The Effect of Cognitive Abilities and Learning Approach on Domain Surface Understanding from a Process Model

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Abstract

Process models are used by information professionals to convey semantics about the business operations in a real-world domain that are intended to be supported by an information system. The understandability of these models is vital to them actually being used. Until now, understandability has primarily been defined as an intrinsic quality of the models themselves. In this paper we conceptualize model understandability as an emergent property and advance an integrative framework to understand the role of the user in the process of understanding process models. Building on cognitive psychology, student learning theory and multimedia learning theory, we identify important factors during the presage and process stages of learning, and hypothesize their contributions to realizing domain understanding from a process model. Through an empirical study, we provide evidence that cognitive abilities, learning style and learning approach influence the development of domain understanding. We detail implications for theory and practice.

Keywords

Process modeling, domain understanding, learning style, cognitive abilities, model comprehension

Introduction

Analysts and designers frequently use graphical models of the business domain they are concerned with for the analysis and design of information systems intended to support the domain. Increasingly, analysts use conceptual models of business processes to assess or build information systems that are "process-aware" (Dumas *et al.*, 2005). At this point, the so-called exercise of 'process modeling' has emerged as a primary reason to engage in conceptual modeling (Davies *et al.*, 2006).

Practitioners have identified process improvement, communication and shared understanding as the three most important process modeling benefits that can be derived from process modeling (Indulska *et al.*, 2009). A prerequisite for realizing these benefits, however, is that process models are understood by their audience, making model understandability an important topic for research relevant to all potential uses of process models (Aguirre-Urreta and Marakas, 2008). For instance, a study of 18 process re-design projects found that accuracy and understandability of process models was a significant predictor to re-design success (Kock *et al.*, 2009). Furthermore, anecdotal evidence reveals that process models are in fact often ill-understood in practice, exemplified by issues like lacking user-buy in and low applicability (Rosemann, 2006). Consistently, such issues have led to practitioners identifying process model composition and user training as key issues that are underrepresented on the research agenda (Indulska *et al.* 2009). In turn, this emphasizes the practical relevance of the process model understandability debate by answering *how a process model is understood*.

Accordingly, our interest in this study is the understandability of process models, specifically, to examine how process models can be used to aid analysts in developing an understanding of (current or future) business domains.

Model understandability can be examined from multiple angles. One stream of research has studied how properties of the process model -- such as control flow logic, soundness, deadlocks or other structural properties -- affect how well users are able to understand characteristics of process models as diagrams, (e.g., Reijers and Mendling, 2011). This aspect of understanding can be labeled *model understanding*. Conversely, our interest is in an aspect of understanding that has been called *domain understanding* – the ability of a model user to understand aspects of the business domain that is depicted in a process model (Gemino and Wand, 2003). This understanding is important because users of a process model, either for purposes of process analysis, performance measurement or re-design, are ultimately dependent on deep knowledge not of the model but of the modeled process.

Our specific motivation is to examine how characteristics of the end user working with the model affect the development of domain understanding. Our research focus is motivated by the observation that understanding a process model is, by nature, a cognitive process and therefore dependent on the skills, attitudes and other characteristics of the person engaging in the understanding process (Moody, 2009). We draw on multimedia learning theory (Mayer, 2001), student learning theory (Biggs, 1987) and cognitive informatics (Wang *et al.*, 2006) to hypothesize that individual differences in cognitive abilities and learning approaches are important predictors of domain understanding generated from a process model. We report on an empirical study where we tested these arguments.

This study makes several contributions to the literature. First, it draws upon student learning theory (Biggs, 1987) to extend the prevalent conceptualization of model understanding (Mayer, 2001) with three stages, and important factors within, of a learning process, viz., presage, process and product. Second, it adds to the existing literature on domain understanding from conceptual models by offering an alternative, user-centric perspective on important antecedents to understanding. Third, it adds to the body of literature on cognitive informatics (Wang *et al.*, 2006) by providing the first empirical test that examines which cognitive abilities are positively and negatively associated with the process of viewing diagrammatic representations.

We proceed as follows: First, we review prior research on process model understandability. Then, we conceptualize the attainment of process model understanding as an extended cognitive learning process, and outline a theoretical framework drawing attention to six important factors alongside three stages of this learning process. Then, we discuss design, conduct and findings of an empirical study to test these arguments. We conclude this paper by providing a discussion of contributions.

Background and Theory

Process Modeling

Process models typically include graphical depictions of the activities, events, states, and control flow logic that constitute a business process. Additionally, process models may also include representations for the involved data, organizational/IT resources and potentially other artifacts such as external stakeholders and performance metrics, to name just a few (Recker *et al.*, 2009).

Most research in the area of process model understandability has attempted to define understandability as an *intrinsic* property of a process model. This means that understandability has been looked at as a function of the design of the process model itself. Understandability factors proposed or used in these studies include, for instance, the notions of connectivity (Vanderfeesten *et al.*, 2008), complexity (Mendling *et al.*, 2007), modularity (Reijers and Mendling, 2008), notational visualization (Agarwal *et al.*, 1999), or diagrammatic presentation (Hahn and Kim, 1999). Factors pertaining to the *person* viewing the model, on the other hand, have been less intensively researched to date. This is not to say that no research as been conducted. In an experiment by Mendling et al. (2007), for instance, participants were characterized based on the number of process models they created and the years of modelling experience they had achieved. Mendling and Strembeck (2008) measured theoretical knowledge of control flow concepts relevant to process modelling in an experiment using yes/no questions. Other studies have examined individual difference factors in other modelling domains (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008).

Still, the research to date has two important limitations. First, the studies have mostly captured individual difference factors as control variables to examine properties of the model and their effect on understanding (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008). Or, other studies have examined individual difference factors and their relation to the attainment of *model* but not *domain* understanding (Mendling *et al.*, 2007; Mendling and Strembeck, 2008; Reijers and Mendling, 2011).

To complement and extend this body of knowledge, we posit that process model understandability can be viewed as, at least in part, an *emergent* property rather than an exclusively intrinsic one. Accordingly, the relation between human and model-based task performance should be taken into account, instead of considering process model understandability as a purely static property of the model itself. And indeed, prior research in other modeling domains (Batra and Davis, 1992; Shanks, 1997) shows that different types of modelers engaged in conceptual modeling processes, and used conceptual modeling outcomes (i.e., the models), in noticeably different ways. Similarly, Khatri et al. (2006) showed empirically that users with different levels of method and domain knowledge performed tasks on the basis of model quite differently. On the basis of these findings, we thus contend that process model understandability is dependent not only on properties intrinsic to the model itself but also on properties of the user working with the model, and properties that emerge in the process of working with the process model. Accordingly, in the following we offer some theoretical arguments that inform an understanding of process model understandability as a property emerging in the process of a human user applying a process model in a work-related task.

Process Model Understanding as a Learning Process

Process models are, in their essence, visual representations of a business domain that comprise both graphic symbols and texts. Prior research (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008) has therefore suggested to view models as explanative multimedia messages from which viewing individuals can develop domain understanding (Mayer, 2001).

Therefore, following Mayer's (2001) cognitive theory on the understandability of graphical and textual information, we view process model understanding as a *learning process*, in which model viewers actively organize and integrate information content in the process model that is presented to them with their own previous experience and existing mental models, to construct new knowledge as an outcome of this learning process (see Figure 1). This conceptualization of model understanding as a learning process has yielded some useful insights in the area of data modeling (Masri *et al.*, 2008) and object modeling (Burton-Jones and Meso, 2006), thereby increasing our confidence that similar patterns will emerge in the context of process modeling.

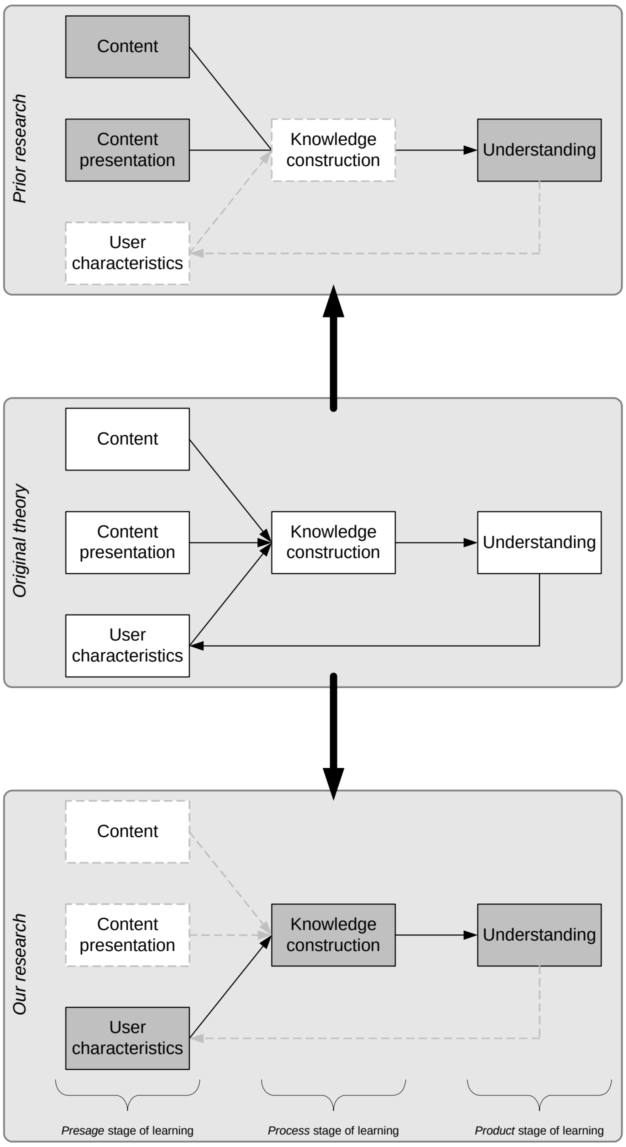

Figure 1: Prior research and focus of study, on basis of (Mayer, 2001) and (Biggs, 1987).

Previous applications of Mayer's (2001) theory of learning to conceptual modeling processes and outcomes examined different *content presentation formats* (e.g., narrative versus diagrammatic representations, Gemino, 2004), or different *contents* (e.g., familiar versus unfamiliar domains, Khatri *et al.*, 2006), and their effect on various forms of *understanding* generated (e.g., deep versus surface domain understanding, Gemino and Wand, 2005). Figure 1 shows that this prior research has not explicitly examined how the knowledge construction process occurred, and also has typically controlled for a limited set of user characteristics such as prior domain or prior method knowledge.

As visualized in the bottom-half of Figure 1, our interest is to extend the existing literature by controlling for content and content presentation factors, and examining specifically important *user characteristics* and the role these characteristics play in the *knowledge construction process* leading to domain understanding generated from a process model.

To conceptualize the knowledge construction process, we draw on Biggs' (1987) 3P model of student learning. The 3P model is rooted in the theory of student approaches to learning (Marton and Säljö, 1976) and has become accepted due to its simplicity, comprehensiveness and parsimoniousness of measurement. The model identifies three stages, being *presage* (what exists prior to the learning process), *process* (the learning process itself) and *product* (the result of the learning process), which, as suggested in Figure 1, fit to three main concepts of Mayer's (2001) theory of multimedia learning.

Focusing on the process stage – the knowledge construction process as per Mayer (2001) - Biggs (1987) suggests that two factors, the **learning motive** and the **learning strategy**, are essential to understanding how students engage in learning activities. The **learning motive** expresses a student's desire as a drive towards learning. The motive is affective in nature and can be used as a frame of reference for the student's perception of learning requirements. Two types of motives can be distinguished, viz., *surface* and *deep* motive (Kember *et al.*, 2004). A surface motive is tailored to the product of the learning process and fuelled by extrinsic motivation, such as, for example, aspiring to meet a superior's expectations or to outperform others in some sort of contest. In contrast, a deep motive considers the intrinsic interest to engage in knowledge creation in anticipation of the outcome; an example being learning for self-development. The **learning strategy** refers to making a plan congruent to the motive about how to learn from a process model. A deep learning strategy implies learning for developing a maximum of understanding. In contrast, a surface learning strategy implies rote learning, viz., learning to memorize enough to meet task or performance requirements.

These two factors are essential in what Biggs (1987) calls the *process* stage of learning, and interact with three important personal factors (we call them 'user characteristics' here) during the *presage* stage of learning – their *prior knowledge*, *ability* and preferred *style of learning* (Biggs *et al.*, 2001).

In terms of *prior knowledge* relevant to learning from process models, research to date has shown that prior domain knowledge (Khatri *et al.*, 2006), prior knowledge of process modeling method (Reijers and Mendling, 2011) as well as self-efficacy beliefs (Mendling and Strembeck, 2008) can influence the development of understanding. We have no interest in revisiting these findings and therefore follow Gemino and Wand (2003) as well as Burton-Jones *et al.* (2009) who argue to examine and control for these prior knowledge factors when examining other antecedents of understanding. Self-efficacy is important because it has been shown that students' learning activities are influenced by their personal expectations about one's ability to successfully perform a specific task or behavior (Zhang, 2000).

In terms of *ability*, reading and understanding process models is essentially a cognitive processing task (Gemino and Wand, 2003). Depending on the viewer's cognitive information-processing activity, the external representation (the process model) may be different to the internal representation (the internal mental model) developed by the viewer.

To determine which cognitive -processing activities are relevant to the model viewing process, we draw on recent work in cognitive informatics towards a layered reference model of the brain (Wang *et al.*, 2006). Based on findings from psychology, cognitive science and neurophilosophy, this model describes six layers of cognitive processes, differentiating sub-conscious life functions such as sensing, perceiving and acting from conscious life functions (meta and higher level cognitive functions). The conscious life functions of the brain are acquired, highly plastic, programmable and come into effect for natural intelligence applications that require higher-order cognitive capacity. Viewing and reasoning about a process model, for instance, is such a natural intelligence application, requiring what Wang et al. (2006) call meta-cognitive functions. Of the seven meta-cognitive functions they suggest, we focus on three functional abilities that we believe are important to viewing and reasoning about process models. These are as follows:

1) **Abstraction ability** is a meta cognitive process that enables an individual to establish an abstract model for an entity of the external world by identifying its common information and relevant attributes or properties. This ability applies to process modeling as these models

themselves represent abstractions from things – individual instances of the process – to classes of things – a common model that encompasses the execution of several process instances (Recker *et al.*, 2009).

2) **Selection ability** is a meta cognitive process that enables an individual to search through a set of correlated objects, attributes or relations to find a given object or set of objects. This ability is conducive to process modeling as these models are typically quite large and rich with informational artifacts, requiring the viewer to select and reason about some but not all of these artifacts.

3) **Conception ability** is a meta cognitive process that enables an individual to construct a "to be" relation between an object or its attributes and other existing objects or attributes. These conceptions are used to classify objects as being of a particular kind, and relating them with other objects, to develop (internalized or externalized) knowledge representation systems. Again, we argue the relevance to process models as these models are themselves graphical articulations of conceptual forms and structures as representation systems for procedural knowledge.

Finally, in terms of *learning style*, students take in and process information in different ways: by seeing and hearing, reflecting and acting, reasoning logically and intuitively, analyzing and visualizing, or steadily and in fits and starts (Felder and Silverman, 1988). Many dimensions exist to differentiate students' approaches to learning, e.g., perception, organization, input, understanding, or processing. Because we are interested in how users learn about a domain from a graphical process model (a question of how an externalized knowledge representation system is perceived), we consider how these models are related to the **perceptual learning styles** of the users. Felder and Silverman's (1988) division between *sensing* and *intuitive* learning style covers this difference, where intuitive learners prefer discovering new relations and grasping new concepts in a holistic way from information material (such as a process model), whereas sensing learners prefer learning and memorizing facts from a process model bit-by-bit.

Having laid out the theoretical foundation to examine important factors related to the learning process and user characteristics, we will now draw several propositions to suggest how these factors will influence the development of process model understanding.

Research Model and Hypotheses

We summarize our expectations about the development of process model understanding in light of the theoretical considerations above in the research model shown in Figure 2. The model proposes that process model understanding (in terms of domain surface understanding) is a function of the cognitive abilities and the learning style of the users working with the model, and the learning motive and learning strategy employed in the process of attaining process model understanding.

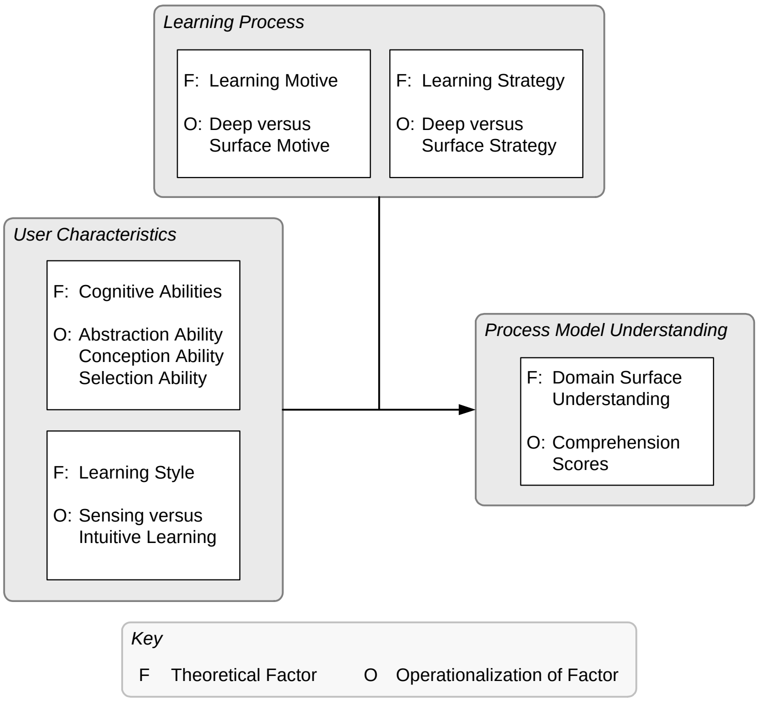

Figure 2: Research Model

First we point out that Figure 2 indicates that we are interested in what is called *domain surface understanding* – the ability of a user to retain (recognize and recall) domain information from the graphical elements in a process model (Mayer, 2001). It therefore refers to the learning product of being able to remember and reproduce information such as "what is the correct procedure for verifying invoices?" or "which options do I have for reimbursing prior expenses?" We need to stress here that this conceptualization of understanding is different from *deep understanding* – the ability to internalize domain information from a process model and to apply this information in problem-solving activities based on the model – an ability required for model application tasks such as process analysis or process re-design, and one which relies on good retention. Deep understanding materializes in an ability to solve problems such as "what can I do if an engine fails?" or "What are possible options to reduce the process cycle time?" We also note that *domain understanding* is different from *model understanding*. The former applies to a user's ability to retain information about the business domain depicted in the model, while the latter applies to a user's ability to understand the grammatical logic with which the model was constructed. Model understanding manifests an ability to understand the grammatical rules that were used to construct a model and pertains to questions such as "is it allowed to connect an activity element directly to another activity element?" or "can two activities connected with an XOR split be executed concurrently?" Prior research on process model understandability specifically (e.g., Mendling *et al.*, 2010; Reijers and Mendling, 2011) has almost exclusively focused on model understanding, a focus of study that we extend in this paper.

Following Figure 2, we now discuss six expected effects on domain surface understanding stemming from individual differences in user characteristics and learning process.

In our initial three hypotheses, we explore how domain surface understanding from a process model will vary dependent on the cognitive abilities brought to bear by the user. The essential argument is that the meta-cognitive functions selection, abstraction and conception ability are important facilitative precursors to learning, comprehension and problem solving, viz., to any subsequent higher-layer cognitive activity such as reasoning, decision making, analysis or explanation (Wang and Chiew, 2010).

Still, with process models themselves being external, conceptualized knowledge representation systems, some of the meta-cognitive functions went into the design of the model, thereby easing the cognitive load of the model viewer. In other words, the models have been created to abstract from, and conceptualize, the variety of process instances that are being executed into a graphical/textual representation to display the objects and attributes common to all (or most) instances. We advance the following hypotheses.

First, we turn to selection ability, which is used to cognitively simplify informational material that contains (some) irrelevant information. Process models are often high in complexity (the amount of information and the flow in which the information is presented, see Lassen and van der Aalst, 2009) because they contain representations of the tasks, events, states, and control flow logic that constitute a business process. They may also capture information about relevant actors, data, systems or other process-relevant artifacts (Recker *et al.*, 2009). To determine whether all or only some of these objects in a model are relevant to a particular question about the domain that is being modeled is therefore a cognitive process of search. It requires the user to evaluate a large amount of information and make a relevant selection to find a set of correlated objects, attributes, or relations for a given object or concept (Wang *et al.*, 2006). Being able to mentally simplify the flow by undoing it from irrelevant parts of a process model is therefore expected to facilitate understanding by reducing the error-proneness of the learner, in turn facilitating model understanding. Therefore, we have:

H1. *Selection ability will be positively associated with domain surface understanding performance.*

Second, we turn to abstraction ability, which is used to simplify information by deducing common attributes. This ability enables individuals to elicit information about a class of objects or attributes from viewing several instances of them. Complex process models are often high in size (the amount of information and the flow in which the information is presented, see Vanderfeesten *et al.*, 2008). Being able to mentally organize process information in mental classes and attributes can therefore be expected to generate benefits and aid the user in enacting a large amount of information from the process model. We state:

H2. *Abstraction ability will be positively associated with domain surface understanding performance.*

Third, we turn to conception ability, which is used to construct a ‘to be’ relation between an object or its attributes, and other existing objects/attributes (Wang *et al.*, 2006). This ability is fundamental for individuals for developing knowledge representation systems in their mental models. Such integrated representation systems allow a deeper form of understanding, and are therefore used in higher order cognitive tasks, such as reasoning and problem-solving (Wang *et al.*, 2006). However, since this study focuses on attaining surface understanding (as in contrast to deep understanding), the formation of 'to be' relations is not strictly relevant. Moreover, process models are externalized conceptualizations themselves. Consequently, when viewing the model, an individual is not required to call intensively on the conception ability of his/her brain, as the required knowledge representation system is (in an externalized manner) already available to the individual. On basis of this argument, we do not expect any significant effect of higher levels of conception ability to an individual's ability to retain domain information from a process model:

H3. *Conception ability will not be significantly associated with domain surface understanding performance.*

Next, we consider the perceptual learning style. Sensing learners tend to like learning facts and memorizing material. Intuitive learners, on the other hand, often prefer discovering possibilities and relationships; they also prefer discovering new relations and are known to be impatient and inferior with details (Felder and Brent, 2005). As the learning goal in our study is set at memorization (retaining information from a process model) rather than knowledge discovery, these differences in style suggest that thorough inspection of the different elements in the process model is expected to prevail over taking a more holistic approach of 'getting the picture'. As such, sensing learners are expected to outperform intuitive learners in developing process model surface understanding:

H4. *Users with a sensing learning style will have a higher domain surface understanding performance than users with an intuitive learning style.*

Moving from the presage stage to the process stage, Biggs (1987) argued that the engagement in learning activity depends on the user's motivation to learn. This motivation can be either intrinsic (intra-personal) or extrinsic (inter-personal). The former relates to following a deep approach aimed at the creation of meaning and individual learning. The latter fuels a surface approach to learning, targeted at meeting exterior expectations and/or outperforming others. Through the way that we measure understanding (surface understanding through comprehension tasks), the learning goal is inclined towards a performance goal (scoring as high as possible in comparison to others) rather than a learning goal – increasing one's competency, understanding, and appreciation for what is being learned (Covington, 2000). The performance goal is an extrinsic motivator, more in line with a surface approach to learning. Therefore, we suggest that users following a surface approach to learning are expected to attain higher levels of process model surface understanding based on a goal-approach compatibility:

H5. *Users' surface learning motive will be positively associated with domain surface understanding performance.*

H6. *Users' surface learning strategy will be positively associated with domain surface understanding performance.*

Due to memorization being a pre-requisite to transfer (and hence, surface understanding being a pre-requisite for deep understanding), we contend that users following a deep approach to learning also attain some level of goal-approach compatibility. Still, their approach to learning, whilst partly addressing the development of surface understanding, is specifically targeted at developing a deep, thorough level of understanding aimed at complex tasks and problems and facilitating discovery of new knowledge. Therefore, we may expect that positive relationships exist to surface understanding performance; yet, these effects are likely not to be significant. This is because a deep learning strategy implies that the user engages in active interaction with the process model, critically examining its soundness and attempting to link its information to existing mental models in attempt to uncover knowledge that is not yet present. In contrast, a surface learning strategy implies simple learning for memorization. The user tries to memorize the information in the process model without questioning it or trying hard to discover underlying patterns. This is likely to yield benefits for model comprehension over and above a deep immersion into the content.

In the following, we describe the design and results of an empirical study we conducted to test these hypotheses.

Research Method

Design

To be able to collect sufficient data whilst maintaining control over potentially confounding external factors, we selected a quasi-experimental design (Cook and Campbell, 1979). In this type of design, no experimental treatment and associated random assignment of participants into the experimental and control groups is provided. Our study follows this design in that our hypotheses pertain to the characteristics of the users without relating to a specific treatment (e.g., different types of models). We furthermore followed the suggestions of Gemino and Wand (2003) to control for those antecedents of model understanding not relevant to the theoretical arguments being advanced.

In our study, we engaged with both domain experts and method experts, as will be further explained in this section. We used paper-based experimental material in the interaction with the former, while an online system was used with the domain experts. Both systems displayed the experimental material in sections, allowing participants to move on from section to section at their own pace. We pilot-tested the experiment with five domain and methodology experts, resulting in minor modifications to instrumentation and procedure. A subsequent ANOVA test confirmed that the mode of experimentation system did not bias the results.

Procedures

Instrumentation was considered in accordance with the three stages of learning suggested by Biggs (1987). The *presage* stage captured user characteristics prior to showing the respondents the process models. The *process* stage gathered the relevant data about the learning approach after having briefly shown the participants the process models. The *product* stage inquired into the level of understanding attained by the participants after having been exposed to the process models.

During the presage stage, the study began with a pre-test of prior domain and method knowledge, as well as basic demographic questions (age, gender, nationality etc.). Next, participants were required to complete tests for the three cognitive abilities considered and their perceptual learning style. After completing the tests, in the process stage, participants were shown two process models, one about the government agency's "Advertising specific vacancies" process, and one about the "Priority placement" process[1]. The choice for two process models was made based on a trade-off between internal and external validity. Clearly, using a greater multitude of models as a treatment would potentially yield higher levels of external validity. But given our study's focus on user characteristics and their learning approach employed, utilizing more models would have potentially introduced a result bias as score differences could have been attributable to model features such as secondary notation or modularization (Reijers and Mendling, 2011), thereby threatening the internal validity of our research. Still, by using two cases, our research design allowed us to replicate our findings in two different settings, thereby providing a stronger test of our hypotheses than would have been possible with a single model case only.

The "Advertising specific vacancies" and "Priority placement" process models were selected for two reasons: First, the models were part of actual process documentation in day-to-day use at the Queensland government agency, thereby increasing practical relevance, ensuring content validity and avoiding inflated researcher bias (through use of an artificially created model). Second, both models were of considerable complexity, which guaranteed that the task of understanding was of substantial difficulty. This was deemed beneficial to generate fluctuations in user understanding which allowed testing for associations with differences in user characteristics. Specifically, the models comprised over 50 objects, a size that was previously shown to affect complexity and understanding levels (Mendling *et al.*, 2010). Also, both models featured several instances of modularization and branching (Muketha *et al.*, 2010).

After being shown the two models briefly, respondents were asked to answer questions about learning motives and strategy. Next, the two process models were displayed again for 5 minutes. The online experimentation system featured a timer that automatically moved on to the next stage, the product stage, which featured the different comprehension questions. In the paper-based variant, the facilitator collected the models after five minutes before allowing participants to move on to the next stage. The

[1] Both process models are part of the questionnaire as shown in the Appendix.

models were removed so that the quality of the mental representation of the domain and the models could be assessed (Gemino and Wand, 2005). Questions about the modeled domains and the models themselves were mixed with no particular order. No post-test was required for our study.

Materials

The study material consisted of an information cover sheet with consent form and directions, and several sections about demographics, cognitive abilities, two process models, learning approaches and model understanding. Each section comprised questions, text- and tick-boxes for answers. The Appendix displays the measurement material used (except for the cognitive abilities tests). We briefly describe important material elements in the following.

- *Pre-test*

  As control variables, we collected data on prior domain knowledge, prior method knowledge and self-efficacy beliefs. The measures for prior knowledge of the relevant process domains were adopted from the measure used by Burton-Jones and Meso (2008). Participants had to rate their own level of domain knowledge on a 7-point Likert scale, for each of the two process domains used ("Advertising specific vacancies" and "Priority placement"). To measure prior method knowledge about process modeling, we used the process modeling method knowledge questions used by Mendling and Strembeck (2008), which quiz respondents' theoretical knowledge of the process modeling method in use. Their questions concern grammatical rules of process model logic, derived from fundamental work in this area (Kiepuszewski et al., 2003). These questions, notably, are grammar-independent, and address the important control flow criteria *reachability* (Verbeek et al., 2007), *deadlocks* (Puhlmann and Weske, 2006), *liveness* (Kindler and van der Aalst, 1999) and *option to complete* (van der Aalst, 1998).

  Last, to measure self-efficacy beliefs, we adapted the action-oriented operationalization of self-efficacy used by Philips and Gully (1997) because we were interested in the task-specific self-efficacy beliefs of our participants. As part of the pre-test, also, several key demographic data was collected (e.g., age, nationality, gender).

- *Cognitive abilities test*

To measure the three types of cognitive abilities we considered, we used the Kit Reference Test for Cognitive Factors by Ekstrom et al. (1976) and the Differential Aptitude Test by de Wit and Compaan (2005). Specifically, to measure abstraction ability, respondents had to undertake the *Abstract Reasoning: Thinking in Figures* test (de Wit and Compaan, 2005), which required them to finalize visual series by deducing their underlying rule. To measure selection ability, respondents had to complete the *Choosing a Path* test (Ekstrom *et al.*, 1976), which required visual scanning to identify one path out of five that adhered to a pre-specified condition. To measure conception ability, respondents had to complete the *Form Board* test (Ekstrom *et al.*, 1976), which required them to decide how many out of five (rotated) pieces should be used to form a large composed figure. We omit the test material from this paper due to space limitations. The material is available from the contact author upon request or else from (Ekstrom *et al.*, 1976) and (de Wit and Compaan, 2005).

- *Learning style test*

To measure learning style, the sensing versus intuitive learning scale by Felder and Soloman (1997) was used. They defined 11 questions mapping a learner's score on the sensing-intuitive learning continuum. These questions were selected based on their succinctness, proven robustness and validity and due to its frequent application in learning in technological contexts (Felder and Spurlin, 2005).

- *Learning approach test*

To measure learning approach in terms of deep and surface learning motive, and deep and surface learning strategy, we used the Revised Learning Process Questionnaire (R-LPQ-2F) by Kember et al. (2004). Because their questions mainly pertain to long-term learning behavior, we revised the questions to fit one-episodic short term learning, as appropriate for our research context. In this way, motives more closely resemble intention, and strategies more closely relate to subsequent behavior.

- *Comprehension test*

  As dependent variables, we measured participants' performance in a comprehension test about the domain modeled (domain surface understanding) twice, once for each of the two process domains ("Advertising specific vacancies" and "Priority placement"). The domain comprehension questions were similar to those asked in prior studies (Recker and Dreiling, 2007; Burton-Jones and Meso, 2008) in that they queried the ability to *retain* different domain information about the process modeled in each of the two cases (Mayer, 2001).

  To be able to contrast the predicted effects about the understandability of a domain from a process model from the ability to understand the models per se, we measured, as a control variable, the participant's ability to comprehend aspects of the process models themselves (*model understanding*). Similar in nature to our measure for prior method knowledge, these comprehension questions quizzed *modularity*, *concurrency, exclusiveness* and *repetition* of the control flow logic (Kiepuszewski *et al.*, 2003) present in the process models.

Participants

In our study, overall 92 individuals participated. The respondents were spread across three groups of modeling practitioners, which we selected based on different levels of domain and method knowledge. One group was selected because of high levels of prior domain knowledge, one group was selected because of high levels of prior method knowledge, and a third group was selected because of medium levels of both prior domain and prior method knowledge. We selected respondents from these three groups to be able to examine our hypotheses across two different types of modeling practitioners (Burton-Jones and Meso, 2008):

(1) experienced domain users, and

(2) external analysts (as method specialists).

Table 1 summarizes the normalized average scores on prior domain and prior method knowledge for each of the three groups of respondents considered.

Table 1: Respondent groups by prior domain and prior method knowledge

Respondent group	**N**	**Average score on prior domain knowledge**	**Average score on prior method knowledge**
Domain experts	35	0.80	0.04
Method experts	22	0.33	0.68
Control group	35	0.34	0.30

The group of domain experts comprised 35 staff members that were selected from a government agency in Queensland, Australia. This group had high levels of prior domain knowledge because all of them were, as part of their jobs, involved in the business processes that were provided as models in this study.

The group of method experts comprised 22 respondents selected due to their expertise in Business Process Modeling. The group consisted of post-graduate students enrolled in a Business Process Management course at Eindhoven University of Technology, academic staff at the University of Innsbruck (Austria), and corporate partners in the Netherlands. As expected, this group had limited domain knowledge but higher levels of prior method knowledge compared to the other two groups (see Table 1).

The control group consisted of 35 respondents, made up of post-graduate students from the Radboud University Nijmegen and Maastricht University, and some Queensland government agency staff members not affiliated with the selected processes. Members of this group did not display high scores on either prior domain or prior method knowledge.

Results

The online system used automatically coded all responses received. 88 usable responses were identified after eliminating three incomplete and one invalid case. The results were examined in two steps. We first screened the data for its conformance with the assumptions of our tests. We then examined the tests of our predictions.

Data Screening and Validation

We started by assessing validity and reliability of the Likert-type measures, viz., prior domain knowledge (PDK-D1 and PDK-D2), self-efficacy (SE), deep/surface learning motive (DM/SM), and deep/surface learning strategy (DS/SS), through a factor analysis implemented in SPSS 19.0 (Tabachnick and Fidell, 2001). Several iterations of the factor analysis were conducted to eliminate problematic measurement items. During this process, it became apparent that the measurement items for surface learning strategy loaded on two distinct factors - surface learning strategy (memorization) and surface learning strategy (minimizing scope of learning). Therefore, we retained two factors for all subsequent analyses. Item properties are shown in Table 2. Table 3 summarizes scale properties. The Appendix summarizes the final items used in our analyses.

As can be seen from Table 3, all constructs have Cronbach's α and composite reliability ρc higher than 0.6. All items load significantly and higher on their presumed constructs (all $\lambda > 0.6$), and the average variance extracted (AVE) for each construct exceeds the variance due to measurement error (i.e., AVE > 0.5). These results suggest convergent validity of the measures. For each construct, the AVE for each construct is also higher than the squared correlation between that and any other construct considered, thereby indicating discriminating validity.

Table 4 gives the correlation statistics between the average total factor scores of the multi-item measures, all other independent variables and the three types of comprehension task scores related to the two domains (Comp-D1, Comp-D2) and the process model (Comp-M). We see that several of the factors considered correlate significantly with the comprehension task scores, suggesting their adequacy as independent factors. We also see that self-efficacy, prior domain and prior method knowledge do not correlate significantly with the two dependent variables but with most of the independent factors, suggesting that we should include these factors as control variables. We further note that all three cognitive abilities correlate as expected and that learning styles correlates strongly with abilities, knowledge and strategies. These results were expected. Overall, we do not find any counter-intuitive correlations in Table 4.

Table 2: Item properties

Item	Mean	St. Dev.	Loading
SE1	3.07	0.94	0.70
SE2	2.76	0.93	0.60
SE3	3.07	0.89	0.77
SE4	3.24	0.92	0.74
SE5	3.26	0.90	0.69
SE6	3.56	0.79	0.70
SE7	2.80	0.89	0.68
DM1	3.38	1.10	0.65
DM2	2.88	1.00	0.60
DM3	3.18	1.26	0.78
DM4	3.81	0.83	0.73
SM1	2.53	1.14	0.69
SM2	3.16	1.13	0.66
SM3	2.58	1.06	0.64
DS1	3.65	0.86	0.83
DS2	3.75	0.63	0.70
DS3	3.81	0.71	0.80
SS(Scope minimization)_1	3.03	0.99	0.83
SS(Scope minimization)_2	2.64	0.83	0.67
SS(Scope minimization)_3	2.60	0.89	0.76
SS(Memorization)_1	2.40	0.88	0.74
SS(Memorization)_2	2.84	1.02	0.69
SS(Memorization)_3	2.51	0.88	0.76

Table 3: Scale properties

Construct	Number of items	Average factor score	St. Dev.	Cronbach's α	ρ_c	AVE
Self-efficacy	7	3.11	0.63	0.83	0.66	0.80
Deep learning motive	4	3.31	0.76	0.68	0.61	0.75
Surface learning motive	3	2.76	0.85	0.63	0.65	0.80
Deep learning strategy	3	3.73	0.57	0.63	0.66	0.78
Surface learning strategy (Scope minimization)	3	2.76	0.73	0.72	0.68	0.81
Surface learning strategy (Memorization)	3	2.58	0.72	0.66	0.68	0.81

Table 4: Correlation Statistics

	Comp-D1	**Comp-D2**	**Comp-M**	**PDK-D1**	**PDK-D2**	**PMK**	**SE**	**AA**	**SA**	**CA**	**LS**	**DM**	**SM**	**DS**	**SS (scope)**
Comp-D2	**0.94**														
Comp-M	0.04	0.10													
PDK-D1	0.00	0.02	0.01												
PDK-D2	-0.02	0.01	0.01	**0.93**											
PMK	0.11	0.11	0.12	**-0.34**	**-0.39**										
SE	0.12	0.12	-0.03	0.09	0.03	0.20									
AA	0.06	0.02	0.03	**-0.40**	**-0.42**	**0.32**	0.16								
SA	**0.28**	**0.29**	0.02	**-0.47**	**-0.46**	**0.39**	0.14	**0.65**							
CA	**0.21**	0.15	-0.03	**-0.25**	-0.19	**0.23**	**0.23**	**0.59**	**0.60**						
LS	**-0.24**	**-0.22**	-0.10	**0.25**	**0.25**	**-0.26**	-0.17	**-0.23**	**-0.40**	**-0.26**					
DM	0.02	0.02	0.00	-0.05	-0.07	**0.25**	0.19	0.05	0.09	0.08	-0.14				
SM	-0.21	-0.15	0.05	-0.12	-0.14	0.09	0.09	0.05	0.11	0.08	0.12	0.39			
DS	0.05	0.02	0.18	0.02	0.00	**0.22**	**0.36**	0.07	0.00	**0.21**	-0.12	**0.45**	0.17		
SS (scope)	0.10	0.06	-0.13	-0.17	-0.18	0.04	-0.11	0.19	**0.28**	0.15	**-0.29**	-0.13	-0.04	**-0.33**	
SS (memo)	0.11	0.15	0.00	0.20	**0.22**	0.05	-0.09	-0.12	-0.19	-0.15	0.10	0.09	0.16	**-0.25**	**0.22**

* Correlations of $p < 0.05$ are shaded in grey.

Hypothesis Testing

We ran two tests to examine our hypotheses.

First, to examine the data collected on hypotheses H1-H3, H5 and H6, we conducted two hierarchical regression analyses (Tabachnick and Fidell, 2001) implemented in SPSS Version 19.0, one for each process model, to investigate the relationship between the suggested independent factors and domain surface understanding. One assumption behind the use of regression analysis is that the variables are measured on a continuous scale and are normally distributed. Our data screening confirmed that the measures for abstraction ability, conception ability, and selection ability, the dependent variables domain surface understanding (for Model 1 and Model 2) as well as the control variables prior domain knowledge and prior method knowledge met these criteria. The principal components analysis for the factors deep learning motive, surface learning motive, deep learning strategy, surface learning strategy (scope minimization) and surface learning strategy (memorization) as well as the control variable self-efficacy allowed us to extract average total factor scores that also satisfied these assumptions.

We ran the two three-step hierarchical regression analyses as follows. In step one, we entered prior domain knowledge, prior method knowledge and self-efficacy as control variables because they are well established in the model understanding literature. In step two, we then entered our scores for the three types of cognitive abilities considered. In step three, we then added the scores for learning motive and learning strategy. This hierarchical analysis allowed us to test whether each of the factors (cognitive abilities, learning process) added significantly to the model. We completed these steps for both the domain surface understanding scores for model 1 and model 2.

Table 5 provides descriptive statistics from the analyses, and Table 6 and Table 7 provide the details of the two hierarchical regression analyses showing the standardized beta coefficients and significance levels.

Table 5: Hierarchical Regression Analyses: Descriptive Statistics

Variable	**Mean**	**St. Deviation**
Domain surface understanding (Model 1)	2.92	1.15
Domain surface understanding (Model 2)	2.13	1.03
Process model comprehension	1.34	0.95
Prior domain knowledge (Model 1)	2.48	1.38
Prior domain knowledge (Model 2)	2.61	1.37
Prior method knowledge	1.74	2.41
Self-efficacy	3.11	0.63
Abstraction Ability score	10.94	4.21
Selection Ability score	5.35	3.53
Conception Ability score	6.34	3.64
Deep Learning Motive score	3.31	0.76
Surface Learning Motive score	2.76	0.85
Deep Learning Strategy score	3.74	0.57
Surface Learning Strategy (scope minimization) score	2.76	0.73
Surface Learning Strategy (memorization) score	2.58	0.72

Table 6: Hierarchical Regression Analysis: Final Model Statistics (Model 1)

Term	1: Controls	2: Cognitive Abilities	3: Learning Process	Collinearity Statistics	
	St. Beta	St. Beta	St. Beta	Tolerance	VIF
Prior domain knowledge (model 1)	0.02	0.12	0.02	0.65	1.54
Prior method knowledge	0.10	0.03	-0.06	0.68	1.47
Self-efficacy	0.10	0.06	0.07	0.79	1.26
Abstraction Ability		-0.25	**-0.29***	0.49	2.04
Selection Ability		**0.41****	**0.52*****	0.39	2.58
Conception Ability		0.12	0.11	0.52	1.91
Deep Learning Motive			0.01	0.66	1.53
Surface Learning Motive			**-0.34*****	0.79	1.26
Deep Learning Strategy			0.15	0.55	1.81
Surface Learning Strategy (scope minimization)			-0.02	0.75	1.33
Surface Learning Strategy (memorization)			**0.29***	0.69	1.44
F	0.62	**2.12***	**2.50****		
F change	0.62	**3.56***	**2.69***		
R^2 change	0.02	**0.11***	**0.13***		
R^2	0.02	0.14	0.27		

* $p \leq 0.05$; ** $p \leq 0.01$; ***$p \leq 0.001$.

Table 7: Hierarchical Regression Analysis: Final Model Statistics (Model 2)

Term	**1: Controls**	**2: Cognitive Abilities**	**3: Learning Process**	**Collinearity Statistics**	
	St. Beta	**St. Beta**	**St. Beta**	**Tolerance**	**VIF**
Prior domain knowledge (model 2)	0.05	0.14	0.00	0.60	1.65
Prior method knowledge	0.11	0.04	-0.07	0.65	1.53
Self-efficacy	0.10	0.08	0.09	0.81	1.23
Abstraction Ability		-0.28	**-0.33***	0.48	2.09
Selection Ability		**0.50*****	**0.62*****	0.39	2.55
Conception Ability		0.02	0.03	0.51	1.95
Deep Learning Motive			-0.01	0.66	1.53
Surface Learning Motive			**-0.28****	0.78	1.28
Deep Learning Strategy			0.14	0.55	1.82
Surface Learning Strategy (scope minimization)			-0.09	0.75	1.34
Surface Learning Strategy (memorization)			**0.34****	0.67	1.49
F	0.70	**2.51***	**2.59****		
F change	0.70	**4.23****	**2.43***		
R^2 change	0.03	**0.13****	**0.12***		
R^2	0.03	0.16	0.27		

* $p \leq 0.05$; ** $p \leq 0.01$; ***$p \leq 0.001$.

We first examine collinearity statistics. Multi-collinearity is present when tolerance is close to 0 (< 0.01; see Tabachnik and Fidell, 2001) or the VIF is high (> 10), in which case the beta and p coefficients may be unstable. The VIF and tolerance measures shown in Table 6 and Table 7 suggest that multi-collinearity is not an issue in our data.

Perusal of the data in Table 6 and Table 7 leads to the following observations.

First, we note that, after controlling for prior domain knowledge, prior method knowledge and self-efficacy, cognitive abilities and learning approach significantly aid the explanation of domain surface understanding in both cases considered. Adding these factors step-by-step increased the R^2 of the regression models to 0.27 (model 1 as well as model 2), with the changes in R^2 being significant in each step (F change = 3.56 and 2.69, both $p < 0.05$ for model 1; and F change = 4.23, $p < 0.01$ and 2.43, $p < 0.05$ for model 2).

Hypotheses H1 and H2 hypothesized different domain surface understanding scores for those users with selection and abstraction abilities. In the final model in Table 6 and Table 7, we see that selection and abstraction ability indeed were significant predictors of process model surface understanding ($\beta = 0.52$, $p < 0.001$, and $\beta = -0.29$, $p < 0.05$ for model 1, and $\beta = 0.62$, $p < 0.001$, and $\beta = -0.33$, $p < 0.05$ for model 2). As expected, selection ability had a strong ($p < 0.001$) positive effect, lending support to hypothesis H1. Abstraction ability had a significant, somewhat weaker ($p < 0.05$) and importantly consistent *negative* effect on domain surface understanding, contrary to our expectation in hypothesis H2.

In hypothesis H3 we expected that conception ability would not show strong effects on domain surface understanding. And indeed, the effects of higher levels of conception ability had only minimal, insignificant positive effects ($\beta = 0.12$ for model 1, and $\beta = -0.02$ for model 2, both $p > 0.05$), thereby supporting hypothesis H3.

H5 and H6 speculated a surface learning approach to be a significant predictor of domain surface understanding. Table 6 shows that surface motive and one of the two surface strategies (memorization) indeed were significant predictors in both cases ($\beta = -0.34$, $p < 0.05$, and $\beta = 0.29$, $p < 0.05$ for model

1; and $\beta = -0.28$, $p < 0.01$, and $\beta = 0.34$, $p < 0.01$ for model 2). However, for the surface learning motive we note a directionality reverse to our initial expectation. We also note the essential non-effect of the surface strategy related to scope minimization in either model cases. In line with our expectations related to H5 and H6, we found that, for both process models, a deep learning approach (motive and strategy) did not emerge as a significant predictor of process model surface understanding.

In a second test, we then examined the data collected on the learning style of the participants (sensing versus intuitive) to examine hypothesis H4. The Felder and Soloman (1997) test results in scores on a continuum between -11 and +11, with negative scores indicating a sensing style and positive scores indicating a preferences for an intuitive learning style.

Therefore, we used an analysis of co-variance technique implemented in SPSS 19.0, with the independent factor learning style, coded as a binary variable (sensing = 0, intuitive = 1) based on the learning style test scores received, and again using prior domain knowledge, prior method knowledge and self-efficacy as covariates. To that end, we created three 0/1 dummy variables, one for each covariate, to divide the total factors score for each covariate by the respective median to create two groups (high and low). All following results, therefore, have been computed whilst controlling for differences in the covariates considered. The two domain surface understanding scores were used as a dependent factor in the two analyses. Table 8 shows mean values and standard deviations and Table 9 gives the results from the two ANCOVA tests.

Table 8: Means and Standard Deviations for Domain Surface Understanding Scores

Independent Factor	**N**	**Model 1**		**Model 2**	
		Mean	**St. deviation**	**Mean**	**St. deviation**
Sensing Learning Style	35	3.25	1.07	2.40	1.01
Intuitive Learning Style	53	2.70	1.15	2.19	1.01

Table 9: Results from Significance Tests (ANCOVA)

Dependent Factor	Source	df	F	p	Partial Eta Squared
Domain surface understanding (model 1)	**Learning Style**	**1**	**5.18**	**0.03**	**0.06**
	Prior Domain Knowledge (model 1)	1	0.96	0.33	0.01
	Prior Method Knowledge	1	0.02	0.88	0.00
	Self-efficacy	1	0.12	0.74	0.00
Domain surface understanding (model 2)	**Learning Style**	**1**	**4.30**	**0.04**	**0.05**
	Prior Domain Knowledge (model 2)	1	1.17	0.28	0.01
	Prior Method Knowledge	1	0.10	0.75	0.00
	Self-efficacy	1	0.09	0.76	0.00

We observe from Table 8 that, as predicted, sensing learners achieved higher domain surface understanding scores than intuitive learners. The data in Table 9 confirms that these score differences are significant at $p = 0.03$ (model 1) and $p = 0.04$ (model 2). These results lend support to hypothesis H4.

Post-hoc analysis

To strengthen the confidence in our predictions, we re-ran the hierarchical regression and the analysis of variance tests, this time using the model comprehension score (Comp-M) as a dependent variable. Recall, our prediction was that none of the independent factors considered (cognitive abilities, learning style or learning approach) would be a significant predictor of model comprehension abilities. This was because model comprehension was previously shown to depend on structural model qualities such as connectivity (Vanderfeesten *et al.*, 2008), complexity (Mendling *et al.*, 2007) or modularity (Reijers and Mendling, 2008).

Although we omit the detailed table of results to conserve space, the results were in line with our predictions. Neither the regression nor the variance analysis showed any significant relationships between any of the factors considered and the model comprehension score, in turn strengthening our confidence in the theoretical propositions advanced.

As an additional post-hoc analysis, we conducted independent samples t-tests between the three groups of participants to ensure that differences in understanding would not result from significant heterogeneity between the respondent groups. All t-tests confirmed that group differences were insignificant.

Discussion

Our empirical study set out to test six hypotheses about the effects of user characteristics and learning process factors on domain surface understanding, using two process models as test cases. Four of our hypotheses received full and strong support from the data, hypothesis H5 received partial support in that the data showed a significant but reversely-directed effect of the surface learning motive, and hypothesis H2 was rejected by the data in that the results suggest a significant negative effect of abstraction ability on the attainment of domain surface understanding.

The cognitive abilities results indicated that selection ability has a positive effect on surface understanding, abstraction ability a negative effect and conception ability has no effect. A possible explanation for this result is that selection is more compatible with memorization due to its faithfulness. Abstraction and conception allow individuals to attain understanding based on elicitation or construction. This might make them inherently subjective because that involves cognitive processes like reasoning, deduction and evaluation (Wang *et al.*, 2006). In contrast, selection might be the most efficient method of the three which makes it compatible with goal attainment under time pressure. Selection can be considered to exert a low amount of cognitive load due to the intake of information as-is. The formation of to-be relations using conception ability or of evaluation and quantification using abstraction ability might exert a higher cognitive load that extends the time that is required to attain understanding (Chandler and Sweller, 1991).

Another interpretation of these results is that abstraction and conceptualization are two fundamental characteristics of any conceptual model. Process models, as other forms of conceptual models, are representations of classes of things (Recker *et al.*, 2009), that is, they describe a domain not in terms of the specifics of any given case but rather in terms of the concepts common to all (or most) cases and scenarios.

Therefore, when viewing a process model, the abstraction to common objects and attributes is already provided. Abstracting further from this information would result in a loss of detail information required to be able to deduce from the abstraction in the process model ("how we do procurement") information about process instances ("how we handled the purchase order 47-11"), which is required when reasoning about the process domain ("what happened to invoice 47-11?"). Our results could therefore suggest that high levels of abstraction ability are in fact counter-productive to being able to retrieve and retain information about the modeled business domain, because the capacity to abstract material that is already abstracted is essentially antidromic to the task at hand.

Our findings about hypotheses H2 and H3 therefore highlight two important cognitive aspects when viewing process models. First, the models provide the domain information in a way that renders the conceptualization skills of the model viewers as largely irrelevant. This situation, in turn, eases the cognitive burden on the model viewer. Second, the models provide the domain information on such an abstract level that model viewers are required to search (and select) the relevant information within this set of abstracted material. Cognitive selection skills assist with this task. Cognitive abstraction skills, however, appear to be largely detrimental to this search for information as they aggregate the (already aggregated) material to an even higher level of abstraction that is counterproductive to understanding specifics about the domain that is presented.

Our results on learning style indicated that a sensing style was more suitable to attain surface understanding than an intuitive style. This situation is attributed to sensing learners' preference for details and facts which suits memorization better than the more holistic and innovative learning goals of an intuitor (Felder and Brent, 2005). Our results are in line with these predictions, lending further credibility to the notion of learning styles.

The results on learning approach were partly counter-intuitive, indicating that motive has a negative effect on surface understanding rather than a positive. By expecting that a surface motive would be conducive to attaining a surface goal, we forwent that motives do not only relate to the initiation of behaviour but also to behavioural composure (Covington, 2000). Consistently, due to surface learners focusing on the learning product rather than the process, a surface motive may have indicated low levels of learning intensity and persistence which would inhibit any type of favourable learning outcome. This type of interpretation can be seen as in line with research on educational strategies that have shown that surface approaches to learning are often associated with a focus on unrelated parts of the learning task, an unreflective association of facts and concepts, and a failure to distinguish common principles from specific examples (Ramsden, 1988). And indeed, our results would suggest that surface motives do not yield the type of approach of learning that would lead to good surface understanding. It is worth noting here, however, that surface motives are not attributes of individuals but rather denote choices towards a learning task (Biggs, 1987). It should therefore be possible to facilitate an environment for model viewing that reduces the chances that individuals opt for a surface approach.

Finally, the goal-strategy compatibility appeared to be more accurate than the goal-motive relation, with our results on learning strategy suggesting that memorization is the most effective strategy for attaining domain surface understanding. In line with our predictions, we also found that strategies focusing on deep understanding indeed did not yield positive contributions to attaining surface understanding. These findings further emphasize the importance of *what actually happens* during the process stage towards the development of process model understanding.

Implications

For Research

The work presented in this paper has important implications for future research. First and foremost, this paper contends and provides evidence that process model understanding should indeed be regarded, at least in part, as an emergent property of the relation between process model and the person viewing the model. Our findings suggest that future research into process model understanding is advised to refrain from taking an exclusively model-centric perspective and consider the inclusion of factors from the presage and process stages of learning. Especially our conceptualization of the knowledge construction as a learning process will be useful for studies that attempt to understand the process through which model content, content presentation and user characteristics interact in developing understanding.

Our results provide a further indication into the empirically invalidated importance of concepts such as chunking and tracing (Cardoso *et al.*, 2006). The empirical absence of the process stage in prior research therefore upholds a black box of how it is that model attributes inhibit or facilitate learning. We believe that our work now serves as a valuable initial contribution to opening this black box.

Additionally, our work provides further evidence for the conceptualization of attaining process model understanding as a cognitive process of learning (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008). Specifically, the effects found in our study add to the explanatory power of prior work and together inform a comprehensive body of knowledge on model understanding. Still, we acknowledge that the proportion of variance explained provides room for improvement. This paper therefore encourages the exploration of alternative presage and process factors to work towards a more integrative understanding of the effect of these stages, be it distal factors like personality (Goldberg, 1990) or higher-order cognitive factors like memorization (Wang *et al.*, 2006).

Finally, future research could extend our approach to measuring aspects of process model understanding. In this paper we chose to examine process model understanding in terms of retention of domain information. Past research suggests that retention is a type of *surface understanding*, which is different from *deep understanding* (Gemino and Wand, 2005; Burton-Jones and Meso, 2008). In fact, both products of understanding can be seen as two ends of a continuum. We focused on individuals' understanding of model elements and the retention of their meaning in a process model (surface understanding), which is fundamental to being able to faithfully and efficiently interpret a process model. Future work could now extend this work and examine the problem solving performance (which is indicative of deep understanding, see Gemino and Wand, 2005; Burton-Jones and Meso, 2008) of individuals who use process models to solve tasks such as organizational re-design, software specification, certification and others.

For Practice

We believe our findings inform a largely neglected aspect of process modeling practice – how to deal with the individuals working with the models. Specifically, our results about the positive effects of selection ability and a sensing learning style suggest that it is more effective to 'walk users through a model step-by-step' rather than focusing more holistically on making them see the bigger picture. This notion is actionable for instructive communication, for instance, in presentations or prefaces, and should motivate researchers and practitioners alike to take on the question of how to make process models easier to search through. Besides, consistent to the findings on self-efficacy beliefs (Mendling and Strembeck, 2008) the effect of learning motive and learning strategy emphasizes that facilitating understanding is not only a matter of training but also of managing expectations. It thereby re-emphasizes the notion of clearly informing users on the purpose of a model in order to prevent them from entering the learning process with a lack of composure. The findings further suggest that the approaches taken by individuals to the process modeling exercise warrants close attention. Motive and strategy can be shaped through appropriate environment-setting and instructions. Therefore, our findings inform organizations how to use educational strategies (e.g., Ramsden, 1988) to facilitate a working environment in which analysts working with process models can put them to their best use.

Conclusions

Using process modeling for the analysis and design of process-aware information systems is a relevant domain in conceptual modeling and IS analysis and design overall. We contribute to the body of knowledge by extending our understanding of individually differing factors and their relevance to domain understanding from process models. We found that different cognitive abilities, different learning styles and different learning motives and strategies are significantly associated with the level of domain surface understanding generated from a process model.

Overall, our results suggest that studies in this area of research need to consider the various types of users involved in the process modeling process. Our findings suggest that individual user characteristics are important elements in such studies, and relevant to the practice of process modeling in general. Our work denotes an important extension to the literature on conceptual modeling, multimedia learning and cognitive informatics, and significantly informs process modeling work and outcomes, and may ultimately lead to more successful process modeling for the analysis and design of process-aware information systems overall.

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