Internet surfen

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.13 E-Mails zur Kommunikation mit Kommiliton(inn)en über auf das Studium bezogene Aufgaben benutzen

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.14 Von der Website/Internetseite der Universität etwas herunterladen bzw. hochladen, oder die Website/Internetseite durchsuchen (z.B. Vorlesungspläne oder Vorlesungs- und Übungsmaterial)

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.15 Ankündigungen auf der Website/ Internetseite der Universität ansehen, z.B. Abwesenheit von Dozent(inn)en

nie oder fast nie

ein- oder zweimal im Monat

ein- oder zweimal in der Woche

jeden Tag oder fast jeden Tag

2.16 Mit Computersimulationen arbeiten

Appendix C - Questionnaire 1

- nie oder fast nie
- ein- oder zweimal im Monat
- ein- oder zweimal in der Woche
- jeden Tag oder fast jeden Tag

Appendix 4 - Questionnaire 2

Fragebogen Studie zu Lernwegen in elektronischen Lernumgebungen

Dieser Fragebogen dient einer wissenschaftlichen Erhebung zu Lernwegen in elektronischen Lernumgebungen.

Bitte unterstützen Sie dieses Vorhaben, indem Sie diesen Fragebogen vollständig und korrekt (bitte nur mit einem Kreuz (auer bei Frage EDIT)?) bei Ankreuzfragen) ausfüllen. Es werden keine personenbezogenen Informationen abgefragt. **1.**

Allgemeine Fragen:

1.1 In welchem Semester studieren Sie zur Zeit?

[1] [2] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12]

1.2 Welches Fach/ Welche Fächer studieren Sie? (Bitte alle zutreffenden Felder ankreuzen!)

B.Sc. Geographie 1-Fach

Geogr. 2-Fächer LA

Geogr. 2-Fächer HDL

Prähist. Arch. 1-F B.Sc. Informatik 1-Fach B.Sc. VWL/BWL 1-Fach

Mathematik 1-Fach

M. Sc./ M.A. (Dann brauchen Sie den Bogen nicht ausfüllen)

Sonstiges

1.3 Für Lehramt Geographie: Bitte geben Sie Ihre weiteren Fächer an.

1.4 Geschlecht weiblich männlich

1.5 Alter

1.6 Haben Sie schon einmal mit einer Lernplattform gearbeitet (z.B. OLAT, Moodle)?

ja nein

2. Fragen zur Computernutzung:

2.1 Wie oft nutzen Sie den Computer für das Studium?

gar nicht

nicht regelmäßig

1-2 mal wöchentlich

3-4 mal wöchentlich

täglich

2.2 Wie lange dauert dann im Schnitt (pro Mal) Ihre PC-Nutzung?

bis 0,5 Std.

0,5-1 Std.

1-2 Std.

2-4 Std.

mehr als 4 Std.

2.3 Wie oft nutzen Sie den Computer für die Freizeit?

gar nicht

nicht regelmäßig

1-2 mal wöchentlich

3-4 mal wöchentlich

täglich

2.4 Wie lange dauert dann im Schnitt (pro Mal) Ihre PC-Nutzung?

bis 0,5 Std.

0,5-1 Std.

1-2 Std.

2-4 Std.

mehr als 4 Std.

2.5 Was machen Sie in Ihrer Freizeit am liebsten am Computer (Mehrfachantwort möglich)?

spielen

kommunizieren (z.B. über Soziale Netzwerke oder E-Mail)

Informationen suchen (Produkte, Nachrichten, ansonsten Wissenswertes)

Musik/Filme herunterladen

Sonstiges:

4. Wie gut beherrschen Sie die folgenden Aufgaben am Computer?

4.1 Programme benutzen, die Computer Viren finden und vernichten.

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.2 Eine Datenbank zur Erstellung einer Adressenliste benutzen.

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.3 Ein Computer-Programm erstellen

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.4 Ein Tabellenkalkulations-Programm verwenden, um ein Diagramm darzustellen

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.5 Eine Präsentation erstellen (z.B. mit PowerPoint©)

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.6 Eine Multi-Media-Präsentation erstellen (mit Ton, Bildern, Video)

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

4.7 Eine Web-Seite konstruieren

Ich weiß nicht, was das bedeutet.

Ich weiß, was das bedeutet, kann es aber nicht.

Ich kann das mit Hilfe von jemand anderem.

Ich kann das sehr gut alleine.

5. Wenn Sie über Ihre Erfahrungen mit dem Computer nachdenken:

Wie sehr stimmen Sie den folgenden Aussagen zu?

5.1 Es ist mit sehr wichtig, mit dem Computer zu arbeiten.

Ich stimme überhaupt nicht zu.

Ich stimme eher nicht zu.

Ich stimme eher zu.

Ich stimme völlig zu.

5.2 Es macht mir wirklich Spaß, mit dem Computer zu arbeiten.

Ich stimme überhaupt nicht zu.

Ich stimme eher nicht zu.

Ich stimme eher zu.

Ich stimme völlig zu.

5.3 Ich benutze den Computer, weil ich sehr daran interessiert bin.

Ich stimme überhaupt nicht zu.

Ich stimme eher nicht zu.

Ich stimme eher zu.

Ich stimme völlig zu.

5.4 Wenn ich am Computer arbeite vergesse ich die Zeit.

Ich stimme überhaupt nicht zu.

Ich stimme eher nicht zu.

Ich stimme eher zu.

Ich stimme völlig zu.

6. Wie oft setzen Ihre Professorinnen und Professoren im Schnitt diese Medien ein?

6.1 Vorlesungsskript/ Fachbuch

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.2 Atlas oder Karten

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.3 Statistiken oder Tabellen

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.4 Fotos oder Bilder

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.5 Originale Gegenstände

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.6 Erlebnis- oder Reiseberichte

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.7 Filme

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.8 Zeichnungen oder Abbildungen

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.9 Schemata oder MindMaps

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.10 Animationen oder animierte Darstellungen

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.11 Präsentationen

Begriff unklar

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.12 Computer-Lernprogramme

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.13 Luft- oder Satellitenbilder

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.14 Aktuelle Zeitschriften oder Zeitungsausschnitte

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.15 Internet

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.16 Geographische Informationssysteme

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

6.17 Computer allgemein

Begriff unklar

nie

selten

gelegentlich

regelmäßig

jede Vorlesung

7. Wie ist Ihr Interesse an diesen Medien?

7.1 Vorlesungsskript/ Fachbuch

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.2 Atlas oder Karten

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.3 Statistiken oder Tabellen

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.4 Fotos oder Bilder

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.5 Originale Gegenstände

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.6 Erlebnis- oder Reiseberichte

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.7 Filme

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.8 Zeichnungen oder Abbildungen

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.9 Schemata oder MindMaps

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.10 Animationen oder animierte Darstellungen

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.11 Präsentationen

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.12 Computer-Lernprogramme

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.13 Luft- oder Satellitenbilder

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.14 Aktuelle Zeitschriften oder Zeitungsausschnitte

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.15 Internet

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.16 Geographische Informationssysteme

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

7.17 Computer allgemein

Begriff unklar

interessiert mich nicht

interessiert mich wenig

teils, teils

interessiert mich

interessiert mich sehr

Appendix 5 - Questionnaire 3

Fragebogen Studie zu Lernwegen in elektronischen Lernumgebungen

Dieser Fragebogen dient einer wissenschaftlichen Erhebung zu Lernwegen in elektronischen Lernumgebungen.

Bitte unterstützen Sie dieses Vorhaben, indem Sie diesen Fragebogen vollständig und korrekt (bitte nur mit einem Kreuz) ausfüllen. Es werden keine personenbezogenen Informationen abgefragt.

1. Allgemeine Fragen:

1.1 In welchem Semester studieren Sie zur Zeit?

1] 2] 3] 4] 5] 6] 7] 8] 9] 10] 11] 12]

1.2 Welches Fach/ Welche Fächer studieren Sie? (Bitte alle zutreffenden Felder ankreuzen!)

B.Sc. Geographie 1-Fach

Geogr. 2-Fächer LA (Lehramt)

Geogr. 2-Fächer HDL (HandelslehrerIn)

Prähist. Arch. (Prähistorische Archäologie)

1-F B.Sc. Informatik 1-Fach B.Sc. VWL/BWL 1-Fach

Mathematik 1-Fach

M. Sc./ M.A. (Dann brauchen Sie den Bogen nicht ausfüllen)

Sonstiges

1.3 Für Lehramt Geographie: Bitte geben Sie Ihre weiteren Fächer an.

1.4 Geschlecht weiblich männlich

3. Bitte kreuzen Sie Zutreffendes an.

3.1 Insgesamt bin ich damit zufrieden, wie leicht die Lernumgebung zum Erlernen der Datenbanknormalisierung zu bedienen ist.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.2 Die Lernumgebung zum Erlernen der Datenbanknormalisierung war einfach zu handhaben.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.3 Ich konnte die Aufgaben durch die Programmbenutzung erfolgreich bearbeiten.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.4 Ich konnte die Aufgaben mithilfe der Lernumgebung schnell bearbeiten.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.5 Ich war in der Lage, die Aufgaben mithilfe der Lernumgebung erfolgreich zu lösen.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.6 Es war angenehm, mit der Lernumgebung zu arbeiten.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.7 Es war einfach, den Umgang mit der Lernumgebung zu erlernen.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu
3.8 Ich denke, ich konnte durch die Programmbenutzung schnell etwas erreichen.	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu

4. Bitte kreuzen Sie Zutreffendes an.

4.1 War die Lerneinheit zur Datenbanknormalisierung für Sie eher zu leicht oder eher zu schwer?	viel zu leicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> viel zu schwer
4.2 Wie stark mussten Sie sich beim Arbeiten mit der Lerneinheit geistig anstrengen?	gar nicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> extrem
4.3 Wie sehr mussten Sie sich bemühen, um die Inhalte der Lerneinheit zu verstehen?	gar nicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> extrem
4.4 Waren die Inhalte der Lerneinheit zur Datenbanknormalisierung Ihnen eher zu einfach oder eher zu komplex?	viel zu einfach <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> viel zu komplex
4.5 Fühlten Sie sich durch die Informationsfülle der Lerneinheit geistig überlastet?	gar nicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> extrem überlastet
4.6 Fühlten Sie sich durch die Komplexität (Auswahlmöglichkeiten, komplizierte Inhalte) der Lerneinheit geistig überlastet?	gar nicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> extrem überlastet
4.7 Wie häufig hatten Sie den Eindruck, dass die Lernumgebung Ihnen zu viele Informationen anbot?	gar nicht <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> extrem häufig
4.8 Wie häufig blieben die Informationen der Lerneinheit für Sie unverständlich?	trifft nicht zu <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> trifft zu

5. Beurteilen Sie bitte nachfolgenden Aussagen unabhängig davon, ob Ihnen diese Elemente in der Lernumgebung angezeigt wurden oder nicht.

5.1 Die Anwendung von Normalisierungsregeln schult Ihre Fähigkeit zum so genannten „deduktiven* Denken“ (*Anwenden allgemeiner Regeln auf Spezialfälle). Das motiviert mich...	gar nicht [] [] [] [] [] [] sehr
5.2 Sie vertiefen Grundbegriffe aus der Datenbanktheorie. (Dieses Themengebiet begegnet Ihnen heutzutage nicht nur in Informatiker-Berufen. Beispiele: Normalform, Attribut oder Redundanz mit den zugrundeliegenden Konzepten.) Das motiviert mich...	gar nicht [] [] [] [] [] [] sehr
5.3 Sie können anderen mit Ihrem Wissen weiterhelfen. Anderen weiterhelfen zu können, motiviert mich...	gar nicht [] [] [] [] [] [] sehr
5.4 „Das Wissen über Datenbannormalisierung hat mich in meiner beruflichen Zeit im Bankensektor dabei unterstützt, Datenbank-Supportvorgänge kompetent zu begleiten - auch als jemand, der nicht im Schwerpunkt für IT-Aufgaben zuständig ist.“ - Absolvent B.A. Business Management - Statements von Berufstätigen zum Nutzen von Datenbanknormalisierungswissen, die NICHT aus den Geo-IT-Berufen kommen, motivieren mich...	gar nicht [] [] [] [] [] [] sehr
5.5 „Wissen über Datenbannormalisierung beim Arbeiten mit GIS-Datenbanken ist wie Zeitmanagement bei Projekten generell - man kann nicht darauf verzichten.“ - Diplom-Geographin, Freiberuflerin - Statements von Berufstätigen zum Nutzen von Datenbanknormalisierungswissen, die aus den Geo-IT-Berufen kommen, motivieren mich...	gar nicht [] [] [] [] [] [] sehr

6. Items des Befindlichkeitstests Bf-SR (= revidierte Befindlichkeits-Skala) nach ZERSSEN & PETERMANN, S. 18

frisch	matt
teilnahmslos	anteilnehmend
froh	schwermütig
erfolgreich	erfolglos
unentschlossen	entschlussfreudig
lustig	bedrückt
gutgelaunt	verstimmt
appetitlos	appetitfreudig
gesellig	zurückgezogen
minderwertig	vollwertig
entspannt	gespannt
glücklich	unglücklich
zurückhaltend	offen
sicher	bedroht
ausgewogen	innerlich getrieben
selbstsicher	unsicher
elend	wohl
beweglich	starr
müde	ausgeruht
zögernd	bestimmt
träge	schwungvoll
nutzlos	unentbehrlich
schwerfällig	lebhaft

Appendix 6 - Process Mining Source Code

createMXMLtime.php

```
<?php
header("Pragma: public");
header("Expires: 0");
header("Cache-Control: must-revalidate ,
post-check=0, pre-check=0");
header("Cache-Control: private", false);
header("Content-Type: text/xml");
header("Content-Disposition: attachment;
filename=\"MeineDatei.xml\"");
header("Content-Transfer-Encoding: binary");
?>
```

MySQLtime.php

```
<?php
```

```
//Datenbankverbindung
```

```
class MySQL
```

```
{          private $_link;
```

```
          function __construct()
```

```
          {
```

```
            $this->_link=@mysql_pconnect ( 'XXX.XXX.XX.XX' , 'user ' , 'password ' );
```

```
            if ( !$this->_link )
```

```
            {
```

```
                die(" Datenbankverbindung kann nicht hergestellt werden:  
                ".mysql_error ());
```

```
            }
```

```
            if ( !@mysql_select_db ( 'user ' , $this->_link ) )
```

```
            {
```

```
                die(" Keine Datenbank ausgew\{a}hlt: ".mysql_error ());
```

```
            }
```

```
                if ( !@mysql_set_charset ( " utf8 " , $this->_link ) )
```

```
                {
```

```
                    die(" Fehler utf8 ".mysql_error ());
```

```
        }
    }
    //gezieltere Datenbankarbeit
    private function query($befehl)
    {
        $result = @mysql_query($befehl , $this->_link);

        if (!$result)
        {
            die("Abfrage nicht möglich: ".mysql_error());
        }

        return $result;
    }

    public function getMXML()
    {
        $res=$this->query("SELECT mdl_lesson_pages.title , mdl_lesson_attempts.userid ,
        mdl_lesson_attempts.correct AS action ,          mdl_lesson_attempts.timeseen AS
        time FROM mdl_lesson_attempts , mdl_lesson_pages WHERE mdl_lesson_pages.id =
        mdl_lesson_attempts.pageid ORDER BY time");
    }
}
```

```

$xml="<?xml version=\`1.0\` encoding=\`UTF-8\` ?>
<!-- MXML version 1.1 -->
<!-- Created by ProM Import Framework, Version 7.0 (Propeller) -->
<!-- via MXMLib Version 1.9 (http://promimport.sf.net/) -->
<!-- (c) 2004-2007 C.W. Guenther (christian@deckfour.org);
Eindhoven Technical University -->
<!-- This event log is formatted in MXML, for use by BPI and
Process Mining Tools. -->
<!-- You can load this file e.g. in the ProM Framework for
Process Mining. -->
<!-- More information about MXML, Process Mining, and ProM:
http://www.processmining.org/. -->
<WorkflowLog xmlns:xsi=\`http://www.w3.org/2001/XMLSchema-instance\`
xsi:noNamespaceSchemaLocation=\`http://is.tm.tue.nl/
research/processmining/
WorkflowLog.xsd\`
description=\`Unified single process\`>
<Data>
    <Attribute name=\`app.name\`>ProM Import Framework
    </Attribute>
    <Attribute name=\`app.version\`>7.0 (Propeller)
    </Attribute>

```

```
<Attribute name=\"java.vendor\">Sun Microsystems Inc.
</Attribute>
<Attribute name=\"java.version\">1.6.0_21
</Attribute>
<Attribute name=\"mxml.creator\">
MXMLib(http://promimport.sf.net/)
</Attribute>
<Attribute name=\"mxml.version\">1.1
</Attribute>
<Attribute name=\"os.arch\">x86
</Attribute>
<Attribute name=\"os.name\">Windows 7
</Attribute>
<Attribute name=\"os.version\">6.1
</Attribute>
<Attribute name=\"user.name\">MH
</Attribute>
</Data>
<Source program=\"CSV files\"/>
<Process id=\"UNIFIED\" description=\"Unified single process\">;
$ProcessInstance = 0;
$Rows = mysql_num_rows($res);
$row = mysql_fetch_array($res, MYSQL_ASSOC);
```



```

while ($row)
{
    $mxml .= "<ProcessInstance id=\"${ProcessInstance}\" description=
    \"Simulated process instance\">";
    $userid=$row['userid'];

    do

        {

            $mxml .= "<AuditTrailEntry<Data<Attribute
            name = \"action\">${row['action']}</Attribute>
<Attribute name = \"userid\">${row['userid']}]
</Attribute>
<Attribute name = \"title\">${row['title']}]
</Attribute>
<Attribute name = \"time\">${row['time']}]
</Attribute>
</Data><WorkflowModelElement>${row['title']}]
</WorkflowModelElement>
<EventType>start </EventType><Timestamp>".date("Y-m-d" ,
$row['time']) . 'T' . date("H:i:s" , $row['time']).
'+02:00'." </Timestamp><Originator>${row['userid']}]

```

```
        </Originator>
        </AuditTrailEntry >";

    } while (($row = mysql_fetch_array($res , MYSQL_ASSOC)) &&
    $row['userid']== $userid);
    $mxml .= "</ProcessInstance >";
    $ProcessInstance++;
}
$mxml .= "</Process></WorkflowLog><!-- Processed $Rows rows. -->";
return $mxml;
}
?>
```

Appendix 7 - Data

Table 1: Appendix - Geography students population

Geography	male				Total	female			
	17-20	21-24	25 and older			17-20	21-24	25 and older	
2011/12	27	148	69	244	244	55	124	34	213
2012/13									
	111	330	207	648	648	155	289	137	581

Table 2: Appendix - Geology students population

Geology	male				female			
	17-20	21-24	25 and older	Total	17-20	21-24	25 and older	Total
2011	55	124	34	213	21	85	21	127
2012								
	17-20	21-24	25 and older		17-20	21-24	25 and older	
	155	289	137	581	22	83	26	131

Table 3: Appendix - Computer Literacy Types in samples, exact values

SAMPLE	ENTHUSIAST	SPORADIC ENTHUSIAST	ADVANCED PRAGMATIST	FREE TIME PRAGMATIST	SPORADIC PRAGMATIST	LURKER	INSTRUMENTAL	SPORADIC UNEXPERIENCED
Geologists 2011/2012 (N=140)	11%	11%	21%	-	30%	-	-	27%
Geographers 2012/13, start	8%	9 (9.49%)%	7%	20%	21%	-	-	34%
Geographers 2012/13, mid-semester	16%	4%	11%	12%	13%	7%	28%	9%
Geographers 2012/13, TELE study	21% (21.42857%)	-	71% (71.42857%)	-	7%(7.42857%)	-	-	-

Table 4: Appendix - Average silhouette width per cluster (geology, N=137)

	FREE TIME PRAGMA- TIST TYPE	ADVANCED PRAG- MATIST TYPE	SPORADIC ENTHUSI- AST TYPE	SPORADIC UNEXPE- RIENCED TYPE	ENTHUSIAST TYPE	SPORADIC PRAG- MATIST TYPE
Percentages in cluster:	0.204379562	0.065693431	0.094890511	0.343065693	0.080291971	0.211678832
Average silhouettes:	0.52031	1	1	0.8534495	0.8181818	0.9473072
Average silhouette width of total data set: 0.8259323						

Table 5: Appendix - Average silhouette width per cluster (geography, N=90)

	FREE TIME PRAG- MATIST TYPE	ADVANCED PRAGMA- TIST TYPE	SPORADIC ENTHU- SIAS TTYPE	SPORADIC UNEXPE- RIENCED TYPE	ENTHUSIAST TYPE	SPORADIC PRAGMA- TIST TYPE	INSTRUMENTAL USER TYPE	LURKER
Percentages in cluster:	0.1222	0.1111	0.0444	0.0889	0.1556	0.13333	0.27778	0.06667
Average silhouettes:	1	0.85	1	1	1	1	1	0.66667

Average silhouette width of total data set: 0.9615385

Table 6: Appendix - Measured correlations between TELE study variables (author's illustration)

VARIABLE N=28	ET ¹	PT	GE	TI	UE	CL	ME	IM	M	A	BCSE
Prior knowledge test (PT)	0	/	/	/	/	/	/	/	/	/	/
learning material experience (GE)	0	0	/	/	/	/	/	/	/	/	/
TELE task interest (TI)	(.22)	(-.28)	0	/	/	/	/	/	/	/	/
Usability experience (UE)	.43	(-.30)	(.24)	.74	/	/	/	/	/	/	/
Cognitive load (CL)	(.31)	(-.33)	(.25)	(-.29)	.98	/	/	/	/	/	/
Motivational elements response (ME)	(.28)	(-.32)	0	.81	.74	.96	/	/	/	/	/
Intrinsic motivation (IM)	(.31)	0	0	.92	.93	.95	0	/	/	/	/
Mood (M)	0	.32	0	0	0	0	0	(-.20)	/	/	/
Computer attitude (A)	0	0	.37	0	.62	.65	0	.49	0	/	/
Basic computer self-efficacy (BCSE)	.30	0	0	0	.51	.48	.40	(.35)	0	.28	/
Advanced computer self-efficacy	(.28)	(-.46)	0	(.23)	.64	.64	.54	.51	0	.37	.49

(values in brackets => not significant);¹ET:e-lesson test; 0: no correlation, .2 < r_s ≤ .5 => small correlation, .5 < r_s ≤ .8 => medium correlation, .8 < r_s ≤ 1.0 => high correlation

Table 7: Appendix - Computer usage - How often do you use the computer for your studies? (author's illustration)

COMPUTER USAGE FREQUENCY	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	4* (N=137)	
Mid-semester	5 (N=90)	4 (N=140)
Technology-enhanced learning study	5 (N=28 from 90)	

*1= not at all, 2 = not regularly, 3 = once or twice a week,
4 = three to four times a week, 5 = every day

Table 8: Appendix - Computer usage - How often do you use the computer in your freetime? (author's illustration)

COMPUTER USAGE FREQUENCY	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	5* (N=137)	
Mid-semester	5 (N=90)	5 (N=140)
Technology-enhanced learning study	5 (N=28 from 91)	

*1= not at all, 2 = not regularly, 3 = once or twice a week,
4 = three to four times a week, 5 = every day

Table 9: Appendix - Computer usage - How long do you use the computer for your studies? (author's illustration)

COMPUTER USAGE DURATION	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	2* (N=137)	
Mid-semester	3 (N=90)	3 (N=140)
Technology-enhanced learning study	3 (N=28 from 90)	

*1= up to half an hour, 2 = half an hour to one hour,
3 = one to two hours, 4 = two to four hours, 5 = more than four hours

Table 10: Appendix - Computer usage - How long do you use the computer in your freetime? (author's illustration)

COMPUTER USAGE FREQUENCY	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	3* (N=137)	
Mid-semester	3 (N=90)	3 (N=140)
Technology-enhanced learning study	3 (N=28 from 90)	

*1= up to half an hour, 2 = half an hour to one hour,
3 = one to two hours, 4 = two to four hours, 5 = more than four hours

Table 11: Appendix - Computer attitude (author's illustration)

COMPUTER ATTITUDE - MEDIAN	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	3* (N=137)	
Mid-semester	3 (N=90)	3 (N=140)
Technology-enhanced learning study	2.75 (N=28 from 90)	

*1 = I do not know what that means. 2 = I know what this means but I cannot do it.
3 = I can do that with the help of others. 4 = I can do that by myself.

Table 12: Appendix - Reliability of computer literacy items (Cronbachs- α values overview for all studies (author's illustration))

ITEM	GEOGRAPHY (START) N=137	GEOGRAPHY (MID- SEMESTER) N=90	GEOLOGY N=140	TELE- STUDY
Basic computer self-efficacy	.46	.58	.56	.42
Advanced computer self-efficacy	.56	.62	.56	.75
Computer attitude	.72	.77	.78	.78

Table 13: Appendix - Preferred computer usage category *Communication* (author's illustration)

COMMUNICATION AS PREFERRED USAGE CATEGORY	GEOGRAPHERS 2012/13, PER- CENTAGES	GEOLOGISTS 2011/12, PER- CENTAGES
Start of the semester	89% (N=137)	
Mid-semester	82% (N=90)	74% (N=140)
Technology-enhanced learning study	86% (N=28 from 90)	
Female students comparison		
Start of the semester	96% (N=70)	
Mid-semester	79% (N=48)	79% (N=57)
Male students comparison		
Start of the semester	83% (N=67)	
Mid-semester	86% (N=42)	72% (N=83)

Table 14: Appendix - Preferred computer usage category *Search for information* (author's illustration)

INFORMATION SEARCH AS PREFERRED USAGE CATEGORY	GEOGRAPHERS 2012/13, PER- CENTAGES	GEOLOGISTS 2011/12, PER- CENTAGES
Start of the semester	72% (N=137)	
Mid-semester	69% (N=90)	79% (N=140)
Technology-enhanced learning study	61% (N=28 from 90)	
Female students comparison		
Start of the semester	67% (N=70)	
Mid-semester	63% (N=48)	86% (N=57)
Male students comparison		
Start of the semester	77% (N=67)	
Mid-semester	76% (N=42)	76% (N=83)

Table 15: Appendix - Preferred computer usage category *Game-playing* (author's illustration)

GAME-PLAYING AS PREFERRED US- AGE CATEGORY	GEOGRAPHERS 2012/13, PER- CENTAGES	GEOLOGISTS 2011/12, PER- CENTAGES
Start of the semester	20% (N=137)	
Mid-semester	22% (N=90)	50% (N=140)
Technology-enhanced learning study	21% (N=28 from 90)	
Female students comparison		
Start of the semester	3% (N=70)	
Mid-semester	4% (N=48)	30% (N=57)
Male students comparison		
Start of the semester	77% (N=67)	
Mid-semester	42% (N=42)	64% (N=83)

Table 16: Appendix - Preferred computer usage category *Download music or films* (author's illustration)

DOWNLOADING MUSIC OR FILMS AS PREFERRED USAGE CATEGORY	GEOGRAPHERS 2012/13, PER- CENTAGES	GEOLOGISTS 2011/12, PER- CENTAGES
Start of the semester	26% (N=137)	
Mid-semester	19% (N=90)	30% (N=140)
Technology-enhanced learning study	14% (N=28 from 90)	
Female students comparison		
Start of the semester	27% (N=70)	
Mid-semester	15% (N=48)	21% (N=57)
Male students comparison		
Start of the semester	26% (N=67)	
Mid-semester	24% (N=42)	36% (N=83)

Table 17: Appendix - Other computer usage categories (free text field), unit: number of times mentioned (author's illustration)

USAGE CATEGORY	GEOGR. 2012/13 START (N=137)	GEOGR. 2012/13 MID-SEM. (N=91)	GEOL. 2011/12 (N=140)
Watch DVDs/ films	4		2
Youtube/ videos	3		1
Watch serials		2	
Watch American TV (e. g. NBC)		1	
TV, streaming		1	3
Work on IT tasks	1		
Work on study tasks	1		1
Music (as radio substitute)	6 (1)	5	6
Use programmes (e. g. make music)	1		
Watch eSports	1		
Blogging (tumblr)	1	1 (1)	
(Look at and) edit pictures	(1) 3		
Image-and audio editing		2	2
Write texts (poetry)		1	
Read			2
Write			1
Be creative			1
Specific work			1
Hobby activities			1
Shopping	1		2
Communities	1		
Internet			1
Spend time/ entertainment		2	

Table 18: Appendix - Learning material experience and task interest of Computer Literacy Clusters (author's illustration)

SAMPLE	ENTHU- SIAST	AD- VANCED PRAG- MATIST	SPORADIC UNEX- PERI- ENCED	LURKER	FREE TIME PRAG- MATIST	SPORADIC ENTHU- SIAST	INSTRU- MENTAL USER	SPORADIC PRAG- MATIST
N=87, n=	17	4	3	13	16	3	24	7
Task interest p=0.000, 2.33E-11) ***								
mean	4.4	4.2	4	2.8	3.5	3.9	2.8	4
median	3.96	4.15	3.47	3.02	3.48	4.16	2.96	4.36

ns: not significant, (*):marginally significant, .10, *:significant, .05, **:very significant, .01, ***:extremely significant .001

Table 19: Appendix - Learning material experience of Computer Literacy Clusters I (author's illustration)

SAMPLE		ENTHU- SIAST	AD- VANCED PRAG- MATIST	SPORADIC UNEX- PERI- ENCED	LURKER	FREE TIME PRAG- MATIST	SPORADIC ENTHU- SIAST	INSTRU- MENTAL USER	SPORADIC PRAG- MATIST
N=87, n=		17	4	3	13	16	3	24	7
Presentations									
p=0.919 (ns)	mean	4.77	4.5	5	4.62	4.54	4.67	4.69	4.14
	median	5	4.5	5	5	5	5	5	5
Specialised book/syl- labus									
p=0.821 (ns)	mean	3.62	4.25	4	4.31	4.31	4.67	4.23	4.14
	median	4	4	4	4	4	5	4.5	4
Drawings or figures									
p=0.339 (ns)	mean	3.23	4	3.67	3.85	4	3.67	3.85	3.71
	median	4	4	4	4	4	4	4	4
Statistics or tables									
p=0.215 (ns)	mean	3.92	2.5	4.33	4	3.92	4	4	3.71
	median	4	2.5	5	4	4	4	4	4
Geographic Information Systems									
p=0.441 (ns)	mean	3.31	3.25	3.33	3	3.15	2.33	2.77	2.86
	median	3	3.5	3	3	3	2	3	3
Computer-based learn- ing programmes									
p=0.114 (ns)	mean	1.92	1.75	2	1.31	1.85	2.67	1.54	2.71
	median	2	2	2	1	2	3	1	3

ns: not significant (*):marginally significant, .10, *:significant, .05, **:very significant, .01, ***:extremely significant .001

Table 20: Appendix - Learning material experience of Computer Literacy Clusters II (author's illustration)

SAMPLE	ENTHU- SIAST	AD- VANCED PRAG- MATIST	SPORADIC UNEX- PERI- ENCED	LURKER	FREE TIME PRAG- MATIST	SPORADIC ENTHU- SIAST	INSTRU- MENTAL USER	SPORADIC PRAG- MATIST
N=87, n=	17	4	3	13	16	3	24	7
Animations or ani- mated illustrations*								
p=0.028 * mean	2.85	1.5	1.33	2.46	2.62	2	2.23	3
median	2	1.5	1	2	3	2	2	3
(Press-clippings of) magazines in their current issue								
p=0.051 (*) mean	2.92	2.5	2	2.46	2.46	2.33	2	2.29
median	3	3	2	2	2	2	2	2
Schemes/ MindMaps	2.77	3.75	3.33	2.62	3	2.67	2.46	3.14
p=0.167 (ns) mean								
median	3	4	3	3	3	3	2.5	3
Photographs or images								
p=0.52 (ns) mean	3.46	4	3.67	3.54	4.23	4.33	3.92	4
median	4	4	4	4	4	4	4	4

ns: not significant, (*):marginally significant, .10, *:significant, .05, **:very significant, .01, ***:extremely significant .001

Table 21: Appendix - Learning material experience of Computer Literacy Clusters III (author's illustration)

SAMPLE		ENTHU- SIAST	AD- VANCED PRAG- MATIST	SPORADIC UNEX- PERI- ENCED	LURKER	FREE TIME PRAG- MATIST	SPORADIC ENTHU- SIAST	INSTRU- MENTAL USER	SPORADIC PRAG- MATIST
N=87, n=		17	4	3	13	16	3	24	7
Internet									
p=0.666 (ns)	mean	3.08	3.25	2.33	2.69	2.69	2.33	2.77	2.57
	median	3	3.5	3	3	2.5	2	3	2
Essays based on per- sonal experience or field reports p=0.314 (ns)									
	mean	2.08	1.5	1.67	1.46	1.92	2.33	1.92	1.57
	median	3	1.5	2	1	2	2	2	2
Atlas or maps									
p=0.346 (ns)	mean	2.38	3.25	3	3.15	2.77	3	3.08	3.29
	median	2	3	3	3	2	3	2.5	4
Original Objects									
p=0.468 (ns)	mean	1.23	1.25	1.33	1.15	1.23	1	0.92	1.57
	median	1	1.5	1	1	1	1	1	2
Films									
p=0.252 (ns)	mean	2.31	2.25	2	2.31	2.77	2.33	2.08	2.57
	median	2	2	2	2	3	2	2	2
Aerial or satellite im- ages									
p=0.877 (ns)	mean	3.15	3	3	3.08	3.38	3	2.85	3.29
	median	3	3	3	3	3	3	3	3
Computers in general									
p=0.533 (ns)	mean	4.85	4.5	5	4.85	4.62	5	4.85	4.57
	median	5	4.5	5	5	5	5	5	5

ns: not significant, (*):marginally significant, .10, *:significant, .05, **:very significant, .01, ***:extremely significant .001

How skilled are you at these computer tasks?

- Use antivirus programmes
- Use a spreadsheet programme to create a diagramme
- Create a presentation
- Create a multi-media presentation including sound, graphics and videos

The Cronbachs- α values are:

- .46 (Geographers 2012/13, start)
- .56 (Geographers 2012/13, mid-semester)
- .56 (Geologists 2011/2012, mid-semester)

Table 22: Appendix - Basic computer self-efficacy (author's illustration)

BASIC COMPUTER SELF-EFFICACY	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester	3.5* (N=137)	
Mid-semester	3.75 (N=90)	3.75 (N=140)
Technology-enhanced learning study	3.67 (N=28 from 90)	

*1 = I do not know what that means. 2 = I know what this means but I cannot do it.
3 = I can do that with the help of others. 4 = I can do that by myself.

Table 23 shows the computer self-efficacy of the tested samples. These question items were used: How skilled are you at these computer tasks?

1. Use a database to create an address list
2. Create a computer programme
3. Build a website

The Cronbachs- α values are:

- .56 (Geographers 2012/13, start)
- .62 (Geographers 2012/13, mid-semester)
- .56 (Geologists 2011/2012, mid-semester)

Table 23: Appendix - Advanced computer self-efficacy (author's illustration)

ADVANCED EFFICACY	COMPUTER	SELF-	GEOGRAPHERS 2012/13, ME- DIAN	GEOLOGISTS 2011/12, ME- DIAN
Start of the semester			2.33* (N=137)	
Mid-semester			2.75 (N=90)	2.67 (N=140)
Technology-enhanced learning study			2.33 (N=28 from 90)	

*1 = I do not know what that means. 2 = I know what this means but I cannot do it.
3 = I can do that with the help of others. 4 = I can do that by myself.

Table 11 shows the self-estimated computer attitude of the tested samples. These question items were used: How skilled are you at these computer tasks?

1. Working with the computer is important to me.
2. I enjoy working with the computer.
3. I work with the computer because I am interested in doing so.
4. When working with the computer I forget all about the time.

The Cronbachs- α values are:

- .72 (Geographers 2012/13, start)
- .78 (Geographers 2012/13, mid-semester)
- .78 (Geologists 2011/2012, mid-semester)

Appendix 8 - Lesson

HANDOUT

Table 1: Appendix - Grundbegriffe

TABELLE	DATEI	RDBMS
Tabellenüberschrift (Table heading)	Dateiname (File name)	Relationenschema (Relation scheme)
Tabelleninhalt (Table)	Datei (File)	Relation (\sim)
Spalte (Column)	Feld (Field)	Attribut (Attribute)
Zeile (Row)	Datensatz (Record/ Case)	Tupel (Tuple)
Kennzeichen (Unique ID)	(Primärschlüssel) Primary Key	Index (\sim)
	Mögliche Werte (Possible values)	Wertebereich (Do- main)

Quellen (angelehnt an):

Heywood, I., Cornelius, S. & S., Carver, S. (2011)
An Introduction to Geographical Information Systems,
3/E. Pearson Education India.

Date, C.J. (1986)
An Introduction to Database Systems, Addison-Wesley, Reading, Mass.)
(Eigene Übersetzung)

1 Attribut

Attribut: wird eingesetzt, um Eigenschaften im Modell abzubilden. Attribute für den Entitätstyp (entspricht dem Relationenschema im Entity Relationship Modell) „Produkt“ können z.B. „Produktname“ und „Lagerbestand“ sein.

Quelle: Jung, R., Enzyklopädie der Wirtschaftsinformatik Zuletzt aufgerufen 17.11.2012, <http://bit.ly/1eg4go5>

2 Normalformen

Erste Normalform

Jedes Attribut der Relation muss einen atomaren Wertebereich haben. Relation hat Primärschlüssel.

Zweite Normalform

Eine Relation ist in der zweiten Normalform, wenn die erste Normalform vorliegt und kein Nichtschlüsselattribut funktional abhängig von einer echten Teilmenge eines Schlüsselkandidaten ist.

Dritte Normalform

Die dritte Normalform ist genau dann erreicht, wenn sich das Relationenschema in zweiter Normalform befindet, und kein Nichtschlüsselattribut von einem Schlüsselkandidaten transitiv abhängt. Die dritte Normalform ist erreicht, wenn sich das Relationenschema in 2. Normalform befindet, und kein Nichtschlüsselattribut von einem anderen Nichtschlüsselattribut funktional abhängig ist.

Quellen:

Codd, E. F. (1970): A Relational Model of Data for Large Shared Data Banks. In: Communications of the ACM, 13(6): 377387. 73, 74

Codd, E. F. (1971): Further Normalization of the Data Base Relational Model. In: IBM Research Report, San Jose, California, RJ909. 73, 74

Lernstudienanleitung

1. Bitte melden Sie sich an einem Rechner mit Ihrer Stu-Kennung an.
2. An Ihre angegebene Mailadresse wurde der Link zur Studie und das Passwort geschickt.
Sie können auch einen Browser öffnen, z.B. Mozilla, und die Adresse manuell eingeben.
3. Klicken Sie auf eine der eingerahmten Optionen. Sie müssen dann Ihre Benutzerdaten eingeben.
Benutzername: XYZ98
Passwort: *****

Zur Nutzung ist ein Login notwendig

Geben Sie Ihren Anmeldenamen und das Kennwort ein
(Cookies müssen in Ihrem Browser aktiviert sein!)

Anmeldename
Kennwort

Login

4. Wählen Sie diesmal 'Lernstudie GIS/WI'
5. Lesen Sie den kurzen Informationstext und wählen Sie dann:
 Datenbanknormalisierung Teil 1
6. Folgen Sie nun bitte den Anweisungen der Lerneinheit bis Ihnen das Ende des ersten Teils angezeigt wird. Beenden Sie diesen Teil bitte mit der angezeigten Option und klicken Sie auf 'Antwort auswählen und absenden'. Gehen Sie bitte erst dann in die Pause.

Wählen Sie bitte eine der unten stehenden Optionen:

Sie haben das Ende des ersten Teils erreicht. Klicken Sie bitte hier. Bleiben Sie bitte eingeloggt.

Zurück zur Aufgabe.

Bitte bleiben sie als Lernstudienteilnehmer(in) eingeloggt, auch in der Pause!

TEIL 2

7. Wenn Sie nun wieder an den Rechner zurückkehren, wählen Sie bitte ‚Datenbanknormalisierung Teil 2‘ wie unten im Bild angezeigt:



8. Klicken Sie bitte auf das Wort ‚Link‘, es sei denn, Sie möchten einen kurzen Rückblick und einen Ausblick. Sie können dann immer noch den Link auswählen.



9. Warten Sie bitte auf die Anweisung, welche Gruppe Sie auswählen sollen.



10. Folgen Sie nun bitte den Anweisungen der Lerneinheit. Diesmal ist es Ihnen überlassen, ob Sie lediglich bis zum empfohlenen Lernziel ‚zweite Normalform‘ dabei bleiben oder ob Sie den Teil ‚dritte Normalform‘ auch noch bearbeiten. Arbeiten Sie in Ihrem persönlichen Tempo.
Bedenken Sie, dass noch ein Kurzfragebogen ausgefüllt werden muss.

Vielen Dank für die Teilnahme!

EINFÜHRUNG

Dieses Prinzip ist in ArcGIS nicht in dieser Weise auffindbar.

Das Verständnis von Datenbanken und Normalisierung ist für die Arbeit mit Geoinformationssystemen dennoch hilfreich.

Bitte wählen Sie zunächst Datenbanknormalisierung 1 aus und folgen Sie dann den weiteren Anweisungen.

Bitte verwenden Sie ausschließlich die Auswahlmöglichkeiten unterhalb des Lernstudientexts und den Button 'Antwort auswählen und absenden' anstatt der Zurück-Funktion Ihres Browsers.

- Datenbanknormalisierung Teil 1
- Datenbanknormalisierung Teil 2

Sie erhalten zunächst eine Übungsfrage -

bitte nicht wundern, wenn Sie Ihre Antwort bestätigen müssen.

Die Erklärungen und die Auflösung folgen nach der Frage zu Ihrem momentanen Interesse am Themengebiet.

Bitte benutzen Sie den Übersichtszeitel zu den Normalformen erst nach dieser Eingangsfrage.

- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen.)
- Zur Übungsfrage

FRAGE ZUM THEMA 'DIE ERSTE NORMALFORM':

Bitte benutzen Sie Ihr Handout erst nach der Beantwortung dieser Frage!

Ist die erste Normalform gewährleistet?

Bestell_ID	Kdn_ID	Vorname	Nachname	Adresse	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm 1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine Antwort auf diese Frage oder eine andere Option:

- Meine Antwort auf die Frage ist: Ja
- Meine Antwort auf die Frage ist: Nein
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)

ANTWORT BESTÄTIGEN ODER KORRIGIEREN

(FRAGE ZUM THEMA 'DIE ERSTE NORMALFORM':)

Ist die erste Normalform gewährleistet?

Bestell_ID	Kdn_ID	Vorname	Nachname	Adresse	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm 1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine Antwort auf diese Frage oder eine andere Option:

- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Nein, weil ein Attribut keine atomaren (d.h., unteilbaren) Werte hat.
- Ich wähle eine andere Antwort: Ja, die Tabelle befindet sich in erster Normalform.

Sie haben die Möglichkeit das Thema **Datenbanknormalisierung*** im Rahmen einer einmaligen E-Learning-Einheit zu erlernen und zu üben

(*Methode zur Vermeidung mehrfach vorkommender Daten und damit widersprüchlicher Datensätze).

Wenn ich für mein Interesse an der Lerneinheit Sterne vergeben müsste,

würde ich auf einer Skala von 0 (gar nicht interessiert) bis 10 Sternen (überaus interessiert) *****

... Sterne vergeben

- 5
- weniger als 5
- mehr als 5

EINFÜHRUNG

Sie werden nun in die Grundlagen der Datenbank-Normalisierung eingeführt.

Es gibt einige kurze Übungsfragen. (Anmerkung: Antworten müssen immer einmal bestätigt werden - bitte nicht wundern!)

Das Lernmaterial dazu wird Ihnen hier vollständig zur Verfügung gestellt.

Wählen Sie bitte eine der unten stehenden Optionen:

- Wozu brauche ich Wissen über Datenbanknormalisierung?
- Ich möchte mit der ersten Normalform starten.
- Mein Interesse am Thema ist begrenzt. Wie profiliere ich dennoch von dieser Lerneinheit?
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen.)

WOZU DATENBANKNORMALISIERUNG?

- Eindeutigkeit der Sachdatensätze
- Keine mehrfach vorkommenden Daten, damit Vermeidung von widersprüchlichen Datensätzen
- Leichte und sichere Aktualisierung von Datensätzen
- Schneller Zugriff auf abgefragte Daten
- Änderung der Daten hat keine Auswirkungen auf die damit verbundenen Anwendungsprogramme
- Wiederverwendbarkeit von Datensätzen

Wählen Sie bitte eine der unten stehenden Optionen:

- Mein Interesse am Thema ist begrenzt. Wie profiliere ich dennoch von dieser Lerneinheit?
- Ich möchte mit der ersten Normalform starten.
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Wozu kann Datenbanknormalisierungswissen gut sein? Hier klicken, um ein Statement aus der beruflichen Praxis zu lesen.

WIE KÖNNEN SIE VON DIESER LERNEINHEIT PROFITIEREN?

- Die Anwendung von Normalisierungsregeln schult Ihre Fähigkeit zum so genannten 'deduktiven' Denken'.
- (*Anwenden allgemeiner Prinzipien auf Spezialfälle;
- Beispiel: Tabellen, die in der ersten Normalform vorliegen, dürfen nur bestimmte Attribute beinhalten.
- Deduktives Schließen bestünde nun darin, eine Tabelle zu erkennen, die die Kriterien nicht erfüllt.
- Sie müssten dann die erlernte Regel anwenden, um die vorliegende Tabelle weiter aufzuteilen.
- Das Ziel ist eine möglichst effiziente Arbeit mit Datenbanktabellen.)
- Sie vertiefen einige Grundbegriffe aus dem Themebereich der Datenbanktheorie. (Dieses Themengebiet begegnen Ihnen heutzutage nicht mehr nur in Informatiker-Berufen, sondern immer häufiger auch in anderen Berufen mit IT-Einsatz, also auch in Geographie-Berufen.)

Wählen Sie bitte eine der unten stehenden Optionen:

- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Wozu kann Datenbanknormalisierungswissen gut sein? Hier Klicken, um ein Statement aus der beruflichen Praxis zu lesen.
- Wozu brauche ich allgemein Wissen über Datenbanknormalisierung?
- Ich möchte mit der ersten Normalform starten.

Als Verantwortlicher für das Business Development habe ich mein Wissen über Datenbanken und deren Normalisierung benötigt um das Team erfolgreich zur Neustrukturierung führen zu können. Auch heute wird diese Struktur als Basis noch benutzt und hat die Anwenderzufriedenheit erheblich erhöht.“

M. Doktor, MBA

Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen!)

Zurück zur vorherigen Seite.

Vertiefte Kenntnisse, wie z.B. über Normalisierung von Datenbanken und der praktische Umgang mit Datenbanksystems wird nach meiner Erfahrung immer mehr von Bewerbern verlangt, die sich auf Stellen in Geodaten verarbeitenden Berufen bewerben, da es sich i.d.R. um sehr große Datenmengen handelt, deren unterschiedlichen Verwendungsmaßstäbe, Fachinhalte und Aktualitäten für ganze Netzwerke konsistent und fachlich korrekt vorgehalten werden müssen.

R. Gabler-Mlecek, Dipl. Ing.-Geomatik

Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen!)

Zurück zur vorherigen Seite.

DIE ERSTE NORMALFORM

ANMERKUNG: Sie dürfen nun zusätzlich Ihren Übersichtszettel mit den Normalformen zur Hand nehmen.

Jedes Attribut*¹ der Relation*² muss einen atomaren*³ Wertebereich haben. Die Relation hat einen Primärschlüssel*⁴.

*¹Attribut = Eigenschaftstyp, z.B. Nachname ('Meier' wäre der Attributswert)

*²Relation = Tabelle.

*³atomar = unteilbar

*⁴Ein Primärschlüssel ermöglicht (häufig numerisch) die eindeutige Identifizierung von Datensätzen (einzelne Zeilen einer Tabelle).

Postleitzahlen als Primärschlüssel sind ungeeignet.

Wenn Sie mehr hierüber erfahren möchten, wählen Sie bitte:

'Exkurs: Anmerkungen Attribut 'Postleitzahl' (Die Problematik wird ansonsten ausgeblendet).'

Kunde	Wann stellt	Liefern bis	Was	Preis
Hans Meier, Holm 5, D, Kiel	01.11.2009	31.11.2009	30 kg Appen- zeller, 10 kg Quark, 3 kg Gorgonzola	510 €, 7 €, 60 €

Wählen Sie bitte eine der unten stehenden Optionen:

- Exkurs: Anmerkungen Attribut 'Postleitzahl' (Die Problematik wird ansonsten ausgeblendet.)
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Ich wähle die Übungsfrage.
- Wozu kann Datenbanknormalisierungswissen gut sein? Hier klicken, um ein Statement aus der beruflichen Praxis zu lesen.

WESHALB POSTLEITZAHLEN ALS PRIMÄRSCHLÜSSEL EHER UNGEEIGNET SIND...

PLZ 25598 beinhaltet:

- Wacken
- Nienbüttel
- Bokeirehm
- Gribbohm

Folge ist im Regelfalle eine Uneindeutigkeit !

Es gibt aber Anwendungen bei denen dies auch funktioniert (von daher auch nur „eher“ ungeeignet!)

Im Regelfalle, wird das PLZ-Problem wie folgt gelöst:

=> über andere Software, welche die Adresse einer PLZ zuweist, z.B. über eine räumliche

Verschneidung (Punkt:„Adresse“ ist enthalten in Polygon:„PLZ-Gebiet XY“)

=> über sog. Denormalisierung, die PLZ wird redundant in die gewünschte Tabelle eingetragen.

Wählen Sie bitte eine der unten stehenden Optionen:

- Ich möchte gern zum Themenblock 'Erste Normalform' zurückkehren.
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)

FRAGE ZUM THEMA 'DIE ERSTE NORMALFORM':

Ist die erste Normalform gewährleistet?

Zur Erinnerung die Definition:

Jedes Attribut der Relation muss einen atomaren Wertebereich haben. Die Relation hat einen Primärschlüssel.

Bestell_ID	Kdn_ID	Vorname	Nachname	Adresse	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm 5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm 1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine Antwort auf diese Frage oder eine andere Option:

- Meine Antwort auf die Frage ist: Nein
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Meine Antwort auf die Frage ist: Ja

Richtig. Das Attribut 'Adresse' ist nicht atomar und müsste noch in die Attribute 'Straße' und 'Hausnummer' zerlegt werden.

Wählen Sie bitte eine der unten stehenden Optionen:

- Sie haben das Ende des ersten Teils erreicht. Klicken Sie bitte hier. Bleiben Sie bitte eingeloggt.
- Zurück zur Aufgabe.

Bitte folgen Sie diesem LINK

- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen.)
- Ich hätte gerne einen kurzen Rückblick der Lerneinheit bisher / einen kurzen Ausblick, bevor ich auf den angegebenen LINK klicke

Bitte folgen Sie diesem LINK

Ihre Antwort: Ich hätte gerne einen kurzen Rückblick der Lerneinheit bisher / einen kurzen Ausblick, bevor ich auf den angegebenen LINK klicke.

Sie haben jetzt die erste Normalform kennengelernt.

Es folgen die zweite und optional die dritte Normalform.

Bitte folgen Sie nun dem obigen Link oder

kopieren Sie bitte diese URL in Ihr Browserfenster:

<http://webcd3top.rz.uni-kiel.de/learnstudie-gis/moodle/mod/lesson/view.php?id=65&pageid=317>

Tina fragt: "Ist der Stille Ozean eigentlich den ganzen Tag still?" Dozent: "Bitte nur vernünftige Fragen!" Tina: "Woran ist eigentlich das Tote Meer gestorben?"

DIE ZWEITE NORMALFORM

Eine Relation ist in der zweiten Normalform, wenn die erste Normalform vorliegt und kein Nichtschlüsselattribut funktional abhängig^{*1} von einer echten Teilmenge^{*2} eines Schlüsselkandidaten ist.

^{*1}Wert des Attributs bestimmt eindeutig den Wert eines anderen Attributs.

^{*2}Gemeint ist der Primärschlüssel selbst oder ein Teil des Primärschlüssels.

Der Primärschlüssel der Tabelle ‚Bestellungen‘ ist aus den Feldern Bestell_ID, Kdn_ID und Waren_ID zusammengesetzt.

Wenn der Schlüssel aus mehreren Attributen besteht,

ist eines dieser Attribute eine ‚echte Teilmenge‘ des Schlüssels.

Um ein Beispiel zu nennen: Die Felder, die Angaben zum Namen

(Vorname, Nachname) und Wohnort des Kunden enthalten, sind vom Feld Kdn_ID abhängig,

aber nicht von den Feldern Bestell_ID und Waren_ID.

Dies verletzt die zweite Normalform,

da diese nicht zum Schlüssel gehörenden Attribute nicht nur von einem Teil des Schlüssels (hier Kdn_ID) abhängen dürfen.

Bestell_ID	Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm	1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine der unten stehenden Optionen:

Ich wähle die Übungsfrage.

Das Wissen über Datenbanknormalisierung hat mich in meiner beruflichen Zeit im

Bankensektor dabei unterstützt, Datenbank-Supportvorgänge kompetent zu begleiten –

auch als jemand, der nicht im Schwerpunkt für IT-Aufgaben zuständig ist.

M. Kumberger, B.A. Business Management

FRAGE ZUM THEMA 'DIE ZWEITE NORMALFORM':

Der Primärschlüssel der Tabelle ‚Bestellungen‘ ist aus den Feldern Bestell_ID, Kdn_ID und Waren_ID zusammengesetzt.

Um ein Beispiel zu nennen: Die Felder, die Angaben zum Namen (Vorname, Nachname) und Wohnort des Kunden enthalten, sind vom Feld Kdn_ID abhängig,

aber nicht von den Feldern Bestell_ID und Waren_ID. Dies verletzt die zweite Normalform,

da diese nicht zum Schlüssel gehörenden Attribute nicht nur von einem Teil des Schlüssels (hier Kdn_ID) abhängen dürfen.

Welches der Attribute verletzt ebenfalls die zweite Normalform?

Bestell_ID	Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm	1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine Antwort auf diese Frage oder eine andere Option:

- Meine Antwort auf die Frage ist: Preis
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Meine Antwort auf die Frage ist: Alle anderen Nichtschlüsselattribute
- Meine Antwort auf die Frage ist: Anzahl

ANTWORT BESTÄTIGEN ODER KORRIGIEREN

Welche Variante wählen Sie?

(FRAGE ZUM THEMA 'DIE ZWEITE NORMALFORM':)

Der Primärschlüssel der Tabelle ‚Bestellungen‘ ist aus den Feldern Bestell_ID, Kdn_ID und Waren_ID zusammengesetzt.

Beispiel: Name und Vorname des Kunden verletzen die zweite Normalform. Welches der Attribute verletzt ebenfalls die zweite Normalform?

Bestell_ID	Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort	B_Date	L_Date	Anz	Waren_ID	Artikel	Preis
1	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	30	1	Appenzeller	510 €
2	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	10	2	Quark	7€
3	1	Hans	Meier	Holm	5	D	Kiel	01.11.2009	31.11.2009	3	3	Gorgonzola	60€
4	2	Heinz	Müller	Holm	1	D	Kiel	02.11.2009	01.12.2009	3	3	Gorgonzola	60€

Wählen Sie bitte eine Antwort auf diese Frage:

- Ich bleibe bei meiner Antwort (Alle anderen Nichtschlüsselattribute).
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Ich wähle eine andere Antwort, nämlich: Preis.
- Ich wähle eine andere Antwort, nämlich: Anzahl.

Kommt ein Vektor zur Drogenberatung: "Hilfe, ich bin linear abhängig..."

LÖSUNG DER ÜBUNGSAUFGABE ZUM THEMA 'DIE ZWEITE NORMALFORM':

Ihre Antwort ist richtig ('Alle anderen Nichtschlüsselattribute verletzen ebenfalls die zweite Normalform'),

weil keines der Attribute von allen Primärschlüsseln (Bestell_ID, Kdn_ID und Waren_ID) zugleich abhängig ist.

Wählen Sie bitte eine der unten stehenden Optionen:

- Zurück zur Aufgabe.
- Weiter zur dritten Normalform!
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)

Susi in der Matheübung: "Herr Dozent, jetzt habe ich die Aufgabe schon acht mal kontrolliert." "Gut, was haben Sie denn herausbekommen?" - "Wollen sie alle acht Ergebnisse wissen?"

DIE DRITTE NORMALFORM -

WIEDERHOLUNG DER ZWEITEN NORMALFORM UND RESULTIERENDE PROBLEME

Zur Erinnerung die Definition der zweiten Normalform:

Eine Relation ist in der zweiten Normalform,

wenn die erste Normalform vorliegt

und kein Nichtschlüsselattribut funktional abhängig von einer echten Teilmenge eines Schlüsselkandidaten ist.

-> PROBLEME, die sich daraus ergeben:

Die Informationen aus diesen beiden Feldern sind,

wie am Beispiel des Kunden Meier zu erkennen, mehrfach vorhanden, d. h. redundant.

Dadurch besteht die Gefahr, dass die Integrität der Daten verletzt wird.

So könnten die Adressdaten im Feld der „Appenzeller“-Bestellung geändert werden, ohne, dass die Daten in den beiden anderen Bestellfeldern geändert werden.

(Update-Anomalie).

Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort
1	Hans	Meier	Holm	5	D	Kiel
2	Heinz	Müller	Holm	1	D	Kiel

Bestell_ID	B_Date	L_Date	Anz	Kdn_ID	Waren_ID
1	1.11.2009	31.11.2009	30	1	1
2	1.11.2009	31.11.2009	10	1	2
3	1.11.2009	31.11.2009	3	1	3
4	2.11.2009	01.12.2009	3	2	3

Waren_ID	Artikel	Preis_kg
1	Appenzeller	17
2	Quark	0,7
3	Gorgonzola	20

Wählen Sie bitte eine der unten stehenden Optionen:

- Wozu kann Datenbanknormalisierungswissen gut sein? Hier klicken, um ein Statement aus der beruflichen Praxis zu lesen.
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Zur Definition der dritten Normalform.

Wissen über Datenbanknormalisierung beim Arbeiten mit GIS-Datenbanken ist wie Zeitmanagement bei Projekten generell – man kann nicht darauf verzichten.

A. Kittler, Dipl. Geogr., GIS.Internet.Datenbanken

Zurück zur vorherigen Seite.

Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen diese Option wählen!)

DEFINITION DER DRITTEN NORMALFORM

ANMERKUNG:

Wenn Ihnen die Erläuterungen zum Vergleich der beiden Normalformen nach Ihrem Empfinden nicht ausreichen,

um die Übungsaufgabe zu bearbeiten, wählen Sie am besten die Option:

'Ich benötige ein Beispiel.'

Die dritte Normalform ist erreicht,

wenn sich das Relationenschema in der zweiten Normalform befindet und ZUSÄTZLICH kein Nichtschlüsselattribut VON EINEM ANDEREN NICHTSCHLÜSSELATTRIBUT funktional abhängig ist.

(Hilfsfrage: Was kenne ich noch,

wenn ich ein bestimmtes Attribut, das nicht Primärschlüssel ist, kenne?)

Kurz zur Erinnerung die Definition der zweiten Normalform:

Eine Relation ist in der zweiten Normalform,

wenn die erste Normalform vorliegt

und kein Nichtschlüsselattribut funktional abhängig

von einer echten TEILMENGE EINES SCHLÜSSELKANDIDATEN ist.

Wählen Sie bitte eine der unten stehenden Optionen:

- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Ich benötige ein Beispiel!
- Ich möchte mit der Übungsaufgabe fortfahren.

Kommt ein Nullvektor zum Psychiater: "Herr Doktor, ich bin orientierungslos!"

DEFINITION DER DRITTEN NORMALFORM

Die dritte Normalform ist erreicht,
wenn sich das Relationenschema in der zweiten Normalform befindet
und ZUSÄTZLICH kein Nichtschlüsselattribut VON EINEM ANDEREN
NICHTSCHLÜSSELATTRIBUT funktional abhängig ist.
(Hilfsfrage: Was kenne ich noch,
wenn ich ein bestimmtes Attribut, das nicht Primärschlüssel ist, kenne?)

Vergleich zweite und dritte Normalform:

ZWEITE NORMALFORM

Alle Nichtschlüsselattribute sind nur vom Primärschlüssel (Kdn_ID) und nicht noch von irgendeinem anderen Nichtschlüsselattribut abhängig

Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort
1	Hans	Meier	Holm	5	D	Kiel
2	Heinz	Müller	Holm	1	D	Kiel

Für die dritte Normalform dürfen aber auch Nichtschlüsselattribute nicht von anderen Nichtschlüsselattributen abhängig sein (z.B. die in einem Ort einmaligen Straßen weisen automatisch auf den Ort hin.)

Kdn_ID	Vorname	Nachname	Str_ID	HNr
1	Hans	Meier	1	5
2	Heinz	Müller	1	1

Str_ID	Str	OID
1	Holm	1

OID	Ort	Land
1	Kiel	D

Wählen Sie bitte eine der unten stehenden Optionen:

- Ich habe die Erklärung verstanden und möchte mit der Aufgabe fortfahren.
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)
- Ich habe die Erklärung NICHT verstanden und möchte dennoch mit der Aufgabe fortfahren.

FRAGE ZUM THEMA 'DIE DRITTE NORMALFORM':

Diese Tabellen befinden sich in der zweiten Normalform.

Welches der Attribute verletzt in den vorliegenden Tabellen die dritte Normalform NICHT?

Anders gefragt:

Welches dieser Attribute muss aus der Tabelle nicht mehr ausgelagert werden, weil die Tabelle sich schon in der dritten Normalform befindet?

Kdn_ID	Vorname	Nachname	Str	HNR	Land	Ort
1	Hans	Meier	Holm	5	D	Kiel
2	Heinz	Müller	Holm	1	D	Kiel

Bestell_ID	Kdn_ID	Waren_ID	B_Date	L_Date	Anz
1	1	1	01.11.2009	31.11.2009	30
2	1	2	01.11.2009	31.11.2009	10
3	1	3	01.11.2009	31.11.2009	3
4	2	3	02.11.2009	01.12.2009	3

Waren_ID	Artikel	Preis_kg
1	Appenzeller	17
2	Quark	0,7
3	Gorgonzola	20

Wählen Sie bitte eine Antwort auf diese Frage:

- Meine Antwort auf die Frage ist: Beide
- Meine Antwort auf die Frage ist: Preis_kg
- Meine Antwort auf die Frage ist: Anzahl
- Ich möchte die Lektion beenden. (Bitte nur in Ausnahmefällen jetzt schon diese Option wählen!)

ANTWORT BESTÄTIGEN ODER KORRIGIEREN

Diese Tabellen befinden sich in der zweiten Normalform:

Weiches der Attribute verletzt in den vorliegenden Tabellen die dritte Normalform NICHT?

Kdn_ID	Vorname	Nachname	Str	HNr	Land	Ort
1	Hans	Meier	Holm	5	D	Kiel
2	Heinz	Müller	Holm	1	D	Kiel

Bestell_ID	Kdn_ID	Waren_ID	B_Date	L_Date	Anz
1	1	1	01.11.2009	31.11.2009	30
2	1	2	01.11.2009	31.11.2009	10
3	1	3	01.11.2009	31.11.2009	3
4	2	3	02.11.2009	01.12.2009	3

Waren_ID	Artikel	Preis_kg
1	Appenzeler	17
2	Quark	0,7
3	Gorgonzola	20

Wählen Sie bitte eine Antwort auf diese Frage:

- Ich wähle eine andere Antwort, nämlich: Anzahl.
- Ich bleibe bei meiner Antwort, nämlich: Preis_kg.
- Ich wähle eine andere Antwort, nämlich: Beide.

LÖSUNG DER ÜBUNGSAUFGABE ZUM THEMA 'DIE DRITTE NORMALFORM'.

Richtig, das Attribut 'Preis_kg' verletzt in den vorliegenden Tabellen die dritte Normalform NICHT.

Die vollständige dritte Normalform sieht folgendermaßen aus:

Kunde

Kdn_ID	Vorname	Nachname	Str_ID	HNr
1	Hans	Meier	1	5
2	Heinz	Müller	1	1

Straße

Str_ID	Str	OID
1	Holm	1

Ort

OID	Ort	Land
1	Kiel	D

Artikel

Waren_ID	Artikel	Preis_kg
1	Appenzeller	17
2	Quark	0,7
3	Gorgonzola	20

Bestellungen

Bestell_ID	Kdn_ID	B_Date	L_Date
1	1	01.11.2009	31.11.2009
2	2	02.11.2009	01.12.2009

Bestellpositionen

BestPos_ID	Bestell_ID	Waren_ID	Anz
1	1	1	30
2	1	2	10
3	1	3	3
4	2	3	3

Wählen Sie bitte eine der unten stehenden Optionen:

- Zurück zur Aufgabe.
- Ich möchte die Lektion beenden (reguläres Ende der Lektion).

Appendix 9 - Questionnaire Items and Scales

Note that the questionnaire language is German and these items are translated from the original version by the author.

Computer Usage Questionnaire

1. General Questions:

1.1 I am: **1** female **2** male

1.2 Age

1.3 Number of semesters:

1.4 Subject:

Major:

Minor:

2. How often do you use a computer or a mobile device for the following activities?

2.1 One-player games

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.2 Collaborative online games

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.3 E-mail to communicate with (assistant) professors about course tasks

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.4 Group work using a university computer with other students

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.5 E-mail in general

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.6 Chat online (e. g. via Skype©)

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.7 Surf the Internet for entertainment (e. g. watch videos on YouTube™)

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.8 Musik, Filme, Spiele oder Software aus dem Internet herunterladen

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.9 Publish and attend to own website or blog

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.10 Take part in social networks (e. g. Second Life©or Facebook™)

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.11 Work on course tasks

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.12 Surf the Internet to work on course tasks

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.13 E-mail to communicate with classmates about course tasks

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.14 Download (e. g. lecture plan or exercise material) from the university website or upload documents or other material

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.15 View announcements on university website (e.g. absence of (assistant) professors)

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

2.16 Work with computer simulations

never or almost never (1)

once or twice a month (2)

once or twice a week (3)

daily or almost daily (4)

1 Have you ever worked with a technology-enhanced learning environment (e.;g. OLAT, Moodle)?

yes no

2. Computer Usage:

2.1 How often do you use the computer for study reasons?

not at all (1)

not regularly (2)

once or twice a week (3)

three or four times a week (4)

daily (5)

2.2 For how long do you use the computer for study reasons?

up to half an hour (1)

half an hour to an hour (2)

one to two hours(3)

two to four hours (4)

more than four hours (5)

2.3 How often do you use the computer in your freetime?

not at all (1)

not regularly (2)

once or twice a week (3)

three or four times a week (4)

daily (5)

2.4 For how long do you use the computer in your freetime?

up to half an hour (1)

half an hour to an hour (2)

one to two hours(3)

two to four hours (4)

more than four hours (5)

2.5 What do you prefer doing with the computer in you freetime? (Multiple answers possible)?

game-playing

communicate (e.g. via social networks or e-mail)

search for information (products, news)

download music/ films

other:

4. How good are you at the following tasks?

(Items to evaluate basic computer self-efficacy:)

4.1 Use programmes to get rid of computer viruses

I do not know what that means. (1)

I know what that means but I cannot do it. (2)

I can do that with the help of someone else. (3)

I can do that on my own. (4)

4.2 Use a spreadsheet programme to create a diagram

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)
- I can do that on my own. (4)

4.3 Create a presentation (e. g. via PowerPoint©)

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)
- I can do that on my own. (4)

4.4 Create a multi-media presentation (including sound, pictures, videos)

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)
- I can do that on my own. (4)

(Items to evaluate advanced computer self-efficacy:)

4.5 Use a database to create an address list

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)
- I can do that on my own. (4)

4.6 Create a computer programme

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)
- I can do that on my own. (4)

4.7 Create a website

- I do not know what that means. (1)
- I know what that means but I cannot do it. (2)
- I can do that with the help of someone else. (3)

I can do that on my own. (4)

5. When thinking about your work with the computer, how much do you agree to the following statements?

5.1 Working with the computer is important to me.

I do not agree at all. (1)

I rather do not agree. (2)

I rather agree. (3)

I entirely agree. (4)

5.2 I enjoy working with the computer.

I do not agree at all. (1)

I rather do not agree. (2)

I rather agree. (3)

I entirely agree. (4)

5.3 I use the computer because I am interested in using it.

I do not agree at all. (1)

I rather do not agree. (2)

I rather agree. (3)

I entirely agree. (4)

5.4 When working with the computer I forget about the time.

I do not agree at all. (1)

I rather do not agree. (2)

I rather agree. (3)

I entirely agree. (4)

6. How often do your professors use these learning materials?

6.1 Specialized book/ syllabus

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.2 Atlas or maps

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.3 Statistics or tables

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.4 Drawings or figures

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.5 Original objects

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.6 Essays based on personal experience or field reports

term unknown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.7 Films

term unknown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.8 Drawings or figures

term unknown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.9 Schemes or MindMaps

term unknown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.10 Animations or animated illustrations

- term unknown (0)
- never (1)
- seldom (2)
- sometimes (3)
- regularly (4)
- every lecture (5)

6.11 Presentations

- term unknown (0)
- never (1)
- seldom (2)
- sometimes (3)
- regularly (4)
- every lecture (5)

6.12 Computer-based learning programmes

- term unknown (0)
- never (1)
- seldom (2)
- sometimes (3)
- regularly (4)
- every lecture (5)

6.13 Aerial or satellite images

- term unknown (0)
- never (1)
- seldom (2)
- sometimes (3)
- regularly (4)
- every lecture (5)

6.14 (Press-clippings of) magazines in their current issue

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.15 Internet

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.16 Geographic Information Systems

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

6.17 Computers in general

term unkown (0)

never (1)

seldom (2)

sometimes (3)

regularly (4)

every lecture (5)

7. How interested are you in these learning materials?

6.1 Specialized book/ syllabus

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.2 Atlas or maps

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.3 Statistics or tables

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.4 Drawings or figures

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.5 Original objects

- term unkown (0)

- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.6 Essays based on personal experience or field reports

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.7 Films

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.8 Drawings or figures

- term unkown (0)
- I have no interest. (1)
- I have little interest. (2)
- It partly interests me. (3)
- It interests me. (4)
- It interests me very much. (5)

7.9 Schemes or MindMaps

- term unkown (0)
- I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.10 Animations or animated illustrations

term unknown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.11 Presentations

term unknown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.12 Computer-based learning programmes

term unknown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.13 Aerial or satellite images

term unknown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.14 (Press-clippings of) magazines in their current issue

term unkown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.15 Internet

term unkown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.16 Geographic Information Systems

term unkown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

It interests me. (4)

It interests me very much. (5)

7.17 Computers in general

term unkown (0)

I have no interest. (1)

I have little interest. (2)

It partly interests me. (3)

[] It interests me. (4)

[] It interests me very much. (5)

TELE-study

2. Imagine you received the possibility to learn about the rules of database normalisation (method to inter alia avoid data redundancies and resulting problems in databases)? How interested are you in this topic?

Task interest according to	RHEINBERG ET AL. 2001
2.1 I enjoy puzzling about these kind of problems.	does not apply [1][2][3][4][5][6][7] applies
2.2 In this kind of setting I like the role of the scientist who discovers problem solutions.	does not apply [1][2][3][4][5][6][7] applies
2.3 Reading the instruction, the lesson seems interesting.	does not apply [1][2][3][4][5][6][7] applies
2.4 I enjoy that kind of lesson, I do not need an incentive.	does not apply [1][2][3][4][5][6][7] applies
2.5 I would work on that kind of topic in my freetime.	does not apply [1][2][3][4][5][6][7] applies
Intrinsic motivation item according to	DECI & RYAN 2003 as cited by ECKHARDT 2010
2.6 I start this kind of task in the Technology-Enhanced Learning Environment without any problems.	does not apply[1][2][3][4][5][6][7]applies
2.7 I continue tasks of this kind until they are done even if I could do other interesting things.	does not apply[1][2][3][4][5][6][7] applies
2.8 I find means to concentrate while working on the computer even if other things could distract me.	does not apply[1][2][3][4][5][6][7]applies
2.9 I find motivation to work on the tasks even if I have little interest in doing so.	does not apply[1][2][3][4][5][6][7]applies

3. How much do you agree to these statements? (Items to evaluate the perceived usability of the TELE according to Lewis 2002, own translation)

3.1 All in all I am satisfied how simple the learning environment for learning about database normalisation can be operated.	does not apply [1][2][3][4][5][6][7] applies
3.2 The Technology-Enhanced Learning Environment for learning about database normalisation is easy to manage.	does not apply [1][2][3][4][5][6][7] applies
3.3 I was able to work on the tasks successfully by using the programme.	does not apply [1][2][3][4][5][6][7] applies
3.4 I was able to work on the tasks quickly by working with the learning environment.	does not apply [1][2][3][4][5][6][7] applies
3.5 I was able to solve the tasks successfully using the learning environment.	does not apply [1][2][3][4][5][6][7] applies
3.6 It was convenient to work with the learning environment.	does not apply [1][2][3][4][5][6][7] applies
3.7 It was easy to learn how to handle the learning environment.	does not apply [1][2][3][4][5][6][7] applies
3.8 I think that I could achieve goals quickly by using the programme.	does not apply [1][2][3][4][5][6][7] applies

4. How much do you agree to these statements? (Items to evaluate the cognitive load of the TELE according to **Urhahne 2002**)

4.1 Was the lesson about database normalisation rather to simple or to difficult?	(to simple[1][2][3][4][5]to difficult)
4.2 How much mental effort was necessary for you to work through the lesson?	(none at all[1][2][3][4][5]extremely much)
4.3 How hard did you have to try to understand the lesson content?	(not at all[1][2][3][4][5]extremely hard)
4.4 Was the lesson content about database normalisation rather to simple or rather to complex?	(much to simple[1][2][3][4][5]much to complex)
4.5 Did you feel overcharged by the amount of information provided by the lesson?	(not at all[1][2][3][4][5]extremely)
4.6 Did you feel overcharged by the complexity (choices, complex content) provided by the lesson?	(not at all[1][2][3][4][5]extremely)
4.7 How often did you experience the presentation of to much information by the learning environment?	(not at all[1][2][3][4][5] extremely often)
4.8 How often did you not understand information by the learning environment?	(not at all[1][2][3][4][5]extremely often)

5. Please rate the following statements regardless of the appearance in the lesson. (Items evaluating the motivational elements response, author's illustration, original language: German)

5.1 Applying normalisation rules trains the ability of deductive thinking, i.e. the ability to apply general rules to special cases.

This motivates me...

little[1][2][3][4][5]very much

5.2 You delve into core concepts of database theory. This topic does not only apply to computer science professions. Examples are: normal form, attribute, redundancy and related concepts.

This motivates me...

little[1][2][3][4][5]very much

5.3 You can help others with your knowledge.

This motivates me...

little[1][2][3][4][5]very much

5.4 *Knowledge about database normalisation has supported me during my time in financial business to professionally manage database support processes.* This applies even to someone who does not primarily work with IT.

“ This statement from a business management graduate, i.e. from a non-geoscience employee motivates me...

little[1][2][3][4][5]very much

5.5 *Knowledge about database normalisation for working with GIS databases is like time management in projects - you can't do without.*

This statement from a geography graduate working as a freelancer, i.e. a geoscience employee motivates me...

little[1][2][3][4][5]very much

Appendix 10 - Data collection standards

Necessity of question items: Unnecessary question items put disadvantageous cognitive load on participants and extend the survey. It is advisable to economize on questions which will only be evaluated eventually or at least go carefully through items which might be unnecessary.

Realization: The itemsets used in the study aimed at analysing technology-enhanced learning preconditions and success factors of geoscience students. Additionally to directly related question, such as e. g. computer self-efficacy, points for correct task answers or the usability of the TELE, learning material experience qualified as well as an important factor determining technology-enhanced learning potentials for geoscience students. Therefore the itemset learning material experience was considered appropriate as evaluated preconditions factor.

Justify repetition of question types: The repetition of question items might be necessary. Then the repetitive function needs to be clear to the investigator. Is it for reliability or answer consistency test reasons?

Realization: In the e-lesson the participants needed to confirm their answers to each questions in order to ensure answer consistency and avoid guesses.

Avoid question item redundancy: Questions and their corresponding items are redundant if the resulting information is accessible in a more efficient manner using sources such as the Internet or bibliographic databases.

Realization: The questionnaire used e. g. by [KLEIN 2008](#) to evaluate the Computer Literacy Types (see [Table 2.4](#)) of her sample also included items about basic computer use, i.e. open a file etc. These items investigate on skills which can be presupposed regarding university students.

Use plain and unambiguous expressions pointing out a single issue: If a question item points out more than a single issue it needs to be split up.

Realization: This requirement was met.

Carefully employ negations Example: The answer *no* to the question *I do not enjoy taking a walk alone.* strictly speaking implies that the person asked likes taking a walk alone due to the double negation. The colloquial meaning could instead suggest the answer *No, I do not enjoy taking a walk alone.*

Realization: Negations were only employed if necessary. *Obtaining rather general answers:* If questions need to be asked in a general manner additional question items or more detailed expressions are needed. This is especially important when emotions, knowledge, attitudes and behaviour are supposed to be distinguished.

Realization: A question item aimed at evaluating the students' preferences when using computers. For answer possibilities such as e.g. *communicate* the explanation e.g. *via social networks or e-mail* was added.

Make sure the participants are able to answer the questions: Questionnaires need to be adapted to the educational level of the participants. Questions should be avoided which the participants might most likely not be able to answer.

Realization: The e-lesson was constructed on a knowledge level corresponding to the level in the respective GIS course which they attended.

Dealing with questions making participants uncomfortable: When these kind of questions are unavoidable it is advisable to position them as much to the end as possible. Further options to mitigate these kind of questions need to be considered.

Realization: At the beginning of the e-lesson a mood level test was conducted. The options the participants had to check revealed superficial but still personal traits. The test supervisor had to ensure the confidentiality of the results especially at this step of the experiment.

Support answering process e.g. by memory hooks: If the answering process can be supported e.g. by memory hooks then this opportunity should be taken considering to provide them to all participants in the same manner.

Realization: The three normal forms taught needed to be presented in their logical

sequence. When explaining the third normal form a reminding explanation of the second normal form was displayed as well.

Appropriate answer possibilities: Answer possibilities need to be a probable answer from the participant perspective as well. If they are not the complete survey results can be influenced.

Realization: Geomedia employed in geoscience courses needed to be media which had a certain probability of being used by instructors.

Influence of question item sequence on answers: If an influence of the item sequence on the answers can be identified a reordering of the items needs to be considered.

Realization: To assess the computer usage of the students the two items *How often do you use the computer in your freetime?* and *How long do you use the computer then?* had to be answered in this order because the second item depended on the first.

Alternating question formats to support motivation: To avoid boredom different materials can be alternated, e. g. graphics, paper-pencil and computer-supported answers.

Realization: The e-lesson participants were supposed to fill up short questionnaires as paper-pencil tests. In combination with the TELE they had alternating question formats and therefore shorter sequences of necessary concentration on one activity which is helpful when concentration ability is not a variable to be measured.

Avoid leading questions: Leading questions might influence the participants' answer, e. g. *Are you sure that this is your opinion?* These question type needs to be avoided.

Realization: There were no leading questions employed in the study.

Scaling distance and answer directions: Answer possibilities regarding corresponding categories need to correspond as well in terms of answer scales.

Realization: An example are the two question itemsets about the computer attitude of students and their computer self-efficacy. The two first items are compared:

Itemset *Computer attitude*, item 1 of 4: Working with the computer is important to me.

4=I entirely agree.

3=I rather agree.

2=I rather do not agree.

1=I do not agree at all.

Itemset *Basic computer self-efficacy*, item 1 of 4: Use of antivirus programmes

4=I can do that on my own.

3=I can do that with the help of somebody.

2=I know what that means but I can not do it.

1=I do not know what that means.

The item sets are used for generating student clusters. The scaling 1-4 and the highest value (4) to signal maximum agreement were chosen intentionally. More details about the scales which were employed can be found in the next chapter.

Set high priority on formulating opening questions: The way the opening questions are formulated might influence the entire process of answering the items.

Realization: The opening instructions and first questions were especially checked. Still a certain amount of flexibility for the practical situation of the survey was required. Serious problems within the study, which might have resulted in invalid study results, could be prevented.

Closing questions and comments: Avoiding the most difficult question items at the end and communicating gratitude for participating help to create a cooperative atmosphere.

Realization: It was ensured that the participants left with all the information they needed and knew how they could obtain the study results when published.

Appendix 11- Statistical Fundamentals

The explanation of all components of correlation measurement goes to far into detail to consider them in the main text of the dissertation. Therefore this chapter is concerned with these fundamentals while it focusses on the product-moment correlation coefficient and its underlying measurements

The product-moment correlation coefficient is defined as the covariance of two variables divided by the standard deviations of the variables.

$$r = \frac{s_{xy}}{s_x \cdot s_y}$$

This is a measure which is invariant regarding changes of scale (BORTZ & SCHUSTER 2010, p. 156). If this is not required, then the covariance is sufficient:

The covariance is a non-standardised measure for how much the changes in two variables relate to each other whereas a linear relationship is assumed (BORTZ & SCHUSTER 2010, p. 143).

It is defined as:

$$\frac{\sum_{i=1}^n (x_i - \bar{x}) \cdot (y_i - \bar{y})}{n-1}$$

The standard deviation (s) is the square root of the variance. It is of special importance as it possesses the same unit as the measured data. (ibid. p. 31.

The variance is the sum of the squared deviations of all measured arithmetic means divided by n-1. (ibid.). The arithmetic mean is the sum of numbers divided by the amount of numbers in a data set (JACOBS 1994).

Variance:

$$s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}$$

The calculation of the variance requires metric traits (ibid.).

Classically interval or ratio scaled data qualify as metric data. An example of interval scaled data is the temperature with constant distances between the scale levels. An example of ratio scaled data such length or weight where the zero value is not arbitrary opposed to the zero value of interval scales such the *zero* on a Celsius temperature scale. Moreover correct mathematical operations such as divisions can be carried with ratio scaled data (ibid., p. 14).

In contrast, ordinal and nominal data are not classically considered as *metric*. On nominal scales objects with the same characteristics possess are numbered the same and object with the different characteristics are numbered differently. Which numbers are used is irrelevant. They cannot be interpreted quantitatively (ibid., p. 17). An example of a nominal trait is gender with the two possible characteristics *male* or *female*.

Ordinal scales involve a rank order which supports sorting of data. However, the distance between objects on a scale is not explicitly defined by an ordinal scale (ibid., p. 18). Whether ordinal scales are classified as metric or not is disputed. This is of importance when applying statistical analyses where a mean value is a basic requirement for further calculations. Scientific practice uses *per fiat* measurements, ie. it is assumed that questionnaires, tests, rating scales etc. measure the relevant metric characteristic (DAVISON & SHARMA 1988, BORTZ & SCHUSTER 2010, p. 23).

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