Measuring Cognitive Load During Process Model Creation

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Abstract While factors impacting process model comprehension are relatively well understood by now, little is known about process model creation and factors impacting the quality of the resulting process model as well as the modeler's cognitive load. In this paper we propose to combine a continuous, psycho-physiological measurement of cognitive load with a detailed analysis of the modeler's interactions of the modeling environment as well as eye movement analysis to obtain task-specific imposed cognitive load values. We present initial results in terms of a tool, lessons learnt from a pilot study and discuss upcoming challenges. This work provides the basis for investigating task imposed cognitive load during process model creation by enabling a dynamic, semi–automatic analysis of cognitive load.

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1 Introduction

Nowadays, business process modeling is heavily used in various business contexts. For instance, process models help to obtain a common understanding of a company's business processes [1], facilitate inter-organizational business processes [2], and support the development of information systems [3]. Still, process models in industrial process model collections often display a wide range of quality problems [4], calling for a deeper investigation of process model quality.

Previous research activities resulted in a good understanding on factors impacting process model comprehension. For instance, notational deficiencies [5], modeling expertise [6], and process knowledge [7] have shown to provide measurable impact on the understandability of a process model. Additionally, [8] pointed out that cognitive abilities, learning style, and learning strategy provide significant impact on process model comprehension. Factors influencing process model quality in the context of process model creation, in turn, are understood to a smaller extent (e.g., [9–11]) and therefore require more attention.

Existing research on process model quality typically measures process model comprehension in terms of accuracy (the number of correct answers about models, e.g., [5, 12, 13]) and answering speed [5, 12]. In addition, [5, 13] consider cognitive load as an additional quality dimension, being measured through self– assessment. While this type of operationalization is suitable in the context of process model comprehension, it is not sufficient for studies on the creation of process models, where the cognitive demands cannot be controlled. Particularly, cognitive demands change during a modeling task considerably: For example, a model's inherent complexity (e.g., the model's size or control flow) changes during model creation whenever model elements are added or deleted.

To systematically investigate the impact of different factors on cognitive load in the context of process model creation, we propose the usage of continuous measurement of cognitive load. In particular, we aim toward a high temporal resolution by implementing psycho-physiological measurements, i.e., pupillometry. We propose to use this data for calculating task-specific cognitive load values (e.g., cognitive load for activity creation versus gateway creation). We propose a solution that uses the user interactions with the modeling environment for mapping concrete measurements in a semi-automated way to specific factors. The dynamic calculation of task-specific load values will enable data analyses that otherwise were unfeasible due to lack of experimental control. In this paper we sketch the approach, present an initial version of the developed tool, and describe initial insights of a pilot study including lessons learnt and upcoming challenges. This way, we hope to gain valuable feedback and inspiration from the research community for our next steps.

The paper is structured as follows. Section 2 illustrates our approach. Section 3 presents initial results including the tool, lessons learnt, and challenges. Section 4 concludes the paper.

2 Continuously Measuring Task-Imposed Cognitive Load

This section sketches our approach toward task-specific measurement of cognitive load: Sect. 2.1 elaborates on continuously measuring cognitive load, whereas Sect. 2.2 details on calculating task-specific cognitive load.

2.1 Continuous Cognitive Load Measurement

In general, mental effort, cognitive load, mental load, and mental workload are often used as aliases, basically describing the same concept [14]. Cognitive load characterizes the demands of tasks imposed on the limited information processing capacity of the brain and constitutes an *individual measure* considering the individual amount of available resources [15]. While cognitive load for model comprehension tasks can be assessed easily using questionnaires [16], investigating task-imposed cognitive demands during process model creation requires more fine-grained measurements. For this, we consider continuous, psychophysiologically measurements of cognitive load, such as ocular–motoric data, pupil diameter, blink rate or heart rate variability [17]. In this work, we focus on the usage of pupil diameter as provided by table-mounted eye trackers for investigating cognitive load (an increase of the pupils' diameter is generally associated with a higher cognitive load). To enable the calculation of task-specific load values, we suggest to integrate the measurement of cognitive load, user interactions, and eye movement parameters as detailed in the next section.

2.2 Dynamic Calculation of Task Specific Cognitive Load Values

To calculate task-specific cognitive load, cognitive load measurements must be associated to a task-specific factor of interest (e.g., cognitive load associated with the creation of different types of model element). We suggest a semi-automatic approach for establishing these associations and calculating task-specific cognitive load (e.g., the average cognitive load for creating activities versus creating gateways). In particular, we suggest the usage of model interactions and eye fixations as vehicle for determining which parts of a modeling process are related to a particular aspect of process modeling. To be more specific, we assume the presence of a log of model interactions (also denoted as PPM instance) that consists of a list of events (i.e., user interactions like add activity A, add edge between start event and activity A, add gateway XOR1) with associated timeframes. Process modeling environments like Cheetah Experimental Platform (CEP) provide for such logs [18]. The log of user interactions can then, for example, be used to determine in which timeframes the modeler was working on activity creation versus gateway creation. In addition, we assume the presence of a log of fixations, comprising for each fixation additional information like timestamp and screen position. Eye fixations could be used, for example, to determine during which timeframes a user was focusing his attention on activities versus gateways. By combining model interactions and eye movement data in a single platform like CEP, we can reconstruct the model for any point in time and connect model elements with the area on the screen the subject was focusing his attention on at this particular point in time. More importantly, we obtain the data not only as part of video recordings (as in some existing software packages for eye movement analysis), but as structured data suitable for a *semi-automated* analysis.

The log of user interactions and the log of eye fixations can be filtered based on event types that are in the analysis' focus, e.g., events of type add activity or add gateway. To assess cognitive load, timeframes are required, e.g., to calculate the average cognitive load involved in activity creation versus gateway creation. This might be done by using a sliding window with a predefined duration, which can be placed on any point in time within the PPM instance. Figure 1 illustrates how the calculation of one specific sliding window might look like.

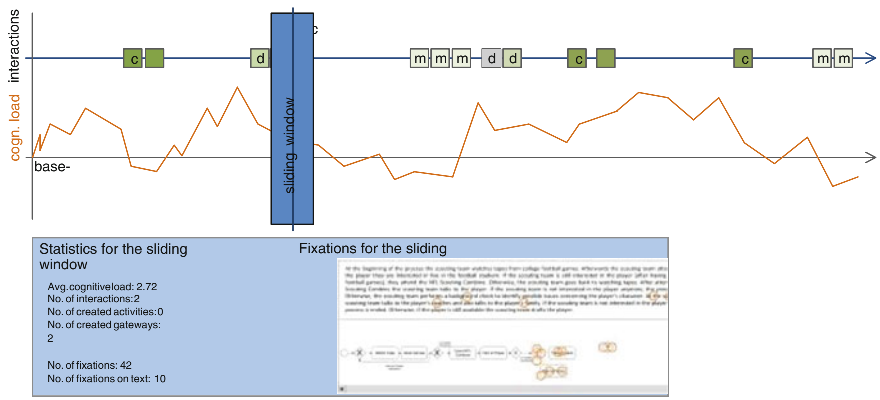

Fig. 1 Integrated PPM view

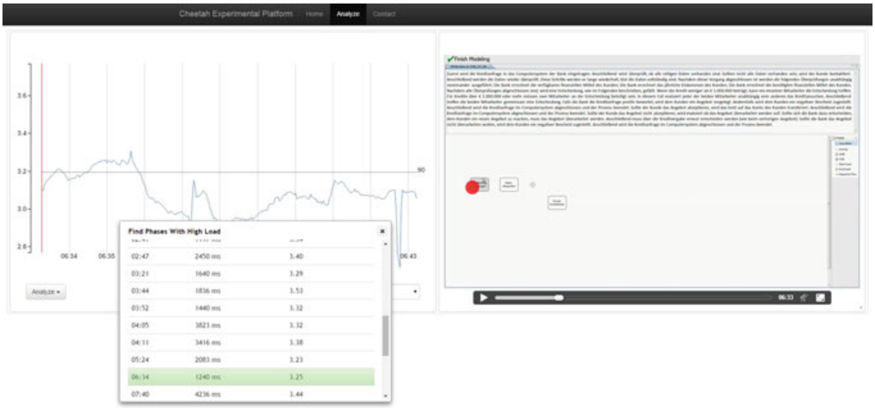

Fig. 2 CEP with cognitive load analysis

3 Initial Results

For testing the reliability of continuous cognitive load measurements, we conducted a pilot study with three participants, i.e., two PhD students and one master student working in business process management. Each participant created a process model consisting of 19 activities, containing the basic control flow patterns: sequence, parallel split, synchronization, exclusive choice, simple merge, and structured loop [19]. As a modeling environment CEP was used, recording all model interactions. A Tobii TX300 eye tracker with 300 Hz sampling rate was used to measure pupil dilation as well as fixations.

As a first step toward the calculation of task-specific cognitive load, we implemented a web application that juxtaposes cognitive load, exported from the eye tracker, with the video recording of the eye tracker. This video recording also shows the modeler's eye fixations (cf. Fig. 2).[1] Further, the user interface allows to search for phases of increased cognitive load. For this, the minimum duration of the respective phase can be set, i.e., only phases with an increased cognitive load longer than the threshold are listed.

We used the web application to explore the data focusing on timeframes with increased cognitive load. For one modeler we observed phases of increased cognitive load whenever this modeler had to name activities of the process model. Similar observations were not made when creating other types of nodes, e.g., XOR gateways. It seems that extracting information from the text (indicated by fixations on the textual description) and abstracting from the text to name the activity was challenging to this specific modeler. For a different modeler, we observed phases of increased cognitive load when correcting previously created parts of the model.

[1] Available from: http://bpm.q-e.at/continuousMeasurement.

For example, this modeler had to include a jump to a previous part of the model, forcing the modeler to move some elements. This was accompanied by increased cognitive load. Further, toward the end, the modeler seemed to validate the process model. During this, the modeler changed some parts of the created model, which was accompanied by increased cognitive load. Even though we feel reinforced in pursuing this direction by the initial results, several aspects need to be considered. With respect to these, we hope for useful comments of the research community via this publication. Most importantly, we need to perform a systematic data cleaning. For instance, similar to [20], we intend to remove data fragments caused by blinks, e.g., by removing outliers larger than three times the standard deviation. Further, the creation of a process model involves motoric actions, e.g., mouse movements and typing, which might cause pupil dilation [21]. This should be considered when performing the data cleaning. Still, we are confident to obtain useful cognitive load measurements for specific timeframes of a PPM instances, since [22] successfully applied the analysis of cognitive load in a Driving Simulator—a task requiring at least the same amount of motoric actions as process modeling. Similarly, when typing, subjects might look at the keyboard, e.g., to find the appropriate finger position. Looking away from the screen and back might cause pupil reactions due to changed light conditions (dark keyboard; bright screen). Therefore, we consider complementing the analysis of pupil dilation with heart rate variability (HRV) analysis [17] to accommodate for potentials shortcomings.

Another challenge we faced during the pilot related to baseline measurement, which we performed for conducting inter–subject comparisons. The naive assumption to ask subjects to “do nothing” incurred increased cognitive load. Therefore, we intend to utilize a dynamic baseline calculation, either immediately prior to the timeframe of interest (cf. [23]), or by averaging cognitive load for the entire duration of the modeling task (cf. [22]).

4 Summary and Outlook

This paper proposes an approach for calculating task-specific cognitive load by integrating continuous cognitive load measurements with user interactions and eye fixations. This way, paving the way for cognitive load measurement in the context of process model creation. More detailed insights into aspects of process modeling contributing to a high cognitive load might be used for giving advice to developers of new modeling notations and tool. The proposed research not only bears significant potential for process modeling research, but might be extended toward conceptual modeling as well as the design of user interfaces in general.

As for future work, we plan to work on the remaining challenges for the continuous measurement of cognitive load before addressing the calculation of task-specific cognitive load. With respect to the raised challenges, we hope to obtain valuable feedback and inspiration from the research community via this publication.

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