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Toward a Taxonomy of Modeling Difficulties: A Multi-Modal Study on Individual Modeling Processes

Completed Research Paper

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Abstract

Conceptual modeling is an essential activity during information systems development and, accordingly, a learning task faced by students of Information Systems. Presently, surprisingly little is known about how learning processes of conceptual modeling proceed, and about modeling difficulties learners experience. In this study, we integrate complementary modes of observation of learners' modeling processes to identify modeling difficulties these learners face while performing a data modeling task using a modeling tool. We use the concept of cognitive breakdowns to analyze verbal protocols, recordings of learner-tool interactions and video recordings of learners' modeling processes and survey learners about modeling difficulties. Our study identifies five types of modeling difficulties relating to different aspects of constructing conceptual data models, i.e., entity types, relationship types, attributes, and cardinalities. The identified types of modeling difficulties motivate a taxonomic theory of modeling difficulties intended to inform design science research on tool support for learners of conceptual modeling.

Keywords: Conceptual modeling, learning, problem solving, modeling difficulty, cognitive breakdown, mixed methods research

Introduction

Conceptual modeling is an essential activity during information systems development and organizational analysis leading to purposeful reconstructions of statements about a domain of discourse using a modeling language, e.g., for data or process modeling (Chen 1976; Hirschheim et al. 2008; Wand and Weber 2002). Accordingly, conceptual modeling is a learning task faced by most students of Information Systems as it is mandated by curricula standards, e.g., by the joint standard curriculum for Information Systems of the Association for Information Systems and Association for Computing Machinery (ACM/AIS 2018). Viewed as a learning task, conceptual modeling involves an intricate array of cognitive processes and performed actions including abstracting, conceptualizing, associating, contextualizing, visualizing, interpreting & sense-making, judging & evaluating, and, in group settings, communicating, discussing and agreeing (Rosenthal et al. 2019). Learning conceptual modeling is, hence, construed as a complex task based on codified as well as tacit knowledge (Polanyi and Sen 2009) and on a learning process involving knowledge acquisition through experience (e.g., Venable 1996). Learning conceptual modeling involves mastering theoretical foundations, modeling languages and methods, applying them to practical problems, and, along the way, critically thinking and reflecting upon the respective modeling objectives and application domain. It is, amongst others, for these reasons that conceptual modeling is often perceived as particular challenging by learners (e.g., Sedrakyan and Snoeck 2017).

Despite its importance and complexity, the learning of conceptual modeling has received only limited attention in research so far (Rosenthal et al. 2019). How learning occurs, how individual learning processes proceed, which modeling difficulties learners experience, and how to overcome these difficulties has been subject to only a few studies (e.g., Serral et al. 2016; Venable 1996). Altogether, we know surprisingly little about the actual act of conceptual modeling by learners, about the reasoning of learning modelers and their corresponding cognitive processes, and whether different (idealized) types of modelers can be identified, e.g., by identifying patterns of modeling processes, and whether these modeler types require different learning support. Related work has mostly focused on business process modeling (Claes et al. 2015; Wilmont et al. 2017), rarely on object-oriented modeling (Sedrakyan et al. 2016) and investigated other related questions, e.g., about differences between non-experienced and experienced modelers (Batra and Davis 1992; Venable 1996).

In this multi-modal study, we integrate complementary modes of observation of learners' modeling processes to identify modeling difficulties these learners face while performing a data modeling task using a modeling software tool. We use the concept of cognitive breakdowns (e.g., Bera 2011; Newell and Simon 1972) to identify modeling difficulties in verbal protocols (think aloud protocols, see Ericsson and Simon 1980) and complement difficulty identification by visually inspecting recordings of modeler-tool interactions as well as video recordings of individuals' modeling processes. We then complement difficulty identification by surveying these individuals about performing the modeling task.

The complexity of the task of learning conceptual modeling is the main rationale for this mixed methods research design with multi-modal observations of individual modeling processes: While think aloud protocols have shown to be promising for understanding cognitive processes of subjects performing general problem-solving tasks (e.g., Batra and Davis 1992; Ericsson and Simon 1980), modeling difficulties will not always be observable from verbal protocols alone but from interactions of modelers with the software tool (think, e.g., of the deletion of model elements), with pen&paper (think of taking notes, returning to notes, or modeling a draft or model fragment on paper) or simply from modeler movements, e.g., erratic changes between looking at the graphical editor on screen and the modeling task provided on paper. Multi-modality of observations is assumed to provide a more complete picture of the phenomenon under investigation (e.g., Venkatesh et al. 2013; 2016): Complementing these different modes of observation on modeling processes allows us to identify a wider range of modeling difficulties by way of cognitive breakdowns as well as corresponding deviating behavior, and is a research strategy common to mixed methods research designs (e.g., Creswell and Plano Clark 2018). However, to ask subjects to think aloud and to complement verbal protocols with observations from recordings of modeler-tool interactions and modeler movements is, of course, a second-best approach, warranted only because it is not possible to directly access and capture cognitive processes and, thus, modeler reasoning while modeling. Modelers may have difficulties verbalizing their reasoning while modeling—a methodological challenge we address below.

The (meta) objective above the primary research objective of identifying modeling difficulties of learners is to inform design science research on developing (tool) support for learners of conceptual modeling: By identifying modeling difficulties and by developing a taxonomic theory of such difficulties over the course of multiple studies, the present research aims to contribute to establishing a theoretical foundation for developing targeted support for learners of conceptual modeling.

After introducing the theoretical background and related work in the next section, the mixed methods research design of this study as well as the multi-modal observations and the data analysis strategy are explained in the subsequent section. Then, we present the findings followed by a discussion of the findings. In the last section, a discussion of limitations of the study and future research directions is given.

Theoretical Background and Related Work

This section provides an introduction of the notion of cognitive breakdowns and a brief overview of main strands of related research, i.e., related prior work investigating individual modeling processes that have been studied from different perspectives and using different approaches as well as focusing on different abstractions (e.g., static and dynamic abstractions). Subsequently, we frame the present study within the research on learning and teaching conceptual modeling.

Cognitive Load Theory and the Concept of Cognitive Breakdowns

Following, e.g., Batra and Davis (1992) and many others, conceptual modeling is viewed as ill-structured problem solving: A modeling task (e.g., a data modeling task) does not imply a clear path to a conceptual model (e.g., a data model)—similar to ill-structured problems where a problem representation does not imply a clear path to a solution of the problem (e.g., Newell and Simon 1972; Pretz et al. 2003). Rather, a modeling task starts from a problem representation in textual form (using natural language) and/or graphical and other visual forms, and requires the application of modeling concepts of a modeling language with a precise syntax and formal semantics to create a conceptual model by purposefully reconstructing the problem representation by means of modeling concepts of the chosen modeling language. The aspired artifact as result of this problem-solving process is the conceptual model (cf. Pinggera et al. 2015, p. 1057).

Cognitive Load Theory (CLT) targets the cognitive resources of humans and how these resources are used in problem solving and learning (e.g., Sweller 1988): Following CLT, humans have limited cognitive capacity in performing complex tasks as the capacity of the working memory is limited at a given time. The cognitive load on a subject performing a problem-solving task can, hence, lead to cognitive difficulties if the capacity of the cognitive resources is exceeded—potentially leading to a *cognitive overload* (Sweller 1988). As complex cognitive task involving several complex cognitive aspects, conceptual modeling is assumed to lead to cognitive difficulties (e.g., Bera 2011, p. 4; Burton-Jones and Meso 2006, p. 54).

Hence, we use the notion of cognitive breakdowns (e.g., Bera 2011; Newell and Simon 1972) to identify modeling difficulties which modelers experience while constructing a conceptual data model. Following problem-solving research (e.g., Newell and Simon 1972) and prior work on cognitive difficulties in problem-solving processes (e.g., Bera 2011; Vessey and Conger 1994), we define a *cognitive breakdown* as a cognitive difficulty which a modeler experiences when constructing a conceptual model based on a natural language description (Bera 2011, p. 4)—*"when a line of thought fails"* (Burton-Jones and Meso 2008, p. 768). Such a cognitive breakdown can manifest itself in a modeler explicitly verbalizing a difficulty while modeling or in interrupting or terminating a modeling activity, e.g., a modeling activity which is not completed, but instead the modeler switches to another activity (Bera 2011, p. 4).

Individual Modeling Processes

Early contributions on individual modeling processes investigate similarities and differences between non-experienced and experienced modelers based on verbal protocols (Batra and Davis 1992). Building on a data modeling task, Batra and Davis derive a process model of conceptual data modeling from analyzing the verbal protocols which distinguishes three distinct levels of abstraction, i.e., the enterprise level, the recognition level and the representation level, as well as the iterations between the levels. The process model is then used to identify similarities and difference between experts and novices (Batra and Davis 1992, p. 97). A subsequent study investigates errors of novice modelers in two laboratory experiments. The study evaluates errors in data models constructed by novices complemented with analyzing think aloud protocols to achieve insights into why these errors had been committed (Batra and Antony 1994, p. 64). As main causes of the identified errors, the authors identify the complexity of the modeling task in terms of the number of possible relationship types increasing at a combinatorial rate with the number of entity types, misapplication of modeling heuristics, and a lack of knowledge about database design—leading to suggestions for supporting novices in data modeling with immediate feedback in supportive tools (Batra and Antony 1994, pp. 66f).

A further study closely related to the present work, targets the behavior of modelers while data modeling (Srinivasan and Te'eni 1995, p. 419). Again, considering conceptual data modeling processes as problem-solving processes, the study reports on two laboratory studies using think aloud protocols. Their research design focuses on the problem representation and problem-solving heuristics, i.e., strategies for controlling cognitive activities, applied by the modelers to overcome cognitive limitations (Srinivasan and Te'eni 1995, pp. 422, 432f). First, a cognitive model of data modeling is developed including problem representation, cognitive activities, heuristics and constraints on the effectiveness and efficiency of the cognitive activities as well as their interdependencies (Srinivasan and Te'eni 1995, pp. 422, 432f). Analyzing the verbal protocols based on the cognitive model led to insights into how individuals use heuristics to control their modeling processes.

Complementing and updating this prior work, the present research aims to deepen our understanding of individual conceptual data modeling processes. In contrast to prior studies, the focus of the research at hand is to identify modeling difficulties from complementary modes of observation including modeler-tool interactions.

In a laboratory setting, Bera (2011) studies how ontological modeling guidelines assist modelers in constructing conceptual models. Also based on the concept of cognitive breakdowns, verbal data protocols of subjects creating UML class diagrams are analyzed. Different from the present work, the data analysis is restricted to quantifying the breakdowns and bases its analysis on numbers of encountered modeling difficulties—suggesting that, as result of the study, modeling guidelines can be helpful but, however, have to be used carefully (Bera 2011, p. 5). The analysis in the present study is based on the notion of cognitive breakdowns as well. In contrast, we further explore the breakdowns using complementary modes of observation to understand what modeling difficulties are indicated by the breakdowns and at which modeling step they occur.

A stream of related research investigates the *process of process modeling*. Limited to the process of business process modeling, this stream of research investigates the process of constructing process models to better understand how humans model and, in addition, how the outcome of the modeling process, i.e., the process model, is affected by different modeling styles (e.g., Claes et al. 2015; Pinggera et al. 2014; 2015). In Pinggera et al. (2015), an exploratory analysis of individual process modeling processes leads to identifying three distinct styles of modeling: (1) an "efficient modeling style" focusing on quickly adding model elements to the model, (2) a "layout-driven modeling style" focusing on a comprehensible model layout and (3) an "intermediate modeling style" between the former two styles. Pinggera et al. also view the act of process modeling as problem solving (2015, p. 1057). The analysis of the modeling processes is based on recording modeler-tool interactions that are analyzed using data mining techniques and cluster analysis (Pinggera et al. 2015, p. 1061). The identified modeling styles are planned to be further explored by developing behavior patterns incorporating modeler-specific and task-specific factors in Pinggera et al. (2014). For that, it is envisioned to track modeler-tool interactions, complemented with think aloud protocols and eye movement data and how the collected data could be visualized (Pinggera et al. 2014). In closely related work, Claes et al. (2015) identify three cognitive process modeling techniques, a flow-oriented and an aspect-oriented process modeling technique and the combination of both techniques. In their studies, subjects working on process modeling tasks are observed and modeler operations are recorded. The modeling processes are analyzed using step-by-step replays of the modeling processes and so-called PPMCharts visualizing the tool operations of a modeler while constructing a conceptual model (Claes et al. 2015, pp. 1404f): All interactions of a modeler with a model element on the canvas constructing a process model are represented as a colored icon with the color depending on the type of interaction and its shape referring to the type of model element involved in the interaction. The icons are positioned on horizontal timelines of which each one refers to a model element. As result of analyzing individual modeling processes and integrating different cognitive theories, a theory, called Structured Process Modeling Theory (SPMT), was developed which explains how the probability of an occurrence of cognitive overload in process modeling processes can be reduced (Claes et al. 2015, p. 1420): It is suggested that the techniques of serializing the construction of the process model, serializing the construction process in a structured fashion and fitting the serialization approach with the modeler's cognitive preferences can lower the chance of cognitive overload. Following these suggestions, Claes et al. (2017) suggest a method which helps process modelers to discover and learn a modeling strategy which fits their individual cognitive preferences and provide an accompanying prototype: After measuring cognitive preferences, a matching process modeling strategy is selected for the modeler according to the SPMT followed by a training of this modeling strategy (Claes et al. 2017, pp. 59–61). In the present work, the replay functionality of modeler-tool interactions and the PPMCharts used in Claes et al. (2015) inspire the data analysis. In contrast to the "process of process modeling" research, the present work does not focus on process modeling processes but on data modeling.

Further related studies' foci differ from those of the present study. For example, there is research taking a communication-based approach to investigate the conceptual modeling process as such (Hoppenbrouwers et al. 2005; 2006). Hoppenbrouwers et al. view conceptual modeling as a dialogue, coining the term "modeling dialogue" (2005, pp. 137f). To capture modeling processes, especially, modeling decisions, Hoppenbrouwers et al. (2006) propose a part of the meta-model of a modeling laboratory aimed at gathering empirical data on the details of modeling processes—closely related to the observation approach used in this study. However, we were not able to find an application of the laboratory suggested by Hoppenbrouwers et al. so far. Further work by Hoppenbrouwers and co-authors investigates cognitive mechanisms of conceptual business process modeling with a focus on collaborative modeling. Wilmont et al. (2010) reports an exploratory study comparing modeling approaches of modeling novices and modeling experts asked to create concept maps. In Wilmont et al. (2013), cognitive processes while modeling are studied to investigate how these processes influence modeling behavior and modeling skills. The study proposes relational reasoning and abstraction as key cognitive processes in modeling. This research is continued by suggesting a method for analyzing collaborative process modeling behavior, aimed at generating insights into psychological mechanisms of modeling skills and related cognitive processes (Wilmont et al. 2017). Methodologically similar to the present study, modeling processes are recorded on video while modelers are asked to think aloud in these studies. Here, we do, however, complement further modes of observation and do not focus on collaborative modeling.

Learning and Teaching Conceptual Modeling

Learning and teaching conceptual modeling has been subject to research for a long time with recent contributions, e.g., focusing on model-driven development (Pastor et al. 2016) or automated personalized feedback to learners (Serral et al. 2016). In a recent literature review, we find 121 research contributions to this field exhibiting a diverse body of knowledge with the themes of learning tool support and feedback to learners as prevalent themes and learning analytics as well as gamification as emerging themes (Rosenthal et al. 2019). Besides the prevalent and emerging themes, it is noteworthy that fundamental considerations about learning processes of conceptual modeling, i.e., how learning processes proceed, and about the act of conceptual modeling by learners have only received limited attention in research on learning conceptual modeling so far. However, calls for a greater attention to fundamental considerations of learning processes have been expressed from IS researchers (e.g., Alavi and Leidner 2001) as well as from education scientists (e.g., Biggs 1996).

In a study closely related to the present work, Venable (1996) provides a teaching strategy supporting novice data modelers to achieve a more advanced level of expertise. For developing the teaching strategy, results from prior studies into data modeling processes are integrated. The strategy includes specifying and explicating differences between novices and experts and, based on that, provides the novices with specific techniques to overcome the expertise gap, i.a., by studying a variety of data modeling approaches as well as several problem domains (Venable 1996, p. 56). The findings of the present study, i.e., the identified modeling difficulties encountered in data modeling processes, are also intended to provide a basis for developing such teaching support.

From the perspective of learning outcomes and with a focus on enterprise modeling, recent research investigates modeling processes of learners and develops a feedback approach based on analyzing the individual modeling processes (Sedrakyan et al. 2014; 2016). In empirical studies, interactions of novice modelers with a modeling tool are recorded during the construction of conceptual models and analyzed by means of process mining techniques based on a differentiation of the semantic quality of the constructed models (Sedrakyan et al. 2014, pp. 488f). Behavioral patterns in the modeling processes associated with better respectively worse learning outcomes are identified relating to modeling and validation activities (Sedrakyan et al. 2016, pp. 370–374). As in this study, conceptual modeling processes are considered as complex problem-solving processes (Sedrakyan et al. 2016, p. 355). Approaches for providing computer-assisted feedback combining cognitive feedback and behavioral feedback based on the prior results are presented in Serral et al. (2016) and Sedrakyan and Snoeck (2017). Similar to this study, modeling processes are analyzed with the overarching goal to provide modeling support. However, this research analyzes data modeling processes and extends the observations of individual modeling processes with further observation modi taking complementary perspectives.

Research Design

This study follows a mixed methods research design (e.g., Creswell and Plano Clark 2018) that "*mixes or combines quantitative and qualitative research techniques, methods, approaches, concepts or language into a single study*" (Johnson and Onwuegbuzie 2004, p. 17). The chosen mixed methods research design (see Figure 1 for an overview) is intended to compensate the respective weaknesses (e.g., when restricting the observations to modeler-tool interactions neglecting the reasoning of modelers), associated with the prospect of insights going beyond results from either type of data separately (e.g., Creswell and Plano Clark 2018, pp. 12f; Johnson and Onwuegbuzie 2004, pp. 14f). The present study builds on a mixed methods research design in the light of two considerations: First, due to the complexity of learning conceptual modeling, learners' modeling processes deserve study from multiple complementary perspectives—a mixed methods design allows to integrate these perspectives. Second, the investigated phenomenon, i.e., individual data modeling processes, has received only little attention so far in research on learning conceptual modeling (Rosenthal et al. 2019). In contrast to extant studies, the present study applies an innovative multi-modal observation approach and an accompanying data analysis strategy: Tracking modeler-tool interactions is combined with recording verbal protocols, videotaping modelers and surveying modelers—serving as basis for data analysis which integrates data from complementary perspectives in an innovative way to identify modeling difficulties. Opting for a mixed methods research design in the present study pursues the objective of *diversity of views* (following, e.g., Venkatesh et al. 2016, p. 442). In line with the purpose of diversity of views, the study at hand applies a *convergent* research design with concurrent data collection with all data provided by the same data sources (subjects) in a *data-transformation variant* allowing a merge of the data bases to analyze the data together (e.g., Creswell and Plano Clark 2018, pp. 65–73). Hence, the applied research design includes two *points of integration*, i.e., the integration of quantitative and qualitative data, one during the observations and one during data analysis (Schoonenboom and Johnson 2017, pp. 115–117)—with the aim to combine the complementary perspectives on the modeling processes.

In the study, eight subjects are observed constructing a conceptual data model using a variant of the Entity-Relationship Model (ER model). The ER model specifies a modeling language for data modeling (Chen 1976) widely accepted as de-facto standard for conceptual data modeling (e.g., Elmasri and Navathe 2017). Starting from a data modeling task described in natural language, the subjects are instructed to construct a conceptual data model (an ER diagram) reconstructing the statements of the problem representation using a browser-based modeling tool. The modeling tool is integrated with a modeling research observatory supporting multi-modal observations and analysis of the collected data (see Ternes et al. 2019). The data modeling task employed for this study (see Appendix) is based in the library domain (LibraryItem, Loan, Copy etc.) in order to reduce effects of varying prior domain knowledge (cf. Bera et al. 2014; Pretz et al. 2003), i.e., we assume participating subjects have sufficient knowledge about the library domain to work on the modeling task, because they are university students.

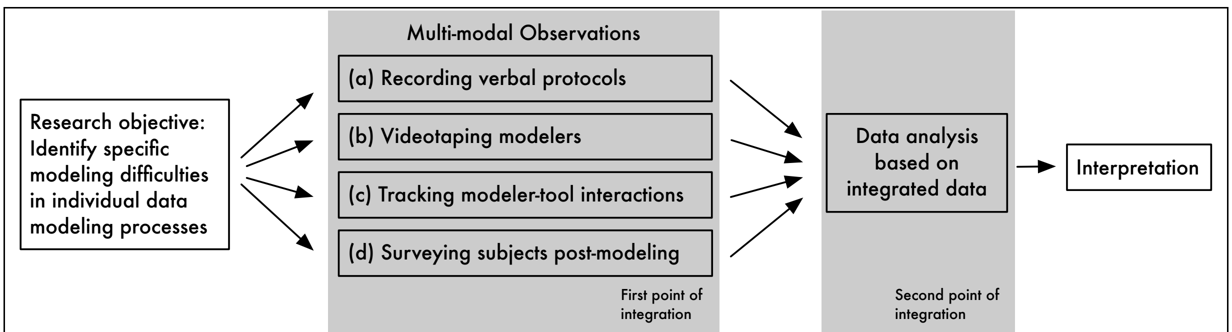

Figure 1. Mixed methods research design (cf. Creswell and Plano Clark 2018, p. 66)

Observations

The multi-modal observations constitute the first point of integration, i.e., all types of data are collected from the same sources (i.e., from the same subjects) concurrently (Schoonenboom and Johnson 2017, pp. 114f). With the aim to go beyond approaches solely considering modeler-tool interactions, complementary modes of observation are combined to take different perspectives on the modeling processes (see Figure 1)—complementing and tying in with prior approaches to investigating individual modeling processes (e.g., Pinggera et al. 2014; Sedrakyan et al. 2014; Wilmont et al. 2017):

(a) *Recording verbal protocols:* This mode of observation targets the reasoning of modelers while modeling via verbalization ('think aloud'). It is aimed at gaining insights into cognitive processes during conceptual modeling. This mode of observation is chosen because its application in problem-solving research has shown promising results (e.g., Ericsson and Simon 1980; van Someren et al. 1994). Subjects are instructed to verbalize all their thoughts while modeling. The subjects' utterances while modeling are audiotaped.

(b) *Videotaping modelers*: This mode of observation targets the modeler's overall interaction with the written material and the software tool for modeling by videotaping the modeler from an 'over-the-shoulder' perspective. The rationale for this mode of observations is that modelers may peruse the written material to draw an initial model before interacting with the software tool and that a recording of the modeler's behavior outside of the modeling tool can support resolving ambiguous situations in think aloud protocols (e.g., Zugal et al. 2013).

(c) *Tracking modeler-tool interactions:* This mode of observation is aimed at observing the modeler's interactions with the graphical model editor. Therefore, every modeler interaction with the graphical editor during the construction of the conceptual model is recorded as a time discrete event. This mode of observation is supported by the modeling observatory integrated with the modeling tool (see Ternes et al. 2019) with which the subjects construct the conceptual data model.

(d) *Surveying subjects post-modeling:* Subjects fill in a survey comprising closed-ended and open-ended questions after modeling. The aim is to gather data on encountered modeling difficulties and challenges, the perceived familiarity and difficulties with the domain of the modeling task, a self-assessment regarding think aloud and demographic information of the subjects.

In addition to observing the modeling process, subjects are surveyed pre-modeling to gather data on prior experience in conceptual modeling, theoretical knowledge of conceptual data modeling and familiarity with the domain of the modeling task. This information is aimed at achieving an overview of the sample of subjects and to identify peculiarities and outliers.

The study was conducted in January 2019 with eight subjects participating individually. The purposeful sampling of subjects is aimed at selecting individuals able to provide in-depth information about the phenomenon under investigation (Creswell and Plano Clark 2018, pp. 175f). We recruited eight bachelor and master students of business informatics or business administration with little experience in conceptual data modeling who we expected to encounter difficulties in constructing conceptual data models—subjects we would characterize as non-experienced modelers. The subjects were offered no other incentives than the opportunity to participate in the study. The sample size of eight is considered suitable: Think aloud protocol analysis is recognized as a labor-intensive approach to achieve in-depth insights into cognitive processes accompanied by relatively small sample sizes (Haisjackl et al. 2016, p. 330; Nielsen 1994).

To ensure comparability, we ran a standardized data collection procedure for all individuals (see Figure 2). During each session, one of two research assistants familiar with the modeling task and tool as well as with the multi-modal observations was present in the same room as observer. The rooms were the sessions took place were designed to ensure a quiet environment and a glass of water was provided to the participants—to make the subjects "feel at ease" as suggested, e.g., by van Someren et al. (1994, p. 41).

After completing a consent form, each individual was required to (1) fill in a pre-modeling survey asking closed-ended and open-ended questions on prior conceptual (data) modeling experience and perceived familiarity with the library domain. In addition, the questionnaire included a test with six yes/no-type questions on theoretical knowledge of conceptual data modeling with the ER model (cf. a test for process modeling in, e.g., Mendling et al. 2012). As the next step, the subjects were provided think aloud instructions (2). The observer instructed the subjects to verbalize all their thoughts while modeling "as if alone in the room" (following, e.g., Ericsson and Simon 1993). We informed the subjects that reminders would be given after a predetermined period of silence of 30 seconds with the precise wording "Bitte sprechen Sie weiter" (engl. "Please keep talking", as suggested by Ericsson and Simon 1993, pp. 82f, 256). These reminders constituted the only (potential) interactions between the subject and the observer during the subject's work on the main modeling task. All subjects received a short description of the semantics of the modeling concepts and the graphical notation of the ER model followed by watching a short video introduction into the used modeling tool of ca. 2 min (3). In a warm-up modeling task (4), the subjects were asked to construct a conceptual data model comprising two entity types and one relationship type from the university domain. This exercise offered the subjects the opportunity to become familiar with the modeling tool and to practice verbalizing their thoughts while modeling (as suggested, e.g., by van Someren et al. 1994, pp. 43f). The observer subsequently answered the subject's questions about the procedure. Next, the subjects were given the main modeling task from the library domain on paper (5) that can be found in the appendix. Subjects provided with colored markers were instructed to first read the modeling task and given the opportunity to mark text in the written task. The subjects were instructed to use the modeling tool to construct a conceptual data model based on the natural language description. During modeling, the verbalizations of the participants and videos of the modelers' behavior were collected using a camcorder. The participants were requested to let the observer know when they had finished the task which happened after 35 minutes the latest. After completing the main modeling task, each participant was required to (6) fill in a post-modeling survey comprising a self-assessment of the participant concerning domain knowledge and difficulties with think aloud in closed-ended questions complemented with open-ended questions on encountered modeling difficulties and challenges. In addition, the questionnaire included closed-ended and open-ended questions on demographic information. Please note that all material was in German as well as the verbalizations. The questionnaires and the supplementary material used in the study (in German and translated to English) are available upon request from the authors.

A pre-test of the data collection procedure was conducted with one researcher familiar with conceptual data modeling in December 2018, i.e., the entire data collection procedure was performed. As results, adjustments were made to the questionnaires to enhance understandability and clarity of the questions as well as to reduce ambiguities. The description of the semantics of the modeling concepts and the graphical notation of the ER model was revised to reduce complexity and to enhance understandability. In addition, the complexity of the main modeling task was reduced in terms of numbers of model elements to be more suitable for the participants of the study—as non-experienced modelers. No technical problems occurred. However, video and audio recording has been adjusted to generate data more suitable for analysis.

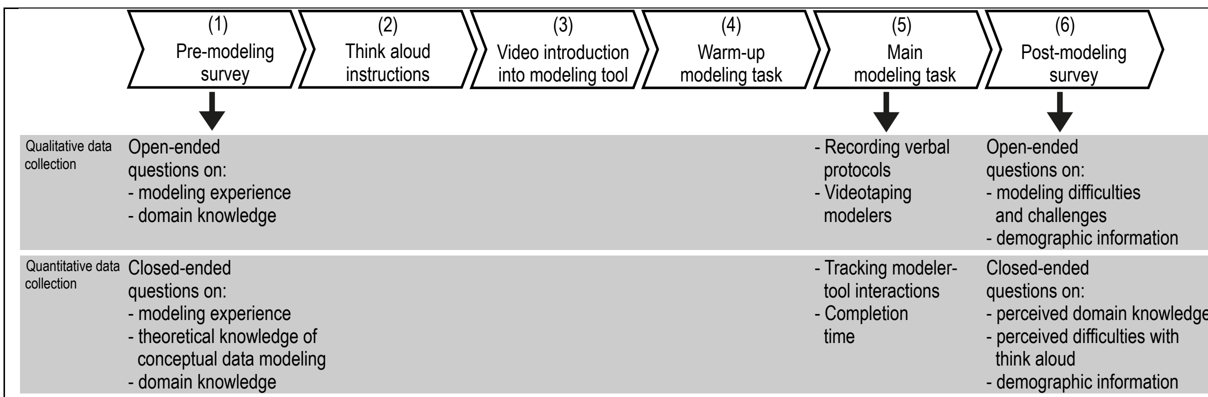

Figure 2. Data collection procedure based on multi-modal observations

Data Analysis and Coding Strategy

The data analysis strategy integrates the data collected in the observations (second point of integration). The purposeful integration of data comprises two steps including data transformation (e.g., Bazeley 2012, p. 819; Creswell and Plano Clark 2018, pp. 224–226):

First, information on open- and closed-ended questions from the pre- and post-modeling surveys are integrated to give an overview of the sample of subjects in the study: Demographic information and information on prior conceptual modeling experience, theoretical modeling knowledge and domain knowledge are integrated into a description characterizing the sample of subjects (discussed as "qualitizing" in literature on mixed methods research, e.g., Bazeley 2012, p. 821; Venkatesh et al. 2016, pp. 446f). The aim of this description is to give an overview of the sample and to characterize outliers and peculiarities.

Second, for analyzing the individual modeling processes, different types of data are combined to identify modeling difficulties and to understand the modelers' reasoning. We combined the video recordings of the modelers' behavior and the think aloud protocols into combined audio and video protocols comprising both observations. To add structure to the data, we coded these videos following, e.g., Miles et al. (2014, pp. 81f) by systematically assigning video segments/clips to codes. We opted for coding the videos directly

Code category	**Cognitive breakdowns**	**General codes**
Codes and sub codes	• Breakdown • Differentiate between entity types* • Decide between entity type and relationship type* • Develop identifiers for relationship types* • Choose data type of attribute* • Determine cardinalities*	• Talking about non-task-related issues • Modeling tool* • Think aloud* • Evaluation of the task at a meta-level • Silent periods • Actions outside of the modeling tool • Reading the modeling task* • Marking the modeling task* • Paper-based modeling*

Table 1. Coding scheme for coding the videos of the individual modeling processes. Codes marked with an asterisk (*) are codes which emerged during coding.

rather than transcribing the verbalizations (which is suggested, e.g., by van Someren et al. 1994, pp. 119f)—to benefit from the complementary angles provided by the respective mode of observation: The verbal protocol is linked and time synchronized to the video recording, and then analyzed using MAXQDA (VERBI Software 2018) which allows for coding of integrated audio and video segments.

As coding strategy, we start with coding cognitive breakdowns with an explicit code "Breakdown" as deductive code. We refer to the notion of cognitive breakdowns serving as an indication for cognitive difficulties in performing the modeling task (e.g., Bera 2011, p. 4; Newell and Simon 1972; Vessey and Conger 1994, p. 105): We mark segments in which the subject encounters a difficulty or an obstacle as cognitive breakdown, i.e., when the subject explicitly verbalizes a difficulty experienced during modeling *or* when the subject interrupts or terminates a modeling activity. This is complemented with codes generally anticipated in think aloud protocols. Following, e.g., van Someren et al. (1994, p. 122), it is suggested to also consider codes not directly relating to the modeling task, but which refer to actions and comments which are an indication of the level of the difficulty of a task: Talking about n*on-task-related issues* for segments in which a subject talks about something other than the modeling task, *evaluation of the task at a meta-level* for a subject evaluating working on the task (e.g., regarding think aloud), *silent periods* for times a subject falls silent for a remarkable period of time (30 seconds) and *actions outside of the modeling tool* for a subject performing an action not directly in the modeling tool but, for example, with the paper-based modeling task. This ex ante coding scheme is based on prior work on cognitive breakdowns (e.g., Newell and Simon 1972; Bera 2011) as well as on analyzing verbal protocols (van Someren et al. 1994). During coding, the coding scheme is complemented with codes and sub codes emerging during the coding process (inductive coding)—allowing for refinements according to the actual behavior exhibited in the observed modeling processes (see Table 1 for the entire coding scheme). It is one aim to develop and iteratively refine sub codes for the code "Breakdown" to group the modeling difficulties inducing the observed breakdowns.

In addition to evaluating and interpreting the combined audio and video protocol, we submit segments to closer inspection by analyzing the recorded modeler-tool interactions in the respective time period to better understand the observed situation, and to decide on assigning a code. This coding step was performed whenever a specific taped situation was recognized as unclear or deviant. In all of these cases, the additional data integration (e.g., Bazeley 2012, p. 821) allowed us to better understand the situation, and to code the segment accordingly. Vice versa, anomalous data in the recorded modeler-tool interactions is identified and further investigated through analyzing the audio-visual protocols. For this coding step, modeler-tool interactions in the specific time frame are stepwise visually replayed as performed by the modeler, and, hence, visually analyzed (Figure 3 top). Each modeler-tool interaction is also plotted as a time discrete event on a timeline as horizontal axis (see Figure 3 bottom) to allow for quick inspection of the type of change of the data model: The vertical axis indicates the consecutively numbered model elements which are created (green circle), changed (blue circle) or deleted (red circle). This visualization is inspired by the PPMCharts visualizing the process of process modeling (Claes et al. 2014) and the Dotted Charts suggested in Song and van der Aalst (2007). The diagrams visualizing the modeling processes are used for further exploring situations identified as deviant or unclear in the audio-visual protocols and for identifying anomalous modeler-tool interactions by manual inspection of the diagrams (e.g., searching for a noticeable number of deleting model elements or changing one model element strikingly frequent). The step-by-step replay (i.e., visually showing every step of model construction) is supplemented by an automatic replay (i.e., visually showing model construction in real-time) to allow for visual inspection of modeling behavior (see Figure 3 top). Supplementing audio-visual protocols with timed modeler-tool interactions allowed us to identify peculiar situations, e.g., when a modeling process strongly deviates from the other displayed modeling processes. The data integration is taken one step further by reviewing the post-modeling survey about perceived modeling difficulties and particular modeling challenges, and, thus, by supplementing another mode of observation (self-disclosure). This coding step proved valuable especially as the perceived difficulties served as indication for closer inspecting and deciding on assigning a code in the audio-visual protocols.

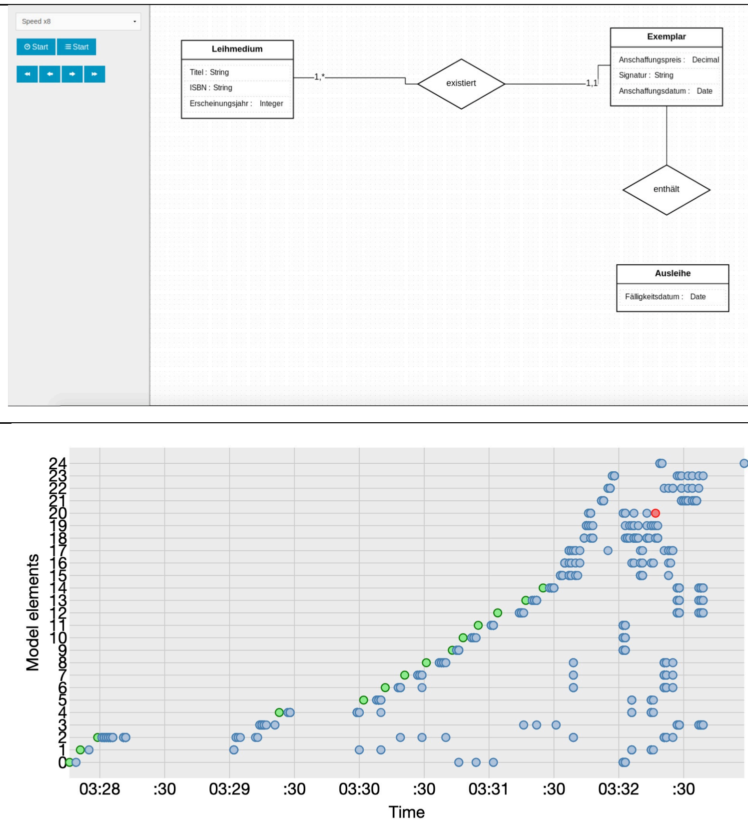

Figure 3. Example of replaying a modeling process in the modeling observatory (top) and of a diagram visualizing a modeling process (bottom)

Findings

Participant Characteristics

Of the eight participants (P1–P8), five subjects were male while three were female with an age ranging between 27 and 52 (with a median of 41,5 years and a mean of 40,5 years). Please note that the university where we recruited the students is characterized by a heterogeneous student body where these ages are not exceptional. As first language, six subjects stated German, one subject English and the other one German and French. Six subjects were bachelor students of Business Informatics (four subjects) or Business Administration (two subjects) including five part-time students and one full-time student of Business Informatics. The remaining two subjects were full-time master students of Business Informatics. Regarding the professional background, seven subjects had work experience of two years and six months to 20 years and 10 months with a median of 14 years and seven months. The professional experience was acquired in the application areas of IT, e-Government, financial services, as well as the insurance, automobile and telecommunications industry—hence, spanning a wide range of application areas.

Seven of the subjects had completed courses on conceptual modeling during their studies including six subjects who attended an introductory course on "Modeling Business Information Systems" dealing with the notational variant of the ER model used in this study (the remaining subject did not further specify the attended course). In the test on theoretical knowledge of conceptual data modeling with the ER model, the number of correct answers to the six yes/no questions ranged from two to six with a median of four. This indicates substantial differences of knowledge of conceptual modeling between the subjects. In addition, three subjects explained prior experience in conceptual data modeling ranging from two months with constructing three conceptual models and reading six models (using the ER model in the context of a training), over about two and a half years with constructing 15 conceptual models and reading 50 (with an idiosyncratic modeling method in a practical context) to almost nine years of experience with constructing 20 conceptual models and reading 200 (with the ER model in the insurance sector). In the light of these characteristics, P8 with the outstanding experience constitutes an exceptional case demanding a special consideration in the analysis. Besides this exceptional case, the characteristics of the subjects suit the intention to study subjects which can be characterized as non-experienced modelers. However, as practical experience is discussed as only one aspect of being an experienced or expert modeler besides theoretical knowledge and training (e.g., Batra and Davis 1992, p. 87; Venable 1996, p. 50), the outlier is included in further analyses.

The modeling task performed by the subjects is situated in the library domain and deliberately designed to balance demand on subjects, time to perform the task and modeling complexity. Domain knowledge required to perform the task does *not* presuppose any particular knowledge of the library sciences. Rather, the modeling task is designed, so that anyone who has visited a library and borrowed a library item shall be able to complete the modeling in no more than 60 minutes. Regarding knowledge of the library domain, all eight subjects stated to have visited a library at least once, ranging from *rarely* to *very often* with a median of *sometimes* (on a scale *not at all – rarely – sometimes – often – very often*). The subjects borrowed 10 to 200 books in a library (with a median of 50) and seven subjects stated that they knew what the term *shelfmark* means in the library domain.

Modeling Difficulties

We observe cognitive breakdowns as indication for cognitive difficulties in seven of eight modeling processes with a wide range of numbers of breakdowns, ranging from zero to six observed breakdowns. However, only three of the eight participants explained encountered difficulties in the post-modeling questionnaire. The observed breakdowns split into five types of modeling difficulties inducing the breakdowns—the types were developed during the coding of the audio-visual protocols as emerging and refined sub codes in the coding scheme. The types of difficulties relate to different aspects of constructing conceptual data models, i.e., entity types, relationship types, attributes, and cardinalities (e.g., Elmasri and Navathe 2017). Note that P8 marks an exceptional case exhibiting no breakdowns during the modeling process and constructing a straightforward solution to the modeling task in only nine minutes—P8 is the outlier regarding prior modeling experience. This observation confirms the deliberate design of the modeling task as demanding for modelers with little experience, but solvable in a straightforward manner for experienced modelers. See Table 2 for an overview of the lengths of the modeling processes including the overall numbers of breakdowns and the numbers specified by type of modeling difficulties inducing the breakdown during the entire modeling process. In the following, each type is discussed and exemplified by providing transcribed examples from the think aloud protocols (translated into English).

Differentiate between entity types: One participant (P3) encountered a difficulty related to creating entity types. The subject's verbal statement on this difficulty sheds light on the reasoning behind this modeling decision: "*Can it be that further attributes have to be added to the entity? I am not sure if I have assigned the entities correctly. Am I assigning too much to the library item now?*" (P3). This difficulty relates to attributes of the entity COPY that the participant erroneously assigned to the entity type LIBRARYITEM—without creating the entity type COPY (see Appendix for a reference solution). The participant terminated the modeling activity switching to another one. However, this type of difficulties could be observed only once.

Decide between entity type and relationship type: We observed three participants (P1, P3, P4) facing difficulties related to modeling decisions as to whether to model an entity type or a relationship type to reconstruct a given statement of the problem representation. All difficulties of this type refer to the entity

Participant	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**#**
Completion time (in minutes)	23	20	35	18	15	17	35	9	172
Breakdowns (overall)	3	2	6	3	2	3	6	0	25
• Differentiate between entity types			1						1
• Decide between entity and relationship type	2		3	2					7
• Develop identifiers for relationship types	1	2	2			1	2		8
• Choose data type of attribute					1		1		2
• Determine cardinalities				1	1	2	3		7

Table 2. Completion times and numbers of breakdowns

type LOAN. For example, a passage from the think aloud protocol of P3 indicates this type of difficulties: "*I think I have too few entities. Hmm... I'm not sure right now [...] or the loan. The users can borrow as many copies of a library item as they like. Hmm... Is it possible to create an entity loan? If it would be so, if I would do that, then... Um, I would have... Where would I do that? I have a user who borrows books, library items, he can borrow several books at the same time. I don't have that at the moment, I can't represent that. I only have the relationship between the user and the library item. So, I will put the loan between*" (P3). Difficulties of this type caused long and severe periods of uncertainty in the modeling processes (of up to 3 min) and, in this sense, are particularly remarkable—especially because this type of difficulties occurred seven times and because two of the respective three participants were not able to find a solution for the difficulty.

Develop identifiers for relationship types: Difficulties of this type occurred in five modeling processes (P1, P2, P3, P6, P7) constituting the most frequent type of difficulties in terms of the total number of occurrences (8) and number of participants concerned (5). This type of difficulties refers to a modeler who creates a relationship type and encounters a problem with finding a descriptive and sensible identifier for the model element. For example, P7 faces a difficulty of this type ("*In any case, we have a relationship type between user and loan here. Hmm... What is the best way to call it that it makes sense somehow... Um, how can we connect user and loan in sensible way? ... Ok, let's do it the other way around...*", P7) as well as P6 ("*Um... I call the relationship um... well, how do you call that? Um... I say, belongs to*", P6).

Choose a data type for an attribute: Encountered by two participants (P5, P7), this type of difficulties relates to the attributes of entity types (note that the chosen variant of the ER model and its notation does not allow for attributes of relationship types, to simplify the learning process for modeling beginners). These two participants faced the difficulty of choosing a data type for an attribute that is adequate in the context of the modeling task. Please note that a full list of predefined data types was included in the instructions and available to subjects throughout the entire modeling process. For example, P7 was in doubt about the data type for the attribute ISBN: "*We also need the ISBN. That is... ISBN is actually alpha-numeric, because there are minuses in it. So, let's take a string... however, you can also write them without minuses. Then it would be Integer... Um... I would say a matter of consideration... We make an integer out of it [...] That fits, right? ... Well, no, moment...*" (P7). P5 encountered a difficulty with the attribute SHELFMARK: "*Each copy has a unique shelfmark... Hmm, could of course also be string, could also be... Uh, a library could also consider... There, you sometimes also have some... Well, maybe I'll change that to String*" (P5).

Determine cardinalities: We identified difficulties with regard to determining cardinalities for relationship types in four modeling processes (P4, P5, P6, P7) with a total of seven occurrences. Remarkably, five of the seven occurrences of this type of difficulties pertain to a relationship type with one-to-one cardinalities. A text passage from the think aloud protocol of P5 illustrates this type of difficulties: "*A loan always refers to exactly one copy, that means 1 and 1. And a loan to one copy, and well, a copy can... yes... hmm... A copy can actually be as many... It can be borrowed or not, I would say now for the one example. It can be borrowed several times, but only once at the same time. So, I would say that now. Does that make sense?... I model it that way for now*" (P5). Also, P6 faced problems related to determining cardinalities that the participant was not able to resolve: "*From every copy... I just have to look again. To each item ... yes... hmm... no, that doesn't work like that... Hmm... Um. Then I would choose another approach first, so that we don't sit here for hours now*" (P6).

Further Observations

The observations indicate that the modeling processes of the eight participants differ in certain respects: First, six of the eight subjects take the opportunity to use the colored markers to mark text segments in the paper-based modeling task while two participants (P4, P8) do not use the markers. In addition, it is noteworthy that P1 deviates from the instructions by creating fragments of the model with pen&paper before interacting with the modeling tool. Second, in creating the conceptual data model with the modeling tool, we observe participants choosing different sequences of creating model elements. Four participants (P3, P4, P5, P6) start by creating entity types, attributes and data types and only then create relationship types and assign cardinalities at the same time. Participants 1 and 2 start by creating entity types as well, but continue by creating relationship types and, in a separate step, determine cardinalities for all modeled relationship types. The remaining two participants (P7, P8) do not exhibit a comparable, traceable sequencing of modeling steps. Third, regarding the length of the modeling processes, we observe a wide range from nine minutes for the outlier P8 and from 15 to 35 minutes for the other seven participants. The modeling process of P3 is noticeable different from the other subjects' modeling processes in terms of speed of tool interaction, in particular, model construction is performed much slower, and the resulting data model is incomplete as it misses several attributes described in the modeling task. Further exploring the modeler-tool interaction and the audio-video protocol reveals that the participant terminated working on the modeling task without finishing. We conclude that the modeling task—as intended—shows a certain complexity posing challenges on the participants.

Interestingly, the verbal protocols entail remarks on the modeling tool only by three modelers (P3, P4, P6). Participants 4 and 6 mentioned criticism of the modeling tool, e.g., regarding the visualization of attributes in entity types, but do not exhibit difficulties with respect to the modeling tool. The recordings of subject P3's interactions with the graphical editor exhibit particular difficulties when adding attributes to entity types (four times). Regarding domain knowledge, i.e., knowledge of the library domain, the participants were asked to self-assess the statements “I understood what the modeling task was about” and “I am familiar with the domain of the modeling task” on a scale from 1 to 7 where 1 corresponds to “I do not agree at all” and 7 to “I agree entirely”. Regarding the first statement, all eight participants entirely agreed. For the second statement, the answers ranged from 2 to 7 with a median of 5,5 which indicates that the participants understood the chosen modeling domain well enough to perform the task.

Analyzing the audio recordings of the eight individual data modeling processes led us to observe substantial differences in how well subjects are able to verbalize their cognitive processes while modeling. Differences in verbalization skills, especially the ease with which people verbalize thoughts, have long been discussed, resulting in the advice to offer think aloud training (e.g., van Someren et al. 1994, pp. 34f)—an advice the present study followed. In about three total hours of verbal protocols, we do not observe a single silent period of 30 seconds or more, and, therefore, conclude that the think aloud instructions were suitable to initiate the intended behavior. In the post-modeling survey, the participants were asked to self-assess the statement “I had difficulties to verbalize my thoughts” on a scale from 1 to 7 where 1 corresponds to “I do not agree at all” and 7 to “I agree entirely”. The answers of seven participants ranged from 1 to 3, with only one participant choosing a 5. This very participant actually exhibited problems in verbalizing thoughts in the first few minutes of the modeling process, explicitly pointing to having two native languages as one reason. However, after a few minutes, the participant started to verbalize her/his thoughts in a comprehensible way, especially regarding modeling difficulties.

Discussion and Conclusion

Integrating complementary modes of observation of eight individual data modeling processes and an analysis using the concept of cognitive breakdowns leads us to identify five types of modeling difficulties these subjects face while performing the data modeling task. We discuss fruitful paths for future research on modeling difficulties and design science research on developing (tool) support for learners of conceptual modeling.

Our findings suggest that the majority of difficulties encountered by the participants in the modeling processes relates to modeling relationship types (difficulties of the types *Decide between entity type and relationship typ*e, *Develop identifiers for relationship types*, *Determine cardinalities*). This observation is in line with prior work on difficulties in conceptual data modeling (Batra 1993) and on cognitive complexity in data modeling (Batra 2007) suggesting that modeling problems are not experienced mainly in modeling entity types and attributes, but in modeling relationship types. Our findings suggest that—in addition to severe problems with deciding whether a relationship type warrants modeling—modelers especially faced difficulties with regard to developing sensible identifiers for relationship types and in determining cardinalities (see Table 2). The exploratory findings of the present study can serve as starting point for future research on individual modeling processes. To better understand typical difficulties encountered in conceptual modeling, further studies into individual modeling processes are encouraged which tie in with the exploratory results of the present study: For example, modeling tasks could aim to induce specific challenges with respect to the identified modeling difficulties or, e.g., with regard to modeling concepts such as generalization/specialization in data or object modeling. The developed mixed methods research design integrates complementary modes of observation of modeling processes in an innovative way—providing a methodical basis for future studies on individual modeling processes.

Within the long-term research program on targeted (tool) support for learners of conceptual modeling, the exploratory results of the present study are intended as a starting point for developing a taxonomy of modeling difficulties over the course of multiple studies, in the sense of a classification or taxonomic theory (following, e.g., Gregor 2006): Such a taxonomy is expected to distinguish modeling difficulties that occur in individual modeling processes based on shared properties and to include decision rules to assign difficulties to the resulting types of difficulties (Gregor 2006, p. 619). The types of modeling difficulties identified in the present study provide a starting point for such a classification system: Further studies have to build on the preliminary classification of modeling difficulties for analyzing further individual modeling processes—refining the classification system by adding emerging types of difficulties on the basis of characteristics of the actual difficulties observed in the modeling processes (Gregor 2006, p. 619). The taxonomy, in turn, is intended to serve as theoretical foundation for design science research on developing (tool) support for learners of conceptual modeling: On the basis of distinctions of modeling difficulties following the taxonomy, support for learners is in prospect that systematically and deliberately targets modeling difficulties. However, a number of further studies is needed to deepen and substantiate our understanding of modeling difficulties.

The observed differences among subjects in the length of the modeling process is in line with earlier work on prior modeling knowledge and modeling experience of conceptual data modeling (e.g., Batra and Davis 1992, p. 94). It is not surprising that P8 exhibits the shortest modeling process with substantially less time spent to complete the modeling task—in the light of 20+ years of modeling experience. Regarding the sequencing of modeling activities (constructing entity types, relationship types, determining cardinalities) in the individual modeling processes, our findings reinforce our presumption that participants would choose different approaches. Hence, a potential path for future research lies in further investigating the modeling approaches exhibited in individual modeling processes. For this path of research, the exploratory findings of the present study can serve as starting point. We deem the distinct styles of modeling identified in Pinggera et al. (2015) and cognitive modeling techniques identified for process modeling in Claes et al. (2015) as further fruitful anchor points. As a subsequent step, we deem exploring the interdependencies between the approaches to modeling and specific modeling difficulties promising—contributing to better understanding modeling difficulties in their genesis and to, subsequently, develop targeted modeler support.

Limitations and Outlook

Principle limitations relate to analyzing think aloud protocols. Generally, it is assumed that thinking aloud does not interfere with thought processes—but as the modeling task includes a visual, non-verbal perceptual component, thinking aloud may slow down the thought processes and/or the modeling performance (Ericsson and Simon 1980). It is important to note that the scope of this study limits findings to conceptual *data* modeling processes—but this limitation is not by principle and the study design could be applied to object-oriented modeling and process modeling as well. Also, please note that we recruited all participants from one university. In future studies, we plan to complement the present study with follow-up studies observing subjects with various backgrounds, e.g., regarding prior modeling experience, and observing not only data modeling processes but also, e.g., process modeling processes—with the overarching aim to integrate all findings in a subsequent step elaborating on similarities and differences in data modeling, object-oriented modeling, and process modeling.

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Appendix

As part of a project for the introduction of a new information system in the university library, you are asked to create a conceptual data model that reconstructs the following facts representing a simplified description of a library:

- **The current stock of the university library includes library items (e.g. books). Library items are described by title and year of publication. In addition, the international standard book number (ISBN) is recorded for unique identification.**
- **There may be one or more copies of a library item. Each copy of a library item has a unique shelfmark. To determine the age of the library's holdings, the acquisition date is recorded for each copy. In order to be able to identify particularly valuable items, the acquisition price is also recorded for each copy.**
- **When registering as user, the first name and last name are recorded. The date of birth is also recorded in order to comply with any age restrictions.**
- **Users of the university library can borrow any number of copies of library items. A loan always refers to exactly one copy. For a loan, the date of the loan and the due date are recorded in order to be able to determine if the loan period is overdue.**

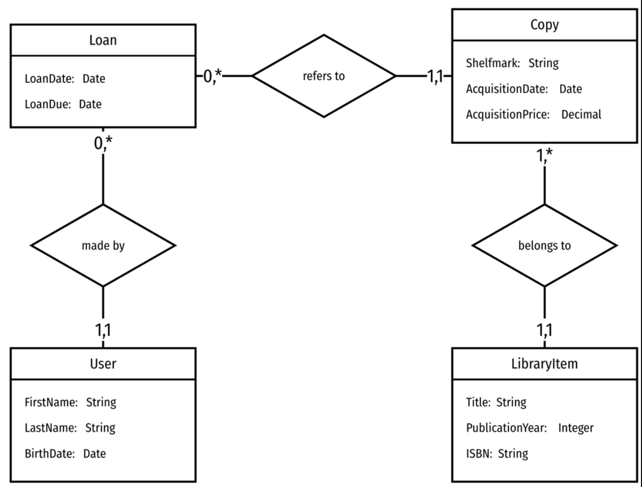

Figure 4. Main modeling task (translated from German into English, on the left) and reference solution (on the right)

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