Cognitive Aspects of Structured Process Modeling

(Position Paper)

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Abstract. After visualizing data of various observational experiments on the way in which modelers construct process models, a promising process modeling style (i.e., structured process modeling) was discovered that is expected to cause process model quality to increase. A modeler constructs process models in a structured way if she/he is working on a limited amount of parts of the model simultaneously. This paper describes two cognitive theories that can explain this causal relation. Cognitive Load Theory (CLT) suggests that the amount of errors increases when the limited capacity of our working memory is overloaded. Cognitive Fit Theory (CFT) states that performance is improved when task material representation matches with the task to be executed. Three hypotheses are formulated and the experimental set-up to evaluate these hypotheses is described.

Keywords: business process modeling, process of process modeling, structured process modeling.

1 Introduction

Between 2009 and 2012 several observational experiments were performed to study different characteristics of how subjects create process models (e.g., [1–9]). The focus was on relating properties of the *process of process modeling* to specific characteristics of, for example, a case description [6], the modeler [7], and the modeling result (i.e., the constructed process model) [4]. Therefore, every activity on the modeling canvas was recorded (e.g., create_activity, create_edge, move_activity, etc.) [1]. We were granted access to the data of these experiments to be able to study them in detail with the use of process mining techniques.

We developed a way to visualize in a more accessible way the raw, uninterpreted data of single process modeling instances: The PPMChart [2] displays the recorded data of the modeling process for one modeling session (see Fig. 1). Each process model element that existed during the modeling process is represented by a horizontal time line. These lines are vertically sorted according to the order a liquid would reach the elements of the process model if it is converted into a flow network. On every line, the operations on the element it represents are displayed as colored dots that are

X. Franch and P. Soffer (Eds.): CAiSE 2013 Workshops, LNBIP 148, pp. 168–173, 2013.

placed according to the time of their occurrence. The color of the dot represents the operation on the element (e.g., create_activity in bright green, create_edge in blue-green, create_gateway in dark green, etc.)

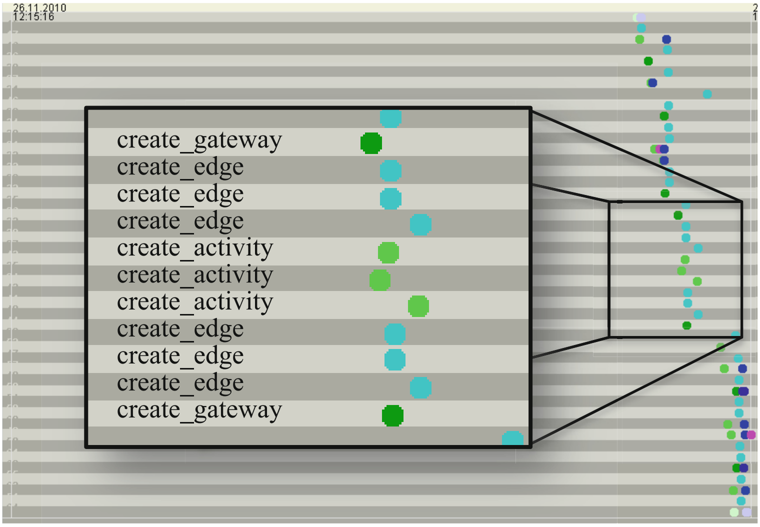

Fig. 1. Example of a PPMChart

Next, to be able to graphically discover reoccurring patterns, various PPMCharts were compared [2]. Each chart was supplemented with the quality measurement of the resulting process model (i.e., mainly soundness [10]). Three conjectures were formulated about the relation of specific properties of the modeling process to the quality of the resulting process model [4]. One of these conjectures involves the concept of structured process modeling. We call a modeling session highly structured if the modeler is working on a limited amount of process model blocks at the same time [4]. A process model block is defined as the collection of elements in two or more optional or parallel paths in the process model: i.e., a split construct, a matching join construct and all according nodes and edges of different paths between both routing constructs (see for example highlighted part of Fig. 1) [4]. The more process model blocks that are simultaneously under construction, the lower the degree of structuredness of the modeling process.

In every dataset we studied, we discovered a highly significant non trivial relation between the degree of structured process modeling and the quality of the resulting process model [4]. Therefore, we will try (i) to explain why a structured process modeling style could lead to high process model quality, and (ii) to prove that a structured process modeling style causes higher process model quality. We refer to [4] for an overview of the metrics we use for the degree of structured process modeling and process model quality.

2 Theory

In order to be able to explain why a structured process modeling style could lead to a higher quality of the resulting process model, in this section cognitive aspects of the processing capabilities of the human brain are addressed.

According to [11] people have three types of memory: sensory memory, working memory, and long-term memory (see Fig. 2). People's observations are firstly stored in the sensory memory for a very short period after which a selection of the information is automatically and unconsciously redirected to the working memory [12]. Next, the information is complemented with existing information from the long-term memory which results in the storage of newly formed long-term information (i.e., transfer) and/or directly leads to specific performances (i.e., reflexes) [13]. For the construction of a process model, the information about observations concerning the process to be modeled is recollected in the working memory (i.e., organization) and combined with other useful knowledge from the long-term memory (i.e., retrieval). Examples of useful knowledge in the long-term memory are domain knowledge, knowledge about modeling, about the modeling language, etc.

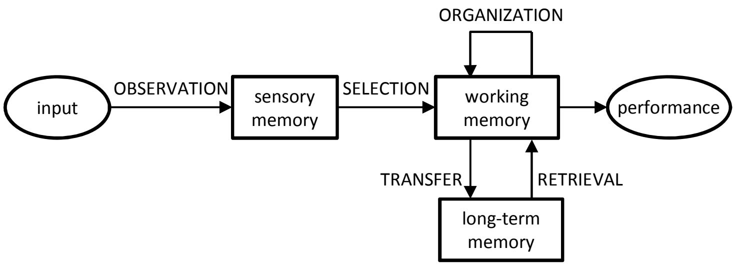

Fig. 2. Sensory memory, working memory and long-term memory

The working memory has a limited capacity of seven plus or minus two 'chunks' of information [14]. The amount of information stored in one chunk depends on the expertise of the subject on the specific task. Our long-term memory is structured in schemas that consist of connected pieces of information. People considered experts at a certain task, generally store more information (larger schemas) and have more efficient access to this information (well-structured and well-connected schemas) [15]. Therefore, they can store more information in a single chunk of working memory (one schema of an expert provides access to more information than a novice's schema). Thus, everybody's working memory has about the same capacity, but differences are related to how efficiently people use the limited working memory.

The efficiency with which our working memory is used is determined by the cognitive load of performing a task [15]. Three types of cognitive load exist: (i) intrinsic cognitive load (i.e., the amount of information needed to perform the task, depending on the task), (ii) extraneous cognitive load (i.e., the amount of information needed to interpret the input, depending on the representation of the task data), and

(iii) germane cognitive load (i.e., the remaining amount of information the subject needs to load in the working memory for performing the task, mainly depending on the expertise of the subject) [13]. CLT suggests that when people encounter a shortage of working memory they tend to make mistakes [15].

For a particular task and a particular task material representation, only the germane cognitive load influences people's performance in the execution of the task. Moreover, as discussed before, experts occupy less working memory than novices to cover this germane cognitive load. However, it is not practical to only focus on the expertise of a subject in task performance to increase her/his effectiveness and efficiency, because training a novice to become an expert takes time. Hence, a technique that reduces the necessary amount of information to be stored *at the same time* in the working memory, is an appropriate candidate to improve a human's effectiveness and efficiency to perform a certain task.

Structured process modeling is a technique that encourages modelers to work on few elements of the process model *at the same time*. Therefore, we argue that less working memory capacity is needed to model in this way than when working on several parts of the model simultaneously. This explains why structured process modeling can cause process model quality increase. Requiring less working memory capacity reduces the chance of making errors [15] and leaves more space for other activities (e.g., lay-out), which, in turn, causes quality improvement [16].

There is another cognitive theory that influences the result of a modeling task. The Cognitive Fit Theory states that when the task material *representation* fits with the *task* to be executed, people tend to be more effective and more efficient in executing the task [17]. For example, a table representation of data is argued to fit better for solving questions that ask about facts, and a graph representation fits better for questions about insightful information derived from the data [18].

Previous research indicates that a breadth-first ordering, according to the process model to be constructed, of the descriptions of activities is related to a higher model correctness than a depth-first or random ordering [6]. Note that the structured process modeling technique is similar to a breadth-first modeling approach (i.e., first finish parallel paths (breadth) before working on the consecutive parts (depth). Therefore, we suspect that a breadth-first ordering of the task description, in combination with a modeling style akin to breadth-first modeling (i.e., structured process modeling), provides the benefits of cognitive fit, and would thus consolidate the effect of structured process modeling on process model quality.

3 Hypotheses

The discussed observations (in Section 1) and theories (in Section 2) inspired us to formulate next three hypotheses:

- H1: Structured process modeling relates to process model quality improvement.
- H2: The quality improvement will be higher for novices than for experts (expertise in the case domain, in modeling, and/or in the modeling language).
- H3: The quality improvement will be higher if the task representation fits with the technique (i.e., a breadth-first ordering of the task description).

4 Research Method

In order to be able to corroborate the hypotheses, we plan to perform a double-blind, randomized, controlled experiment (see Fig. 3). The targeted subjects are a group of 150 master students that take a Business Process Management course. The students will be randomly appointed to a treatment and a control group. The treatment group (T) will be instructed to model using the structured process modeling style. The control group (C) will have a fake treatment (half of them get no instructions, half of them learn a technique that can be considered as depth-first modeling). In each group (T and C) an equal amount of participants will receive a breadth-first sorted, a depth-first sorted, and a randomly sorted task description.

The session will start with a short tool tutorial and a pre-test case to determine initial degree of structured process modeling (ST1, SC1) and process model quality (QT1, QC1). Next, the instructions of the treatment and fake treatment will be given. Finally, the experiment case has to be solved by the participants and the altered degree of structured process modeling (ST2, SC2) and process model quality (QT2, QC2) will be measured. We can check if the treatment had effect through the comparison of the degree of structured process modeling before and after treatment.

The hypotheses can be evaluated using the process model quality measurements in different subgroups before and after the treatment. To investigate H1, the results of T and C should be compared (75 students each). H2 can only be studied if there are enough domain experts for the particular cases among the students or by comparing to results from new experiments with more experienced subjects. For H3, the students from T with a breadth-first ordered text (25 students) can be compared to the other students in T (50 students), and with the part from C that has received a depth-first ordered text and the depth-first modeling instructions (13 students).

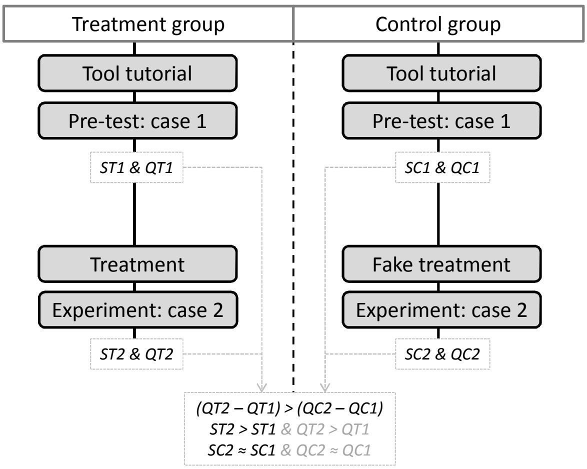

Fig. 3. Experiment set-up (S: structuredness, Q: quality, T: treatment group, C: control group) Fake treatment: depth-first modeling in one session (Ca), extra exercise in other session (Cb)

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