Teaching Process Patterns in BPMN to Novice Modelers via Token Animations

Completed Research Paper

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Abstract

This study explores how token-based animations affect novice modelers' comprehension of BPMN process patterns. Using a survey-based experiment (N=140), we examined the impact of animation on cognitive load—distinguishing between intrinsic and extraneous components—and comprehension. While animations did not significantly improve comprehension scores directly, they significantly reduced extraneous cognitive load (ECL), which in turn positively influenced comprehension. Structural equation modeling confirmed that this effect was fully mediated through ECL. Process modeling expertise also reduced both intrinsic cognitive load (ICL) and ECL and directly enhanced comprehension. Qualitative feedback indicated that animations improved clarity, attention, and engagement, but learners preferred more interactivity and voice-over guidance. The findings suggest that token animations are effective in reducing representational complexity and supporting novice learners when combined with multimodal instructional strategies.

Keywords: Business Process Modelling, Process Modelling Education, BPMN, Token Animation, Cognitive Load, Process Modelling Expertise

Introduction

Process Modeling (PM) typically involves transforming textual descriptions into graphical depictions, aiming to improve communication between business and IT, clarify employee roles, streamline or restructure workflows, and support automation through enterprise software systems. Business Process Model and Notation (BPMN) has become the prevailing industry benchmark, necessitating skilled PM professionals (Dumas et al., 2018; Winter et al., 2021) and is the notation used throughout this study.

The clarity and comprehensibility of process models are among their most essential characteristics (D. L. Moody & Shanks, 2003), heavily shaped by how individuals perceive and engage with them (Figl, 2017). Often, process model comprehension is understood as objective (correct answers, time to answer) and subjective (perceived difficulty to understand a process model) (Figl, 2017). Overall, correct comprehension is a prerequisite for further learning (Rosenthal et al., 2019).

For novices, accurately understanding process models is difficult due to the absence of systematic analytical approaches (Aysolmaz & Reijers, 2021; Figl, 2017). PM education is typically unsystematic, *ad hoc* and lacks rigorous empirical methods validating the learning approaches (Maslov et al., 2024; Maslov et al., 2025; Rosenthal et al., 2019). According to Bogdanova and Snoeck (2019), educators in modelling should rely on learning objectives in alignment with Bloom's taxonomy. In process modelling, there is a typical set of BPMN elements and patterns used as learning objectives (Wohed et al., 2005; Dumas et al., 2018). Understanding modelling elements and higher-order patterns then weaves into the broader PM competence, as modelers apply the knowledge of semantics of patterns in reading, designing new models and other modelling activities (Soyka et al., 2023). Simultaneously, educators encounter challenges in efficiently conveying PM concepts, as educators lack a clear understanding of students' specific reading patterns and comprehension techniques of process models (Winter et al., 2021).

A method for enhancing process model comprehension involves employing animation and visualization strategies, such as token-based animations or highlighting process model paths (Emens et al., 2016; Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024). Animations can better illustrate the progression of process model activities and clarify interactions and behaviors among different model elements (Aysolmaz & Reijers, 2021). However, while empirical studies clearly support animations to enhance comprehension (Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024), research on how novice modelers benefit from animations to improve their learning outcomes and how they interact with animations in PM education context remains limited (Maslov & Poelmans, 2023; Maslov & Poelmans, 2024; Aysolmaz & Reijers, 2021).

This research specifically examines the aiding effect of token-animations to improve comprehension of BPMN process elements and patterns, as an initial step toward deeper comprehension and learning (Maslov & Poelmans, 2024a; Rosenthal et al., 2019). The underlying research contributes to a broader research agenda focused on enhancing BPMN 2.0 education and designing an animation-based instructional framework for PM training (Maslov & Poelmans, 2023).

This study employs a survey-based experimental approach in line with literature (Maslov & Poelmans, 2024a; Aysolmaz & Reijers, 2021). Our experiment is similarly conducted through a survey methodology targeting novice modelers in a higher education setting. We use a selection of often-used BPMN elements and BPMN-instantiated process patterns (Wohed et al., 2005; Dumas et al., 2018) to validate the effectiveness of process animations in enhancing process model comprehension. The study applies an adapted theoretical framework proposed by Aysolmaz & Reijers (2021) that relies on cognitive load theory and multi-media learning theory. The research seeks to address the following Research Questions (**RQs**):

RQ1. *Do token-animated explanations improve novice modelers' comprehension of process model patterns?*

RQ2. *What are the novice modelers' perceptions concerning the use of token-animated explanations to improve their learning of process model patterns?*

RQ1 aims at assessing the impact of using animations in explaining process patterns on the comprehension of process models, by examining their effects on the cognitive load. In this context, comprehension is understood as the first step towards the learning of process patterns. The findings in studies on the effects of animation on cognitive load differ between Aysolmaz and Reijers (2021), and Maslov and Poelmans (2024), with the former stating that it decreased cognitive load, whereas the latter stated that animations sometimes increased cognitive load. These studies lack a specific focus on the mechanism of studying process model animations effect on intrinsic cognitive load (i.e., the inherent difficulty of the content) and extraneous cognitive load (i.e., the difficulty bearing the representation of that information). We argue that this distinction is important, as animations are expected to reduce extraneous cognitive load in particular. The analysis is done using a group of 140 unexperienced students and PLS-structured equation modeling (SEM) procedures.

RQ2 is a supplementary question, and it is to gain insight into the positive effects of token animations on process pattern comprehension by scrutinizing novice modelers' feedback on their interactions with the token animations (Maslov & Poelmans, 2024a).

The paper is structured as follows. Section 2 provides an overview of extant literature. Section 3 provides a theoretical framework and develops hypotheses. Section 4 outlines the design of the experiment applied to validate the research framework and hypotheses. Section 5 presents findings from PLS-SEM and qualitative feedback from the novice modelers of the experiment. Section 6 discusses the results, limitations, threats to validity, and future research directions. The research concludes with Section 7.

Extant literature

Process Modeling (PM) entails externalizing internal cognitive representations into external visual models to promote shared understanding among business stakeholders (Aysolmaz & Reijers, 2016; D. Moody, 2009). PM encompasses both interpreting and constructing models, where clarity and readability take precedence over mere syntactic or semantic correctness (D. L. Moody & Shanks, 2003). Nevertheless, interpretation inconsistencies persist, emphasizing the necessity of correct comprehension (Dumas et al., 2018). This research centers on understanding and interpreting process models.

Comprehension can be assessed objectively through the number of correct answers and response time, and subjectively through perceived difficulty (Figl, 2017). The factors influencing PM comprehension include (1) individual (i.e., modeler) attributes, (2) model-specific characteristics, and (3) model-modeler interaction, such as reading strategies (Bardone & Secchi, 2018; Figl, 2017; Maslov & Poelmans, 2024a).

Individual attributes generally encompass cognitive factors essential to comprehension, such as cognitive load capacity, which is shaped by working memory (Figl, 2017). Higher levels of education improve comprehension accuracy (Maslov, 2022, May), domain familiarity reduces cognitive strain (Figl, 2017), and age influences fixation frequency (Winter et al., 2021). Additionally, cultural background affects reading preferences and expectations (Duggan & Payne, 2009). External cognitive resources, or model factors, also impact comprehension. These include the modeling language (Figl, 2017), model complexity (Aysolmaz & Reijers, 2021), and semantic richness, such as detailed task descriptions (Figl, 2017).

Model attributes significantly affect comprehension. Complex logic, characterized by infrequent elements, can hinder understanding (Aysolmaz & Reijers, 2021). However, explicit business rule articulation enhances precision and alleviates cognitive burden (Wang et al., 2022). The arrangement of process elements, including bends and modularity, plays a pivotal role in readability (Lübke et al., 2021). Furthermore, visual enhancements, such as task coloring, reduce cognitive effort and support knowledge retention (Petrusel et al., 2017). These visual elements align with animations, which can further enhance comprehension.

Finally, **human-model interaction** represents a key set of factors in process model comprehension, bridging intrinsic (modeler) and extrinsic (model) influences into an effectively structured engagement (Maslov & Poelmans, 2024a). Model reading approaches also affect understanding, as both modeler experience and layout structure influence cognitive processing (Lübke et al., 2021). Reading behaviors are frequently analyzed through eye-tracking studies (Winter et al., 2021), though quantitative surveys or qualitative feedback are often employed to study the interactions (Maslov & Poelmans, 2024a). These behaviors include tracking the process flow with occasional regressions—revisiting prior elements, skimming, or initiating central-focused trials (Duggan & Payne, 2009). Participants may bypass complex sections, identifying congruence points, or cognitive reference markers to revisit later (Winter et al., 2021). Novice readers typically process models sequentially, exhibiting more fixations and extended reading durations, whereas experienced modelers focus on critical components such as decision points, indicating their proficiency with higher-level structures (Figl, 2017). Reading effort correlates inversely with knowledge, as lower familiarity results in increased rereads and intensified cognitive engagement (Petrusel et al., 2017).

The integration of **Visualization, Animation, and Simulation (VAS)** techniques enhances process model comprehension (Figl, 2017; Maslov & Poelmans, 2024a). Visualization makes process information more digestible through graphical representations. Animation incorporates motion to clarify process flows, while simulation enables real-world or hypothetical process scenarios, facilitating "what-if" analyses (Maslov & Poelmans, 2023). Animated process models offer significant cognitive advantages, as graphical depictions are easier to process than abstract, formal representations (Aysolmaz & Reijers, 2021). Animations improve model element clarity, making them more intuitive while offering real-time feedback on correctness (Aysolmaz & Reijers, 2021; Emens et al., 2016; Figl, 2017). By directing focus toward relevant process elements and their interactions, animations assist in reducing cognitive load and enhancing working memory efficiency (Aysolmaz & Reijers, 2021; Figl, 2017).

Among the most effective animation techniques is **token-based visualization**, in which colored markers (tokens) move dynamically through a process model, representing its execution logic (Maslov & Poelmans, 2024a). Another widely used technique is process path highlighting, illustrating the behavior of an active process instance (Aysolmaz & Reijers, 2021). Despite strong empirical evidence supporting their efficacy, research on animations in PM education remains limited. The limitation is largely a reflection of the lack of empirical evidence and systematic approaches in PM education (Maslov et al., 2024; Rosenthal et al., 2019; Maslov et al., 2025). There is yet a lack of studies focusing on empirically validating learning approaches centered around learning objectives, the knowledge of which is crucial prerequisite for an effective PM (Bogdanova & Snoeck, 2019; Dumas et al., 2018; Soyka et al., 2023; Maslov et al., 2025).

The use of visualization and animation is highly recommended in the educational approaches in process modelling (Maslov & Poelmans, 2024a; Winter et al., 2021; Aysolmaz & Reijers, 2021). **Token-Based Process Modeling (TBPM) education** posits that VAS techniques, particularly token-based animations, serve as essential tools for PM education (Maslov & Poelmans, 2023). This approach promotes dynamic interaction with process models, fostering improved knowledge acquisition and deeper comprehension (Maslov, 2022; Maslov & Poelmans, 2023). The following section explains further the theoretical framework and the development of hypotheses in this study.

Theoretical framework and hypothesis development

We present the theoretical framework of the study in Figure 1. According to cognitive load theory (Leppink & van den Heuvel, 2013; Klepsch et al., 2017), intrinsic cognitive load (ICL) arises from the complexity of process models, requiring users to interpret hidden dependencies, infer execution flows, and manage numerous interacting elements, making comprehension inherently challenging. Extraneous cognitive load (ECL), on the other hand, stems from the way process models are presented, such as static representations that force users to mentally simulate process execution, increasing cognitive effort compared to more intuitive visualizations (Aysolmaz & Reijers, 2021). We employ an 8-item survey by Leppink and van den Heuvel (2013) on a 1-6 Likert scale, where 1 is very low CL, and 6 is very high CL. An example of an ICL item is *"The content of this experiment was very complex."* An example of an ECL item is *"I invested a very high mental effort in unclear, ineffective explanations and instructions in this activity."* We treated ICL and ECL as latent factors measured by survey items (from an 8-item cognitive load instrument) and CL as a factor reflected by those two dimensions (Becker et al., 2012).

In Partial Least Squares Structural Equation Modeling (PLS-SEM), hierarchical component models (HCM) allow researchers to model complex constructs efficiently by structuring them as higher-order constructs (Sarstedt et al., 2019). The current model conceptualizes Cognitive Load (CL) as a second-order reflective construct, composed of Intrinsic Cognitive Load (ICL) and Extraneous Cognitive Load (ECL) as first-order reflective components (Leppink & van den Heuvel, 2013; Klepsch et al., 2017). This Reflective-Reflective Hierarchical Component Model (HCM) is a well-established approach in SEM for latent constructs with multiple dimensions (Becker et al., 2012). A reflective higher-order construct assumes changes in the overall CL will be reflected by proportional changes in both ICL and ECL – an assumption aligned with CLT (e.g. when total load is high, usually at least one of its sub-dimensions is high) and supported by prior use of multi-dimensional cognitive load scales (Klepsch et al., 2017).

This hierarchical modeling improves parsimony – reducing model complexity by replacing multiple correlated outcomes (ICL, ECL) with one higher-order construct – and avoids suppressor effects between ICL and ECL when predicting other variables. Notably, our PLS implementation used the repeated-indicators approach for the second-order factor (CL), meaning all items of ICL and ECL were used as indicators for CL (Sarstedt et al., 2019). This technique enables estimation of the higher-order construct in a single stage and is recommended for reflective-reflective HCMs (Sarstedt et al., 2019). We therefore propose:

H1. *Intrinsic Cognitive Load (ICL) is a significant reflective dimension of Cognitive Load (CL).*

H2. *Extraneous Cognitive Load (ECL) is a significant reflective dimension of Cognitive Load (CL).*

Cognitive load that arises from the reading of process models is typically considered the core study factor in its impact on the process model comprehension (Figl, 2017; Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a). The study operationalizes comprehension of process patterns as the number of correct answers (Figl, 2017) about a selection of six often-used BPMN-instantiated elements and process patterns (Wohed et al., 2005; Dumas et al., 2018). This mirrors the experimental setup in (Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a). We detail how we developed the explanations (see an example in Figure 2) and the modelling tasks to test the comprehension (see an example in Figure 3) in the Methodology section below. Hence, we suggest:

H3. *An increase in Cognitive load reduces comprehension of process patterns.*

Animations can be used to decrease the cognitive load of the participants (Aysolmaz & Reijers, 2021). This may work via different principles, such as the signaling principle, attention guidance, enabling function, and facilitating function (Aysolmaz & Reijers, 2021). In the theoretical setup of Aysolmaz and Reijers (2021), ***Multimedia learning theory*** (Mayer, 2005) suggests that animations enhance learning by guiding attention and reducing extraneous cognitive load, making complex concepts easier to understand. ***Cognitive load theory*** (Sweller, 2011) supports this by emphasizing that animations reduce the number of processed elements at once, lowering visual complexity and minimizing the need to cross-reference elements, which decreases intrinsic cognitive load. At the same time, animations can reduce extraneous cognitive load by providing visual cues and minimizing the effort required to infer hidden dependencies, allowing users to focus their cognitive resources on meaningful learning and problem-solving tasks (Aysolmaz & Reijers, 2021).

By tackling intrinsic and extraneous cognitive loads separately, it is possible to address the challenges of students at general learning and then suggest potential solutions using the concepts of these theories (Mayer & Moreno, 2003). According to Mayer and Moreno (2003), this approach helps address Type 3 cognitive overload: when extraneous information (the means of representation) interferes with the comprehension of the underlying material. For this, animation will be used as a signaling method to help highlight the most relevant information for the students to focus on.

In PLS-SEM with the repeated-indicator approach the predictor can be linked to the first-order components to ensure all indirect paths are captured (Becker et al., 2012). We adopted this approach for our treatment variable and expertise variable – effectively modelling their influence on CL via ICL and ECL. By doing so, we are aligning the structural paths with the theoretical structure of CLT (as discussed above) and adhering to HCM best practices (Becker et al., 2012; Sarstedt et al., 2019). Thus, the animation will be tested for its effect on CL via mediation through ICL and ECL. We hence propose the hypotheses that the animation reduces ICL and ECL:

H4. *Animation reduces overall Cognitive Load (CL).*

  H4.1. *Animation reduces Intrinsic Cognitive Load (ICL).*

  H4.2. *Animation reduces Extraneous Cognitive Load (ECL).*

H5. *Animation improves comprehension of process patterns.*

  H5.1. *Animation has a direct positive effect on comprehension.*

  H5.2. *The positive effect of Animation on comprehension is mediated by ICL.*

  H5.3. *The positive effect of Animation on comprehension is mediated by ECL.*

PM expertise factor is operationalized via measuring participants' knowledge in a pre-test on 10 questions about a model. The pre-test was identical to both conditions. Questions measured participant's correct knowledge about the common BPMN syntax and basic semantics. The examples are shown below in the methodology section.

PM expertise is often used both as a control factor and as a study focus (Aysolmaz & Reijers, 2021; Figl, 2017). Novices tend to have more struggles with being cognitively overloaded even with simpler components, whereas process modelling experts tend to be able to capture larger mental chunks of higher-level patterns. This is because experts are known to possess more detailed and interconnected mental schemata, enabling them to process complex structures more efficiently (Glaser, 1984; Boutin et al., 2022). Consequently, experts can often infer implicit information from models based on subtle cues, while novices rely more on generalizations and require more visual guidance (Lurigio & Carroll, 1985; Boutin et al., 2022).

Because of this, experts and novices may require varying levels of visual cueing (Aysolmaz & Reijers, 2021). Whereas novices may require an extensive and most basic explanation of the elements, experts may demand more nuanced animations and visualizations of the specific elements and patterns (Burattin et al., 2018). Thus, we propose that PM expertise can directly and indirectly affect the comprehension in modelling tasks, as mediated via the CL. Prior studies suggest that PM expertise affects understanding primarily through its impact on the cognitive processing of syntax and semantics (Boutin et al., 2022). Per HCM best practices (Becker et al., 2012; Sarstedt et al., 2019), the PM expertise effect on CL will be tested via mediation through ICL and ECL and no direct effect on CL is to be tested (like with the animation). We thus propose:

H6. *PM expertise reduces Overall Cognitive Load (CL).*

H6.1. *PM expertise directly reduces Intrinsic Cognitive Load (ICL).*

H6.2. *PM expertise directly reduces Extraneous Cognitive Load (ECL).*

H7. *PM expertise improves comprehension of process patterns.*

H7.1. *PM expertise has a direct positive effect on comprehension.*

H7.2. *The impact of PM expertise on comprehension is mediated by ICL.*

H7.3. *The impact of PM expertise on comprehension is mediated by ECL.*

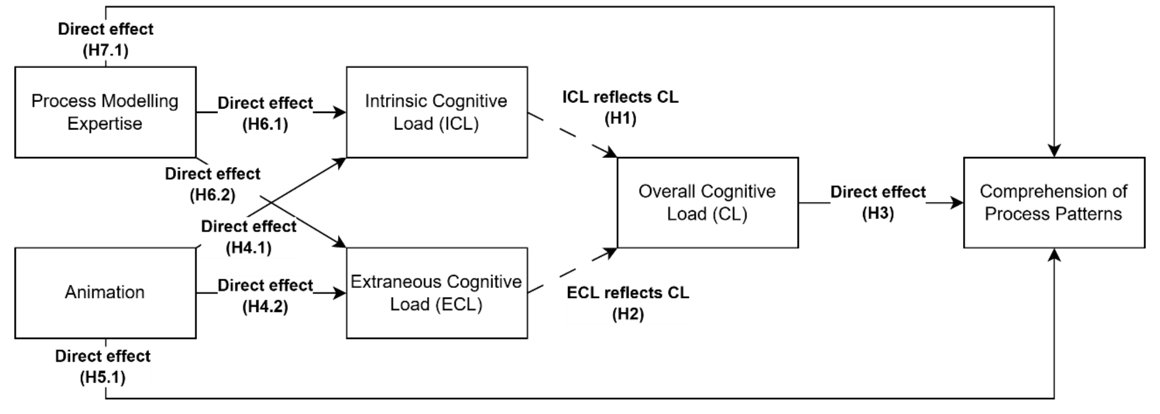

Figure 1. Theoretical Framework and Theoretical research Model

Methodology

To address the research questions and examine the differences in how token animations influence process pattern comprehension, we conducted a survey-based experiment. This approach is a widely recognized empirical method for assessing process model comprehension and is among the most effective for hypothesis validation (Winter et al., 2021; Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a). Building on prior research (Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a), we adopted an extended experimental framework to investigate our research questions and test the hypotheses. The subsequent section outlines the participants, experimental setup, and materials used.

Participants were recruited in the Fall semester of 2023 from two courses at an Austrian higher education institution (TU Wien). The first was a Master's-level course, Enterprise and Process Engineering, with 85 enrolled students. The second was a Bachelor's-level course, Information Systems Engineering, with 121 enrolled students. Each course was led by a separate lecturer. In total, 140 students participated in the study, thus a high response rate of about 70%. Among participants, 82 had not yet obtained a Bachelor's degree, 53 held a Bachelor's degree, and 5 held a Master's degree. The business-oriented backgrounds of the participants align with typical process modeling stakeholders in industry.

Participation in the study was entirely voluntary. Students were invited during class announcements and via email to take part in a voluntary online experiment hosted on Qualtrics. They were informed that the purpose of the study was to improve educational methods for process modeling. To encourage engagement, students were offered a small bonus point for participation, regardless of their performance, provided they completed the survey in one sitting and without consulting external materials.

The study received institutional approval and followed all ethical research guidelines applicable at TU Wien and KU Leuven. Informed consent was obtained electronically at the start of the survey, where students were informed about the voluntary nature of participation, the anonymity of their responses, the data protection procedures, and their right to withdraw at any time without penalty.

The experiment was conducted at an early stage of both courses, after students had received only two introductory lectures on BPMN, where students were taught the basics, such as typical gateways' behavior. Students were also taught token animations. This timing ensured that participants had sufficient familiarity to engage with basic modeling tasks as novice modelers, while still lacking comprehensive exposure to the full range of BPMN patterns—thereby preserving the intended naivety for the study.

Prior to testing the effects of animation, we prepared a 10-item questionnaire concerning the modelers' knowledge of BPMN elements' names (8 questions) and semantic behavior (2 questions), using a first pre-test process model. For instance, a syntax question that was asked: *"What are the full arrows as seen between A and B called in BPMN?"* to which the correct answer is *"Sequence flow."* An example of a semantic question related to the knowledge of the behavior of Parallel Gateway: *"Activities C and D will only start at the same time."* Participants had 4 options and could also answer *"I don't know"* to diminish guessing.

In this BPMN knowledge pre-test, modelers have shown to have some basic proficiency, but they also lack some knowledge (M=6.1 out of 10; SD=2.5). We also employed a composite measure incorporating the number of models read, created and the self-rated familiarity with process modeling (Aysolmaz & Reijers, 2021). Using this measure, we find that participants have on average a score of 7.07 out of 16 (SD=3.03). Most participants also had at least some limited knowledge about the meaning of tokens, thus knowing how to read token-animated explanations. Consequently, we assess the participant sample as relatively homogeneous in terms of educational background and process modeling expertise, demonstrating moderate proficiency in process modeling while actively furthering their education and capable of understanding process patterns explained in the experiment.

Utilizing the BPMN 2.0 standard, we instantiated explanations of 6 patterns, supported with a textual description of the semantics and 6 exercise process models that contain 4 options, one of which is true. Participants also had the option to select "*I don't know*", which was coded as a false answer (0 points). Figures 2 and 3 below contain an example of boundary and intermediate (non-)interrupting pattern token-animated video explanations and a model to test the comprehension. The semantics of the following BPMN elements and patterns were explained to the participants: (1) basic sequence flow and gateways (i.e., parallel (AND) and exclusive (XOR) gateways); (2) inclusive gateway (OR) (i.e., multichoice pattern); (3) event-based gateways; (4) intermediate interrupting / non-interrupting boundary and catch timer events; (5) deadlocks (i.e., lack of synchronization); (6) livelock (i.e., infinite loop). The process models were semantically abstract, minimizing the influence of domain expertise and English proficiency on process model understanding (Aysolmaz & Reijers, 2021). All models were designed to be read from left to right, following the BPMN standard as recommended by (Lübke et al., 2021).

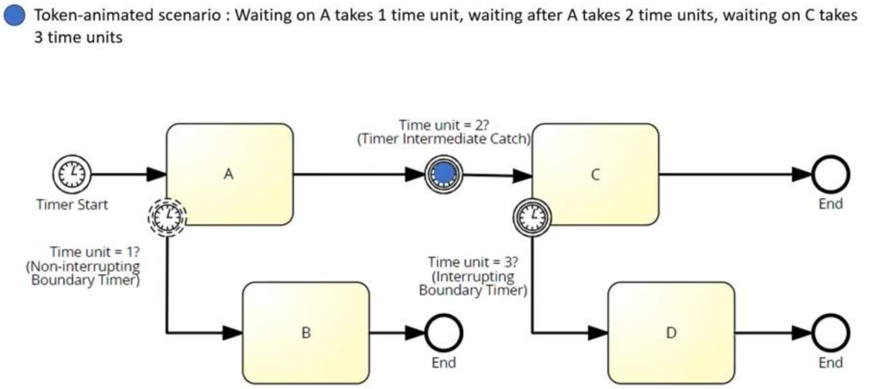

Figure 2. Example of a token-animated process pattern explanation (note: the tokens are moving in videos, and static condition had no tokens)

For a cohort that got explanations of process patterns with tokens, these models were animated following (Maslov & Poelmans, 2024a). In the token-animated condition, every pattern explanation involved pre-recorded video featuring animations aimed to aid in supporting the textual explanations in a visual format (i.e., animations aimed at conveying meaningful semantic information about BPMN behavior to aid in answering the questions about the patterns, that were static). Participants were randomly assigned to either the token-animated BPMN condition (N = 67) or the static/non-animated condition (N = 73).

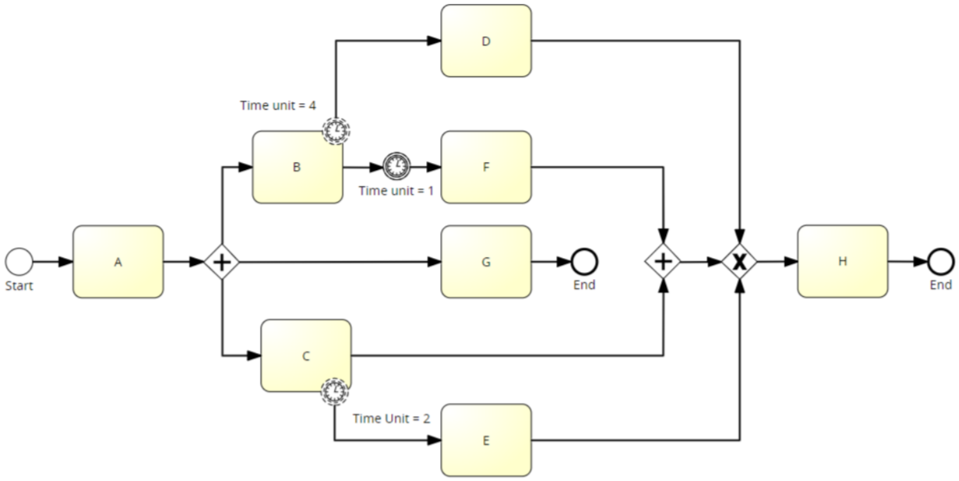

Figure 3. Example of a model to test comprehension after explanations (note: the testing models are identical in both conditions)

For students in the animated condition, the survey concluded with open-ended questions soliciting participants' feedback on their usage of animations and general insights on their effectiveness in improving comprehension and process modeling education. Specifically, participants were asked to identify benefits, drawbacks, and suggestions for enhancing the process of modeling education through animations. Responses were recorded, transcribed, and subjected to an inductive thematic analysis using qualitative analysis software (Saunders et al., 2009). Before roll-out, we validated and improved the survey on 3 PhD students to participate and provide us with feedback.

In the subsequent section, we present an overview of the data alongside the quantitative and qualitative analysis of objective and subjective comprehension, as well as model-user interactions.

Data analysis results

Hypothesis testing using PLS-SEM

Table 1 presents an overview of descriptive statistics comparing the means of correct answers with and without animation explanations of 6 frequently used BPMN patterns, adapted from Wohed et al. (2005) and Dumas et al. (2018). We calculated the mean number of respondents (in percentage) who correctly answered a comprehension task in both conditions. For instance, an inclusive-OR was correctly answered by 39 out of 67 participants in animation-facilitated explanations (or 58.2%) and 33 out of 73 participants (or 45.2%).

To test statistical differences in performance between the conditions, we conducted two-proportion z-tests, which are appropriate for comparing binary outcomes (correct vs. incorrect) between two independent groups (Field, 2013). This method directly assesses whether the proportions of correct answers differ significantly between the animation and static conditions. Across all six patterns, the results showed no statistically significant differences between the conditions (all p-values > .10), suggesting that the animation did not lead to a significant improvement in comprehension accuracy for individual patterns.

To complete tasks in animated condition on average took M=33.3 minutes (SD=65.9), whereas in static it took M=17 minutes (SD=7.8). We performed a two-sample T-test assuming equal variance (p = .038), thus finding that participants in the animated condition spent more time with the explanations, fully in line with previous literature (Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a).

Table 1. Comparison of Proportion of Correct Answers Between Animation and Static Conditions (n = 140)

Pattern	Percentage of correct answers with Animated explanations (n=67)	Percentage of correct answers with Static explanations (n=73)	p-value
Simple XOR, AND gateway	67.2%	71.2%	0.60
Inclusive-OR	58.2%	45.2%	0.12
Event-based gateway	52.2%	43.8%	0.32
Timer events	31.3%	30.1%	0.88
Deadlock	47.8%	45.2%	0.76
Livelock	50.7%	56.2%	0.52

To test the difference between ECL and ICL, we also performed a two-sample T-test assuming equal variance. Mean scores on the 4 ECL items were significantly lower for the animation condition (M = 2.01 on 6, SD = 0.74) compared to the static condition (M = 2.52, SD = 0.99), with p < .001. In contrast, no significant difference was found in ICL scores across conditions: animation (M = 3.16, SD = 0.87) versus static (M = 3.42, SD = 0.85), with p = .08. Within both conditions, ICL scores were significantly higher than ECL scores (p < .001). Overall cognitive load (CL), based on an average of 8 items, was also significantly lower in the animation condition (M = 2.59, SD = 0.66) compared to the static condition (M = 2.97, SD = 0.78), with p < .01. These findings suggest that animation primarily reduces extraneous cognitive load, while intrinsic load remains unaffected.

Consequently, we developed an explanatory model utilizing PLS-SEM to examine the direct and mediating influences. The model is illustrated in Figure 4 below.

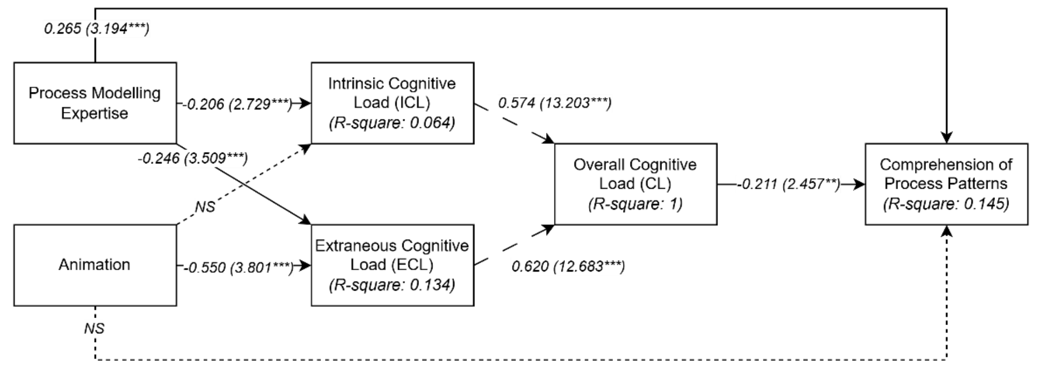

Figure 4. Structural model with path coefficients and t-values.
(* p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001)

To assess the measurement model for latent constructs, we analyzed individual item reliability, internal consistency, and discriminant validity (see Table 2). Item reliability was confirmed, as factor loadings exceeded 0.70 except for Overall Cognitive Load, which contains two sub-factors, as expected. Cronbach's alpha was above 0.65 (Table 2). Convergent and discriminant validity were ensured, given that the Average Variance Extracted (AVE) for all latent constructs surpassed 0.50, except for a second-factor CL, as expected (Joseph et al., 2010; Chin, 1998). The model followed Repeated Indicators Approach with a second-order factor, and the Variance Inflation Factor (VIF), measuring the multicollinearity between predictor constructs in PLS-SEM models, was all below 3, indicating no further action needed to treat the second-order factor of CL, composed of ICL and ECL (Hair et al., 2019).

Table 2. Consistency and validity of the latent constructs

Latent construct	AVE	Composite Reliability	Factor loadings	Cronbach α
Overall Cognitive Load (CL; 8 items)	0.443	0.86	0.682; 0.613; 0.596; 0.689; 0.684; 0.635; 0.687; 0.730	0.82
Extraneous Cognitive Load (ICL; 4 items)	0.649	0.88	0.836; 0.739; 0.776; 0.866	0.82
Intrinsic Cognitive Load (ECL; 4 items)	0.618	0.87	0.822; 0.824; 0.723; 0.771	0.80

The Heterotrait–Monotrait Ratio of Correlations (HTMT) evaluates the average correlation of indicators across constructs in PLS-SEM (Table 3). For adequate discriminant validity, HTMT values should be below 0.85 (Henseler et al., 2015), which holds true for all variables, except for ICL and ECL, which are supposed to form CL.

Table 3. Heterotrait-monotrait ratio (HTMT)

	Original sample (O)
CL <-> Animation	0.27
ECL <-> Animation	0.30
ECL <-> CL	1.03
ICL <-> Animation	0.17
ICL <-> CL	1.03

ICL <-> ECL	0.49
Pattern Score <-> Animation	0.05
Pattern Score <-> CL	0.31
Pattern Score <-> ECL	0.26
Pattern Score <-> ICL	0.27
Pre-test Score <-> Animation	0.01
Pre-test Score <-> CL	0.29
Pre-test Score <-> ECL	0.27
Pre-test Score <-> ICL	0.23
Pre-test Score <-> Pattern Score	0.32

Table 4 presents the structural results of direct effects. Further, Table 5 depicts the structural model's indirect (mediating) effects following the recommendations of (Hair et al., 2017). We employed bootstrapping with 5000 subsamples to determine statistical significance.

Cognitive Load (CL) is conceptualized as a second-order latent construct, fully composed of its two first-order dimensions: Intrinsic Cognitive Load (ICL) and Extraneous Cognitive Load (ECL). In our model, CL was specified using a formative higher-order measurement approach, with ICL and ECL as its formative components. The bootstrapped weights from both dimensions were statistically significant (ICL: $\beta = 0.574$, $t = 13.203$, $p < .001$; ECL: $\beta = 0.620$, $t = 12.683$, $p < .001$), and no multicollinearity was detected (VIFs < 3). Furthermore, the R^2 for CL was 1.00, indicating that CL is mathematically and theoretically fully formed by ICL and ECL, consistent with hierarchical component modeling principles (Becker et al., 2012) and the multidimensional structure of cognitive load theory (Sweller et al., 2011; Leppink & van den Heuvel, 2013; Leppink & van den Heuvel, 2015). H1 and H2 are thus supported. Furthermore, CL significantly reduced comprehension of process patterns ($\beta = -0.21$, $p = .014$). This finding confirms H3 and emphasizes the cognitive costs associated with understanding complex BPMN structures (Figl, 2017).

More interestingly, animation significantly reduced extraneous cognitive load (ECL) ($\beta = -0.55$, $p < .001$), supporting H4.2, while its effect on intrinsic cognitive load (ICL) was just above the threshold of significance ($\beta = -0.30$, $p = .064$), leading to the rejection of H4.1. These findings offer a nuanced perspective on prior claims by Aysolmaz and Reijers (2021), who suggested that animation could improve both types of cognitive load. Our results suggest a more selective impact: animation, as an additional representational layer on top of the static BPMN notation, effectively reduces ECL—that is, it improves the mode of information presentation—but does not reduce the inherent complexity of the content itself (ICL). Thus, animation supports learners in managing how the process information is delivered, rather than making the process logic inherently easier to grasp.

Table 4 also reveals that PM expertise significantly reduces both intrinsic and extraneous cognitive load, supporting H6.1 and H6.2. Specifically, the path from PM expertise to ICL is significant ($\beta = -0.21$, $p = .006$), as is the path to ECL ($\beta = -0.25$, $p < .001$). These findings align with cognitive load theory, which posits that individuals with greater prior knowledge can more easily process complex content (lower ICL) and are less dependent on instructional support (lower ECL) (Sweller et al., 2011). In this context, students with stronger BPMN expertise appear better equipped to handle the inherent difficulty of process models and are less burdened by the way the information is presented. This reinforces the theoretical expectation that prior knowledge mitigates both types of cognitive load during model comprehension tasks.

Table 4. Structural results.

Hypothesis	Path	Path Coefficients (β)	T-statistics	P-values	Result
H1	ICL -> CL	0.57	13.20	0.000	Confirmed
H2	ECL -> CL	0.62	12.68	0.000	Confirmed

H3	CL -> Comprehension of Process Patterns	-0.21	2.46	0.014	Confirmed
H4.1	Animation -> ICL	-0.30	1.85	0.064	Rejected
H4.2	Animation -> ECL	-0.55	3.80	0.000	Confirmed
H5.1	Animation -> Comprehension of Process Patterns	0.00	0.02	0.983	Rejected
H6.1	PM Expertise -> ICL	-0.21	2.73	0.006	Confirmed
H6.2	PM Expertise -> ECL	-0.25	3.51	0.000	Confirmed
H7.1	PM Expertise -> Comprehension of Process Patterns	0.27	3.19	0.001	Confirmed

Bootstrapping analysis confirms most of the significant indirect effects in the structural model (see Table 5). Furthermore, the effect of PM expertise on pattern comprehension is partially mediated via ECL (β = 0.03, p = .040), confirming H7.3, while the path via ICL is not significant (β = 0.02, p = .069), thus rejecting H7.2. Most importantly, animation also had a significant indirect effect on pattern comprehension via ECL and CL (β = 0.07, p = .0492), supporting H5.3, while the corresponding pathway via ICL was not significant (β = 0.04, p = .159), rejecting H5.2. This aligns with prior assumptions that animation reduces extraneous but not intrinsic cognitive load.

Additionally, as seen in Table 4, the direct effect of animation on pattern comprehension was non-significant (β = 0.00, p = .983; H5.1 rejected), this demonstrates a full mediation through ECL. In contrast, PM Expertise did significantly predict pattern comprehension (β = –0.21, p = .014), confirming H7.1. These findings reinforce the theoretical expectation of PM expertise and animation in managing cognitive load in order to enhance process pattern comprehension.

Table 5. Indirect (mediating) effects in the structural model.

Hypothesis	Path	Path Coefficients (β)	T-statistics	P-values	Result
H5.2	Animation -> ICL -> CL -> Comprehension of Process Patterns	0.04	1.41	0.1591	Rejected
H5.3	Animation -> ECL -> CL -> Comprehension of Process Patterns	0.07	1.97	0.0492	Confirmed
H7.2	PM Expertise -> ICL -> CL -> Comprehension of Process Patterns	0.02	1.82	0.0688	Rejected
H7.3	PM Expertise -> ECL -> CL -> Comprehension of Process Patterns	0.03	2.06	0.0399	Confirmed

Additional analysis: qualitative feedback about the use of token animations at comprehending and learning process patterns

We first asked participants from the animated condition (N=67) to reflect on 9 possible effects of token animations, which we came up with through our previous experience in using tokens in our own practice and from semi-structured interviewing novice modelers using the token-animations. Participants reflected that using token animations reduced the complexity of understanding patterns (n=55), improved attention (n=50), engagement (n=48), entertainment (n=35), enjoyment (n=35), motivation (n=33), facilitated thinking (n=31), and improved concentration (n=24) and confidence (n=24). The findings support that novice modelers found tokens as an external device that supported their cognitive function when understanding the patterns (Maslov & Poelmans, 2024a). To a lesser extent, tokens were also emotionally engaging, and the tokens could have been somewhat "fun" to use, which is following the suggestion of using gamification in PM education (Rosenthal et al., 2019). We then analysed their qualitative feedback.

The **benefits** of token-based videos in learning BPMN elements and patterns emerged in several key themes. Many participants (34) highlighted that the visual representation in animations made it easier to see and illustrate processes clearly, the semantics of gateways. Some (9) pointed out that animations helped in following the sequence and flow of processes. In particular, the benefits were associated by many (34) that the videos enhanced comprehension by making the content clearer and easier to understand, almost being *"self-explanatory"* as one cited. Some participants (16) appreciated the efficiency of learning through videos, mentioning that it simplified the learning process compared to reading, though the explanations supported their understanding well to some.

Participants generally found no **disadvantages**. There were, however, some minor remarks. Several (11) indicated that a lack of explanation embedded within the animation itself made it difficult to fully understand the concepts. Some participants (9) mentioned that the videos were overly simplistic and lacked depth, failing to cover more complex scenarios, hence likely hindering transferring of knowledge. A few responses (5) pointed out issues with visual clarity, describing parts of the videos as unclear (i.e., lacking *"self-explanatory"* attribute, mentioned by some in advantages or for more complex patterns). Aesthetics were cited as somewhat troubling, though not hindering. Some participants (4) found the animation speed problematic, with animations being either too fast or too slow. Additionally, a small number of responses (3) noted that the absence of audio support or narration made the learning experience less effective.

Finally, we asked participants about their suggestions for potential **improvements** in their learning approach using token animations in the future. Many participants (10) emphasized the need for more interactive elements, such as engagement through discussions or questions, which extends the notion of (Aysolmaz & Reijers, 2021) for PM education by proposing other set of *"interactive features"* and that interactivity is only in the degree of selecting the scenarios to run. A similar number of responses (10) highlighted the importance of providing more (voiced) explanations to clarify concepts presented in the videos, as in Maslov and Poelmans (2024). Some participants (9) suggested that animated process models should not be overly simplistic compared to the exercise models, suggesting that the gap between the two was too high to allow for successful knowledge transfer. A few responses (4) indicated that better pacing of the animations, such as slowing them down, would improve comprehension.

Discussion of the results, limitations, and future work

This study examined the effects of token animations on the comprehension of BPMN process patterns, with a focus on their impact on cognitive load (intrinsic and extraneous) and the broader learning experience of novice modelers. While no significant differences were found in overall comprehension scores between the animated and static conditions, the analysis revealed that token animations significantly reduced extraneous cognitive load (ECL) but had no direct impact on intrinsic cognitive load (ICL). These findings clarify prior conflicting results in the literature, where Aysolmaz and Reijers (2021) suggested that animations reduce both ICL and ECL, whereas Maslov and Poelmans (2024) reported an increase in cognitive load with animations. Our study suggests that animations primarily influence how information is presented (ECL) rather than the inherent complexity of the content (ICL).

The observed reduction in extraneous cognitive load aligns well with Mayer's signaling principle, which suggests that guiding learners' attention to essential elements helps minimize the processing of non-essential or distracting information (Mayer & Moreno, 2003; Mayer, 2005). Token animations likely served this signaling function by dynamically illustrating the execution flow and emphasizing critical transitions and behaviors in the model explanations, thus reducing representational overhead and enhancing perceptual organization (Aysolmaz & Reijers, 2021). The modality principle is also pertinent: several participants expressed a desire for voice-over explanations, indicating that integrating spoken text with visual animation could improve working memory efficiency by leveraging both auditory and visual channels (Mayer, 2005). This aligns with Aysolmaz and Reijers' (2021) emphasis on adhering to multimedia learning principles, such as temporal and spatial contiguity, signaling, and modality, to optimize animation-based instruction. Future implementations of token animations should more explicitly operationalize these principles—not only to reduce extraneous cognitive load, but also to maximize learner engagement, attentional focus, and ultimately the instructional value of animated process representations.

The results support cognitive load theory (Sweller, 2011), particularly the idea that ECL can be mitigated through effective instructional design. In this case, token animations likely helped reduce the mental effort needed to track process flow and decision points, making the visual representation of process models more intuitive. However, since ICL is inherent to the complexity of BPMN elements and patterns, animation alone may not be sufficient to simplify complex logic or improve deep structural understanding. This aligns with multimedia learning theory (Aysolmaz & Reijers, 2021), which posits that animations serve as external cognitive aids that direct attention but do not inherently alter the difficulty of the content itself.

The importance of other elements is further stressed in the modest explanatory power of the model: the R^2 for comprehension of process patterns was 15%. This suggests that other factors are likely at play, potentially interacting in more complex ways. For instance, the mode of explanation delivery may play a critical role in how animations are processed by learners. Maslov and Poelmans (2024) found that novice modelers expressed a preference for educator-led, voiced explanations combined with high interactivity. These elements were perceived to better support the use of token animations in conveying BPMN semantics. Moreover, ensuring that novice modelers know how to use the animations to realize the benefits is important by offering them guidelines (Maslov & Poelmans, 2023). This points to a broader need for multimodal and personalized instructional design, especially for novice learners.

While reducing extraneous cognitive load with animations can be beneficial as a scaffolding tool (Aysolmaz & Reijers, 2021; Maslov & Poelmans, 2024a), overly simplifying tasks through animation may inhibit learners from engaging in deeper cognitive processing. As Schnotz and Rasch (2005) warn, excessive facilitation with animations can lead to passivity, preventing learners, especially those with sufficient prior knowledge—from performing essential mental simulations on their own.

Qualitative feedback highlighted several key advantages of token animations. Participants emphasized that animations enhanced clarity, improved engagement, and facilitated attention and comprehension. Many noted that visualizing token movements helped them track process execution more effectively than static models. These align well with the structural results. However, some respondents found that animations, while useful, lacked depth and could oversimplify certain concepts, making it harder to transfer knowledge to more complex, real-world BPMN applications. Additionally, some participants expressed a desire for interactive features, such as the ability to pause, rewind, or explore alternative process paths dynamically, aligning with prior work on interactive process model simulations (Aysolmaz & Reijers, 2021).

The findings suggest that animations should be used strategically in PM education rather than as a one-size-fits-all solution. While animations are beneficial for improving models, their effectiveness may be maximized when paired with other instructional strategies. For instance, integrating animations with interactive elements, allowing learners to explore different process scenarios dynamically rather than passively viewing pre-recorded sequences. We suggest providing guided explanations alongside animations, ensuring that key BPMN semantics are explicitly reinforced rather than implicitly assumed. Furthermore, gradually transitioning from animated models to static process models, enabling learners to develop independent model comprehension skills over time. These findings align with prior calls for more structured and empirically validated PM education frameworks (Maslov & Poelmans, 2023; Rosenthal et al., 2019). Furthermore, tokens may be used for improving interest and engagement to aid in the satisfaction of learners (Nikou et al., 2021).

This study has several limitations that should be considered. The sample size (N=140) may limit generalizability to different educational levels and professional contexts, necessitating further research with larger and more diverse populations. Additionally, the study relied on pre-recorded animations, preventing learners from actively engaging with the models, which may have influenced cognitive load differently than high-interactivity animations. Future research should compare the effects of low- and high-interactivity BPMN animations using real-time simulation tools. Another limitation is the lack of a long-term assessment to determine whether animations improve knowledge retention and skill transfer over time. Follow-up studies are needed to examine sustained learning outcomes. Furthermore, the study did not compare instructional methods, such as text-based explanations versus animations, which could provide valuable insights into optimizing BPMN education. Finally, the qualitative responses about the user experience may have typical mixed methods limitation issues (Maslov et al., 2024).

Moving forward, research should explore high-interactivity BPMN animations (Aysolmaz & Reijers, 2021), allowing learners to modify and test animations dynamically. Eye-tracking analysis could provide deeper insights into user engagement with different animation styles (Maslov & Poelmans, 2024b). Additionally, multi-modal learning strategies—integrating animations with voice-over explanations, real-time feedback, and interactive exercises—should be. Longitudinal studies could assess whether animation-driven improvements in comprehension translate into long-term knowledge retention and real-world BPMN application.

Conclusions

This study investigated how token-based animations influence novice modelers' comprehension of BPMN process patterns, with a focus on cognitive load. While animations did not lead to significantly higher comprehension scores directly, they effectively reduced extraneous cognitive load, supporting their role in improving the clarity of information presentation, hence indirectly improved comprehension. Intrinsic cognitive load remained unaffected, suggesting that the inherent complexity of BPMN elements still poses challenges for novices. The effects of both animation and prior PM expertise were largely mediated through cognitive load, particularly ECL, emphasizing its critical role in model comprehension. Qualitative feedback reinforced the value of animations for engagement and attention, though also highlighted the need for depth, interactivity, and educator guidance. Future PM education should integrate token animations with multi-modal strategies—such as voice-over explanations and interactive exploration—to better support novice learners and promote transferable BPMN competence.

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