The Influence of Cognitive Abilities and Cognitive Load on Business Process Models and Their Creation

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Abstract While factors impacting process model comprehension are relatively well understood by now, little is know about process model creation and factors impacting process model quality. This paper proposes a research model to investigate the influence of cognitive abilities and a continuous psycho-physiological measure of task imposed cognitive load of process model designers on process model quality. The proposed research will not only contribute a better understanding of process model creation, but bears significant potential for improving existing modeling notations as well as for developing process modeling environments.

Keywords Cognitive load · Working memory · Executive functions · Reasoning ability · Business process modeling

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1 Introduction

According to Burton-Jones and Meso [1] conceptual models are used by practitioners for analyzing business domains and for an easier development of information systems. Relevant information regarding the business domain, such as states, events, tasks and business rules are illustrated in various graphical and textual notations as business process models [2]. These process models often play a crucial role in re-designing business domains and in organizational analysis [3], and due to the wide range of problems displayed by industrial process models [4, 5] an in depth understanding of factors influencing process model quality is in demand. Past research has shown that complex process models tend to contain more errors [4], whereas modeling expertise [6, 7], process knowledge [7], activity labeling [8], routing symbol design [9], notational deficiencies [10], and *cognitive abilities*, learning style and learning strategy [11] provide measurable impact on process model comprehension. Moreover, it has been demonstrated that characteristics of the modeling task are influencing process model quality [12]. While factors determining process model comprehension are relatively well understood by now, only a few studies focused on process model creation (e.g., [4, 13, 14]).

The creation of process models is characterized as design activity [15, 16] and imposes a variety of challenges which include the construction of a mental model of the domain as well as the externalization of the mental model by mapping the mental model to the modeling elements provided by the modeling notation using a modeling tool [17]. The cognitive demands imposed on the process model designer (designer for short) herby depend on task-specific factors like the task's inherent complexity, the modeling notation, and the modeling tool support. These demands are commonly described as *cognitive load* (CL) [18, 19]. In addition, the crucial role of *cognitive abilities* for process model quality is stressed, e.g., [10, 15, 20]. To gain deeper insights regarding the creation of process models cognitive abilities as well as the occurring CL should be considered (e.g., [10, 20]).

Our research will be a similar approach as [10], but shift the focus from process model comprehension to process model creation. This work will provide a better understanding of factors impacting process model quality by integrating task-specific factors through continuous CL measurement and human factors in form of cognitive abilities into a single study. In the remainder of this paper we will provide theoretical backgrounds and introduce the research model including research questions.

2 Theoretical Background

Following [15, 16], and in line with [14] we interpret process model creation as a cognitive *design activity* within the field of problem solving [13]. As pointed out previously, our research will focus the cognitive abilities of designers and the influence of task imposed CL on process model quality. As stressed by [20] cognitive abilities such as *reasoning ability* (RA), *working memory* (WM) and *executive functions* (EF) are crucial for creating process models of high quality, and for design activities, and problem solving in general [13]. In addition to the cognitive abilities the designer's CL plays a key role for problem solving and design activities [21–23].

To assess the interaction of those cognitive abilities and task specific factors within a long-running design activity, we are going to use psychophysiological measures of CL.WM, RA, and EF therefore are our independent constructs, and the quality of process models stands as dependent construct. CL takes a special role in our research, because of the possibility to utilize CL either as independent construct or as dependent construct, as pointed out in the following section.

CL, mental effort, mental load, and mental workload are widely used as aliases, basically describing the same concept [18]. According to [19], CL characterizes the demands of tasks imposed on the limited information processing capacity of the brain in the same way that physical workload characterizes the energy demands upon muscles. CL therefore represents an individual measure considering the individual amount of available resources and task-specific factors imposing CL. As independent construct, CL predicts performance for task execution, since high CL leads to poor task-performance and to wrong decisions, e.g., [21–23]. CL, on the other hand, is influenced by cognitive abilities. As pointed out by [21], RA reduces load on WM by utilizing former knowledge and experience by linking strategies to goals and both, WM and RA are guided by EF as they regulate thought and action, e.g., [20, 21, 24]. This leads to CL as dependent construct. During process model creation the designer will face a variety of task-specific challenges like the construction of a mental model of the domain and the externalization of the mental into a process model. This requires the usage of different modeling elements (e.g., gateways, activities, edges) and chunks of these modeling elements, e.g., when creating loops. While existing studies on process model comprehension typically assess cognitive load once after task completion [10, 25], this is not sufficient for accurately assessing the cognitive demands implied by a (long-running) design activity. However, applying a continuous measurement of CL with high temporal resolution such as pupillometry and heart rate variability [21], additionally to the post hoc assessment by a widely used questionnaire (i.e., NASA-TLX [26]), allows to investigate CL regarding both, process model quality and task specific factors. For this, the measurements of CL either can be aggregated for the entire task with the overall quality in scope, or for task specific factors of interest.

RA refers to the process of drawing conclusions or inferences from different information. This always requires going beyond the information that is given and, thus, is closely related to other domains of human intelligence [24]. The reasoning process within process modeling can be described as combining given environmental input about a domain with previously made experiences or knowledge with the objective of externalizing a model representing the actual domain [20]. Previous knowledge and experience within a domain therefore enhances the reasoning process and helps to link strategies to goals freeing WM resources for problem solving tasks [27–29]. To assess RA, psychometric tests like, e.g., the raven's progressive matrices [30] will be utilized.

The cognitive system of WM provides temporary maintenance of relevant information required for task performance [31, 32]. Because of its limitation to about four items [32] WM is a central predictor for inter-individual differences in complex cognitive tasks, e.g., [33–35] including process model creation [13]. Therefore, WM is mostly defined as a construct consisting of a set of cognitive processes, with at least two distinguishable components, namely *holding and processing* and *relational integration* [36, 37]. Holding and processing quantifies the ability to hold limited amounts of information (e.g. letters, symbols) outside the focus of attention, while other information (e.g. calculations, sentences) is processed simultaneously. Relational integration measures the ability of building new relations between elements such as single dots into a pattern [38]. The central role of WM in process modeling is well known [20, 25, 39–41], but most often only theoretically implemented. Only a single study empirically tested the role of WM for process model creation [13] and one study focused on related concepts in the context of process model comprehension, e.g., [11]. Our assessment of WM will be in line with [13].

EF, seen as the cognitive control processes that regulate thought and action, are represented by multiple correlated but separable functions [42, 43]. From the perspective of cognitive psychology, executive functions regulate lower level cognitive processes and therefore shape complex performance. In general, EF play a key role for complex cognitive activities [21, 42, 44], in a variety of work-related tasks, e.g., [21, 45, 46], and EF are essential for designing process models [20]. The three most frequently investigated components are *response inhibition* (inhibition), *updating working memory representations* (updating), and *set shifting* (shifting) [42]. Inhibition therefore, is seen as the ability to inhibit dominant, automatic responses. Updating, on the other hand describes the ability to appropriately update incoming information of relevance for the task at hand by replacing old, now irrelevant information with newer, relevant information. Shifting describes the ability to flexibly switch back and forth between tasks or different mental sets. For instance, [20], -in line with [47]-, stresses the importance of EF for the process of creating process models in terms of attentional control, goal maintenance and suppression of distracting information, error monitoring, and effortful memory search. Our psychometric assessment of EF will go in line with [42, 48].

Process model quality is used as dependent construct for our research. In line with [49], we are going to consider *syntactic errors* (e.g., violations of the soundness property) and *semantic errors* as quality measures of the process model. Semantic errors are referring to the validity of the model (i.e., statements within the model are correct and related to the domain) and completeness (i.e., all relevant and correct statements to solve a problem are contained by the model). We will utilize existing automated techniques, e.g., [50] to quantify syntactic errors. For assessing semantic quality, due to the absence of a fully automated approach [17], we will apply a semi-automated approach. In addition, expert assessments in form of an iterative consensus building process [14] will be carried out for measuring semantic quality.

3 Research Approach

In line with the theoretical background discussed above, we argue that the quality of process models strongly depends on the cognitive abilities (working memory, executive functions, reasoning ability) of the designer, as well as on the interaction of those cognitive abilities and task-specific factors resulting in CL (Fig. 1).

As pointed out by [20], cognitive abilities such as *reasoning ability*, *working memory,* and *executive functions* are crucial for designing process models of high quality, and for design activities, and problem solving in general [13]. According to the research model we state our first research question:

Q 1: Designer's cognitive abilities, namely working memory, executive functions, and reasoning ability positively predict process model quality.

Cognitive load is described as demands on the cognitive system imposed by a task and depends on the available cognitive resources [21]. Subjects with higher working memory capacity executing the same task show lower cognitive load [21]. Reasoning ability, in turn, helps to link strategies to goals freeing resources of working memory [27–29], thus, leading to reduced cognitive load. Further, executive functions are seen as cognitive control processes regulating thought and action [21], which ensure task focus, and therefore, reduce cognitive load. According to our research model we state our second and third research question as follows:

Q 2: Higher cognitive load during task execution leads to lower process model quality.

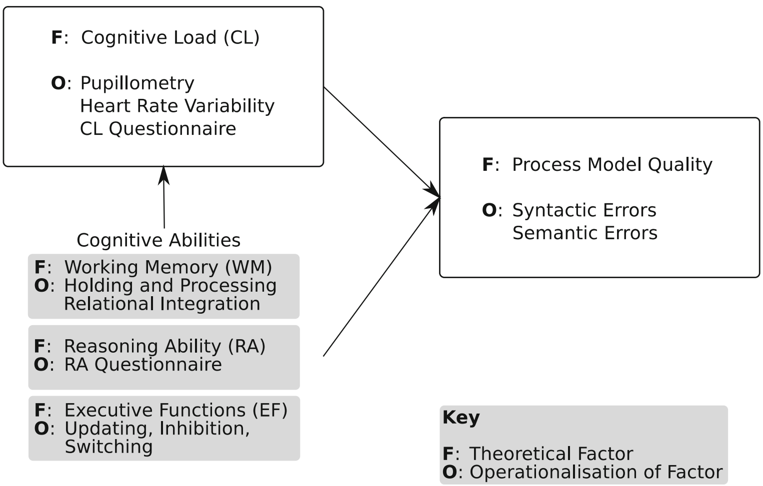

Fig. 1 Research Model

Q 3: Within subjects executing the same modeling task, higher individual capabilities regarding working memory, executive functions and reasoning ability lead to lower cognitive load.

While subjects execute modeling tasks containing a variety of different task-specific factors cognitive load is imposed on the designer's cognitive system, e.g., [21]. Depending on the level of demands imposed by a specific part of the modeling task (e.g., building of a mental model) different amounts of cognitive load should be apparent. This leads to our fourth research question:

Q 4: Which task-specific factors within the process of designing process models are most demanding?

Currently, we are finishing the planning-phase of our research and within the next months we will carry out data collection. We are going to assess the constructs described above on 80 subjects without previous modeling experience to control the influence of former process modeling knowledge. This research is going to shed some light on the cognitive requirements for creating process models and how cognitive abilities, namely working memory, executive functions, and reasoning ability and the resulting cognitive load imposed by the interaction of those cognitive abilities and the modeling process itself affect the creation of process models and the achieved process model quality. Moreover, by applying continuous measurements of cognitive load, the identification of the most demanding factors within the process of creating process models should be possible, giving advice to the improvement of modeling notations and associated tool support.

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