Process Model Comprehension:
The Effects of Cognitive Abilities, Learning Styles and Strategy

Abstract

Process models are used to convey semantics about business operations that are to be supported by an information system. A wide variety of professionals is targeted to use such models, including people who have little modeling or domain expertise. We identify important user characteristics that influence comprehension of process models. Through a free simulation experiment, we provide evidence that selected cognitive abilities, learning style and learning strategy influence the development of process model comprehension. These insights draw attention to the importance of research that views process model comprehension as an emergent learning process rather than as an attribute of the models as objects. Based on our findings, we identify a set of organizational intervention strategies that can lead to more successful process modeling workshops.

Keywords

Process modeling, learning style, cognitive abilities, model comprehension

Introduction

When analysing or designing information systems, analysts frequently use graphical models of the relevant business domain to aid the determination of requirements. To that end, analysts often use conceptual models of business processes (process models) to assess or build information systems that are process-aware (Dumas *et al.*, 2005). Process modeling is a primary reason to engage in conceptual modeling (Davies *et al.*, 2006) and has been shown to be a key success factor in organizational and systems re-design projects (Kock *et al.*, 2009).

Because of the relevance of process modeling during the analysis and design of information systems, the evaluation of process modeling-related phenomena is an active research area (Burton-Jones *et al.*, 2009; Recker, 2013). Current research in this area can be classified in two streams. One stream is devoted to enhancing the *support* for process modeling, for example, by examining technological support for requirements modeling (Dennis *et al.*, 1999) or by providing support for collaboration during modeling activities (Dean *et al.*, 2001; Recker *et al.*, 2013). The other stream, which is important to the line of research presented in this paper, has examined how process modeling is *applied*. This stream is pursued with the aim of understanding how individuals learn how to model (Agarwal *et al.*, 1999), determining the performance benefits and usefulness of models for different tasks (Figl *et al.*, 2010; Recker *et al.*, 2011) or understanding how process models can be designed such that comprehension of these models can be maximized (Reijers and Mendling, 2011; Reijers *et al.*, 2011; Mendling *et al.*, 2012). Our research follows this tradition and examines how end users comprehend the content of process models, that is, how much they learn about the domain that is visualized in the process model (Gemino and Wand, 2003). This question is important because the usage of a process model, either for purposes of process analysis, performance measurement or re-design, are ultimately dependent on how well individuals can comprehend the modeled process (e.g., Dean *et al.*, 2001; Burton-Jones and Meso, 2008; Mendling *et al.*, 2012).

Specifically, we are interested in examining *dynamic* traits of business users who wish to comprehend a process model. Dynamic traits are those user characteristics that can be influenced by organizational interventions, i.e., that can be shaped and triggered through appropriate learning stimuli within the setting of a process modeling workshop. This focus of our work, therefore, contributes new knowledge on learning requirements from process models (e.g., Sheetz *et al.*, 1997). Through this focus, we extend the literature that has largely focused on traits of the models themselves – e.g., their visual design (Figl *et al.*, 2013), the use of different grammar constructs (Recker, 2013), or the use of modularization (Reijers *et al.*, 2011) and labeling (Mendling *et al.*, 2010b) – rather than those of the model users.

We draw on multimedia learning theory (Mayer, 2009) and student learning theory (Biggs, 1987) to hypothesize that individual cognitive abilities, learning style and learning strategy are important predictors of process model comprehension. We report on a free simulation experiment that we conducted to test these hypotheses. Our findings suggest several intervention strategies that provide relevant stimuli to increase the influence of the identified enabling traits, while disabling the influence of traits that inhibit model understanding.

Our study makes several contributions to the literature. First, it draws upon student learning theory (Biggs, 1987) to extend the prevalent conceptualization of model understanding (Gemino and Wand, 2005) with three stages of a learning process, viz., presage, process and product. Second, it adds to the existing literature on conceptual model comprehension (e.g., Agarwal *et al.*, 1999; Reijers and Mendling, 2011) by offering an alternative, user-centric perspective on important antecedents to model comprehension. As will be discussed, the state-of-the art puts the emphasis on the intrinsic properties of a process model as the prime factor in making sense of these. Third, it adds to the body of literature on cognitive abilities (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 comprehension. Then, we conceptualize how comprehending a process model can be seen as an extended one-episode learning process. We will draw attention to six important factors alongside three stages of this learning process. Then, we discuss design, conduct and findings of a free simulation experiment to test these arguments. Based on the results, we provide a discussion of actionable items that can be expected to improve the use of process models by business users. Finally, we conclude this paper by providing a discussion of contributions.

Background and Theory

Process Modeling

The essence of process modeling is to capture and represent information about business processes (Dennis *et al.*, 1999). To that end, 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).

Process models are used as an externalized representation of the problem space for an unstructured problem, be it that of redesigning the organizational work procedure to improve its performance (Danesh and Kock, 2005) or that of designing an IT-based system to enact or automate parts of the process (Reijers *et al.*, 2003). To support such problem-solving, a fundamental requirement is that users faithfully comprehend the content of the conceptual models of the process domain (Burton-Jones and Meso, 2008).

Most research in the area of process model comprehension has attempted to define process model comprehension as a function of *intrinsic* properties of a process model. This means that comprehension has been looked at as a function of the design of the process model itself (e.g., Hahn and Kim, 1999; Reijers *et al.*, 2011). Factors pertaining to the *person* viewing the model have only scarcely been investigated (e.g., Khatri *et al.*, 2006; Burton-Jones and Meso, 2008; Reijers and Mendling, 2011), but the focus of these studies has been on *static* features of the user of a model (such as level of expertise or level of familiarity of the domain). Whilst improving our knowledge to date, we argue that these contributions are not comprehensively capturing the process of developing process model understanding. We posit that process model comprehension is an *emergent* property rather than an intrinsic one. This view takes into account the relation between individual traits in the specific context of a model-based task performance.

Process Model Comprehension as a Learning Process

Prior research (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008; Mayer, 2009) has suggested that models can be viewed as explanative multimedia messages from which individuals can develop domain understanding. In line with this view, we conceptualize process model comprehension as a one-episode *learning process*. 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. This learning process will then result in the construction of new knowledge (Mayer, 2009). In the middle part of Figure 1, this process is captured in the framework developed by Mayer (2009). This conceptualization of model comprehension as a one-episode learning process has yielded some useful insights in the area of data modeling (Masri *et al*., 2008), object modeling (Burton-Jones and Meso, 2008) and process modeling (Recker and Dreiling, 2011), thereby increasing our confidence that the framework is an appropriate conceptualization of process model comprehension.

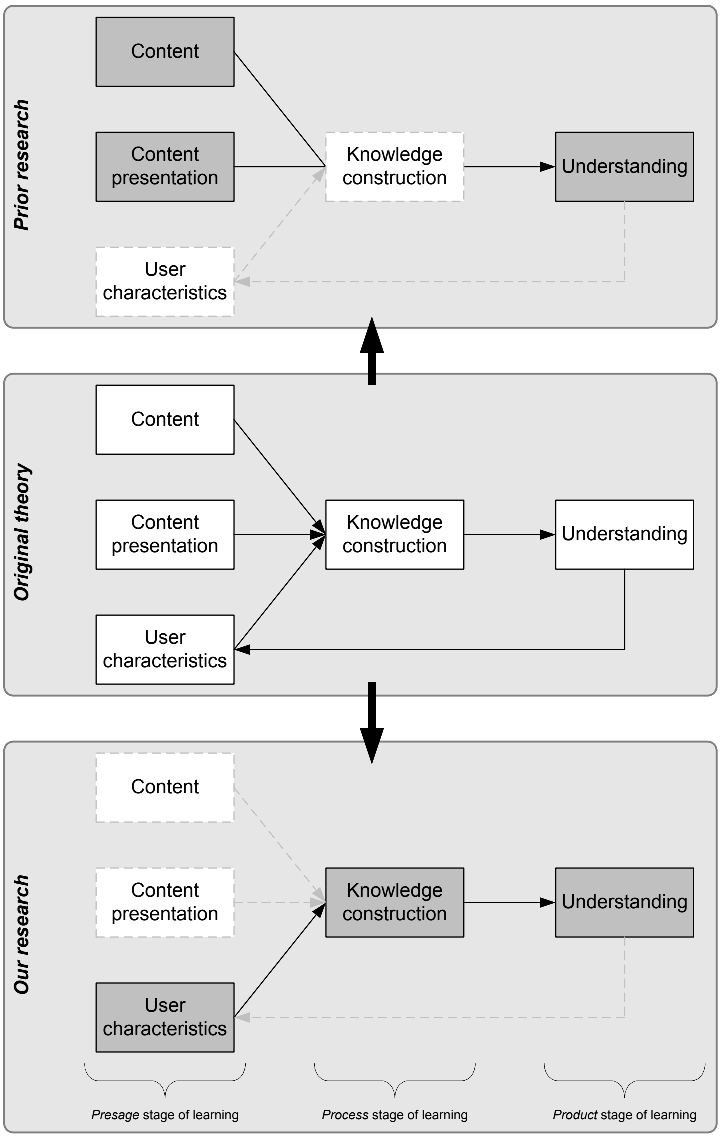


Figure 1: Prior research, theory and focus of study, on basis of (Mayer, 2009) and (Biggs, 1987)

As visualized in the upper part of Figure 1, the existing literature has examined this framework mostly with a focus on content and content presentation in a model, e.g., the use of optional properties (e.g., Bodart *et al.*, 2001) or the use of different grammars to present the content in a model (e.g., Recker and Dreiling, 2011), and typically has controlled for user characteristics in these studies. At this point, it has not examined in detail the knowledge construction process (indicated in the upper part of Figure 1 through dashed lines). To complement and extend this focus, we will therefore control for content and content presentation factors. We will do so by examining important *user characteristics* and the role these characteristics play in the *knowledge construction process* that leads to domain understanding generated through process model comprehension. This focus in our research is indicated through grey highlighting and shaded lines in the framework shown in the bottom part of Figure 1.

Our specific interest is in those user characteristics that can be shaped through short-term organizational interventions, namely those that fall within the scope of a modeling workshop. Such characteristics are called *dynamic* traits. Dynamic traits are situation-specific, individual differences that affect responses to stimuli within a specific situation (Thatcher and Perrewe, 2002). Dynamic traits differ from stable traits in that training, incentives or other environmental stimuli can be used to promote or prevent their influence on behavior whilst stable traits exhibit largely constant effects (such as levels of experience or familiarity).

Knowledge Construction in Process Model Comprehension

To conceptualize the knowledge construction process in Mayer's (2009) theory of multimedia learning, we draw on Biggs' (1987) 3P model of 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). During the process stage, 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 and in turn determines student's perception of learning requirements. Two types of motives can be distinguished, *surface* and *deep* motive

(Kember *et al.*, 2004). A surface motive is tailored to the product of the learning process and is 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, importantly, are not static properties of individuals. Rather, they are context-dependent, meaning that they can be influenced within the learning setting (Biggs, 1987). Therefore, learning motive and learning strategy denote choices relevant to the learning task at hand, and as such can be influenced through appropriate intervention strategies.

The choice of learning motive and strategy depend on three important user characteristics during the *presage* stage of learning: 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) and *prior method knowledge* about process modeling (Reijers and Mendling, 2011) can influence the development of understanding. Research in education has further shown that *self-efficacy* is a third important factor because students' learning activities are influenced by their broad expectations about one's ability to successfully perform a specific task or behavior (Zhang, 2000).

These three factors correspond to broad and stable traits of individuals, which have been shown to predispose individuals in task-based performances, but do so in a consistent manner (Bandura, 1997) and thus exert a less pervasive influence on dynamic individual differences (Day and Silverman, 1989). Given that these traits cannot easily be subjected to influence through short-term interventions within the scope of a modeling workshop, and because their broad influence on model-based task performance has been demonstrated in prior research, we have no interest in revisiting these findings. Therefore, we will control for these prior knowledge factors when examining other antecedents of understanding.

In terms of **ability**, comprehending process models is essentially a cognitive processing task (Gemino and Wand, 2003). Users need to comprehend the provided conceptualization, abstract from irrelevant details provided and instead select those informational objects relevant to the problem-solving task at hand. Depending on the viewer's cognitive information-processing abilities, the external representation (the process model) may be different to the internal representation (the internal mental model) developed by the viewer. We argue, therefore, that understanding *which* cognitive abilities are important to the process of understanding process models will be key to designing incentives or stimuli in workshop settings that can appropriately stimulate the relevant cognitive abilities.

From the literature we have identified two cognitive abilities that are important to developing an understanding from content displayed in a process model:

Abstraction ability is a 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 (Bennedsen and Caspersen, 2006). 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. The ability to abstract is a fundamental prerequisite to classification (assigning elements to groups of entities based on shared characteristics), which is a key purpose of conceptual models of any sort (Parsons and Wand, 2008).

Selection ability is a 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 relevant to process modeling as these models are typically quite large and rich diagrams with many informational artifacts, requiring the viewer to select the relevant information from the diagrams to reason about their use for the task at hand (Winn, 1993). The ability to select, therefore, provides an account for how well individuals can identify and retrieve relevant information from visual diagrams such as process models (Winn, 1990).

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). 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. 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. Again, we note that the learning style is a dynamic, task-dependent choice of the individual and is therefore susceptible to context-specific environmental stimuli.

Research Model and Hypotheses

The instantiation of our adaptation of Mayer's framework as applied to process model comprehension (see Figure 1) in a research model is shown in Figure 2. Our primary conjecture is that *process model comprehension* is a function of the learning style, learning motive, and learning strategy of the users working with the model, as well as of two relevant cognitive abilities.

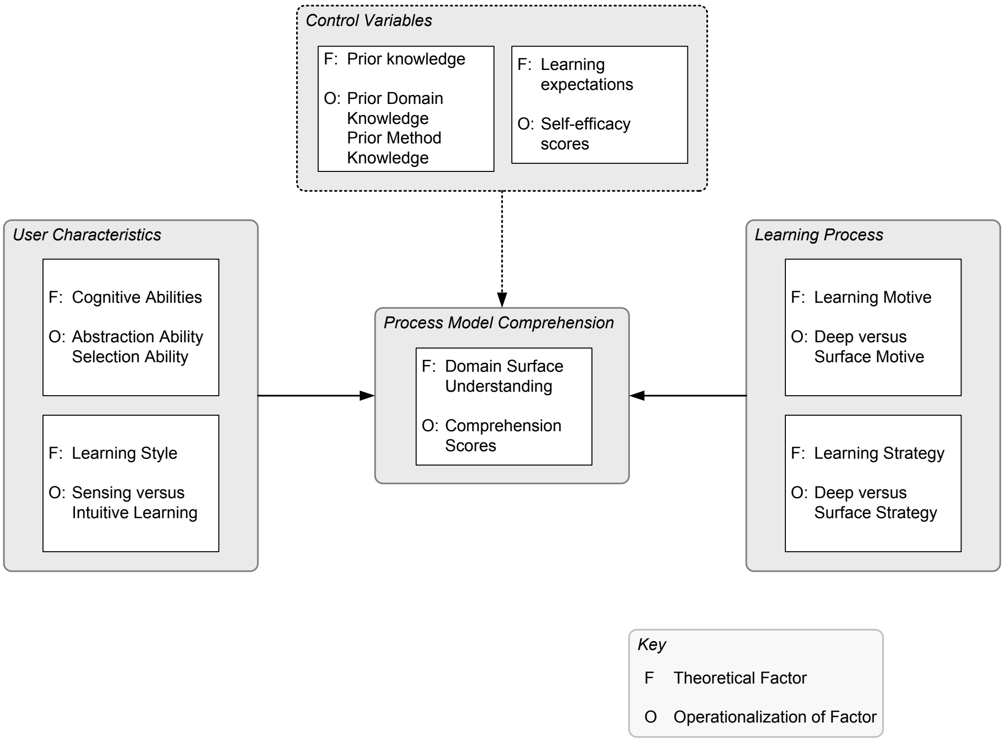


Figure 2: Research model

For the purpose of our study, we define process model comprehension as the ability of a user to retain domain information from the elements in a process model (Mayer, 2009). 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?"

This definition of model comprehension relates to a user's ability to retain information about the business domain depicted in the model, as used in the study in (Recker and Dreiling, 2011), which is different from the definition of comprehension as a user's ability to understand the grammatical logic with which the model was constructed (Mendling *et al.*, 2012). It is also different from deep domain understanding, that is, a user's ability for problem-solving on the basis of a model (Gemino and Wand, 2005). Our focus on comprehension is justified because comprehension of the domain information in a process model is a necessary prerequisite for all model-based problem-solving tasks, such as systems analysis, communication, design, organizational re-engineering, project management, end user querying and others. In other words, for a model to be useful for any modelling-related task, it is imperative that the stakeholders doing these tasks are able to comprehend the model well and timely (Mendling *et al.*, 2012).

We now discuss five expected effects on process model comprehension stemming from our conceptualization.

In our initial two hypotheses, we explore how process model comprehension will vary dependent on the cognitive abilities brought to bear to this task by the user. The essential argument is that the cognitive functions of abstraction and selection 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).

First, we turn to selection ability, which is used to simplify the cognitive model of 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 process model comprehension performance.*

Second, we turn to abstraction ability, which is used to simplify information by deducing common attributes. In this respect, it is important to stress that a process model itself can already be seen as a procedural *abstraction* of how individual cases (or instances) are dealt with in a certain organizational context. To attain a domain understanding of the procedure that is captured in a process model it is essential that the meaning and location of individual elements of a process model are specifically retained. The very reason that individual elements appear in a process model is that they either (1) show important points of differentiation between dealing with slightly different cases or (2) show distinctive stages in dealing with one single case. Increased attempts to invoke one's abstraction abilities on such a process model may therefore work counter-productively, in the sense that important, granular information from the model is neglected and aggregated to an overly simplistic mental image. Therefore, we state:

H2. *Abstraction ability will be negatively associated with process model comprehension performance.*

Next, we consider the perceptual learning style. Sensing learners tend to focus on 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 setting is set at memorization (retaining information from a process model) rather than knowledge discovery (developing novel knowledge based on the content of the model to solve new problems), these differences in style suggest that thorough bit-by-bit 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 understanding:

H3. *Users with a sensing learning style will achieve a higher process model comprehension performance than users with an intuitive learning style.*

Biggs (1987) argued that the engagement in learning activity depends on the user's motivation to learn. This motivation can be either intrinsic (deep motive) or extrinsic (surface motive). 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 our focus on process model comprehension, 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 understanding based on goal-approach compatibility:

H4. *Users' surface learning motive will be positively associated with process model comprehension performance.*

H5. *Users' surface learning strategy will be positively associated with process model comprehension performance.*

Due to memorization being a pre-requisite to transfer (and hence, process model comprehension being a pre-requisite for problem solving), 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 domain understanding, is specifically targeted at developing a 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 domain 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.

Research Method

Design

To be able to collect sufficient data whilst maintaining control over potentially confounding external factors, we designed a free simulation experiment (Fromkin and Streufert, 1976). Free simulation experiments are different from traditional factorial experiment designs in that subjects are placed in a complex environment resembling a real-world situation as closely as possible where they are free to behave (within the required boundaries of the study, e.g., the rules of the task setting at hand) and are asked to make decisions and choices as they see fit. Free simulations do not involve preprogrammed treatments, and thus allow the values of the independent variables to range over the natural range of the subject's experience. In effect, the experimental tasks induce subject responses, which are then measured via the research instrument. This research design was applicable because our hypotheses pertain to the characteristics of the users without relating to a specific treatment (e.g., different types of models). Instead of random assignment of participants to groups, we collected and examined several key demographic variables to evidence appropriate variety in the responses (see below). Furthermore, we followed the suggestions of Gemino and Wand (2003) to control for those antecedents of model understanding that are considered not relevant to the theoretical arguments we advanced.

In our study, we engaged with both domain experts and method experts. 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, which resulted 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).

During the *presage* stage, we 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 two cognitive abilities considered and their perceptual learning style. After completing the tests, in the *process* stage, participants were shown two process models. One model dealt with a government agency's "Advertising specific vacancies" process, and the other with a "Priority placement" process. Appendix A shows the used models. The choice for the two process models was made based on a trade-off between internal and external validity. 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, utilizing more models potentially introduces a result bias. After all, score differences may be 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 increasing external validity. This provided for 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 government agency. This increased the ecological validity of the study whilst 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 comprehension tasks were of substantial difficulty. This can be considered beneficial to generate fluctuations in comprehension performance, 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.*, 2010a; Recker, 2013). Also, both models featured several instances of modularization and branching (Muketha *et al.*, 2010).

After the respondents were shown the two models briefly, they 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 of the free simulation experiment. In the paper-based variant, the facilitator collected the models after five minutes before allowing participants to move on to the next stage. Last, in the *product* stage, the 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 materials consisted of an information cover sheet with consent form and directions, as well as different sections about demographics, cognitive abilities, two process models, learning approaches and model understanding. Appendix A displays the measurement material used (except for the cognitive abilities tests). We briefly describe important material elements in the following.

1. *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 (PDK-1 and PDK-2) 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 (PMK), we used the set of process modeling method knowledge questions used in related studies (Mendling *et al.*, 2012; Recker, 2013). This set quizzes respondents' theoretical knowledge of the process modeling method in use. The questions concern grammatical rules of process model logic, derived from fundamental work in this area (Kiepuszewski *et al.*, 2003), and address control flow criteria such as *reachability* (Verbeek *et al.*, 2007), *deadlocks* (Sadiq and Orlowska, 2000), *liveness* (Kindler and van der Aalst, 1999) and *option to complete* (van der Aalst, 1998).

   To measure self-efficacy beliefs (SE), 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 were collected (e.g., age, nationality, gender).

2. *Cognitive abilities test*

   To measure abstraction ability (AA), 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 (SA), 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. We omit the test material from this paper due to space limitations. The material is available from the Kit Reference Test for Cognitive Factors (Ekstrom *et al.*, 1976) and the Differential Aptitude Test (de Wit and Compaan, 2005).

3. *Learning style test*

   To measure learning style (LS), the sensing versus intuitive learning scale by Felder and Soloman (1997) was used. These authors defined 11 questions, which allow the mapping of 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).

4. *Learning approach test*

   To measure one's learning approach in terms of deep and surface learning motive (DM and SM), and deep and surface learning strategies (DS and SS), 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 selected and revised the questions to fit one-episodic short term learning, as appropriate to our research contextThis way, motives more closely resemble intention, and strategies more closely relate to subsequent behavior.

5. *Comprehension test*

   As dependent variables, we measured the participants' performance in a comprehension test about the domain modeled (comp-D1 and comp-D2), 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 (Burton-Jones and Meso, 2008; Recker and Dreiling, 2011) in that they queried the ability to *retain* different domain information about the process modeled in each of the two cases (Mayer, 2009).

To be able to contrast the predicted effects about the understandability of a domain from a process model on the one hand with the ability to understand the models per se on the other, we measured, as a control variable, the participant's ability to comprehend grammatical process modeling rules as they apply to the process models themselves (comp-M), as used in the literature (Mendling *et al.*, 2012; Recker, 2013). Similar in nature to our measure for prior method knowledge, these comprehension questions quizzed *modularity*, *concurrency, exclusiveness* and *repetition* of the control flow logic present in the process models.

Participants

Overall, 92 individuals participated in our study. The respondents were spread across three groups of modeling practitioners, which we determined based on different levels of domain and method knowledge. The grouping was applied to approximate the different cohorts of business users typically engaging with process models. 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, in line with the broad community of business users that can be expected to interact with process models. 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 scored highly on 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. This group of individuals, therefore, can be considered a proxy for domain experts that take part in process modeling workshops.

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). This group of individuals, therefore, can be considered a proxy for method experts that take part in process modeling workshops.

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.

To ensure that pooling of the data from the three samples was appropriate, we conducted independent samples t-tests between the three groups of participants and relevant independent and dependent variables 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, except for the score differences in prior domain and method knowledge shown in Table 1.

Results

After eliminating three incomplete and one invalid case, 88 usable responses were identified. The results were examined in two steps. We first screened the data for its conformance with the assumptions of our tests, after which we 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 an exploratory factor analysis implemented in SPSS 19.0 (Tabachnick and Fidell, 2001). Several iterations of the factor analysis were conducted to eliminate problematic measurement items and to see whether our item adaptations to the one-episode learning setting was appropriate. It became apparent that some measurement items for surface learning strategy needed to be culled due to bad loading. We retained a three item-measure that appropriately captures a surface strategy to memorize material in the learning task at hand. Item properties are shown in Table 2. Table 3 summarizes scale properties. Appendix A summarizes the final measurements used in our analyses.

Table 2: Item properties

Item	**Mean**	**St. Dev.**	**Loading**
PDK-D1	2.48	1.38	0.92
PDK-D2	2.61	1.37	0.92
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
SS1	2.40	0.88	0.74
SS2	2.84	1.02	0.69
SS3	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 (SE)	7	3.11	0.63	0.83	0.66	0.80
Deep learning motive (DM)	4	3.31	0.76	0.68	0.61	0.75
Surface learning motive (SM)	3	2.76	0.85	0.63	0.65	0.80

Construct	Number of items	Average factor score	St. Dev.	Cronbach's α	ρ_c	AVE
Deep learning strategy (DS)	3	3.73	0.57	0.63	0.66	0.78
Surface learning strategy (SS)	3	2.58	0.72	0.66	0.68	0.81

As can be seen from Table 3, all constructs have Cronbach's α and composite reliability ρc higher than 0.6, which is acceptable given that these scales were developed and used for the first time in a process modeling context. 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 appropriate 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, which indicates discriminating validity.

Appendix B gives the correlation statistics between the average total factor scores of the multi-item measures and all other items, i.e., the single-item scores for previous method knowledge, the two cognitive abilities, the learning style and the three types of comprehension task scores related to the two domains (comp-D1, comp-D2) and the grammatical rules instantiated in the process model (comp-M). It can be seen that several of the considered factors 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. They do correlate with most of the independent factors, however, which suggests that we should include these factors as control variables as visualized in our research model (see Figure 2). We further note that both 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 Appendix B.

Hypothesis Testing

We ran two tests to examine our hypotheses.

First, to examine the data collected on hypotheses H1-H2, H4 and H5, we conducted two hierarchical regression analyses (Tabachnick and Fidell, 2001) as implemented in SPSS Version 19.0, one for each process model. These analyses were carried out to investigate the relationship between the suggested independent factors and domain understanding.

One assumption behind the use of regression analysis is that the variables are normally distributed. Our data screening confirmed that these criteria were met for the measures for abstraction ability and selection ability, the dependent variables comp-D1 and comp-D2, as well as for the control variables prior domain knowledge and prior method knowledge. The principal components analysis for the factors deep learning motive (DM), surface learning motive (SM), deep learning strategy (LS) and surface learning strategy (SS), as well as the control variable self-efficacy (SE) 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 (PDK-1 and PDK-2), prior method knowledge (PMK) and self-efficacy (SE) as control variables. This was done because they correspond to broad, stable traits whose impacts are well established in the model understanding literature. In step two, we entered our scores for the two types of cognitive abilities considered, as dynamic traits of relevance to the model-based task at hand. In step three, we added the scores for learning motive and learning strategy as further dynamic traits. This hierarchical analysis allowed us to test whether each of the dynamic traits considered (cognitive abilities, learning process) added significantly to the model. We completed these steps for both the domain understanding scores for model 1 and model 2.

Table 4 provides descriptive statistics from the analyses. Table 5 and Table 6 provide the details of the two hierarchical regression analyses showing the standardized beta coefficients and significance levels.

Table 4: Hierarchical Regression Analyses: Descriptive Statistics

Variable	**Mean**	**St. Deviation**
Model comprehension model 1 (comp-D1)	2.92	1.15
Model comprehension model 2 (comp-D2)	2.13	1.03
Prior domain knowledge model 1 (PDK-1)	2.48	1.38

Prior domain knowledge model 2 (PDK-2)	2.61	1.37
Prior method knowledge (PMK)	1.74	2.41
Self-efficacy score (SE)	3.11	0.63
Abstraction Ability score (AA)	10.94	4.21
Selection Ability score (SA)	5.35	3.53
Deep Learning Motive (DM)	3.31	0.76
Surface Learning Motive (SM)	2.76	0.85
Deep Learning Strategy score (LS)	3.74	0.57
Surface Learning Strategy score (SS)	2.58	0.72

Table 5: Hierarchical Regression Analysis (dependent variable: Comp-D1)

Term	**1: Controls**	**2: Cognitive Abilities**	**3: Learning Process**	**Collinearity Statistics**	
	St. Beta	**St. Beta**	**St. Beta**	**Tolerance**	**VIF**
PDK-1	0.02	0.13	0.03	0.66	1.52
PMK	0.10	0.03	-0.07	0.69	1.45
SE	0.10	0.07	0.08	0.80	1.25
AA		-0.21	**-0.25***	0.55	1.83
SA		**0.46****	**0.56*****	0.47	2.12
DM			0.01	0.66	1.52
SM			**-0.34****	0.80	1.25
DS			0.18	0.60	1.67
SS			**0.29***	0.74	1.34
F	0.62	**2.40***	**3.04****		
F change	0.62	**4.97****	**3.45****		
R^2 change	0.02	**0.11***	**0.13***		
R^2	0.02	0.13	0.26		

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

Table 6: Hierarchical Regression Analysis (dependent variable: Comp-D2)

Term	**1: Controls**	**2: Cognitive Abilities**	**3: Learning Process**	**Collinearity Statistics**	
	St. Beta	**St. Beta**	**St. Beta**	**Tolerance**	**VIF**
PDK-2	0.05	0.14	0.01	0.63	1.59
PMK	0.11	0.04	-0.06	0.66	1.52

SE	0.10	0.08	0.10	0.82	1.22
AA		**-0.28***	**-0.32***	0.54	1.85
SA		**0.51*****	**0.61*****	0.48	2.08
DM			-0.01	0.66	1.52
SM			**-0.28***	0.79	1.27
DS			0.16	0.59	1.68
SS			**0.32****	0.72	1.38
F	0.70	**3.04***	**3.16****		
F change	0.70	**6.41****	**2.94***		
R^2 change	0.03	**0.13****	**0.11***		
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 5 and Table 6 suggest that multi-collinearity is not an issue in our data.

Perusal of the data in Table 5 and Table 6 leads to the following observations.

First, we note that, after controlling for prior domain knowledge (PDK), prior method knowledge (PMK) and self-efficacy (SE) as stable traits, cognitive abilities (AA and SA) and learning approach (DM, SM, DS, and SS) as dynamic traits significantly aid the explanation of domain understanding in both cases considered. Adding these factors step-by-step increased the R^2 of the regression models to 0.26 (for comp-D1) and 0.27 (for comp-D2), with the changes in R^2 being significant in each step (F change = 4.97 and 3.45, both $p < 0.01$ for model 1; and F change = 6.41, $p < 0.01$ and 2.94, $p < 0.05$ for model 2).

Second, hypotheses H1 and H2 hypothesized different levels of domain understanding depending on selection and abstraction abilities. In the final models in Table 5 and Table 6, we see that abstraction and selection ability indeed were significant predictors of domain understanding ($\beta = 0.56$, $p < 0.001$, and $\beta = -0.25$, $p < 0.05$ for comp-D1, and $\beta = 0.61$, $p < 0.001$, and $\beta = -0.32$, $p < 0.05$ for comp-D2). 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 consistently *negative* effect on the comprehension scores, as per our expectation in hypothesis H2.

Third, hypotheses H4 and H5 speculated a surface learning approach to be a significant predictor of domain understanding. Table 5 and Table 6 show that surface motive and surface strategy indeed were significant predictors in both cases ($\beta = -0.34$, $p < 0.05$, and $\beta = 0.29$, $p < 0.05$ for comp-D1; and $\beta = -0.28$, $p < 0.05$, and $\beta = 0.32$, $p < 0.01$ for comp-D2). However, for the surface learning motive we note a directionality reverse to our initial expectation. In line with our expectations related to H4 and H5, we found that, for both process models, a deep learning approach (motive and strategy) did not emerge as a significant predictor of process model comprehension.

In a second test, we examined the data collected on the learning style of the participants (sensing versus intuitive) to examine hypothesis H3. 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 the 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 understanding scores were used as a dependent factor in the two analyses. Table 7 shows mean values and standard deviations and Table 8 gives the results from the two ANCOVA tests.

Table 7: Means and Standard Deviations for Process Model Comprehension Scores

Independent Factor	**N**	**Comp-D1**		**Comp-D2**	
		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 8: Results from Significance Tests (ANCOVA)

Dependent Factor	**Independent Factor**	**df**	**F**	**P**	**Partial Eta Squared**
Comp-D1	**Learning Style**	**1**	**5.18**	**0.03**	**0.06**
	Prior Domain Knowledge model 1 (PDK-1)	1	0.96	0.33	0.01
	Prior Method Knowledge (PMK)	1	0.02	0.88	0.00
	Self-Efficacy (SE)	1	0.12	0.74	0.00
Comp-D2	**Learning Style**	**1**	**4.30**	**0.04**	**0.05**
	Prior Domain Knowledge model 2 (PDK-2)	1	1.17	0.28	0.01
	Prior Method Knowledge (PMK)	1	0.10	0.75	0.00
	Self-Efficacy (SE)	1	0.09	0.76	0.00

We observe from Table 8 that, as predicted, sensing learners achieved higher domain understanding scores than intuitive learners. The data in Table 8 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, we used the *model comprehension score* (comp-M) that related to understanding the grammatical rules by which the process models were constructed 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 this comprehension score. Our line of thinking here is that comprehension of process modeling rules was previously shown to depend on structural model qualities such as connectivity (Vanderfeesten *et al.*, 2008), complexity (Recker, 2013) or modularity (Reijers *et al.*, 2011).

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 comp-M score. This, in turn, strengthened our confidence in the theoretical propositions advanced.

Discussion

Our empirical study set out to test five hypotheses about the effects of dynamic user characteristics and learning process factors on process model comprehension, using two process models as test cases. Four of our hypotheses received full and strong support from the data. Regarding Hypothesis H4 we found that the data showed a significant but reversely-directed effect of the surface learning motive. Five key findings of our empirical study are worth discussing.

1. Dynamic traits are of relevance to process model comprehension.

   This finding suggests that appropriate organizational interventions within the scope of a modeling workshop can be expected to increase domain understanding. The hierarchical regression analysis shows that when controlling for stable traits (such as prior knowledge), dynamic traits significantly increase the explanatory power of the model.

2. Selection ability has a positive effect on domain understanding, while abstraction ability shows a negative effect.

   These findings highlight an important cognitive aspect when viewing process models. 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.

   These results are of interest in that they confirm that (a) different types of cognitive abilities are relevant to comprehending a process model, and (b) different cognitive abilities have *opposite* influences on comprehension. Our results show that process model comprehension is not merely dependent on people having "better" cognitive abilities, but rather that some of these abilities (such as selection ability) are highly relevant while others (such as abstraction ability) are detrimental. Knowing about these oppositional effects is key to designing organizational interventions that provide appropriate stimuli that both focus and increase positive influences whilst limiting or prohibiting negative influences.

3. A sensing learning style is more suitable to attain domain 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.

4. A surface learning motive has a negative effect on process model comprehension rather than a positive.

   The results, on first sight, appear counter-intuitive. However, by expecting that a surface motive would be conducive to attaining a memorization 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. Clearly, these factors 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 suggest that surface motives do not yield the type of approach of learning that would lead to good process model comprehension. Since surface denote choices towards a learning task (Biggs, 1987), this finding is instrumental to design an environment for model learning that reduces the chances that individuals opt for a surface approach.

5. A memorization strategy is an effective approach for attaining domain understanding.

   our data about the impact of learning strategies suggest that goal-strategy compatibility appears to be more accurate than a goal-motive relation. In line with our predictions, we also found that strategies focusing on deep understanding did not yield positive contributions to developing a domain understanding. These findings further emphasize the importance of *what actually happens* during the process stage towards the development of process model understanding.

Theoretical Implications

Our paper provides evidence that process model comprehension should be regarded 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 comprehension should refrain from taking an exclusively artifact-centric perspective. Instead, the inclusion of factors from the presage and process stages of learning should be considered. Additionally, our work provides further evidence for the conceptualization of attaining process model comprehension as a cognitive process of learning (e.g., Gemino and Wand, 2005; Burton-Jones and Meso, 2008; Recker and Dreiling, 2011). 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. This paper specifically 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 comprehension. In this paper we chose to examine process model comprehension in terms of retention of domain information. Past research suggests that retention is a measure of memorization, different from using knowledge for problem-solving or other transfer tasks (Gemino and Wand, 2005; Burton-Jones and Meso, 2008; Recker and Dreiling, 2011). Future work could extend our work on model comprehension and examine the domain understanding of individuals who use process models to solve problem tasks such as organizational re-design, software specification, certification and others.

Practical Implications

We believe our findings inform a largely neglected aspect of process modeling practice – how to instruct and guide individual business users working with the models. Indeed, identifying appropriate intervention strategies would address one of the top noted issues in current process modeling, viz., defining an appropriate governance of modeling workshops (Indulska *et al.*, 2009). Our focus in this work has been on dynamic traits, that is, characteristics of the model user and the learning process that can be influenced through appropriate stimuli. Therefore, we can derive from the empirical findings a set of strategies to define interventions that maximize the development of domain understanding in process modeling workshops. Specifically, we identify three broad, complementary strategies:

1) *Design appropriate cognitive exercises*. Cognitive abilities have both positive and negative influences on process model comprehension. It is thus instrumental to identify appropriate stimuli to activate (only) the relevant cognitive activities immediately prior to the workshop. Similar stimulus/activation techniques are widespread in creative problem-solving (e.g., Martinsen, 1993), and our findings suggest applying similar techniques in process modeling workshops. Precisely, cognitive selection activities should be stimulated while cognitive abstraction abilities should be prohibited, where possible. This could be achieved, either through appropriate instructive communication ("make sure that you try not to abstract the information in the model") or, potentially more effectively, through relevant warm-up exercises, such as those provided in the Kit of Factor-referenced Cognitive Tests (Ekstrom *et al.*, 1976), or through the design of new stimuli techniques.
2) *Use appropriate instructive communication.* The positive effects of selection ability and a sensing learning style suggest that it is more effective to have people walk through a model step-by-step rather than have them focus more holistically on making sense of the bigger picture. This is a highly actionable item for instructive communication, for instance, in presentations or prefaces. An appropriate instructive communication message could, for example, make use of multimedia techniques that explain how to inspect process models. Multimedia messaging is a highly effective technique promoted in learning contexts (Mayer, 2009). One way to operationalize this technique in process modeling workshops is to have the flow of tokens through process models displayed in an animated and narrated video sequence.
3) *Implement expectation management.* The effects of learning motive and learning strategy emphasize that facilitating understanding is not only a matter of training but also of managing expectations. It thereby re-emphasizes the notion of clearly informing business users on the purpose of a model in order to prevent them from entering the learning process with a lack of composure. Our findings further suggest that the approaches taken by individuals to make sense of a process model warrant 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 business users working with process models can put them to their best possible use.

Conclusions

Process modeling is a popular and relevant use of conceptual modeling for systems analysis and design tasks. We contribute to the related body of knowledge by extending our understanding of individual difference factors and their relevance to process model comprehension. We found that different cognitive abilities, different learning styles and different learning motives and strategies are significantly associated with the level of comprehension of domain information generated from a process model.

Overall, our findings suggest that individual dynamic user characteristics are important elements in such studies, and relevant to the practice of process modeling in general. Our work informs process modeling work and outcomes, and may ultimately lead to a more successful application of process models by identifying actionable items on preparing business users to their use.

References

Agarwal, R., P. De, and A. P. Sinha (1999) "Comprehending Object and Process Models: An Empirical Study", *IEEE Transactions on Software Engineering* (25)4, pp. 541-556

Bandura, A. (1997) *Self-Efficacy: The Exercise of Control*, New York, New York: W. H. Freeman

Bennedsen, J. and M. E. Caspersen (2006) "Abstraction ability as an indicator of success for learning object-oriented programming?", *ACM SIGCSE Bulletin* (38)2, pp. 39-43

Biggs, J. B. (1987) *Student Approaches to Learning and Studying*, Hawthorn, Australia: Australian Council for Educational Research

Biggs, J. B., D. Kember, and D. Y. P. Leung (2001) "The Revised Two-Factor Study Process Questionnaire", *British Journal of Educational Psychology* (71)1, pp. 133-149

Bodart, F., A. Patel, M. Sim, and R. Weber (2001) "Should Optional Properties Be Used in Conceptual Modelling? A Theory and Three Empirical Tests", *Information Systems Research* (12)4, pp. 384-405

Burton-Jones, A. and P. Meso (2008) "The Effects of Decomposition Quality and Multiple Forms of Information on Novices' Understanding of a Domain from a Conceptual Model", *Journal of the Association for Information Systems* (9)12, pp. 784-802

Burton-Jones, A., Y. Wand, and R. Weber (2009) "Guidelines for Empirical Evaluations of Conceptual Modeling Grammars", *Journal of the Association for Information Systems* (10)6, pp. 495-532

Covington, M. V. (2000) "Goal Theory, Motivation, and School Achievement: An Integrative Review", *Annual Review of Psychology* (51), pp. 171-2000

Danesh, A. and N. Kock (2005) "An Experimental Study of Two Process Representation Approaches and their Impact on Perceived Modeling Quality and Redesign Success", *Business Process Management Journal* (11)6, pp. 724-735

Davies, I., P. Green, M. Rosemann, M. Indulska, and S. Gallo (2006) "How do Practitioners Use Conceptual Modeling in Practice?", *Data & Knowledge Engineering* (58)3, pp. 358-380

Day, D. V. and S. B. Silverman (1989) "Personality and Job Performance: Evidence of Incremental Validity", *Personnel Psychology* (42)1, pp. 25-36

de Wit, J. and E. Compaan (2005) *DAT NL A | Differentiële Aanleg Test voor Onderwijs Versie A: Havo/Vwo*, Amsterdam, The Netherlands: Pearson Assessment and Information B. V.

Dean, D. L., J. D. Lee, R. E. Orwig, and D. R. Vogel (2001) "Technological Support for Group Process Modeling", *Journal of Management Information Systems* (11)3, pp. 43-63

Dennis, A. R., G. Hayes, and R. M. Daniels (1999) "Business Process Modeling with Group Support Systems", *Journal of Management Information Systems* (15)4, pp. 115-142

Dumas, M., W. M. P. van der Aalst, and A. H. M. ter Hofstede (2005) *Process Aware Information Systems: Bridging People and Software Through Process Technology*, Hoboken, New Jersey: John Wiley & Sons

Ekstrom, R. B., J. W. French, H. H. Harman, and D. Dermen (1976) *Manual for Kit of Factor-referenced Cognitive Tests*, Princeton, New Jersey: Educational Testing Service

Felder, R. M. and R. Brent (2005) "Understanding Student Differences", *Journal of Engineering Education* (94)1, pp. 57-72

Felder, R. M. and L. K. Silverman (1988) "Learning and Teaching Styles in Engineering Education", *Engineering Education* (78)7, pp. 674-681

Felder, R. M. and B. A. Soloman (1997) "Index of Learning Styles", http://www.ncsu.edu/felder-public/ILSpage.html (current October 14, 2010, 2010)

Felder, R. M. and J. Spurlin (2005) "Applications, Reliability and Validity of the Index of Learning Styles", *International Journal of Engineering Education* (21)1, pp. 103-112

Figl, K., M. Derntl, M. C. Rodriguez, and L. Botturi (2010) "Cognitive Effectiveness of Visual Instructional Design Languages", *Journal of Visual Languages and Computing* (21)6, pp. 259-373

Figl, K., J. Recker, and J. Mendling (2013) "A Study on the Effects of Routing Symbol Design on Process Model Comprehension", *Decision Support Systems* (54)2, pp. 1104-1118

Fromkin, H. L. and S. Streufert (1976) *Laboratory Experimentation*, Chicago, Illinois: Rand McNally College Publishing Company

Gemino, A. and Y. Wand (2003) "Evaluating Modeling Techniques based on Models of Learning", *Communications of the ACM* (46)10, pp. 79-84

Gemino, A. and Y. Wand (2005) "Complexity and Clarity in Conceptual Modeling: Comparison of Mandatory and Optional Properties", *Data & Knowledge Engineering* (55)3, pp. 301-326

Goldberg, L. R. (1990) "An Alternative "Description of Personality": The Big-Five Factor Structure", *Journal of Personality and Social Psychology* (59)6, pp. 1216-1229

Hahn, J. and J. Kim (1999) "Why Are Some Diagrams Easier to Work With? Effects of Diagrammatic Representation on the Cognitive Integration Process of Systems Analysis and Design", *ACM Transactions on Computer-Human Interaction* (6)3, pp. 181-213

Indulska, M., J. Recker, M. Rosemann, and P. Green (2009) “Process Modeling: Current Issues and Future Challenges”, in van Eck, P., J. Gordijn, and R. Wieringa (eds.) *Advanced Information Systems Engineering - CAiSE 2009*, Amsterdam, The Netherlands: Springer, pp. 501-514

Kember, D., J. B. Biggs, and D. Y. P. Leung (2004) "Examining the Multidimensionality of Approaches to Learning through the Development of a Revised Version of the Learning Process Questionnaire", *British Journal of Educational Psychology* (74)2, pp. 261-279

Khatri, V., I. Vessey, V. Ramesh, P. Clay, and P. Sung-Jin (2006) "Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge", *Information Systems Research* (17)1, pp. 81-99

Kiepuszewski, B., A. H. M. ter Hofstede, and W. M. P. van der Aalst (2003) "Fundamentals of Control Flow in Workflows", *Acta Informatica* (39)3, pp. 143-209

Kindler, E. and W. M. P. van der Aalst (1999) "Liveness, Fairness, and Recurrence", *Information Processing Letters* (70)6, pp. 269-274

Kock, N., J. Verville, A. Danesh-Pajou, and D. DeLuca (2009) "Communication Flow Orientation in Business Process Modeling and Its Effect on Redesign Success: Results from a Field Study", *Decision Support Systems* (46)2, pp. 562-575

Lassen, K. B. and W. M. P. van der Aalst (2009) "Complexity Metrics for Workflow Nets ", *Information and Software Technology* (51)3, pp. 610-626

Martinsen, Ø. (1993) "Insight Problems Revisited: The Influence of Cognitive Styles and Experience on Creative Problem Solving", *Creativity Research Journal* (6)4, pp. 435-447

Marton, F. and R. Säljö (1976) "On Qualitative Differences in Learning: 1 - Outcome and Process", *British Journal of Educational Psychology* (46)1, pp. 4-11

Masri, K., D. C. Parker, and A. Gemino (2008) "Using Iconic Graphics in Entity-Relationship Diagrams: The Impact on Understanding", *Journal of Database Management* (19)3, pp. 22-41

Mayer, R. E. (2009) *Multimedia Learning*, 2nd edition, Cambridge, Massachusetts: Cambridge University Press

Mendling, J., H. Reijers, and W. M. P. van der Aalst (2010a) "Seven Process Modeling Guidelines (7PMG)", *Information and Software Technology* (52)2, pp. 127-136

Mendling, J., H. A. Reijers, and J. Recker (2010b) "Activity Labeling in Process Modeling: Empirical Insights and Recommendations", *Information Systems* (35)4, pp. 467-482

Mendling, J., M. Strembeck, and J. Recker (2012) "Factors of Process Model Comprehension — Findings from a Series of Experiments", *Decision Support Systems* (53)1, pp. 195-206

Muketha, G. M., A. A. A. Ghani, M. H. B. Selamat, and R. Atan (2010) "A Survey of Business Process Complexity Metrics", *Information Technology Journal* (9)7, pp. 1336-1344

Parsons, J. and Y. Wand (2008) "Using Cognitive Principles to Guide Classification in Information Systems Modeling", *MIS Quarterly* (32)4, pp. 839-868

Phillips, J. M. and S. M. Gully (1997) "Role of Goal Orientation, Ability, Need for Achievement, and Locus of Control in the Self-efficacy and Goal-setting Process", *Journal of Applied Psychology* (82)5, pp. 792-802

Ramsden, P. (1988) *Improving Learning: New Perspectives*, London, England: Kogan Page

Recker, J. (2013) "Empirical Investigation of the Usefulness of Gateway Constructs in Process Models", *European Journal of Information Systems* (22), pp. forthcoming

Recker, J. and A. Dreiling (2011) "The Effects of Content Presentation Format and User Characteristics on Novice Developers' Understanding of Process Models", *Communications of the Association for Information Systems* (28)6, pp. 65-84

Recker, J., J. Mendling, and C. Hahn (2013) "How Collaborative Technology Supports Cognitive Processes in Collaborative Process Modeling: A Capabilities-Gains-Outcome Model", *Information Systems* (38)8, pp. 1031-1045

Recker, J., M. Rosemann, P. Green, and M. Indulska (2011) "Do Ontological Deficiencies in Modeling Grammars Matter?", *MIS Quarterly* (35)1, pp. 57-79

Recker, J., M. Rosemann, M. Indulska, and P. Green (2009) "Business Process Modeling: A Comparative Analysis", *Journal of the Association for Information Systems* (10)4, pp. 333-363

Reijers, H. A., S. Limam, and W. M. P. van der Aalst (2003) "Product-Based Workflow Design", *Journal of Management Information Systems* (20)1, pp. 229-262

Reijers, H. A. and J. Mendling (2011) "A Study into the Factors that Influence the Understandability of Business Process Models", *IEEE Transactions on Systems Man & Cybernetics, Part A* (41)3, pp. 449-462

Reijers, H. A., J. Mendling, and R. M. Dijkman (2011) "Human and Automatic Modularizations of Process Models to Enhance their Comprehension", *Information Systems* (36)5, pp. 881-897

Sadiq, W. and M. E. Orlowska (2000) "Analyzing Process Models Using Graph Reduction Technique", *Information Systems* (25)2, pp. 117-134

Sheetz, S. D., G. Irwin, D. P. Tegarden, H. J. Nelson, and D. E. Monarchi (1997) "Exploring the Difficulties of Learning Object-Oriented Techniques", *Journal of Management Information Systems* (14)2, pp. 103-131

Tabachnick, B. G. and L. S. Fidell (2001) *Using Multivariate Statistics*, 4th edition, Boston, Massachusetts: Allyn & Bacon

Thatcher, J. B. and P. L. Perrewe (2002) "An Empirical Examination of Individual Traits as Antecedents to Computer Anxiety and Computer Self-Efficacy", *MIS Quarterly* (26)4, pp. 381-396

van der Aalst, W. M. P. (1998) "The Application of Petri Nets to Workflow Management", *The Journal of Circuits, Systems and Computers* (8)1, pp. 21-66

Vanderfeesten, I. T. P., H. A. Reijers, J. Mendling, W. M. P. van der Aalst, and J. Cardoso (2008) "On a Quest for Good Process Models: The Cross-Connectivity Metric", in Bellahsene, Z. and M. Léonard (eds.) *Advanced Information Systems Engineering - CAiSE 2008*, Montpellier, France: Springer, pp. 480-494

Verbeek, H. M. V., W. M. P. van der Aalst, and A. H. M. ter Hofstede (2007) "Verifying Workflows with Cancellation Regions and OR-joins: An Approach Based on Relaxed Soundness and Invariants", *The Computer Journal* (50)3, pp. 294-314

Wang, Y. and V. Chiew (2010) "On the Cognitive Process of Human Problem Solving", *Cognitive Systems Research* (1)81-92

Wang, Y., Y. Wang, S. Patel, and D. Patel (2006) "A Layered Reference Model of the Brain (LRMB)", *IEEE Transactions on Systems, Man and Cybernetics - Part C* (36)2, pp. 124-133

Winn, W. D. (1990) "Encoding and Retrieval of Information in Maps and Diagrams", *IEEE Transactions on Professional Communication* (33)3, pp. 103-107

Winn, W. D. (1993) "An Account of How Readers Search for Information in Diagrams", *Contemporary Educational Psychology* (18)2, pp. 162-185

Zhang, L.-F. (2000) "University Students' Learning Approaches in Three Cultures: An Investigation of Biggs's 3P Model", *The Journal of Psychology: Interdisciplinary and Applied* (134)1, pp. 37-55

Appendix A

Questionnaire material used (final items after factor analysis)

1. **Control Variables**

Self efficacy, adapted from (Phillips and Gully, 1997)

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1 2 3 4 5
1. I feel confident in my ability to perform well on the upcoming assessment.	☐ ☐ ☐ ☐ ☐
2. I am not confident that I will do as well on this assessment as I would like.	☐ ☐ ☐ ☐ ☐
3. I don't feel that I am capable of performing as well on this assessment as others.	☐ ☐ ☐ ☐ ☐
4. I am a fast learner for these types of assessments, in comparison to other people.	☐ ☐ ☐ ☐ ☐
5. I would have to practice for a long time to be able to do well on this assessment.	☐ ☐ ☐ ☐ ☐
6. I think that my performance will be adequate on this assessment.	☐ ☐ ☐ ☐ ☐
7. I am sure that I can learn the techniques required for the next assessment in a short period of time.	☐ ☐ ☐ ☐ ☐
8. On average, other individuals are probably not as capable of doing as well on this assessment as I am.	☐ ☐ ☐ ☐ ☐

Prior Domain knowledge, adapted from (Burton-Jones and Meso, 2008)

Very Low	Low	Average	High	Very High
1	2	3	4	5

	1 2 3 4 5
1. Compared to other staff working in the area of processing vacancies, I would rate my level of knowledge in this area as:	☐ ☐ ☐ ☐ ☐
2. If I were asked a question about priority placements, I would rate the likelihood of my being able to answer this question correctly as:	☐ ☐ ☐ ☐ ☐

Prior Method Knowledge, adapted from (Mendling et al., 2012)

True	False
1	2

	True	False
1. For exclusive choices, exactly one of the alternative branches is activated.	☐	☐
2. Exclusive choices can be used to model a repetition.	☐	☐
3. If two activities are concurrent, then they are executed at the same time.	☐	☐
4. If an activity is modelled to be part of a loop, then it has to be executed at least once.	☐	☐
5. For joining multiple paths out of an OR split, you can use either XOR or AND gateways.	☐	☐
6. An OR gateway activates either one or all outgoing paths.	☐	☐
7. Every task in a process model has to be executed at least once.	☐	☐
8. A process model can have multiple starts and ends.	☐	☐

2. User Abilities

Learning Style, adapted from (Felder and Soloman, 1997)

1. I would rather be considered
    a) realistic
    b) innovative
2. If I were a teacher, I would rather teach a course
    a) that deals with facts and real life situations
    b) that deals with ideas and theories
3. I find it easier
    a) to learn facts
    b) to learn concepts
4. In reading non-fiction, I prefer
    a) something that teaches me new facts or tells me how to do something
    b) something that gives me new ideas to think about
5. I prefer the idea of
    a) certainty
    b) theory
6. I am more likely to be considered
    a) careful about the details of my work
    b) creative about how to do my work
7. When I am reading for enjoyment, I like writers to
    a) clearly say what they mean
    b) say things in creative, interesting ways
8. When I have to perform a task, I prefer to
    a) master one way of doing it
    b) come up with new ways of doing it
9. I consider it higher praise to call someone
    a) sensible
    b) imaginative

10. I prefer courses that emphasize

  a) concrete material (facts, data)

  b) abstract material (concepts, theories)

11. When I am doing long calculations,

  a) I tend to repeat all my steps and check my work carefully

  b) I find checking my work tiresome and have to force myself to do it

Abstraction Ability and Selection Ability

The material is available from (Ekstrom *et al.*, 1976; de Wit and Compaan, 2005) or from the contact author upon request.

3. Approach to Learning

Deep Motive, adapted from (Kember et al., 2004)

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1 2 3 4 5
1. I feel that nearly any topic can be highly interesting once I get into it.	☐ ☐ ☐ ☐ ☐
2. I come to most (refresher) courses with questions in mind that I want answered.	☐ ☐ ☐ ☐ ☐
3. I find I am continually going over my work in my mind at times like when I am on the bus, walking, or lying in bed, and so on.	☐ ☐ ☐ ☐ ☐
4. I like to do enough work on a topic so that I can form my own conclusions before I am satisfied.	☐ ☐ ☐ ☐ ☐

Surface Motive, adapted from (Kember et al., 2004)

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1 2 3 4 5
1. I will be discouraged by a poor result on this assessment and will worry about how I will do in future assessments. 2. Whether I like it or not, I can see that doing well in assessments is a good way to move up the corporate ladder. 3. I desire to get good qualifications in assessments like this because I feel that I will then be able to get a reward later on.	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐

Deep Strategy, adapted from (Kember et al., 2004)

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1 2 3 4 5
1. I will try to relate what I learn in this assessment to what I have learned in other situations.	☐ ☐ ☐ ☐ ☐
2. As I am engaged in the assessment I will try to relate new material to what I already know on that topic.	☐ ☐ ☐ ☐ ☐
3. When I undertake this assessment I will try to understand what the modeller meant with the model.	☐ ☐ ☐ ☐ ☐

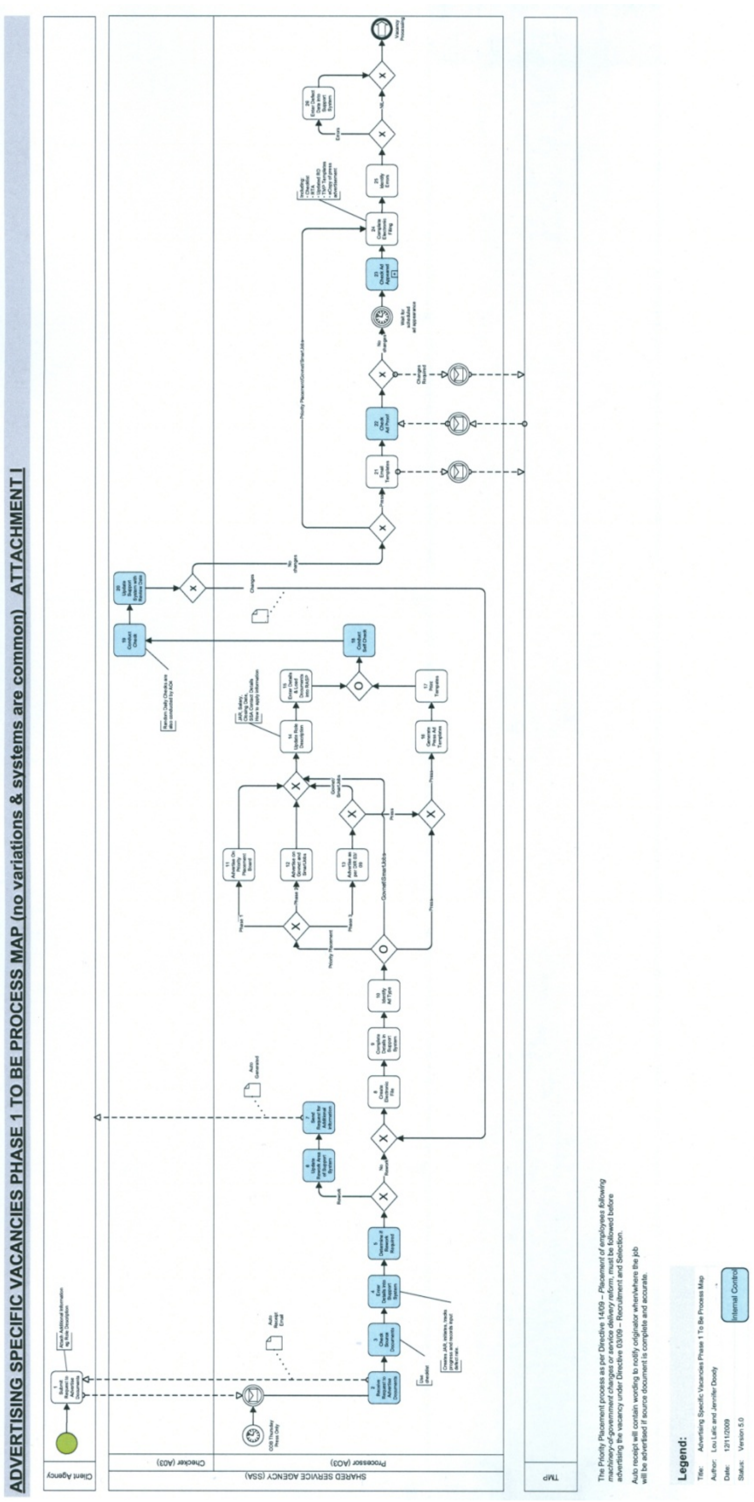
Surface Strategy, adapted from (Kember et al., 2004)

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

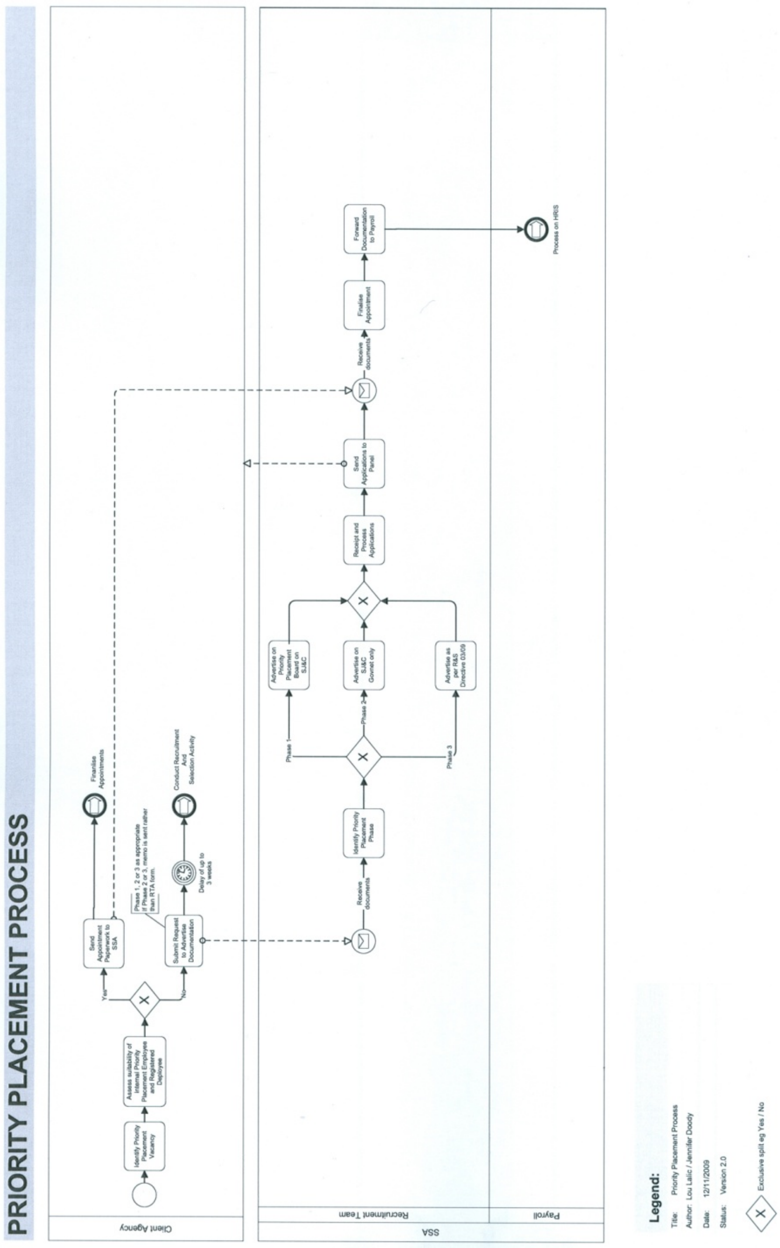
	1 2 3 4 5
1. I will aim to memorise the models by repetition, going over and over them until I know them by heart even if I do not understand them.	☐ ☐ ☐ ☐ ☐
2. I find the best way to pass assessments is to try to remember answers to likely questions.	☐ ☐ ☐ ☐ ☐
3. I find I can get by in most assessments by memorising key sections rather than trying to understand them.	☐ ☐ ☐ ☐ ☐

4. Model Understanding

Advertising Specific Vacancies Process Model



Priority Placement Process Model



Domain Surface Understanding Questions - Advertising Specific Vacancies process [Yes/No]

1. An Agency is required to go through the priority placement process prior to sending government agency documentation to request advertising for a vacancy.
2. The government agency Recruitment Team is responsible for identifying the priority placement phase appropriate for each vacancy in line with the documentation provided by the Agency.
3. The process depicted in the model has only one possible end state.
4. Creating an appointment vacancy within the support system is a responsibility of the government agency Recruitment Team.
5. For every vacancy processed, the identification of the priority placement phase is completed before sending applications to the panel.

Domain Surface Understanding Questions - Priority Placement process [Yes/No]

1. Checking for errors and checking for changes involve the same remedial action when an error or change is identified.
2. An ad could have multiple priority placement phases but must have at least one.
3. The determination of a priority placement phase must be done at the same time as arranging the press placement for each vacancy.

Process Model Comprehension Questions [Yes/No]

1. The process 'Advertising Specific Vacancies' is a part of the 'Priority Placement' process.
   [Modularity]
2. A Processor can 'Conduct a Self Check' at the same time that the Checker is doing the task of 'Conduct Check' but they don't always have to be done at the same time.
   [Concurrency]
3. 'Update Role Description' and 'Enter Details & Load Documents into RASP' are tasks which must be completed for every vacancy that is advertised.
   [Exclusiveness]
4. For every vacancy processed the task 'Complete Details in Support System' is executed only once.
   [Repetition]

Appendix B

Correlation Statistics

	Comp-D1	Comp-D2	Comp-M	PDK-D1	PDK-D2	PMK	SE	AA	SA	LS	DM	SM	DS
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**					
LS	**-0.24**	**-0.22**	-0.10	**0.25**	**0.25**	**-0.26**	-0.17	**-0.23**	**-0.40**				
DM	0.02	0.02	0.00	-0.05	-0.07	**0.25**	0.19	0.05	0.09	-0.14			
SM	-0.21	-0.15	0.05	-0.12	-0.14	0.09	0.09	0.05	0.11	0.12	0.39		
DS	0.05	0.02	0.18	0.02	0.00	**0.22**	**0.36**	0.07	0.00	-0.12	**0.45**	0.17	
SS	0.11	0.15	0.00	0.20	**0.22**	0.05	-0.09	-0.12	-0.19	0.10	0.09	0.16	**-0.25**

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