Towards Understanding the Process of Process Modeling: Theoretical and Empirical Considerations

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Abstract. Empirical studies of business process modeling typically aim at understanding factors that can improve model quality. We identify two limitations of such studies. First, the quality dimensions usually addressed are mainly syntactic and pragmatic, not addressing semantic quality sufficiently. Second, while findings related to model understanding have been anchored in cognitive theories, findings related to model construction have remained mostly unexplained. This paper proposes to study the process of process modeling, based on problem solving theories. Specifically, the work takes the approach that problems are first conceptualized as mental models, to which solution methods are applied. The paper suggests that investigating these two phases can help understand and hence improve semantic and syntactic quality of process models. The paper reports on an empirical study addressing the mental model created during process model development, demonstrating the feasibility of such studies. It then suggests designs for other studies that follow this direction.

Keywords: Process modeling, Problem solving, Empirical study

1 Introduction

The importance of empirical studies in general and experimental studies in particular in the area of business process modeling has been recently acknowledged, giving rise to increasing body of such reported experiments. These experiments promote the understanding of how better support can be given to the human tasks involving the use of process models and increase the quality of the outcomes of these tasks. Following the SEQUAL framework [7], quality dimensions of models include syntactic, semantic, and pragmatic quality. Syntactic and semantic quality relate to model construction, and address the correct use of the modeling language and the extent to which the model truthfully represents the real world behavior it should depict, respectively. Pragmatic quality addresses the extent to which a model supports its usage for purposes such as understanding behavior or developing process aware systems. Considering process models whose purpose is to develop an understanding of real world behavior, pragmatic quality is typically related to the understandability of the model [6].

Following this, experimental studies in the area of conceptual process modeling can be classified as studies addressing model construction, and studies addressing model understanding. The former are intended to improve syntactic and semantic model quality. The latter are intended to increase pragmatic model quality. Empirical investigations of process understanding rely on theories related to the cognitive processes involved in this task (e.g., [12]). The underlying assumption of such studies is that understanding the cognitive processes involved in reading and comprehending a model can lead to models that better support these tasks and hence improve pragmatic quality of process models.

The situation regarding model construction is different. Reviewing empirical investigations of process model construction, this paper indicates two gaps. First, the main quality attribute investigated is syntactic quality. Syntactic quality often refers to formal model correctness in terms of properties such as soundness. Such properties do not address the extent to which the model truthfully represents domain behavior. Clearly, an unsound model is both semantically and syntactically incorrect. However, sound models can still be semantically incorrect, inaccurately depicting the domain they intend to represent. To the best of our knowledge, this issue has hardly been investigated so far. Second, empirical investigations have identified correlations between process models properties such as size and complexity and quality attributes (measured by error probability). However, most of these observations are still unexplained theoretically. In other words, we are aware of certain phenomena and can derive practical conclusions from them (e.g., the seven process modeling guidelines – 7PMG [11]), but we do not understand *why* they exist.

We suggest that deeper understanding of the process of process model creation can be obtained by making a clear distinction between two phases in the modeling process. The first phase is the creation of a mental model of the domain, where observed behavior is conceptualized and abstracted. The second phase involves mapping the mental model to a process model. We suggest that using this two-phase approach in empirical studies of model creation can result in better understanding of difficulties and of opportunities for improving the quality of process models.

In the following, Section 2 reviews empirical studies of process modeling. Section 3 discusses cognitive theories as a basis for empirical studies of process modeling. Section 4 discussed the implications of the theories on empirical studies and describes an empirical study following this approach to demonstrate the feasibility of such studies and their potential benefit. Section 5 concludes the paper.

2 Empirical Studies in Business Process Modeling

Several empirical studies investigated the quality of process models, mainly focusing on syntax and pragmatics. For example, the impact of structural model properties on pragmatic quality has been studied [17, 23]. Significant correlations between control flow complexity (i.e., structural complexity in terms of split and join types) and process understandability and modifiability in BPMN models with different structural characteristics is reported in [19]. Another structural metric, termed cross connectivity, has been found to affect model understanding [26]. These findings have been explained based on cognitive considerations.

A number of studies (e.g., [12][13][22][10]) focused on factors of the modeler and of model representation, including labels, icons, and layout. They found significant connection between these factors and model understandability. These studies, as well as others, used the theory of multimedia learning, originating from cognitive science

[8]. According to this theory, content, content presentation, and user characteristics can influence pragmatic quality [12].

Several empirical studies deal with content representation in terms of modeling languages and their connection to pragmatic quality. For example, [21] compared EPC with Petri Nets, finding that end users considered the EPC approach of using connectors superior to the token game, but the EPC OR-connector has a negative impact on model comprehension. In another experiment, students were trained in EPC and then given either EPC models or BPMN models (a language they were not trained in) [17]. No significant differences were found between the groups in terms of model comprehension (recall questions about basic features of the process model) and problem solving (questions that require solutions to problems based on the process models, but not directly included in them). The authors concluded that the knowledge required for model understanding is of conceptual nature rather than syntactic one.

As opposed to the relative abundance of empirical studies of model understanding, only few have addressed model creation. The main property that has been investigated is error probability, which basically relates to syntactic quality. Findings indicate that certain properties of a model increase the likelihood of syntax and logical errors (e.g., deadlocks, lack of soundness). Some studies [9][14] identified types of error patterns in SAP reference model and linked them to the model size (e.g., number of functions) and to model complexity metrics (e.g., split-join ratio). Note that a trivial explanation to these findings is that as there are more elements in a model, its error probability increases. Yet, some of these findings have been explained using cognitive theories about the process of model construction. For example, the cognitive load theory was used for explaining the increase of error probability with model size, implying that human modelers lose track of interrelations in large models due to their limited cognitive capabilities. This can lead to errors that would be avoided in smaller models [3]. However, no comprehensive cognition-based explanation has addressed the correlation between numbers of splits and joins in a model and its error probability. Pragmatically, guidelines such as the 7PMG [11] exist, following empirical findings to increase model quality (syntactic and pragmatic). However, we are still far from understanding why these practices can promote quality.

A study to understand the creation of a model by novices with no knowledge in modeling languages [18] identified five process design types ranging from purely textual to purely graphical representation forms. The authors evaluated the semantic quality of the models, and found that over a certain level of graphics use, the quality of the models decreases with the increased use of graphics. The “optimal” level was of hybrid designs, featuring appropriate text labels and abstract graphical forms.

Other empirical studies aimed at understanding model creation in the context of model variations. When a modeling language has more than one construct for expressing a certain phenomenon (construct overload), the modeler needs to decide which of these options to use. The result is variations among different models of the same domain. While this is not usually perceived as a model quality problem, it can impose difficulties on model understanding and on specific uses of models. Studies addressing this issue measure the number and types of variations (e.g., [23] with respect to conceptual models, followed by [1] with respect to process models), and use it as a predictor for possible difficulties in the process of modeling.

Summarizing the current state of empirical studies, we found two main gaps. First, the studies focus on syntactic and pragmatic quality, and hardly on semantic quality, namely, the extent to which the model truthfully represents domain behavior. Second, cognition-based explanations are mainly related to how a process model is read and understood, identifying affecting factors such as content (e.g., model size, complexity), content representation (modeling language, labeling) and user characteristics. In contrast, extant studies approach model creation by practical guidelines rather than based on cognitive considerations of process modeling.

3 The process of process modeling

We turn to research in the area of human cognition and problem solving for guidance in gaining better understanding of the cognitive processes involved in model creation. According to [16], when facing a task, the problem solver first formulates a mental representation of the problem, also termed "the problem space", and then uses it for reasoning about the solution. The cognitive fit theory [5][27] adopts on this view, stressing that matching information types along this process support high performance in the problem solving task. In process modeling, the task is to create a model which represents the behavior of a domain. We therefore distinguish two phases in the construction of a process model. First, the modeler forms a mental model[1] of domain behavior. Second, the modeler maps the mental model to modeling constructs. Each of these steps may incur specific difficulties. Thus, to identify problems that arise in process model construction and find how the construction process can be supported, it would be logical to study the two phases separately.

Two characteristics of problem solving, indicated by [16], are of particular interest. First, the shape of the mental model is affected by the characteristics of the task and the methods for achieving it. Hence, the concepts available to the modeler for reasoning about the domain may affect the mental modeling process even before an actual mapping to constructs is performed. Second, the process of forming mental models and applying methods for achieving the task is not done in one step applied to the entire problem. Rather, due to the limited capacity of short term memory, the problem is broken down to pieces that are addressed sequentially, chunk by chunk.

Consider now the formation of a mental model of the process behavior. This requires gaining an understanding of the domain and its behavior, conceptualizing and abstracting this behavior so it can then be mapped to modeling constructs. Different types of domain information may require different levels of effort. For example, an actor performing a task is a concrete part of the domain, easy to recognize and conceptualize in terms which are possible to include in a process model. An activity is also observable and easy to identify as such, but there might be different ways of scoping it and different granularity levels by which it can be addressed. Routing decisions, on the other hand, are not directly observable. Rather, they abstract different possible occurrences of the process (this is why they are considered decisions). Hence, conceptualizing routing decisions might require a higher cognitive effort than conceptualizing actors or activities. In terms of the cognitive fit theory, the fit between domain concepts and modeling concepts for actors and activities is better

[1] Note, we use the terms mental model and mental representation interchangeably

than for routing decisions. To illustrate, consider the commonly used token semantics of process modeling languages. When the intended model is based on token semantics, the modeler needs to conceptualize domain behavior in terms of tokens. However, tokens are abstractions rather than observable phenomena. They do not have a good fit with domain concepts. Hence, additional effort might be needed.

Consider now the phase of mapping the mental representation into modeling constructs. This task follows conceptualization and is of a more technical nature. This is where the expressiveness of modeling languages and modeling practices may play a role. For example, construct overload may impose a difficulty in deciding whether to represent an organizational unit as a pool or as a lane in BPMN. In contrast, token semantics, which, as mentioned, may impose difficulties in conceptualization, can make the mapping itself easy to achieve. As well, as discussed, the problem is usually not addressed at once in its full scope. Rather, it is broken down to chunks that are addressed sequentially, so the process model is gradually constructed. Modeling practices such as constructing well-structured or block-structured processes may support the formation of "natural" problem chunks, easier to map to a process model.

It follows that a variety of research questions can guide empirical studies that may promote the understanding of process modeling and help improve the quality of the resulting models. In particular, mental model formation is related to the semantic quality of process models because imprecision and incompleteness of mental representations will be carried through the mapping phase. In comparison, the actual mapping to modeling constructs is mainly associated with syntactic quality (incorrect mapping may however also result in reduced semantic quality).

Given the different impacts of conceptualization and mapping, we are faced with the challenge of how to differentiate these impacts in empirical studies. One possible way is through think-aloud exercises with protocol analysis to distinguish the two phases. However, such techniques are mostly appropriate in exploratory studies and are less suitable when seeking quantitative results and hypotheses testing. We now describe an empirical approach that can isolate the effects of conceptualization.

4 Empirical Research Directions

This section discusses possible directions for empirical research that may emerge when considering the two phases of model construction separately. We start by describing an empirical study which has already been performed following this line of research, as an example demonstrating how such studies can be performed. In particular, we provide an in-depth discussion of the considerations that drove the experimental design. We then suggest how these ideas can be generalized and suggest other research questions about model construction and principles for designing empirical studies to address such questions.

4.1 Empirical study addressing mental models

Focus and hypotheses: The focus of the empirical study described here is on the mental model formed before the actual creation of a process model. Two assumptions underlie the study. First, for the resulting process model to represent domain behavior completely and accurately (namely, to be of high semantic quality) the mental model must reflect this behavior faithfully. Second, the faithfulness of the mental model to the actual behavior will be affected by the reasoning "tools" used by the modeler.

The first assumption implies that the quality of the mental model can be measured in terms of domain understanding gained while developing a process model. In studies of conceptual modeling, domain understanding has been measured by comprehension and problem solving questions [4]. Since the purpose is to measure domain understanding prior to model creation, this approach requires testing understanding of domain behavior *independent of the model*. The empirical task can be performed before or after a process model has been constructed, but must be done after subjects have engaged in cognitive processing activities related to domain behavior in a process. Considerations as to when evaluation of the mental model should take place are discussed later with respect to our specific study and on a general level.

Our study focuses on situations modeled as split and merge structures in process models. Empirical studies reviewed in Section 2 (e.g., [15]) have indicated that these situations are associated with high error probability in the resulting models. While this phenomenon has been observed and corroborated, its roots have not been explained theoretically so far. Following the above two assumptions, we suggest that (a) this high error probability is related to difficulties in forming a complete and accurate mental model of branching situations, and (b) the outcome of modeling can be improved by supporting the reasoning process with appropriate "thinking tools".

Cognitive fit theory [5] [27] indicates that a good fit between concepts used in problem domain description and concepts used for problem solving can improve problem solving performance. For split and merge structures, the concepts modelers typically use to reason about behavior are driven by the commonly used modeling language constructs (mainly AND, OR, XOR). We posit, however, that node types available in process modeling languages do not match the full range of actual behaviors which should be represented by branching nodes. It follows that a poor fit exists between problem domain phenomena and problem solving concepts.

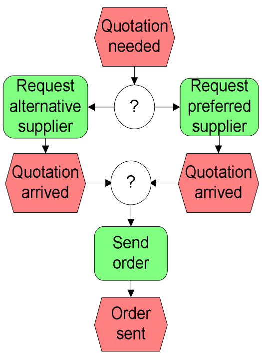
Based on this, we hypothesize that a set of concepts which better represent real world behavior at split and merge situations would better support the creation of the mental model. Such a set of concepts has been theoretically developed [25] based on ideas presented in [24]. It has resulted in a catalog of split and merge behaviors, which includes four split types and eight merge behaviors for binary nodes (two branches). In comparison to the Workflow patterns collection [20], which is the most comprehensive set of behaviors available so far, the catalog includes split and merge types which are not recognized there.

We propose that the catalog can help analysts conceptualize branching situations by classifying them in terms similar to human perceptions of domain behavior. Classifying a situation, an analyst can infer additional information about it and possibly ask additional questions to better understand it.

Method: The catalog was evaluated in an experiment that measured domain understanding. The treatment group received the catalog, and the control group a comparable list of split and merge cases taken from the workflow patterns collection [20]. The study focused on the mental model created while developing a process model. Since the purpose was to compare the "sets of tools" used (the catalog and the workflow patterns list) independent of any modeling language, we tested domain understanding without asking subjects to create a process model.

A main challenge faced when designing the experiment was to design a task that would enable assessing the quality of the mental model while ensuring that it relies on the "set of tools" given. To address this challenge, we designed a task focusing on understanding the situations without actually modeling them. In particular, we tested the success in classifying control flow situations and the understanding developed following this classification. Understanding was evaluated by asking subjects to make inferences about the situations, not directly answerable from the material.
The task comprised two types of assignment that had to be done in sequence for five short cases (an example case is given in Fig. 1).

(a) Diagram:



(b)Case description : In a purchasing department ,buyers always seek quotations from a preferred supplier and from an alternative supplier for an additional and possibly better quotation .If the preferred supplier's quotation arrives first – the buyer proceeds to send an order ;the additional quotation from the alternative supplier is saved for future use .If the first quotation to arrive is from the alternative supplier – the buyer waits for the preferred supplier's quotation before deciding from whom to order.

(c) Understanding questions (*answers in italic*):
For each of the following sentences, indicate "true" if it is possible based on the above case description, "false" otherwise, and provide a brief explanation.

1. The preferred supplier's quotation arrived yesterday but no supplier is selected yet.
   False. If the preferred supplier's quotation arrives, the buyer sends an order.
2. The preferred supplier's quotation arrived, so an additional inquiry (alternative supplier) is not needed and is not made.
   False. Both quotations are always asked.
3. If there are two quotations, two orders are made.
   False. One supplier is selected.
4. The order was sent even though one of the quotations has not arrived yet.
   True. If the quotation from the preferred supplier arrived first.
5. It might be that the worse quotation (higher price) is accepted.
   True. If the preferred supplier's quotation arrives first.

(d) Split Rule: Parallel split
Merge Rule: If preferred supplier's quotation arrives first – Structured discriminator
If alternative supplier's quotation arrives first – Synchronization

Fig. 1: An example case including: (a) Diagram, (b) Case description, (c) Understanding questions and expected answers (in italics), (d) Logical rules as can be specified using the workflow patterns list

Each case included a textual description (Fig. 1(b)) and an EPC-like diagram, where the logical connectors were left blank (Fig. 1(a)). The EPC representation was chosen since the subjects were familiar with this notation, but it could be replaced by any other graphical notation.

The first part of the task (sub-task "Rule") required the subjects to assign the correct logical rule to each connector using one of two methods: (1) identifying the specific case (from the catalog or from the workflow patterns list, for the treatment and control groups respectively), or (2) providing a logical expression specifying the behavior of the process at the specific node in a process model fragment (for example, see Fig. 1(d)). The Rule task, done first, "forced" subjects to engage with the details of the case and with the concepts of the list they were given, and to actually use these concepts in the mental model they were forming.

The second part of the task performed for each case (sub-task "Understanding") was intended to evaluate the understanding the subjects had gained while forming the mental model. It included five "true/false" questions relating to possible process behavior (when enacted). For example, see Fig. 1(c). The subjects were also required to explain their answers. While the Rules task used the catalog or the workflow patterns list as a classification scheme for the situation at hand, the Understanding task could be viewed as reflecting inferences based on the classification. The task materials were designed to include some cases which were directly available as entries in both the catalog and the workflow patterns list (termed the “WF direct set”), and some cases which were only directly available in the catalog (termed “non WF direct set”). When not directly available in a given list, the cases could be described by combining up to three entries in a logical rule.

The experiment was conducted with 54 senior IS students in a course on Enterprise Resource Planning (ERP) systems and business process design. The students were randomly assigned to the treatment group or to the control group. Each group received one hour of training on the catalog (treatment group) or workflow patterns list (the control group). To avoid any effect of differences of training materials (except differences in contents), an effort was made to maximize the equivalence and appearance of the workflow pattern list and the catalog as provided to the subjects. The task was performed immediately after training. A printout of the training materials was handed to the subjects so they could use it as a reference list when performing the task. No time limit was placed for the assignments. To increase the motivation of the students, a bonus of up to 10 points in the lab component (30% of the course grade) was promised to the students, based on their performance.

The dependent variables were performance scores on the Rules and on the Understanding tasks. These were graded based on a defined grading scheme. Since the non WF direct cases did not have directly matching entries in the workflow patterns list, we expected the performance of the treatment group to be better than the control group in the non WF direct cases. We did not expect differences in the WF direct ones. Accordingly, we formulated two sets of hypotheses, considering the two sub-tasks and the two sets of cases.

Findings: The findings, reported in detail in [25], supported our hypotheses. Considering the non WF direct set of cases, the treatment group outperformed the control group with a high level of significance for the Rule assignment (P-value =0.000) and with significance for the Understanding assignment (P-value = 0.017). As expected, no significant performance differences were found for the WF-direct cases, directly available in both lists. These findings are not surprising with respect to the Rule sub-task. Clearly, conceptualizing a situation is easier when a matching concept is available in a given list than when an appropriate rule combining several concepts needs to be logically defined. However, considering the Understanding sub-task, the findings indicate that the quality of the mental model is affected by the set of concepts used. This was not a predictable result, as it indicated the understanding gained of the situations was not the same. This goes against the common belief that process models are constructed based on deep understanding of the behavior to be depicted. This understanding directly affects the semantic quality of the resulting process model. Our findings indicate that domain understanding cannot be taken for granted. Furthermore, the study shows that understanding can be improved when using an appropriate set of “thinking tools” or concepts. These indications are obtained despite the small scale of the study, which is its main limitation. In addition, the results provide an explanation for the difficulties found in other works with respect to correctly modeling routing situations. The concepts “borrowed” from modeling languages might not support conceptualization well enough.

4. 2 Designing empirical studies to separately address modeling phases

The empirical study described above demonstrates how studies to test understanding of domain behavior can be designed and the non-trivial results that can be obtained, leading to improved model quality. We now generalize these ideas by outlining possible research questions about mental model formation (independent of the process model), and suggesting experimental designs to address them.

Empirical evaluations related to model construction have so far focused on the properties of a developed process model to form dependent variables. This approach does not allow separating the two phases – domain conceptualization and model construction. Hence, the effect of modeling languages, domain knowledge, model size and model complexity, cannot be attributed to a specific phase. However, as shown, such differentiation can provide useful (and even unexpected) results. Evaluating each phase separately gives rise to a variety of research questions that can be studied by experiments, whose possible variables and measurement points are now discussed.

Independent variables: various factors may affect the mental model, its mapping to a process model, or both. These include modeling languages, conceptualization tools (e.g., tokens, catalog), problem characteristics (e.g., process size and complexity), modeling practices, and modeler’s experience.

Dependent variables: the mental model can be evaluated by the level of domain understanding the modeler gains. Domain understanding, as a dependent variable, can be measured as performance in answering questions about the domain, either before or after the actual process model is constructed. Given an accurate and complete mental model, mapping to modeling constructs may still yield errors. These errors might be of two origins [2]. First, they may be syntactic, suggesting syntactic quality as a second type of dependent variable, which can be evaluated by itself or with respect to domain understanding. Second, expressiveness deficiencies of modeling grammars might affect semantic quality. Finally, dependent variables might relate to the process of modeling rather than the outcome (the model). In particular, the effort required for mapping the mental model to a process model (e.g. measured by time required) might depend on various factors. This indicates a third type of dependent variable.

Point of measurement: domain understanding can be evaluated prior to or after model construction. If the manipulation is related to the modeling language or practice, evaluation should be done after model construction. Since the phases of modeling may apply separately to chunks of the process, the full effect of the treatment can only be measured after a model has been constructed, but should reflect domain understanding. If the manipulation is not related to modeling language or process, domain understanding may be evaluated before model construction.

Examples of research questions that can be asked together with basic features of possible experimental designs are summarized in Table 1. The table presents for each research question possible independent and dependent variables, and specifies when the dependent variable should be measured.

Table 1. Possible experimental studies

Research question	**Independent variable**	**Dependent variable**	**Point of measurement**	**Comments**
How to support mental model creation	Conceptualizing tools (tokens, catalog)	Domain understanding	Prior to model construction	Measure deep understanding by problem solving questions not directly answerable from the materials, related to the domain.
	Modeling language	Domain understanding	After model construction	
How is the mental model affected by process size and complexity	Process size and complexity	Domain understanding	Prior to model construction	Relates to the domain behavior – requires suitable process metrics
Do modeling practices (e.g., well structuredness) affect the mental model	Modeling practices	Domain understanding	After model construction	Task should be related to domain understanding
Is poor syntactic quality attributed to problems of conceptualization or of mapping		Correlation of domain understanding and syntactic model quality	After model construction	Test correlation between variables (use “difficult” – error prone processes)
Conceptualization effect on the mapping	Conceptualizing tools (tokens, catalog)	Domain understanding	Prior to model construction	Evaluate syntactic quality with respect to domain understanding and the modeling time. Evaluate model correctness (e.g. by subject matter expert)
		Modeling time	During model construction	
		Model correctness	After model construction	
		Syntactic quality		

5 Conclusion

Empirical studies of process modeling are aimed at gaining an understanding that can guide the development of higher quality models. However, the quality dimensions usually addressed are mainly syntactic and pragmatic, while semantic quality has not been addressed sufficiently. In addition, while empirical findings related to model understanding have been anchored in cognitive theories, findings related to model construction have remained mostly unexplained.

In this paper, we propose based on cognitive theories of problem solving, to view the process of process modeling as comprising two phases ***conceptualization*** (creation of a mental model), and ***mapping*** of the mental model to process modeling constructs. We suggest that empirical investigations separating these phases can lead to a better understanding of process modeling rather than relying on the final model created. Furthermore, we claim that improving the quality of the mental model formed is a key to achieving semantic quality, since a mental model reflecting flawed domain understanding will result in a semantically flawed process model.

To demonstrate how such research can be done, the paper described an experiment to test process domain understanding. The results of the study showed the feasibility of such studies and their potential benefits. We discussed the considerations that drove the experimental design of the reported study, in particular, the operationalization of evaluating the mental model separately from a process model. These considerations were then generalized to other experimental designs that can be used for addressing various research questions that emerge from the two-phase view.

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