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Animation as a dynamic visualization technique for improving process model comprehension

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ABSTRACT

Process models are widely used for various system analysis and design activities, but it is challenging for stakeholders to understand these complex artifacts. In this work, we focus on the use of dynamic visualization techniques, in particular animation, to help reduce users' cognitive load when making sense of process models. We built on the principles of the cognitive theory of multimedia learning, cognitive load theory, and cognitive dimensions framework to develop an adaptive animation solution. Our experiments suggested that process model comprehension improves when users of process models are provided with animation features; the effect is moderated by process modeling expertise according to a *U*-shape. Our study contributes to the field of conceptual modeling by making a strong case for the use of animation to support complex problem-solving tasks. Moreover, our animation solution offers ample opportunities for being integrated into industrial modeling tools.

1. Introduction

The design of an information system often includes conceptual models as diagrammatic representations of the domain [1]. Conceptual models are used to communicate domain knowledge among diverse information system stakeholders and to establish a common understanding of the system [2]. Business process models, or *process models* for short, are among the most frequently used conceptual models [3]. These process models graphically visualize how organizations perform their business processes [4]. Process models are used in various practices, such as requirements analysis, process improvement, process reengineering, and project management [4,5]. New technologies such as robotic process automation, blockchain, smart services, and Internet-of-Things have further diversified the scenarios where process models are employed [6]. For example, a software developer may design a blockchain-supported process model for execution in a process automation system [7], an analyst could investigate conformance issues by inspecting a process model that is automatically generated by a process mining application [8], or a manager may monitor and predict process performance using a process model [9].

Understanding process models is not a trivial task for any category of process model users because these models are inherently complex [10, 11]. Therefore, many studies have investigated how to help users comprehend process models [12–14]. The methods proposed for this purpose involve visualization techniques that affect the so-called secondary notation, or visual appearance, of a model [15–19]. However, few studies have considered the use of dynamic visualization techniques, specifically animation, to increase the comprehensibility of process models [12,20] or conceptual models in general [2].

Animation is a prevalent multimedia technique used to support the learning of dynamic physical mechanisms [21,22], as well as to provide instruction regarding abstract phenomena, such as computer algorithms [23,24]. Animation provides various mechanisms to help reduce the cognitive load during the learning process, specifically for dynamic phenomena [25]. Motivated by the findings of computer-based learning studies, we consider that the comprehension of process models may be improved by supporting users with animated process models. In particular, the behavioral perspective provided by process models, which represents *the order in which* activities are performed, is crucial information captured about processes [26,27], but it is the hardest part to comprehend [16]. This type of order behavior, which is dynamic in nature, is traditionally conveyed to users of process models via static visualizations of process elements. Static process visualizations are difficult to understand because they require that users infer hidden behavior that is not made explicit in the model [11]. To address these causes of cognitive overload, we investigated the possibility of

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employing animation as a dynamic visualization feature for process models.

In the present study, by building on the principles established by the *cognitive theory of multimedia learning* [28] and *cognitive load theory* [29], we investigated how animation can be used by diverse users to improve the comprehension of process models. There are good reasons to expect benefits from using animation but we also acknowledge (cf. the *cognitive dimensions framework* [30]) that process models are inherently complex artifacts. In addition, even if animation is beneficial, it is important to establish how it affects users with different levels of expertise because there is a lack of consensus regarding this issue in previous studies [12].

To test whether animation has a positive and significant effect on the comprehension of process models, we provided various process model users with a set of problem-solving tasks under experimental conditions. Our results confirmed that animation can be used to provide cognitive support to users with various levels of expertise in process modeling. We also discovered that the impact of animation on the comprehension of process models was moderated by process modeling expertise according to a *U*-shape, where the effect was stronger for users with either low or high expertise compared with users who had moderate expertise. Overall, we conclude that our proposed adaptive animation solution allows users to dynamically balance their cognitive load in the task conducted. These findings are important given that organizations may have hundreds or thousands of process models for various organizational tasks [31,32]. Clearly, users need to comprehend the process models related to their tasks well to make effective use of these models [12].

Our study also contributes to the wider information systems literature regarding the use of animation for the purpose of comprehension. Previous studies often focused on the use of animation for a *simple* task, particularly drawing a user's attention to a *single* piece of information (cf. [33]), mostly in e-commerce settings (e.g., [34]). Our study broadens this perspective by showing how animation can help to support *problem-solving tasks* that involve the analysis of *complex, multi-faceted artifacts*, such as process models in our case.

In Section 2, we discuss the theoretical background of our study. We then develop our central hypotheses in Section 3. We describe our research methodology in Section 4. We present our experimental results In Section 5, and discuss their implications and limitations in Section 6. Finally, we present our conclusions in Section 7.

2. Background

In this section, based on the *cognitive load theory* and *cognitive dimensions framework*, we first establish why it is difficult to comprehend process models (Section 2.1). We then examine whether animation may be helpful for improving the process model comprehension (Section 2.2). Finally, in Section 2.3, we consider theories regarding the helpfulness of animation for users with different levels of expertise.

2.1. Cognitive challenges in process model comprehension

According to cognitive load theory [29], the capacity of human working memory to process novel information is limited. Comprehending material and performing problem-solving tasks based on the knowledge acquired imposes high demands on the cognitive capacity [35]. The central capacity theory applied in information systems studies conducted to examine how users allocate their attentional resources while visiting web pages (e.g., [33,34]) also considers how multiple tasks will compete for limited mental resources during information processing [36]. In particular, intrinsic cognitive load is introduced due to the complexity of the material under study [29]. The cognitive dimensions framework identifies aspects of visual notations that are cognitively relevant when users try to comprehend material [37]. In the following, we identify four dimensions of the cognitive dimensions framework related to the complexity of process modeling notations, which help to explain the challenge of understanding process models.

- The *hidden dependencies* in visual notations may make it difficult to discover relationships among different elements [37]. The notational semantics of process models allow a user to infer when activities are accomplished with respect to each other [38]. The connectors in complex process models make this particularly difficult, especially determining which alternative flows exist throughout a process [11].
- The *abstraction gradient* refers to the capacity of a visual notation to support users in mentally grouping parts of a model as independent entities. Process flow notations can be specifically classified as "abstraction hating" because a mechanism is not available to group process elements [37,39], which makes it difficult to find activities that are related to each other when a model becomes complex.
- The *role expressiveness* is low in process modeling notations because the user needs to study each activity and connector to understand the process flow and make high-level judgments [30].
- *Hard mental operations* are required to understand process models with high complexity [11]. Different types of connectors can be used in various combinations, so the number of possible process flows and thus the complexity of a model increases disproportionately even after adding only a few connectors [38].

In the last decade, many studies have focused on using visualization techniques to overcome difficulties in comprehending process models, as mentioned above. In particular, in order to make hidden dependencies more visible, additional explicit cues in the form of secondary notations have been applied to process models [11,18]. However, it has been observed that there is still much potential for improving the comprehension of process models through the use of dynamic visualizations [12].

2.2. Animation and its relevance to process models

Given the difficulty comprehending process models, our key idea involves applying dynamic approaches to mitigate this challenge. Animation is defined as the act of exposing a user to a series of changing multimedia frames and potentially including user interaction to identify how these frames change [40].

In information systems research, the use of animation has mainly been investigated in the context of websites, particularly e-commerce. Studies have shown that animated ads affect the recall and click-through rates for an advertised product [34]. These studies have provided insights into the mechanism of attention guidance and how cognitive resources are used in the context of animation [33]. However, previous studies used animation for different objectives compared with our study, where they focused on drawing the attention of users to a single piece of information, such as a target product [41], or supporting browsing and searching tasks, particularly when navigating websites [42]. These applications are *retention* tasks, which require the capture and retention of specific superficial information [28]. By contrast, tasks related to the use of process models require a deep understanding of the underlying concepts. Process models facilitate the solving of novel problems by applying acquired knowledge to other situations, which are generally known as *transfer tasks* [35,43]. The cognitive requirements and impacts of visual cues differ considerably between retention and transfer tasks [44]. Process models are particularly complex artifacts [15], and thus transfer tasks that require the extraction and application of knowledge for various purposes are even more challenging, e.g., the complexity of assessing the compliance of a business process, including all the relevant organizational regulations and policies. Thus, in the following, we consider previous research into learning and the use of animation for problem-solving tasks rather than search tasks.

It is recognized that animation has great potential for improving learning during the education of students because it can involve different mechanisms for utilizing the human working memory and engaging users in a cognitive process with respect to static instructions [40,45,46]. In order for a user to correctly understand visual materials, the mode of presentation for the material related to the task should be suitable for the comprehension task [37,47]. In particular, when using animation, certain prerequisites must be satisfied by the material and its related concepts. First, it should be necessary to use visuals or graphics to present the material [40]. This naturally applies to conceptual models because they are abstractions of real-life concepts visualized as symbolic elements in a visual notation [48]. Another prerequisite indicated by the *congruence principle* [49] is that the material should contain concepts that change over time. Thus, the material and its presentation using animation correspond in a natural manner. It has been shown that animation is suitable for presenting procedural knowledge comprising procedures with an order in time, rather than declarative knowledge that involves facts [40,45,50]. Process models, especially those with flow-based notations, include procedural knowledge about activities performed over time. Therefore, we consider that animation may be suitable for representing process models.

Animation has been employed in educational studies that employ multimedia techniques to improve learning. These studies provide useful guidance but transferring their findings to our setting is not straightforward, mostly due to differences between the typical learning materials and process models. Thus, we considered learning cases where the material involves a dynamic concept visualized as a graphical representation. Computer algorithms comprise a domain that can benefit from dynamic visualizations in a comparable manner to process models. In particular, algorithms are usually visualized in the form of nodes and edges, and they represent procedural knowledge with possibly alternating behavior [51]. It has been shown that animation can help to explain the behavior of algorithms and improve learning [50,52]. However, previous studies in this domain: (i) focused only on comparing animation with textual descriptions [53], (ii) did not follow a formal evaluation procedure [24], or (iii) did not consider dynamic interactivity features [23,54]. Therefore, the use of animation to improve the comprehension of process models merits further investigation.

Few previous studies have investigated the dynamic representation of process models [12]. In particular, four studies introduced animation techniques for process models, where one considered the visualization of continuous movement by allowing tokens to flow from one node to another [55], another employed highlighted objects [56], and the other two used a token animation tool to detect model issues [57,58]. All of these studies provided qualitative rather than quantitative arguments that their techniques may enhance understanding. Different forms of animation are currently available in industrial practice. Animation has been implemented in popular process modeling tools such as Signavio and Visual Paradigm. In summary, previous practical and theoretical studies suggest that animation may be a promising technique for improving the comprehension of process models. However, previous studies did not consider the impact of animation on the analysis of rather complex artifacts for challenging problem-solving tasks. This issue requires further investigation because process models are complex and various cognitive challenges arise when trying to comprehend them. Moreover, it is not clear how the impact of animation might differ in terms of the cognitive requirements of different users, as discussed in the following.

2.3. Animation and expertise

In addition to previous indications of the benefits of animation, some studies found no effect or even negative outcomes [40]. This may be expected because the learning effects of animation depend on many factors, including the user's characteristics, learning material, and design of the animation [45,49]. The most important cognitive characteristics of users are their expertise and knowledge [59], and there are profound differences in how novices and experts investigate conceptual models [60]. Thus, an instructional environment developed for a novice

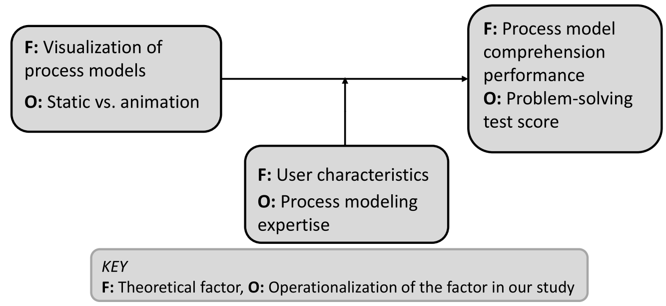


Fig. 1. Research model.

user may not be as effective for more proficient users, or it might even impede them [61]. An instruction for a novice user can be helpful for improving their search strategy, and for discovering the concepts and relationships in learning material. However, for an expert user who has already built up knowledge structures of some concepts, an extraneous cognitive load may be introduced to process the same instruction because it introduces redundancy to them [62], which is called the *expertise reversal effect* [61]. The reversal effect also occurs with high level of expertise, where a learning environment that supports an expert user in the deep exploration of concepts may overload the working memory of a novice [63]. The expertise reversal effect has also been shown to take place in instructional environments that use dynamic visualizations [62,63].

A potentially effective approach for addressing the expertise reversal effect involves creating a tailored instructional environment based on the level of a user's expertise, which is called an *adaptive learning environment* [59]. Few studies have considered the development and evaluation of adaptive learning environments [64,65]. Some approaches applied in education involve tailoring the environment before providing instruction using a knowledge test and gradual adaptation based on an assumed knowledge level [66,67]. These approaches are suitable when the learning materials and users are known. In contrast to educational settings, the organizational contexts where conceptual models are employed are highly dynamic, where any type of user may need to investigate any set of models based on the requirements of their task at a specific time. Thus, the users who investigate models and the models that they need to comprehend are highly variable [68]. Therefore, our main aims in the present study were:

- To investigate the application of an adaptive environment to allow the dynamic use of conceptual models [2,69], specifically process models [18]; and
- To determine whether this environment might have different effects on the comprehension of users with various levels of expertise.

3. Research model and hypotheses

According to the discussion given above, several relevant theories are considered in our research model, as shown in Fig. 1. The model aims to examine the effects of two related factors on process model comprehension. The first factor concerns the *visualization of process models* in a static manner versus the use of animation. Animation appears to be a promising technique for improving the comprehension of process models but we should also consider the specific characteristics of users, which can be measured in terms of their expertise regarding process models. We are interested in how this second factor moderates the effect of animation on the comprehension of process models. The standard practice in conceptual modeling for evaluating this factor involves measuring the performance of subjects at problem-solving tasks [1,43]. We employed the same approach to measure the comprehension of process models in our study. In the following, we outline the cognitive principles that support the use of animation as a beneficial approach for

Table 1
Cognitive principles that can be employed in an animation to overcome the challenges of model comprehension.

Principle	Challenge	Application in process model animation
Signaling principle	Abstraction gradient	Use visual cues to highlight elements that are related to each other, which support the user in the logical grouping of elements. Perceptual cues also support the user in finding the next relevant element.
Attention guidance mechanism	Role-expressiveness	Direct the user's attention to the right places at the right time as well as off-loading the working memory to investigate each process model element efficiently.
Enabling function	Difficult mental operations	Trigger the user to allocate more cognitive load to investigating the process model by interacting with the animation.
Facilitating function	Hidden dependencies	Explicate the meaning of notational semantics through the timing and order of visual cues, which makes cognitive processing easier for a user to discover hidden dependencies in the model.

improving the comprehension of process models as well as for overcoming the challenges mentioned in the previous section. We develop our hypotheses accordingly.

3.1. Impact of animation on process model comprehension

Animation may be used to address the challenges mentioned in our discussion of the cognitive dimensions in Section 2.1. Using animation to reduce the cognitive load associated with comprehending complex process models may work via different principles. Table 1 provides an overview of these principles. Based on the *signaling principle* of the theory of multimedia learning [28], animation provides cues to highlight the related elements in the model. In this manner, animation helps users to cope with the challenges of the abstraction-gradient dimension. The perceptual cues in the visuals of a notation may help users to logically group process elements [30]. The dynamic nature of process models is reflected by presenting these cues in a particular order in time, and the complex behavior represented in the model is made explicit. The *attention guidance mechanism* is implemented with dynamic cues, which may help the user to direct their attention to the right places at the right time. This mechanism helps to reduce the cognitive load by off-loading some working memory for search operations [25], which improves the role-expressiveness of the model because the user may require less cognitive resources to understand the process flow. Animation may trigger an *enabling function* by motivating the user to perform hard mental operations [62], such as discovering different alternatives of a process flow by manipulating the animation. The *facilitating function* refers to the ability of animation to lower the cognitive load required to understand complex materials by providing external support [25]. In the context of process models, the facilitating function of animation may be activated when the animation supports a user in the discovery of hidden dependencies by making the semantics of the notation explicit [25]. Therefore, assuming that these principles can be effectively employed in an animation environment, we propose the following hypotheses.

H1: Users of animation for process model visualization will have a higher comprehension performance than users of static process model visualizations.

3.2. Impact of animation according to expertise

According to the expertise reversal effect (see Section 2.3), users with different levels of process modeling expertise may experience diverse challenges and have different requirements in terms of cognitive support in a learning environment, which might sometimes conflict with each other. Table 2 summarizes these challenges and the cognitive principles that can be applied through process model animation to overcome them. *Low interactivity* is crucial for ensuring that low expertise users benefit from animation [53,62] because interactivity may introduce additional cognitive load. Thus, continuous animation is usually applied, where the user simply watches the animation without the need for interaction. The *worked example* principle is found to be effective for novices as a passive learning method in the initial stages of a learning process [70]. The *segmentation principle* [71] suggests that the material needs to be presented in a form that the user can segment during its investigation. Unlike novices, users with a higher level of expertise already have knowledge structures regarding basic concepts. Therefore, these users have the necessary working memory to explore a phenomenon themselves [53,62]. A low interactivity environment can increase the cognitive load for these users [62] because their knowledge may overlap with the guidance provided by the instructional environment, thereby underwhelming the user and wasting resources [59]. The interactivity principle suggests that learning is improved when users can create and test hypotheses themselves, such as by investigating alternative process executions through interactive visualizations [71]. In this manner, animation can create cognitive challenges for the expert user and increase engagement [52].

In summary, the benefits of animation for novices and experts appear to be related to different cognitive mechanisms triggered by the use of animation. Furthermore, some of the requirements contradict each other, where a feature designed for novices (e.g., low interactivity) would impede the comprehension of experts, and vice versa. Therefore, we expect that animation is not used by different users in the same way and does not lead to similar benefits for them. Thus, we propose the following hypothesis.

H2: The effect of animation on process model comprehension will differ according to process modeling expertise of a user.

The cognitive principles that can be implemented to deal with the expertise reversal effect target users with a low or high level of expertise. Previous studies that considered differences in expertise levels have investigated the effects of cognitive interventions for either novices or experts [59,62,63]. The exact cognitive principles that directly benefit users with moderate expertise are unclear. Thus, our expectations relate to users with low and high levels of expertise who may be expected to

Table 2
Cognitive principles that can be employed by animation to overcome expertise-specific challenges.

Principle	Challenge	Related Expertise	Application in process model animation
Low interactivity	Interactive learning material increases cognitive load of novices [62,72]	Low	Provide animation with low interactivity, e.g., through continuous animation.
Worked example	Novices benefit more from a passive experience [70]	Low	Show continuous animation depicting the complete execution of a process instance
Segmentation	It should be possible to segment a continuous animation [71]	Low	Provide necessary controls to partition a continuous animation (e.g., pause) [65].
Interactivity	Low interactivity can underwhelm users with sufficient knowledge, who require a cognitive challenge	High	Provide high interactivity so users can test alternative process executions.

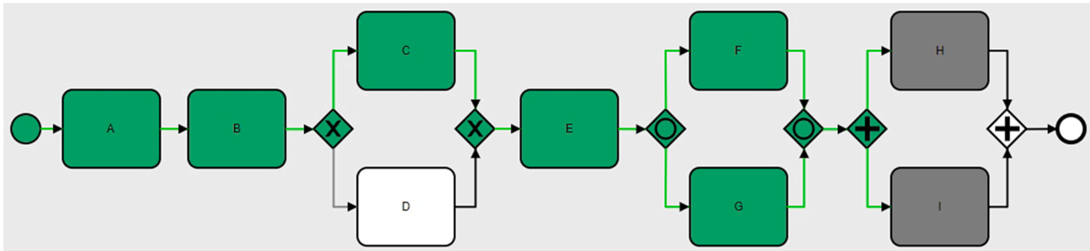


Fig. 2. Example of a Business Process Model and Notation (BPMN) process model that includes all types of control-flow elements.

benefit from how we design the animation environment for them, rather than for those with a moderate level of expertise. Animation is expected to have a *U*-shaped effect on comprehension as the expertise level increases from low to moderate to high. Therefore, we propose the following sub-hypotheses.

H2a: The effect of animation on process model comprehension will be greater for users with low expertise than those with a moderate level of expertise.

H2b: The effect of animation on process model comprehension will be greater for users with high expertise than those with a moderate level of expertise.

Previous studies of the comprehension of process models differ in terms of their conclusions regarding the effects of visualizations among diverse users [12]. In general, it is considered that novices will require more cognitive support [15], but experimental results may support (e.g., [16]) and ignore (e.g., [18]) or refute (e.g., [73,74]) this requirement. Therefore, it is important to investigate how different users might benefit from animation. In the following section, we explain the experimental design used to test our hypotheses.

4. Research method

We conducted an online experiment to test the hypotheses described in Section 3. Experimentation is a common research method for comprehension-related studies in the information systems field [2,16]. We used the guidelines from the software engineering domain to design, implement, analyze, and report the experiments [75,76].

4.1. Instrumentation

We developed an adaptive animation environment as the instrument to assess animation in the experiment. According to the theoretical background discussed in Section 2, we considered that animation may improve the comprehension of process models. However, the design of the animation environment is crucial for achieving any benefits from animation. Our aim of designing an animation environment that could serve the cognitive needs of diverse users led to several challenges. In the following, we describe the animation environment that we designed based on the principles in the relevant theories mentioned above. First, we explain the design of the visual characteristics of the animation as a dynamic visualization on top of the visuals for a process model. We then describe the design of the interactivity features applied to allow the environment to adapt to a user's needs.

4.1.1. Visual characteristics of animation

The animation approach employed in our study belongs to the *transformation type* [77], which means that we dynamically change the visual properties of objects, i.e., the elements of a process model in our case. We explain the specific visual and temporal animation aspects as follows.

Color transformation: We applied incremental signaling by color transforming the process elements to show how a specific instance of a process is executed in a step-by-step manner. This type of visualization is an established method for guiding the user's attention and enhancing comprehension [35]. An example snapshot of an animated process model is shown in Fig. 2, where the green color transformation has advanced until the last block of parallel activities (the last green diamond shape with +). According to Fig. 2, previously signaled elements that have already changed color remain that color and new signaled elements are added, thereby guiding the user's attention to the new signals while keeping the trace visible. Thus, the formal notation is overlaid with the secondary notation as the color type, which is detected much faster than other visual primitives in serial scanning [78]. In this method, only a smaller number of elements in a process model are cognitively handled at the same time, which potentially lowers the element interactivity in the visuals, which refers to the need to examine other elements to understand a particular element, resulting in a lower intrinsic cognitive load [79]. In the experiments, we used the conventional graphic representations of process models, which are known to be a good practice for improving comprehension [80].

Status change for activities: To reflect the semantics of the notational elements of a process model, the activity status was colored as *enabled* for an activity that was ready to be executed at any time (gray color in Fig. 2) and *executed* when the activity was complete, and the status of an activity changed to *executed* only when an enabled activity was marked as performed (green color in Fig. 2). We illustrate alternative instances for exclusive choices in Fig. 2.

Temporal design: We used the same timing for all activities as an abstraction of the fact that the time required to execute each activity in reality typically differs. In traditional process representations, such as text or static models, the semantics of the model are naturally hidden and there are many possible sequential variations for the same case. Animation is subject to temporal constraints because it visualizes a change in time, and thus it is mandatory to show the change in a particular sequence [25]. It is essential to present the animation to users so that they can grasp the possibilities, while also preventing any incorrect inferences because other possible alternatives are not shown. To address this problem, we followed the various principles listed below.

Based on the *congruence principle* [71], we did not use an exact depiction of the process behavior as performed in token-based process model simulations, but instead we simplified how activities are exactly executed. The simple model in Fig. 2 illustrates our method. In this process, activities *H* and *I* both need to be completed so the entire process can end. However, there is an infinite number of possibilities for the execution timings of activities *H* and *I*. For example, *H* and *I* can start and finish at the same time (perfect synchronization) or after any other time interval (*H* starts one second after *I*, and so on). We show parallel activities (*H* and *I* in this case) by initiating them one after the other but in close succession. Their coloring follows this pattern. Overall, our method expresses the semantics of parallelism by showing that the activities need not start exactly at the same time and they may run simultaneously for some time.

4.1.2. Interactivity features

Based on the visual characteristics explained above, we created an environment where users could view process models. We incorporated two different levels of interactivity features in this environment according to the principles discussed in Section 3. In our instrument, a user was first exposed to low interactivity, followed by a high interactivity option. The user could switch between different interactivity levels. Thus, the environment could be adapted based on the process model under consideration and the user's current and changing knowledge level regarding the model. Next, we explain the design of the low and high interactivity features and how they could be adapted.

Level 1: Low interactivity in an animated video format: Our environment exposed a user to a continuous automated animation where the user watched a single possible instance of the process (which is also known as a simulation type animation (cf. [62]). The following controls were available to the user: pause, replay, and skip to another point (or the end). In this initial low interactivity stage, we aimed to provide the following cognitive benefits to different users.

- The cognitive load required to process the controls was eliminated by showing an animation with elements of low interactivity.
- The behavior of a process model was explained by showing one example run of the process according to the *worked example principle*. Thus, the user's curiosity was triggered to explore without any additional cognitive load.
- The user became acquainted with the animation feature, which was specifically important for the initial use in an environment, and it could help to lower the extraneous cognitive load due to a new technological environment [65].
- The user had access to basic but limited controls so they could segment the material as required. This allowed us to control the extraneous load caused by the technology-based learning environment due to the high level of user control [65]. These basic controls also helped to make the material more enjoyable and the user could allocate the attention better on the difficult parts [71,81].
- All of the users were exposed to the animation so their problem-solving cognitive processes were affected. The short duration of the animation allowed a user to focus on the animation.

Level 2: High interactivity with a dynamic animation: When the animated video ended, the environment automatically switched to the highly interactive animation feature, and the user was encouraged to manipulate the animation. The user could decide not to take this opportunity or switch back to the low interactivity option. Unlike the continuous animation in the previous step, this animation feature was designed to be performed in a step-wise manner. The animation only continued when the user selected the next activity to be executed by clicking on it from among the activities enabled at the moment. Therefore, the pace of the animation was user controlled. This type of interactivity can help to reduce the extraneous cognitive load when the material is complex [50], as well as providing external support to solve the problem under consideration. This feature could allow the following benefits to be obtained.

- The user could manipulate the animation to discover possible alternative flows in a process, which might be an infinite number. This could improve the learning of notational semantics by explicating their meaning under different circumstances [29], while also cognitively challenging the user [52].
- The user could control the pace and receive the animation in segments in a step-wise animation approach, which might have helped users to deal with cognitive difficulties due to transient information in the animation [82].
- No additional cognitive load was introduced if the user preferred not to use the animation either because they did not require it (due to high knowledge-level and/or simple model) or it might increase the cognitive load (due to their low knowledge level regarding the model considered).

Adaptiveness between high and low interactivity: In this two-level interactivity design, we applied the two best practices for algorithm animations: (1) providing resources that could help users to interpret the animation before having to control it themselves; and (2) adapting to the knowledge level of the user by providing optional advanced features [52]. Thus, we aimed to create an animation environment that could improve the comprehension of process models by diverse users of process models. The use of process models in an organizational setting could be facilitated by the adaptiveness of the animation. In particular, depending on the complexity of process models under investigation, each user could adjust the animation according to their specific and changing cognitive needs. The following benefits could be obtained due to the adaptiveness of the animation.

- The user transitioned from passively studying examples to actively solving problems in a guided manner, as suggested by the *worked examples principle* [83], following the *guidance fading effect* [29].
- The user could return back to the low interactivity format to explore the process in a less cognitively demanding manner.

4.2. Participants

We recruited participants from undergraduate courses in the Netherlands, graduate courses in the Netherlands and Turkey, and consultancy companies and university research groups in the Netherlands and Turkey. The participants had different levels of expertise in process modeling. The undergraduate students had received entry-level training, the graduate students had undergone more extensive training, and the consultants and researchers used process models intensively in their daily work. All of the participants completed the test voluntarily due to their intrinsic motivation to test themselves on process modeling topics, improve their understanding of process models, and learn about innovative methods in this domain. To identify the expertise levels of participants at process modeling, we measured their self-reported process modeling intensity in the last year, their familiarity with notation, and their years of modeling experience. These measures were used as accepted and valid practices in previous process model comprehension studies [4,27,84,85]. According to our knowledge of the backgrounds of the participants, we anticipated three levels of process modeling expertise among the participants; low, moderate, and high.

4.3. Task

Comprehension tasks can be performed as transfer tasks for problem solving when the model is available, or as recall tasks when the model is removed [43]. To evaluate the deep understanding of the concepts by the participants, we presented them with transfer tasks that required solving novel problems, as applied in multimedia learning studies [35]. Based on an approach used to measure the deep understanding of conceptual models [69], we designed the tasks so the participants were required to investigate the relationships among the model elements instead of individual elements. The design of the process models and questions are explained in the following sections.

4.3.1. Process models

As a modeling notation, we used the Business Process Modeling and Notation (BPMN) [86]. BPMN is an industrial standard for process modeling and it is commonly used for communicating and transferring process knowledge [87]. We aimed to measure the comprehension of the behavioral properties of a process model, so we only used the following control flow elements in the process models: (1) activities; (2) XOR, OR, and AND connectors; (3) start and end events; and (4) sequence flows. We did not incorporate organizational and informational elements such as roles and outputs. An example of a BPMN process model with control flow elements is shown in Fig. 2 (a typical process model in BPMN does not include colors). In this example, the process is triggered when the start event (circle with the thin border) is activated. The first activity to be performed is A. After activity A is complete, B can start, which is

Fig. 3. Experimental procedure.

indicated by the sequence flow connection between them. The XOR connector (diamond shape with X) that follows indicates a decision. Accordingly, after the completion of B, the process continues with either C or D but not with both. The next XOR connector indicates that after the completion of the chosen activity (either C or D), E can be performed. Next, the OR connector (diamond shape with O) allows the flow to continue with either F or G, or both. After completing the selection of the activities, which is indicated by the next OR connector, the next part starting with an AND connector (diamond shape with +) is activated. Activities H and I both need to be performed for the process to be completed, which is indicated by reaching the end event (circle with the thick border). In practice, process models are often not as well structured and simple as this example [38]. In fact, connectors can be combined in various ways, and thus models that capture flows are often much more difficult to grasp than our example.

In order to measure the deep understanding of the process modeling concepts among the participants and cover a wide range of model element characteristics, we designed 10 process models for incorporation in our experiment. In a previous study, using a number of process models per participant was shown to be effective for extensively evaluating the comprehension of process models [11]. In addition, it was necessary to create a challenge to motivate the users [45]. To benchmark and adjust the complexity of the process models in the experiment, we compared the models with the metrics determined for a collection of 1400 real-life process models, as reported by Kunze et al. [88], and used the complexity benchmark based on this collection developed by Recker [89]. The size complexity values were in the range of average to high complexity, and these values are commonly observed in real-life models. The number of nodes per model ranged between 25 to 31, where a model with 13 nodes had average complexity and that with 50 nodes had high complexity [89]. Similarly, the number of arcs ranged between 29 and 39, and the benchmark values were 13 and 50 for average and high complexity models, respectively. The average connector degree ranged between 3.00 to 3.40, which are similar to the values observed in real-life models [88]. We also ensured that the models contained different process model structures, such as different connector types, rigids, and process flow issues with deadlocks and livelocks. Figs. A-4–A-13 in the Appendix show the process models used in the experiment.

In order to ensure that the participants focused only on comprehending the behavioral aspects of the process models, we used abstract labels (e.g., *A, B*, and *C*) for the activities. This allowed us to evaluate whether a reader could correctly comprehend the notational aspects independent of the label meanings, domain knowledge, and length of the label [1,11,15,90].

4.3.2. *Questions*

Based on an approach employed in previous process model comprehension studies, we identified four types of control flow related questions for each process model (cf. [11,16,27,84]). These questions were related to the execution order, exclusiveness, concurrency, and repetition among process activities. These questions were found to have acceptable internal consistency and they covered diverse aspects of a process flow [16]. In total eight closed questions with answers selected from "yes," "no," or "I don't know" were asked for each process model and there were two questions per type. In addition, one open-ended question asked the participant to explain whether there was a problem with the process (e.g., proper completion, deadlock, or livelock) and to describe it if this was the case. Three expert researchers individually checked the process models, performed pilot runs, and established the correct answers to the questions. The answers to the open-ended question were evaluated individually by two different researchers. For both the closed and open-ended questions, the experts discussed any mismatch between the scores until they reached an agreement. We used the scores for the participants comprising the correct number of answers to the questions for all process models as the outcome variable, which could range between 0 and 100.

4.4. *Experimental factors*

In our experiment, we employed a between-groups design with two experimental factors. For the first factor comprising visualization of the process models, the factor levels were "*without animation*" (or "*static*") and "*with animation*" (or "*animation*"). For the static group, the task (explained in Section 4.3) and procedure (explained in Section 4.5) were the same. The only difference was that the participants were shown the process models in the regular static form without receiving the animation environment as the instrument, as explained in the following section. The second factor comprising the user characteristic was operationally defined as the process modeling expertise of each participant as a continuous variable obtained by self-reported measures, as explained in Section 4.2.

4.5. *Procedure*

To investigate our hypotheses, an on-line environment was developed to conduct a self-administered experiment. The environment was developed with HTML5, PHP, Javascript, and the bpmn-io library[1], and run on a PHP server. We followed a homework-style approach where the participants were allowed to take as much time as they required to answer the questions (cf. [23]). The participants could complete the task online at the time and place they preferred. We advised the participants to complete the task on one occasion to ensure that they were focused on the task, and controlled for this later. We prevented the participants to work in teams to perform the task together by showing the models in random order. The environment led the participants through five successive parts, as shown in Fig. 3. The complete online experiment can be examined by using the links provided in the Appendix.

1-Introduction: Basic information, expectations of the participant, time information, and voluntary participation information were provided. Participants could continue by acknowledging their voluntary participation and consent to the use of their data.

2-Background survey: All participants were requested to provide information regarding their demographics, experience with process modeling, and level of familiarity with process modeling notations to determine their process modeling expertise based on self-reported data, as employed in previous studies [11,84].

3-Tutorial: Depending on a random draw, each participant was assigned to either the static or animation group. The participant was then exposed to a tutorial that introduced the user interface and features of the learning environment (for either static or animation), as well as the BPMN constructs employed.

4-Test: Subsequently, the participant was shown a page containing a

[1] https://bpmn.io/

Table 3
Demographic data for the participants in the static and animation groups.

	Total (n = 194)		Static (n = 93)		Animation (n = 101)		Test of difference
	Mean/Count	SD/%	Mean/Count	SD/%	Mean/Count	SD/%	
Age	24.96	5.77	24.53	5.65	25.37	5.88	$U = 5242, p = .161$
Gender							
Male	108	56%	51	55%	57	56%	
Female	86	44%	42	45%	44	44%	
Background							
Undergraduate student	62	32%	30	32%	32	32%	
Graduate student	106	55%	51	55%	55	55%	
Professional	26	13%	12	13%	14	13%	
Country							
Netherlands	176	91%	85	91%	91	90%	
Turkey	18	9%	8	9%	10	10%	
#Read (1-5)	2.45	0.90	2.48	0.88	2.42	0.92	$U = 4492, p = .573$
#Created (1-5)	2.31	0.98	2.31	0.98	2.31	0.99	$U = 4727, p = .934$
Familiarity (1-5)	4.12	1.29	4.18	1.24	4.07	1.33	$U = 4293, p = .285$
#Years (1-5)	2.96	1.09	2.94	1.03	2.98	1.15	$U = 4703, p = .987$
Expertise (1-15)	7.89	2.43	7.99	2.35	7.79	2.50	$U = 4393, p = .433$

Background = Participated in the study as an undergraduate student, graduate student, or professional from a company. #Read = Number of process models read in the last year (1:None, 5:More than 50). #Created = Number of process models created in the last year (1:None, 5:More than 25). Familiarity = Self-reported level of knowledge about process modeling notation (1: not familiar at all, 7: very familiar). #Years = Amount of time passed since learning process modeling (1: none, 5: more than three years ago). Expertise = Combined measure of process modeling expertise.

process model and nine questions related to the process model, as described in Section 4.3. Based on the assigned group, the process model presented to the participant was either a static visualization or the animation environment introduced in Section 4.1. The participant had to answer all of the questions to continue to the next page and analyze another process model. The process models were presented in random order to each participant. The screen shots in the Appendix (Figs. A-1–A-3) show examples of the online environment.

5-Feedback Survey: In the last part, feedback was requested from the participants. The overall perceived difficulty of each of the process models was measured on a Likert scale (1–7). For the animation group, the participants were also requested to evaluate the perceived usefulness of the animation feature (1–7) and to provide additional comments in an open-ended question.

5. Results

We examined the results obtained in our experiment in three steps. First, we screened the data to ensure its conformance with several quality criteria as well as performing reliability analysis (Section 5.1). We then tested our hypotheses (Section 5.2). Finally, we explored the data further to discover how the animation environment was actually used and perceived by the participants (Section 5.3).

5.1. Data screening and reliability assessment

In total, 221 participants participated in the study, but 17 were excluded because they did not complete the test for all of the process models in the experiment. We also controlled for the time spent on the test. We checked whether the participants completed the overall test and the set of questions for each individual model excessively quickly or slowly. An excessively fast or slow completion time could indicate that the participant did not apply sufficient cognitive capacity and focus to read and answer the questions. We removed 10 participants because they worked excessively quickly or slowly (e.g., spending 12 s and 40 min on a single process model, respectively). The final screened data set included 194 participants (available at [92]). These participants performed the whole test in times between 22 min 20 s and 2 h 03 min 50 s, with an average of 58 min 50 s. In the screened data set, 93 participants received the task with a static visualization and 101 participants were exposed to animation. Table 3 summarizes the key descriptive statistics for the participants. The data did not follow a normal distribution, so we conducted Mann Whitney U tests to check whether the age, self-reported process modeling intensity (number of process models read and created in the last year), notation familiarity, years of process modeling experience, and combined process modeling expertise (described below) differed between the static and animation groups. The test results indicated that there were no significant differences between the groups in terms of any of these variables.

We used four measures of self-reported process modeling expertise, which were used frequently in previous studies and found to be relevant for distinguishing process model users according to their expertise [14,27,93]. We detected strong and moderate correlations between the number of process models read and created in the last year and notation familiarity (Spearman's ρ coefficients of.76 and.50 respectively), and weak correlations between the number of years of process modeling experience and these three measures (Spearman's ρ coefficients of.29–.36), where all were significant at the.01 level. The values were strongly correlated, so we created a combined measure of process modeling expertise using the process modeling intensity and familiarity measures. We excluded the number of years of modeling experience because how actively a person used process modeling in practice was

Table 4
Descriptive statistics for the participants regarding process modeling expertise per expertise group.

	Total (n = 194)		Expertise group Low (n = 59)		Expertise group Moderate (n = 108)		Expertise group High (n = 27)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
#Read (1-5)	2.45	0.90	1.64	0.48	2.52	0.54	3.93	0.73
#Created (1-5)	2.31	0.98	1.37	0.49	2.41	0.53	3.96	0.76
Familiarity (1-7)	4.12	1.29	2.97	1.16	4.33	0.72	5.81	0.96
#Years (1-5)	2.96	1.09	2.56	0.92	2.93	1.03	3.96	1.09
Expertise (1-15)	7.89	2.43	5.34	1.06	8.22	1.07	12.11	1.65

Table 5
Pearson correlation coefficients between demographic variables and the dependent variable.

	Test score	Age	Expertise	Gender	Country	Undergraduate	Graduate	Professional
Test score	-	.089	**.311**	**.141**	-.096	**-.291**	**.186**	**.126**
Age		-	**.349**	.094	**.376**	**-.480**	.030	**.612**
Expertise			-	**.143**	-.014	**.480**	**.231**	**.319**
Gender				-	-.108	-.056	.000	.077
Country					-	**-.219**	-.101	**.448**

Correlations and significance levels $p \leq 0.05$ (one-sided) are shown in bold.

found to be more important than when the person actually learned about it [11,27]. This was also supported by the weak correlation in our data. We used the combined process modeling expertise as a continuous measure for testing the hypotheses. In our analysis of the impact of animation on different expertise groups, we performed k-means cluster analysis based on the process modeling expertise, which yielded three groups: 59 participants with low process modeling expertise, 108 with moderate expertise, and 27 experts. Table 4 summarizes the descriptive statistics for the participants regarding their process modeling expertise. Clearly, the group of experts was the smallest of the three groups because the professionals who mainly comprised this group had limited time available during their working hours to participate in experiments. It should be noted that we consider having a relatively large representation of experts as a strength in this study.

In our reliability assessment, we checked the internal consistency of our measure comprising the problem-solving test score. The test score was calculated by adding the test scores for 10 process models. We calculated Cronbach's α based on the individual process model test scores. The accepted value of Cronbach's α is 0.7 or higher in order to combine multiple items into one index [94]. Our Cronbach's α value of 0.81 suggests that the reliability was adequate. The score did not increase after deleting any item. Thus, we retained all of the process model test scores to measure the overall test score.

Next, we examined the Pearson correlation coefficients between our demographic variables and the dependent variable, as shown in Table 5. In particular, moderate correlations were observed between being an undergraduate student or a professional and age or expertise. Also, a weak correlation was observed between age and expertise. These correlations are logical because being an undergraduate student typically indicates a younger age and less expertise than a professional, and vice versa.

$$Score = \beta_0 + \beta_1 * Animation + \beta_2 * Expertise + \beta_3 * Expertise^2 + \beta_4 * Animation * Expertise + \beta_5 * Animation * Expertise^2 + \beta_6 * Gender + \beta_7 * Age + \beta_8 * Country + \beta_9 * Undergrad + \beta_{10} * Grad + \beta_{11} * Prof + \xi \quad (1)$$

5.2. Tests of Hypotheses

We used SPSS Version 26 to analyze the data. We performed ordinary least squares (OLS) multiple regression analysis to test the formulated hypotheses [95]. The regression model is shown in Equation 1. We specified the model to test the main and interaction effects of process model visualization (animation vs. static, denoted as Animation) and expertise on the dependent variable comprising the problem-solving test score (denoted as Score), as well as with the control variables age, gender, country, and background (coded as dummy variables Undergrad, Grad, and Prof).

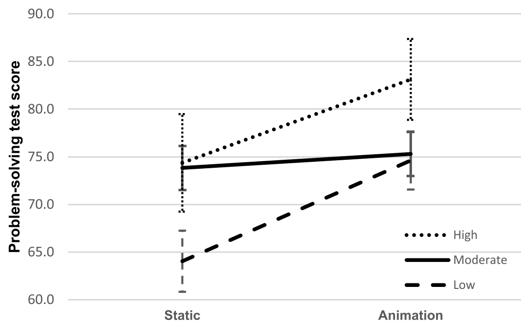
The factor Animation was added to the model to test H1. To evaluate the effect of expertise on a participant's test scores, the terms Expertise and Expertise^2 were inserted. The latter was used because we expected a concave curve shape for the test scores as expertise increased from low to high [14]. Next, to test whether the process model visualization and expertise interacted, as suggested by H2, we added the terms Animation*Expertise and Animation*Expertise^2. The latter term allowed us to test the difference in the curvilinear relationships between the static group and animation group for the impact of expertise. Assuming that the effect of animation on process model comprehension was confirmed (H1) and that the quadratic term was significant with a positive coefficient, then based on its interaction with animation, the results indicated that the effect of expertise differed and it had a U-shape (convex curve), with higher effects for users with low and high levels of expertise (H2a and H2b).

Table 6
OLS regression model results.

Factor	β	Standardized β	p
Constant	45.341		.000
Animation	44.559	2.302	.000
Expertise	7.224	1.807	.000
Expertise^2	− .353	.110	.002
Animation*Expertise	− 9.154	− 4.059	.000
Animation*Expertise^2	.492	2.343	.000
Gender	1.439	.074	.242
Age	− .264	− .157	.080
Country	− 5.514	1.165	.026
Grad	4.914	.253	.004
Prof	10.341	.364	.001

$N = 194$, $F = 8.202$ ($p < 0.001$), adjusted $R^2 = .272$

Table 6 shows the OLS regression results obtained for the model, as described above. Before adding the interaction terms, we controlled for multicollinearity among all of the independent variables. The variance inflation factor (VIF) statistics were well below the threshold value (VIF = 10), thereby confirming that our analysis was not affected by multicollinearity problems. We found a significant and positive regression coefficient for *Animation* (β=44.559, p <.001), and thus H1 was supported. The factors *Expertise* (β=7.224, p <.001) and *Expertise*^{2} (β=-.353, p <.005) were also significant. Considering that the quadratic term had a negative sign, these coefficients showed that expertise was indeed a significant factor for the comprehension of process models and the curve had a concave shape. The regression coefficients for the terms $Animation * Expertise$ (β=-9.154, p <.001) and $Animation * Expertise^2$ (β=.492, p <.001) were also significant and the latter had a positive sign, thereby demonstrating that the effect of animation on process model comprehension in our experiment differed according to the level of process modeling expertise (H2). Furthermore, the curve representing this effect had a convex shape, i.e., a *U*-shape. The significant



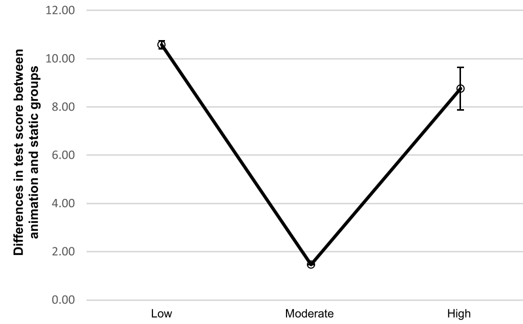


Fig. 4. Test scores plotted according to process modeling expertise (left), and differences in the performance of process model comprehension by the process model visualization groups depending on expertise (right.)

coefficients and the directions of the curves confirmed both H2a and H2b.

We visualized the difference in the test scores with respect to the expertise groups defined (as described in Section 5.1) in Fig. 4a and b. Fig. 4a shows the test scores when the participants received static or animated process visualizations for each expertise group. The results showed that the changes in the scores for the participants from the low and high expertise groups had steeper slopes when animation was used compared with the moderately skilled participants. Figure 4 b shows the differences among groups and it confirms the *U*-shaped effect of animation on the comprehension of process models according to the curve (which was also supported by regression analysis for the three separate expertise groups). Overall, these findings support the claim that process modeling expertise moderated the effect of animation on the comprehension of process models, with a *U*-shaped curve, thereby supporting hypotheses H2, H2a, and H2b.

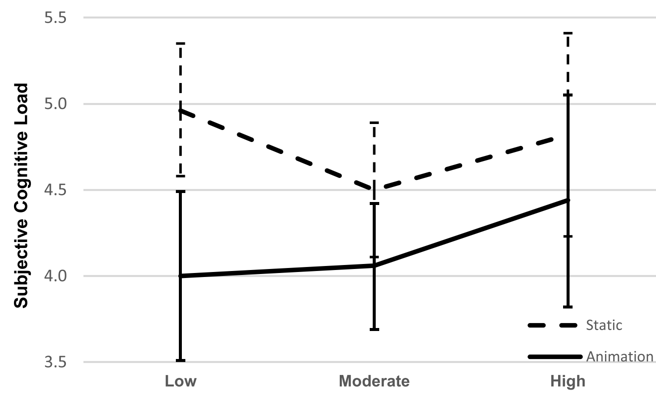


Fig. 5. Subjective cognitive load perceived by users with different process modeling expertise according to the process model visualization group.

5.3. Further analysis of results

Our empirical results supported the benefits of using an animation environment to enhance the comprehension of process models by users with different levels of process modeling expertise. We then explored our data further to obtain deeper insights into how the users responded to animation.

5.3.1. Comprehension time and subjective cognitive load

Previous studies of model comprehension often incorporated a measure of comprehension efficiency as an additional measure of comprehension performance [16,39,48,69]. The idea is that modifying a graphical notation or changing the presentation of a model may improve the understanding of that model, but it should not come at the expense of requiring excessive additional time to make sense of the model. According to previous studies, it is not clear how animation would perform in this respect. In particular, the time required to search for information can be decreased considerably by the attention guiding mechanism provided by animation [44]. However, animation may enhance the engagement of the user and increase the time spent examining the relevant parts of the material [96]. Thus, we investigated whether the time spent on the comprehension tasks was affected by the independent factors. We conducted Kruskal–Wallis tests because the time spent was not normally distributed. The test outcomes showed that there were no significant effects of expertise ($\chi^2(2)$=.73, p = .67) and animation ($\chi^2(1)$=.0, p = .97) on the overall test time. We also found no significant effect of time on the test score. According to these test results, we do not consider that users spent more time on comprehension tasks when they used animation compared to when they did not.

Many previous studies also hypothesized an increased subjective cognitive load (the perceived difficulty of understanding the models) in the case of notational quality issues or when using different grammars [48,69]. However, recent findings do not always agree with previous suggestions regarding this measure. Only a few studies have investigated the perceived difficulty of conceptual models when visualizations are used, so we considered this issue in our study. It may be expected that animation will cause the user to perceive less cognitive load by explicating the meaning of the material [52]. By contrast, animation users explore the phenomenon themselves in more detail, so they may be more challenged and become more aware of difficulties [62]. After rejecting the assumptions of equal variances and normality for the subjective cognitive load, we performed Kruskal–Wallis tests with the subjective cognitive load when understanding the process models as the dependent variable (on a scale of 1 = very easy to 7 = very difficult) and animation and process modeling expertise as the factors. The results showed that animation significantly decreased the subjective cognitive load of the participants ($\chi^2(1)$=.8.42, p = .004) but there was no effect of expertise ($\chi^2(2)$=1.67, p = .44). The mean values are shown in Fig. 5. Our findings indicate that animation helped to alleviate the subjective cognitive load of the users when they investigated process models for problem-solving tasks, thereby agreeing with our findings regarding the benefits of animation in terms of comprehension performance. These results also demonstrate that the cognitive principles required to overcome the challenge of comprehending process models (as noted in Section 3) are indeed employed through animation.

5.3.2. Use of the animation environment

We investigated how the participants used the animation environment, particularly to determine whether there was a relationship between its use and their comprehension performance. To understand how the participants used the animation environment, we first checked the correlation between the time spent using low interactivity animation (video time) and the number of clicks that occurred during high interactivity animation (clicks). There was a weak negative correlation between the number of clicks and the video time ($r = -0.25$, p = .007), which suggests that participants who preferred to rely on low interactivity animation tended to have less interest in using the high interactivity animation. However, participants who were interested in investigating the model with high interactivity (as indicated by clicking more often on the interactive elements) preferred to spend less time on the video animation. Investigation of the data obtained for individual participants showed that the most common way of using the animation environment was watching the video until the end, before moving on to the high interactivity animation. In addition, two further usage modes were observed frequently, where some participants watched the video more than once while hardly using the high interactivity animation, whereas some others interrupted the video before it finished and continued their investigation with the high interactivity animation. These different usage modes indicate that the environment could accommodate different cognitive preferences by the participants.

Next, we checked whether the number of clicks and the video time affected the comprehension performance in the animation group. We performed analysis of variance (ANOVA) test using the number of clicks and the video time as covariates. The effect of the number of clicks on the test score was significant ($F(1,97) = 21.23$, $p = .000$), whereas the effect of the video time was not ($F(1,97) = 1.1$, $p = .30$). These results suggest that participants who made more use of the high interactivity animation feature performed better at comprehension. It should be noted that our findings provide some indications regarding the use of the animation environment, but we cannot draw decisive conclusions about the usage patterns or how different usage patterns affect process model comprehension. The usage of the animation environment was a cognitive experience and it could not be observed exactly based on the website data alone. Finally, the perceived usefulness of the animation feature was scored very highly by the participants (mean score of 6.1 on a 7-point scale, where 7 was the highest) and there were no significant differences according to process modeling expertise.

6. Discussion

In this section, we discuss the implications of our work for research and practice. We also reflect on the limitations of this study.

6.1. Implications for research

The results obtained in this study have four main implications for research. First, we introduced animation as a new visualization technique for the comprehension of process models. Our interpretations of the *cognitive theory of multimedia learning* [28], *cognitive load theory* [29], and *cognitive dimensions framework* [30] appear relevant to understanding the effects of animation in the context of process models. For example, our findings indicate that animation has a cognitive fit with process models, which is a requirement for a material to be comprehended based on its visualization [40]. Furthermore, as suggested by the aforementioned theories, the cognitive principles of animation that can help to manage the cognitive load are likely to be pertinent to process models.

In the wider information systems literature, the focus has mostly been on the use of animation for simple retention tasks rather than our consideration of problem-solving tasks that involve complex and multifaceted artifacts. Our findings agree with animation studies in computer-based learning [21,97,98] and they add to this body of knowledge by applying and evaluating animation in a new context. In the conceptual modeling literature, researchers have investigated the factors that affect comprehension and developed new visualization techniques (e.g., [48] and [99]). Animation has been identified as having great potential [12], but it is interesting that only few studies have considered using animation for improving the comprehension of process models. However, these studies did not include theoretical cognitive justifications or empirical evaluations, possibly due to the difficulty of designing suitable animations for the user and material without increasing the cognitive load, as acknowledged in computer-based learning studies [21,29,49]. We discuss this point further in the following.

Second, our results imply that animation can be used to improve the comprehension of process models by users who differ in terms of their process modeling expertise. This is remarkable in the context of the comprehension of process models because it was previously shown that novices benefited from support with comprehension rather than experts (e.g., [15] and [16]). Personal factors have been shown to affect the comprehension of process models [91], but few studies have compared the effect of visualizations on different process model users [27]. The *expertise reversal effect* related to the cognitive load theory suggests that visualizations may affect novices and experts differently [61]. In accordance with this theory, our findings suggest that the impact of animation differed with respect to process modeling expertise. In particular, low and high expertise users benefited more from animation compared with moderate expertise users. This *U*-shaped moderating effect of expertise is particularly interesting in the context of visualizations. One explanation of this pattern is that our environment provided support through low interactivity as well as high interactivity. The continuous automated animation in the former mode may have helped low expertise users to understand process models better compared with their presentation in static form. This benefit may have been small for users with more than a basic level of expertise, but it might not have been trivial in helping them to effectively apply the features in the high interactivity mode, i.e., manipulating the animation to solve a particular problem, and this may have been something that only the users with the highest expertise could perform effectively. Cognitive principles specifically target low and high expertise users, and thus it seems that users with moderate expertise cannot benefit as effectively from the cognitive support aimed at either low or high expertise users. This is an important finding because previous studies mostly compared low and high expertise levels, but not moderate [59].

As a third implication, our study provided insights into how users engage with an animation environment, and thus we complement and extend the literature on conceptual modeling. In particular, the time spent on the comprehension task and the perceived cognitive load have been used as additional indicators of comprehension performance (e.g., [48] and [69]), but previous findings were not consistent. In our study, the time spent by the static and animation groups was comparable, thereby suggesting that the animation did not result in users investing more time in the problem-solving task. Our findings also indicate that animation can assist users by mitigating the perceived difficulty of a task. The high usefulness ratings of the animation environment further highlight the perceptual benefits of animation.

Fourth, our preliminary investigation of the use of adaptive animation suggests that users followed certain patterns when using the low and high interactivity animation modes interchangeably, probably because adaptiveness allowed a user to follow a usage pattern that suited their cognitive needs. Examining the factors related to these patterns, such as other user characteristics, cognitive preferences, and model properties, may give further insights to help improve the support provided by animation [20]. Previous studies have indicated that user characteristics other than expertise are related to the comprehension of process models to some extent [27,39]. Further research may also consider the use of low and high interactivity animations separately to better understand their effects on comprehension, particularly regarding the *U*-shaped moderating effect of expertise. Research methods that are effective for analyzing patterns when examining learning materials, such as eye-tracking [96] and think-aloud protocols [69], can be applied to investigate the use of animation features.

Overall, we consider that the findings obtained in this study suggest new opportunities and researchers can investigate the use of dynamic visualization techniques for other conceptual models. The comprehension of conceptual models other than process models is also challenging and new approaches have been developed [2,68,69]. In addition to comprehending a certain type of conceptual model, it is difficult for users to follow up the information derived from multiple types of conceptual models [100]. Animation can provide substantial support to help users discover related elements across multiple conceptual models.

6.2. Implications for practice

We identified two implications for practice based on our results. First, we successfully implemented an adaptive animation environment. Tool developers can directly use or draw inspiration from this environment to integrate animation into their own modeling environment. Our solution is suitable for diverse users, so it would not be necessary to develop multiple tools targeted at different users of process models in an organization. A high number of employees in an organization may engage with process models because they are used for various purposes [3]. Thus, an animation environment that helps diverse process model users may lead to substantial overall improvements in an organization in terms of how process models are understood and used.

Second, our findings indicate that users with different levels of expertise should be considered when designing visualizations to improve conceptual model comprehension. Experts also make use of visualizations [60] but the current solutions mostly target novices (e.g., [15]). Our findings demonstrate that visualization solutions may be developed to support novices but also experts in a single environment. We consider that it would be relatively easy to integrate our animation support method within existing process modeling tools for both academic and commercial purposes.

The use of animation in practice can be broadened further by incorporating process perspectives other than the behavioral perspective that formed the focus of the present study. Other perspectives are also relevant to practice [101], e.g., from an organizational perspective, animation can be implemented to allow users to investigate the activities of a particular organizational role or department [20]. From an informational perspective, users can examine the activities that all interact with a certain artifact, such as a dedicated database. A similar method was implemented previously as a highlighting technique [15], but animation can potentially help to improve the understanding of complex temporal interactions with this type of database.

6.3. Limitations

We consider that important contributions were generated by our study but it also had some limitations. The number of traces grows combinatorially with the number of activities in a process model, which requires that the user spends more time with the animation. Therefore, we limited the size of the models so the participants could finish the task within a reasonable time without losing focus. When a user investigates a model, the domain knowledge and modeling knowledge elements interact [14]. We removed domain knowledge by using abstract labels so we could disentangle the domain and modeling knowledge elements in the comprehension process. These design decisions limited the real-world representativeness of the models but helped us to exclude those factors that could affect the use of animation.

Numerous different notations are used for process modeling, but many of them share a similar set of elements for depicting process flows [48]. Users have been shown to obtain similar scores in comprehension tasks developed with different notations [39]. We decided to use the BPMN notation, which is the industry standard for process modeling. Future studies could investigate the applicability of results to other notations.

The use of students as proxies for professionals has been criticized in previous studies, but students and novice professionals have been shown to exhibit similar performance [11]. To confirm the suitability of the participants, we applied measures that have been shown to differentiate process model users [27].

The sizes of the samples in our experiment were moderate. In our instrument design, we opted for generalizability by developing an extensive set of process models and questions. Thus, the task was performed by a fair number of participants and we ensured that they were willing to dedicate time and focus to the task. Similar settings have been employed, particularly in computer-based learning studies [62,63,102]. We obtained strong statistical evidence in all of the tests of the assumptions and hypotheses. Therefore, we consider that the significance of the results would probably have been similar even if we used a large sample size.

7. Conclusion

In this study, we investigated how process model users can be supported to better understand the dynamic aspects of process models. For this purpose, we employed animation as a multimedia technique to dynamically visualize the behavioral perspective of processes. We designed an adaptive animation environment to accommodate the diverse cognitive needs of process model users. We evaluated the impact of animation on the performance of users at comprehending process models according to their process modeling expertise with a between-groups experimental design. To measure their performance at process model comprehension, we devised a task comprising 10 process models with varying complexity and formulated problem-solving questions for each model.

We obtained support for our hypotheses regarding the benefits of animation for comprehending process models and the moderating effect of process modeling expertise. We discovered that users with low and high levels of expertise benefited more from animation than users with a moderate level of expertise, which contrasts with the findings obtained in previous process modeling studies where only novices usually benefited from comprehension support. Our findings also indicated that user engagement increased and diverse cognitive preferences were supported through adaptive animation. Thus, our research adds to the emerging body of knowledge regarding the use of visualizations for improving the comprehension of process models. Moreover, our animation environment may be promising for application in practical settings.

Overall, this study suggests new opportunities for both research and practice. To further improve animation as a new visualization technique, researchers might investigate how different users engage with different types of animation in greater depth. Considering the benefits obtained from process models, it would be worthwhile investigating the use of animation for other types of conceptual models. For developers, the findings obtained in this study may suggest new ways of integrating visualization into the modeling tools that they employ. Finally, by improving the use of models for diverse information systems users, our results could help to improve their performance in a wide range of complex but relevant organizational tasks.

CRediT authorship contribution statement

Banu Aysolmaz: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Visualization. **Hajo A. Reijers:** Conceptualization, Methodology, Validation, Investigation, Writing - review & editing.

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Appendix A. Experimental Materials

The first three figures below show examples of the online tool interface during the test part of the experiment. The remaining figures show the process models used in the experiment. The material for the

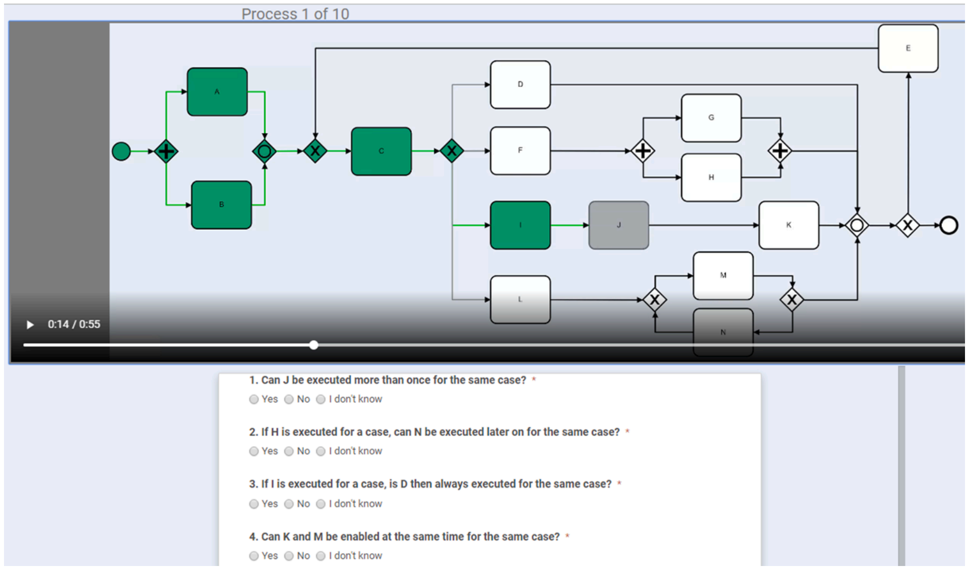

Fig. A-1. Screen shot of the online tool during the test part with low interactivity animation in use.

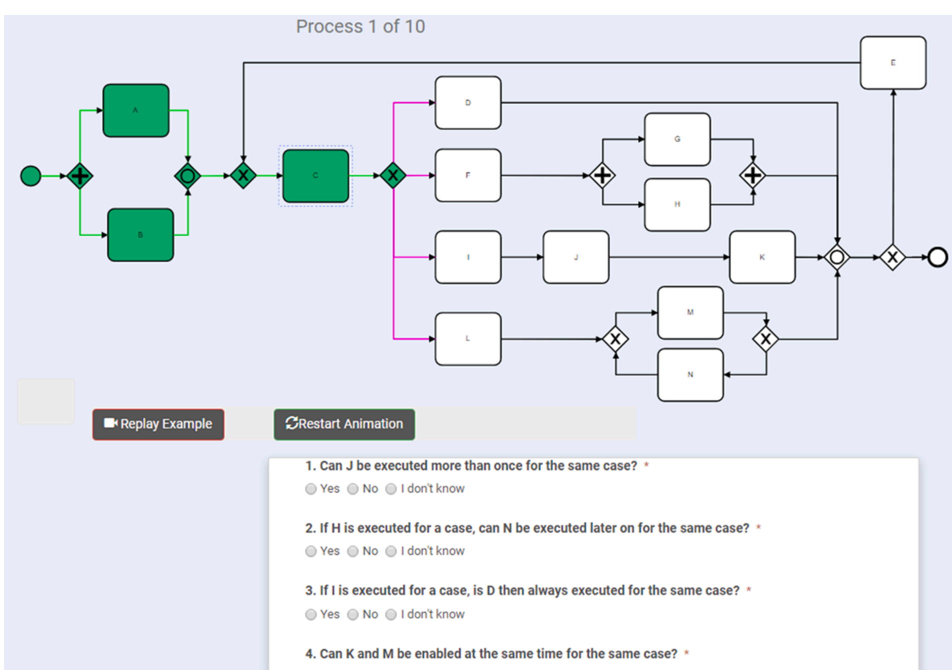

Fig. A-2. Screen shot of the online tool during the test part with high interactivity animation in use.

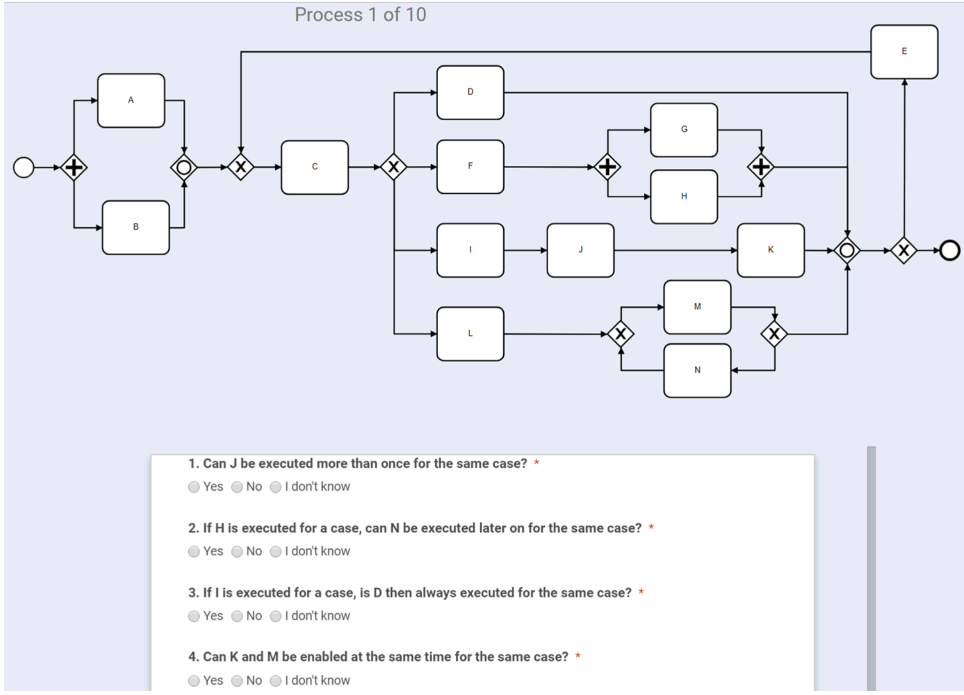

Fig. A-3. Screen shot of the online tool during the test part for the static group.

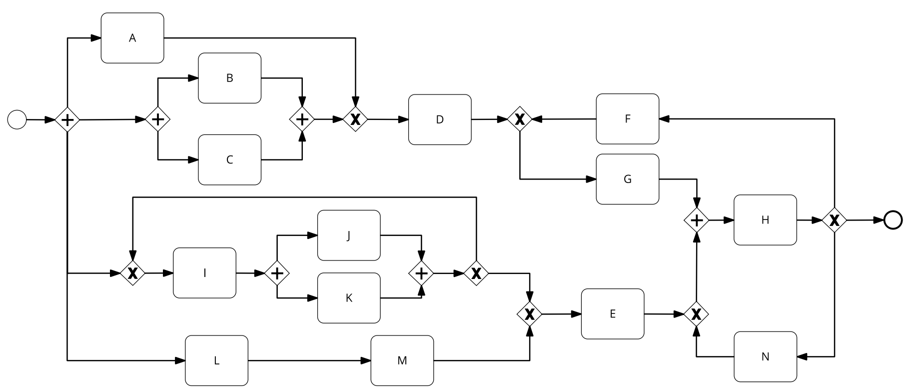

Fig. A-4. Process model 1 used in the test.

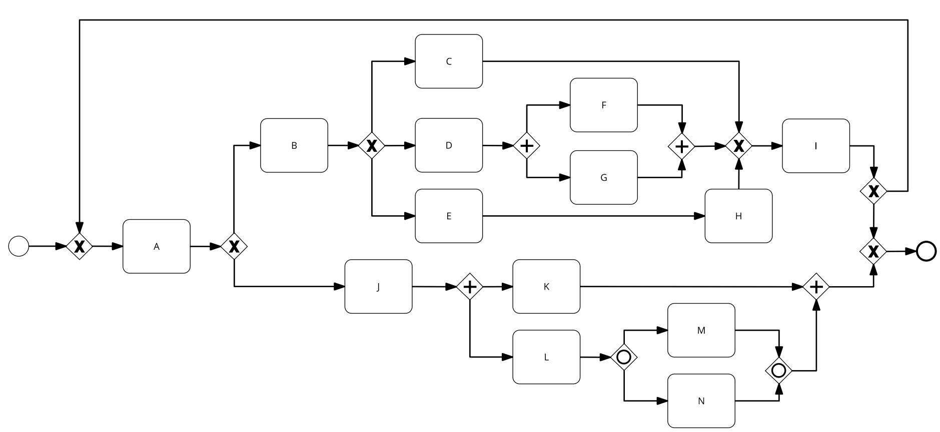

Fig. A-5. Process model 2 used in the test.

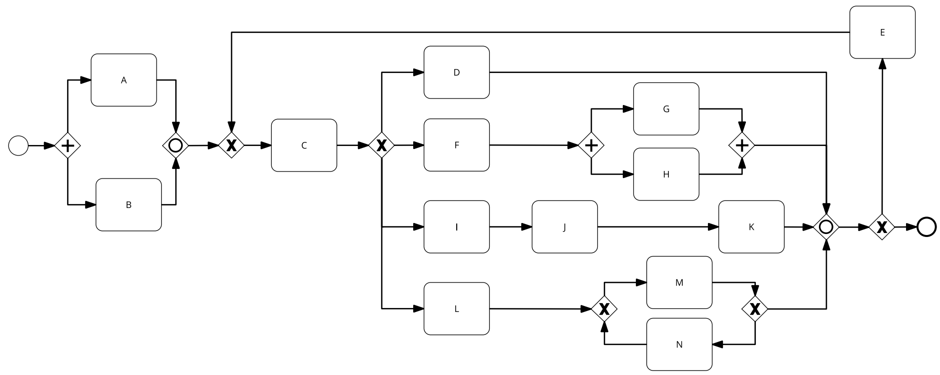

Fig. A-6. Process model 3 used in the test.

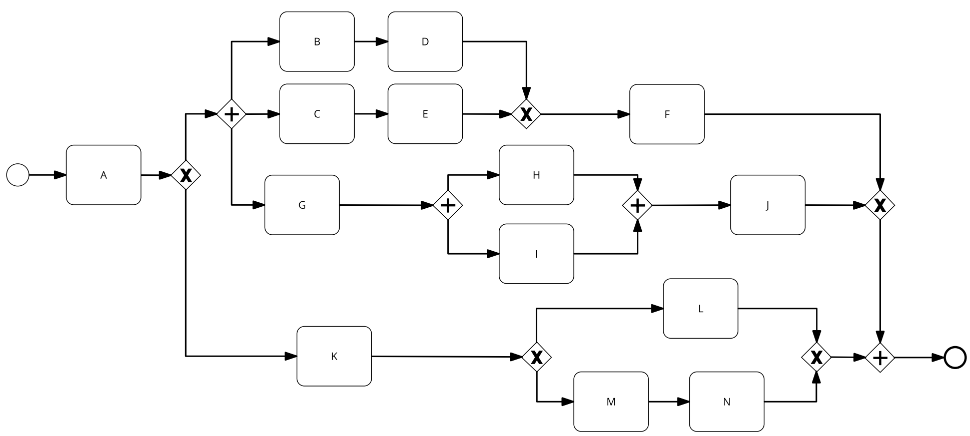

Fig. A-7. Process model 4 used in the test.

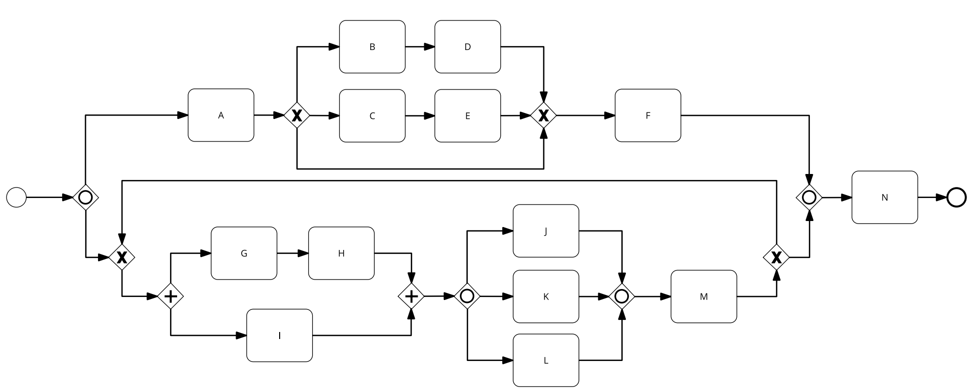

Fig. A-8. Process model 5 used in the test.

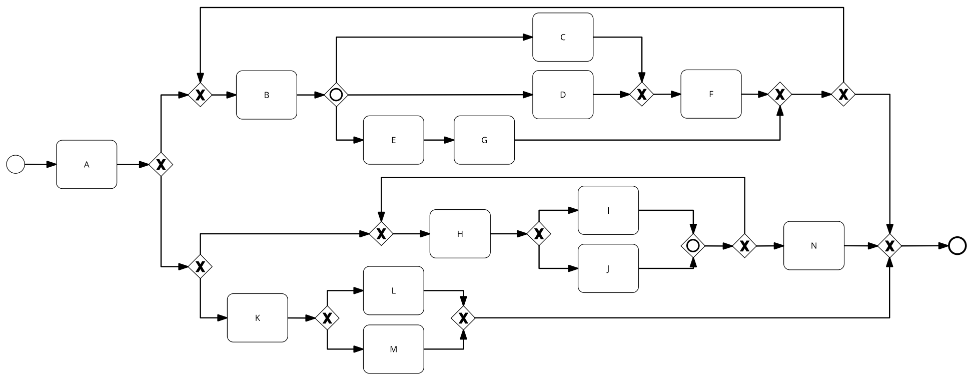

Fig. A-9. Process model 6 used in the test.

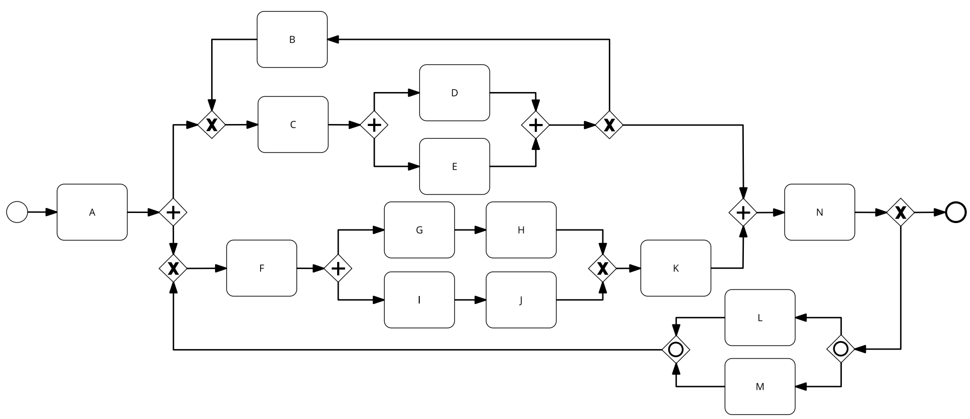

Fig. A-10. Process model 7 used in the test.

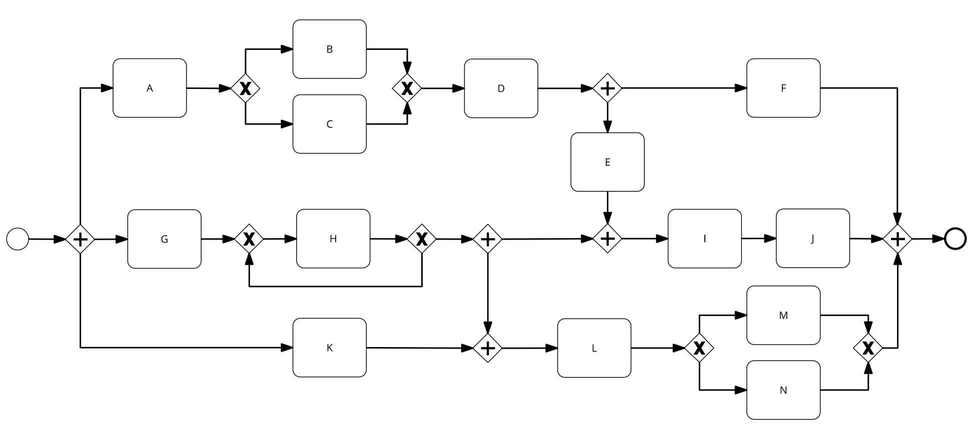

Fig. A-11. Process model 8 used in the test.

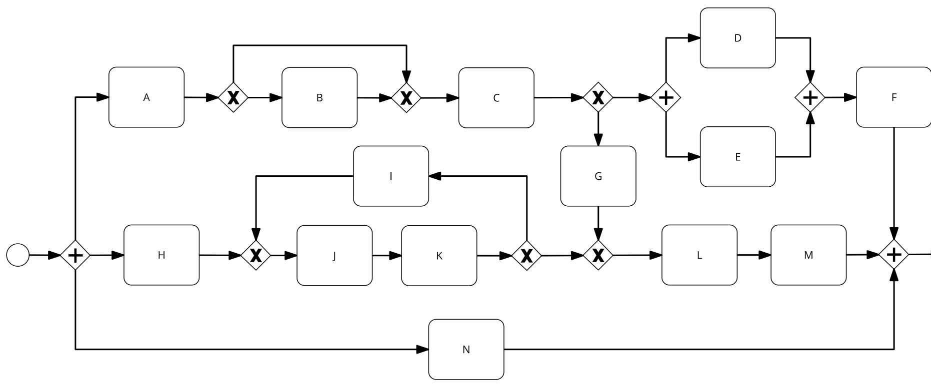

Fig. A-12. Process model 9 used in the test.

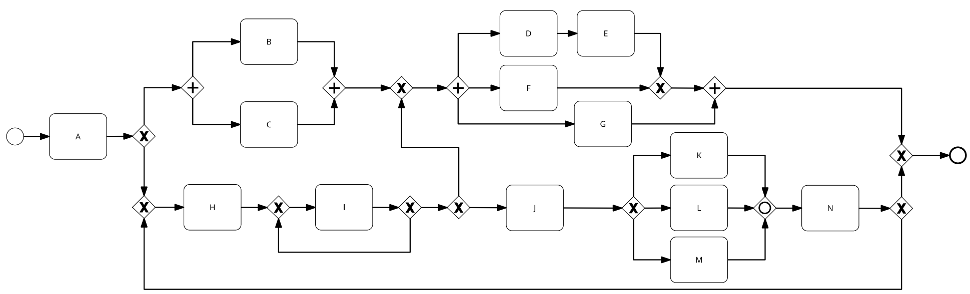

Fig. A-13. Process model 10 used in the test.

overall experiment procedure depicted in Fig. 3 can be accessed online from the following pages.

Static treatment: http://www.expertjudgment.com/ProcessModelAnimation/exps.html

Animation treatment: http://www.expertjudgment.com/ProcessModelAnimation/expa.html

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