On the Relationship Between Semantic Transparency and Cognitive Load: Does Context Matter In Process Models?

Amine Abbad-Andaloussi[1], Dung My Thi Trinh[2], Barbara Weber[1], and Hugo A. López[2]

[1] University of St Gallen, St Gallen, Switzerland
{amine.abbad-andaloussi, barbara.weber}@unisg.ch
[2] Technical University of Denmark, Kongens Lyngby, Denmark,
s204468@student.dtu.dk, hulo@dtu.dk

Abstract. Declarative process models offer flexibility in representing complex processes, but can be difficult to understand due to their implicit control flow. Improving their representation, particularly by investigating and enhancing their semantic transparency, can help address this challenge. This paper proposes an empirical research model to examine how varying levels of semantic transparency, encoded in different visual notations of declarative models, affect users' cognitive load and visual behavior in the presence and absence of contextual information. The findings will lead to a better understanding of the effects of semantic transparency and will support the design of understandable declarative models.

Keywords: Declarative Process Models . Semantic Transparency . ContextualInformation . Cognitive Load . Eye-tracking

1 Introduction

Process models enable automation and facilitate the communication between domain experts and IT specialists [1]. These models are typically designed using modeling languages along the imperative-declarative paradigm [2]. Imperative languages define explicit control flow, fitting structured processes with few alternatives, while declarative languages specify constraints, allowing any execution that adheres to them. This flexibility enables a concise representation of complex processes with many execution alternatives, but can reduce understandability due to the implicit control flow in declarative process models [2–4].

Several studies have investigated and attempted to enhance the understandability of declarative process models (e.g., [5–10]), notably through guided simulations to clarify the model behavior [7, 9] and representation enhancements [5, 8, 10–12]. Our research aligns with the latter, by specifically investigating the semantic transparency (i.e., the clarity of a symbol's meaning based on its appearance [13].) of constraints in declarative models, as these constraints are among the most challenging aspects to understand in this type of models [9, 14, 15].

In this paper, we present an empirical research model to investigate how variations in semantic transparency affect users' cognitive load [16, 17] and visual behavior [18] when process models include or omit contextual information allowing the reader to interpret the semantics of the model (i.e., information derived, for instance, from the process model event names [19] or annotations [9, 20]). To the best of our knowledge, the impact of semantic transparency and the role of contextual information on cognitive load and visual behavior have not yet been investigated in the context of declarative process models. To address this gap, we formulate the following research question: "*How does semantic transparency, in the presence or absence of contextual information, affect users' cognitive load and visual behavior when interpreting declarative process models?*".

We focus on Dynamic Condition Response (DCR) Graphs [21] as an instance of declarative modeling languages that have gained traction in both academia and industry [22, 23]. We compare the semantic transparency of three visual notations that have been proposed for DCR Graphs (cf. Fig. 1): the original DCR visual notation proposed by Hildebrandt and Mukkamala [21] ($DCR_{original}$), a DCR UX-driven visual notation proposed by Trinh et al. [12] (DCR_{ux}), and a very recent DCR visual notation proposed by DCR Solutions[3] ($DCR_{solutions}$), a tool vendor specializing in DCR Graphs. The research model presented in this work is designed to guide a future eye-tracking experiment.

Our research aligns with the growing NeuroIS field, which advocates for incorporating neurophysiological approaches to deepen our understanding of the cognitive and behavioral aspects guiding users' interactions with information systems [24,25]. Among these methods, eye-tracking has emerged as a powerful technique for objectively assessing cognitive load and visual behavior in real-time, offering detailed insights into users' mental processing during IS-related tasks [26], such as process model comprehension. Building on this foundation, our research uses eye-tracking measures to examine indicators of cognitive load and visual behavior in the context of understanding declarative process models with different levels of semantic transparency. In doing so, it extends the methodological advancement of NeuroIS to process modeling, where effective comprehension relies heavily on visual representations. Additionally, by responding to the calls for NeuroIS research to generate actionable and socially relevant outcomes [26], our research will offer design-oriented recommendations for enhancing the clarity of visual notations used in process models.

The implications of this research are twofold. First, it advances our understanding of

[3] See https://documentation.dcr.design/introduction-to-business-rulesvalue

how semantic transparency affects cognitive load and whether contextual information can mitigate the impact of low semantic transparency in declarative process models. Second, it provides a research method for empirically evaluating visual notations, which is particularly relevant for modeling languages such as Declare [27] and Entity Relationship (ER) diagrams [28], where various visual notations have been proposed (cf. [27–32]).

The remainder of this paper is structured as follows. Sect. 2 outlines the theoretical background guiding our study, Sect. 3 presents our research method, and Sect. 4 concludes the paper.

2 Theoretical Background and Underpinnings

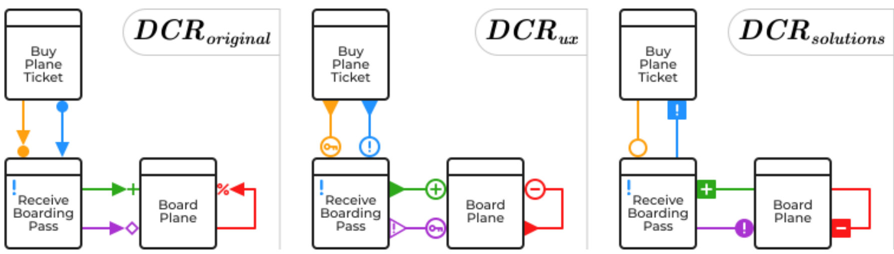

Fig. 1. An example of the same DCR Graph depicting the process of traveling by airplane using the three different visual notations.

The Dynamic Condition Response (DCR) Graphs. A DCR Graph is a directed graph that consists of nodes that represent events (i.e., process activities visualized as rectangles) and edges that represent relations between events (i.e., process constraints). Additionally, events have markings defining their state. For brevity, we refer the reader to [21] for a detailed presentation of the DCR semantics. Fig. 1 depicts three DCR Graphs describing the process of traveling by airplane, where the semantics of the graphs are the same. The difference emerges only from their visual notation, corresponding to the three versions investigated for semantic transparency in our research (cf. Sect. 1).

The DCR Graph visualized with DCR*original* in Fig. 1 shows a *condition relation* (→•) between the two events "Buy Plane Ticket" and "Receive Boarding Pass". It indicates that before "Receive Boarding Pass" can be executed (done), "Buy Plane Ticket" must be done at least once in the past. Additionally, between the two events is also a *response relation* (•→). This relation indicates that after "Buy Plane Ticket" is done, "Receive Boarding Pass" becomes required (i.e. pending) and needs to be done before the process can finish. Between the two events “Receive Boarding Pass” and “Board Plane” is a *milestone relation* (→◊). This relation indicates that: While “Receive Boarding Pass” is required to be done (i.e. pending) “Board Plane” is blocked from being done; i.e., “Board Plane” cannot be done while “Receive Boarding Pass” is pending; it can only be done after “Receive Boarding Pass” has been done. The “Board Plane” event has an *exclude relation* (→%) to itself which means that: When “Board Plane” is done, it is removed from the process, implying that you cannot “Board Plane” again. If you wish to be able to “Board Plane” again, you must reintroduce it to the process by performing “Receive Boarding Pass” again, which is done with the *include relation* (→+). This relation indicates that when “Receive Boarding Pass” is done, “Board Plane” is added (back) into the process. DCR*original* was used in this example. However, by mapping the colors and placements of DCR relations across the other DCR visual notations, the same semantics apply.

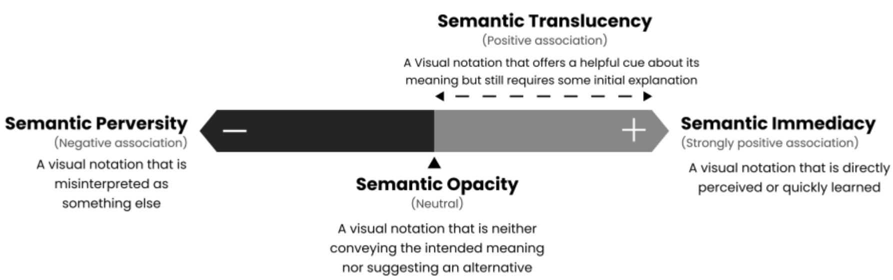

Fig. 2. The semantic transparency spectrum, adapted from [12, 13].

Semantic Transparency states that a visual notation should be directly perceived or easily learned [13]. As depicted in Fig. 2, semantic transparency ranges from *semantic immediacy* (i.e., a visual notation that is directly perceived or quickly learned) to *semantic perversity* (i.e., a visual notation that is misinterpreted as something else), with *semantic opacity* in between (i.e., a visual notation that is neither conveying the intended meaning nor suggesting an alternative) [13]. Additionally, situated along the continuum from semantic opacity to semantic immediacy is *semantic translucency* (i.e., a visual notation that offers a helpful cue about its meaning but still requires some initial explanation) [13]. In process modeling, semantic transparency has been studied concerning the clarity of routing symbols [33] and the consistency of routing directions [34] within imperative process models. In this work, we explore semantic transparency in the context of *constraints* within *declarative process models*.

Two studies have analyzed the semantic transparency of DCR graphs. Initially, López and Simon [35] evaluated the cognitive effectiveness of DCR*original* as a whole, using Moody’s Physics of Notations [13]. This study highlighted that some visual elements, such as events and markings could be perceived as semantically immediate, whereas other symbols (e.g., relations) could be perceived as semantically perverse. The work in Trinh et al. [12] studied the strengths and weaknesses associated with the perception of the visualization of $DCR_{original}$, focusing on the representation of relations. It was found that some symbols used to represent relations in this notation may be semantically opaque, such as a neutral circle for condition (→•) and response (•→) relations. In addition, the exclude relation (→%) symbol could be semantically perverse, potentially implying a percentage. Lastly, the conventional arrows could be incorrectly perceived as flows instead of constraints. Based on these findings, a new design (DCR_{ux}) was proposed. This design was guided by two primary objectives to enhance the semantic transparency: (1) ensuring that graphical symbols accurately reflect the semantics of DCR relations (cf. [12] for a more detailed discussion on this relationship), and (2) maintaining the visibility of the direction of DCR relations while avoiding potential misinterpretation of DCR Graphs as imperative process models. These challenges were addressed by using more semantic immediate symbols based on expert interviews and moving the arrowhead to the start of the relations.

The third notational variant selected, $DCR_{solutions}$, is introduced by one vendor commercializing products based on DCR graphs. While the design decisions behind the changes are not publicly available, one could argue that in contrast to $DCR_{original}$, $DCR_{solutions}$ offers more semantically immediate symbols for response (), milestone (), and exclude () relations. However, the removal of intuitive directional indicators might lower its semantic transparency. Here, contextual information could be helpful. For instance, in Fig. 1, common knowledge of the relationship between the events “Buy Plane Ticket” and “Receive Boarding Pass” can aid in inferring the direction and thereby the meaning of the condition and response relations.

Cognitive Load is the mental effort required to process information in working memory [16, 17]. When this load exceeds the available capacity of the memory, one experiences cognitive overload, leading to difficulties in processing and understanding information [16, 17, 36]. Cognitive load is categorized into *intrinsic*, *extraneous*, and *germane* load [16]. In process models, intrinsic load stems from the complexity of the process behavior. Extraneous load arises from the model’s visual representation quality, depending on whether it is poorly designed or well-structured. Germane load emerges from the effort to build mental schemes for understanding the process [16, 37]. Since our study examines semantic transparency related to the model representation, extraneous load is the most relevant component of cognitive load.

Semantically transparent notations are likely to reduce extraneous cognitive load as the underlying symbols act as memory aids, easing comprehension [13]. In contrast, low-transparency notations may require a greater load for interpretation. However, contextual information derived, for example, from the process event names [19] or model annotations [9, 20], may reduce reliance on semantic transparency, by enabling schema activation, i.e., prompting readers to use their existing knowledge structures to integrate and interpret new information [38]. Contextual information is, for instance, used when model readers try to disambiguate ambiguous parts in process models [39]. Likewise, readers may also rely on contextual information when semantic transparency is low to mitigate uncertainty. Hence, contextual information could moderate the effect of semantic transparency on cognitive load.

Cognitive load can be captured with different measures [17]. *Subjective measures* capture perceived difficulty, typically through self-assessment questionnaires [40]. *Performance measures* assess cognitive load through response time and task accuracy [41]. *Physiological measures* track changes in physiological states [42], with the Low/High Index of Pupil Activity (LHIPA) [43] being a key eye-tracking metric used in that regard [37, 44]. *Behavioral measures* analyze changes in user behavior, often via eye-tracking [20, 37, 45–49]. Two key metrics are average fixation duration (average time spent fixating on a stimulus, e.g., a DCR Graph) and saccadic amplitude (eye movement distance between pairs of fixations) [18]. Higher cognitive load correlates with high perceived difficulty, long response times, and low answer accuracy. It is also reflected in low LHIPA, longer fixations, and shorter saccades [37]. The measures outlined in this section will be used to estimate extraneous cognitive load as part of a hypothesis-testing research model aiming at evaluating the impact of varying levels of semantic transparency on this component of cognitive load in the presence and absence of contextual information (cf. Sect. 3).

Visual Behavior. Studying user engagement is essential for understanding behavioral processes linked to semantic transparency and contextual information. Herein, three key analyses are relevant. The *scan-path analysis* [18] examines whether users follow a structured reading order or struggle with interpreting process models with different characteristics. *Attention distribution* [50] identifies which model elements attract the most focus, while *visual associations* [50] reveal how users integrate information across different model elements. These analyses are important to explore the influence of semantic transparency on visual behavior in the presence or absence of contextual information. This exploratory angle will help to extend the confirmatory findings of our hypothesis-testing model focused on the impact of semantic transparency and contextual information on extrenous cognitive load.

Altogether, semantic transparency can mitigate extraneous cognitive load by making the intended meaning of constraints in declarative process models more apparent, thereby reducing interpretative effort and supporting model comprehension. Contextual information can moderate this effect, as readers may rely on event names or model annotations to interpret semantically opaque or perverse symbols. This interplay is likely to shape users' visual behavior leading to the observation of specific scan-path patterns, different attention distribution across process model elements, and visual association patterns, depending on the level of semantic transparency together with the presence and absence of contextual information. This integrative perspective offers a cohesive theoretical grounding for the subsequent research model, illustrating how semantic transparency and contextual information jointly influence users' cognitive load and visual behavior.

3 Research Method

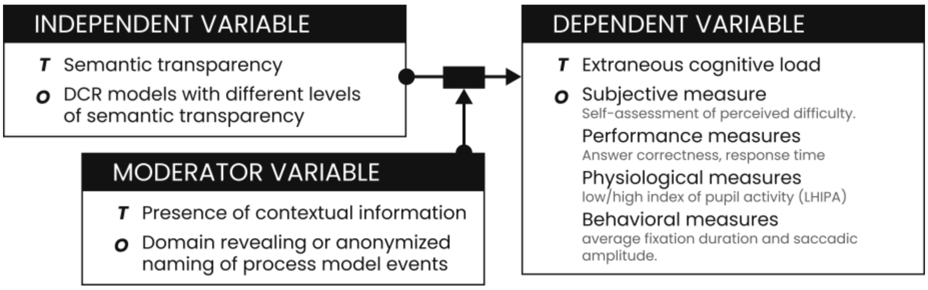

Fig. 3. Research model. T: Theoretical construct; O: its operationalization

Building on the theoretical foundation in Sect. 2, our research investigates the following hypothesis: "*The impact of semantic transparency on cognitive load is moderated by contextual information in process models*." Specifically, we expect semantic transparency to affect cognitive load primarily when contextual information is absent, but less so when it is present. To test this hypothesis, we propose the research model in Fig. 3. Semantic transparency (*independent variable*) will be operationalized using DCR Graphs with three semantic transparency levels (cf. Fig. 1). Extraneous cognitive load (*dependent variable*) will be measured using the metrics presented in Sect. 2. Contextual information (*moderator variable*) will be operationalized through event naming. Some models will include meaningful event names that clarify the process domain and aid control flow interpretation, while others will use anonymized names to avoid domain information.

Our hypothesis-testing research model will be complemented by a qualitative investigation of users' behavior when engaging with DCR Graphs of different semantic transparency levels in the presence and absence of contextual information. Therein, the scan-path analysis [18], attention distribution [50] and visual associations [50] will be used for the purposes outlined in Sect. 2. Moreover, we plan to gather post-experiment verbal insights on participants' preferences regarding the visual notations used.

The material for the experiment will consist of different DCR Graphs with the aforementioned characteristics and a set of comprehension tasks. Eye-tracking data will be collected using Tobii Pro Fusion 250 Hz[4], being a research-grade eye-tracking device providing high data accuracy and precision. Moreover, we plan to extend the data collection software EyeMind [51], currently supporting only imperative process models, to accommodate DCR Graphs and thus allowing us to run our experiment. This extension leverages EyeMind's capability to automatically detect areas of interest [18] (corresponding to process model events and relations in our context) in

[4] See https://connect.tobii.com/s/fusion-get-started?language=en_US

dynamic stimulus presentation (large and interactive process models), which is essential for analyzing users' scan-path, attention distribution and visual associations at a fine-grained level. Moreover, EyeMind offers experiment setup mechanisms and data analysis features designed particularly to accelerate the processing of eye-tracking data collected during process model comprehension experiments [51].

4 Conclusion

This paper introduces a research model to investigate how semantic transparency in declarative process models affects cognitive load and visual behavior in the presence and absence of contextual information.

This research will yield actionable guidelines for both modelers and language designers. On the one hand, modelers will be encouraged to incorporate contextual infor-mation more prominently when working with notations that have limited semantic transparency. On the other hand, language designers will gain a deeper appreciation of why semantic transparency is crucial for clearer, more intuitive notation constructs. Furthermore, our empirical approach provides a replicable blueprint for future eye-tracking studies aimed at investigating different facets of (conceptual) model comprehension . Finally, the results of the experiment will support the creation of more intuitive declarative notations, facilitating their adoption in the community as an alternative to imperative process notations.

As a future work, we are planning to conduct an eye-tracking experiment leveraging this research model to guide our empirical investigation. We also encourage the broader modeling community to extend our work to additional modeling languages and to integrate other neurophysiological measures beyond eye-tracking (e.g., electro-encephalography – EEG) to deepen our collective understanding of how semantic transparency and contextual information interact across diverse modeling contexts.

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