

On the Task-specific Effects of Fragmentation in Modular Process Models

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Abstract. Modularization has been extensively investigated for its role in enhancing the comprehension of process models by dividing them into smaller, self-contained and manageable modules. However, existing studies have reported inconclusive results, prompting further exploration into when modularization supports or impedes process comprehension. Among the key factors suggested to influence the effect of modularization is the type of the task at hand. Indeed, the fragmentation of information across several modules caused by modularization can challenge readers' comprehension of process models, especially if the task is not confined to a single module. While the effect of fragmentation has been explored for flow-based tasks, requiring understanding procedural aspects of process models, our work extends to circumstantial tasks, which instead demand comprehending model rules and constraints that rely on the broader context associated with specific process parts. Using eye-tracking, we investigate how the fragmentation of information caused by modularization impacts cognitive integration (i.e., the collection and synthesis of dispersed information) and its subsequent effect on cognitive load and model comprehension. Our findings demonstrate that fragmentation significantly affects cognitive integration in flow-based tasks only. Moreover, our results show that cognitive integration is linked to both cognitive load and readers' comprehension of process models. The outcome of this work provides a detailed model, explaining the task-specific effects of fragmentation. Practically, our findings highlight the need for modeling tools that dynamically adjust their user interface to reduce cognitive integration demands, thereby enhancing model comprehension.

Keywords: Process model Comprehension · Eye-tracking · Cognitive Integration · Cognitive Load.

1 Introduction

Understanding complex processes using process models is key to performing management and technical tasks, ranging from strategic decision making to effective process redesign and enhancement [18,28]. Modularization has been widely investigated, in this vein, for its role in supporting the comprehension of complex

processes through the division of these processes into smaller, self-contained, and manageable modules (cf. overview in [62]). Yet, there is no consensus on whether modularization supports or hinders model comprehension, which prompts further exploration into the conditions under which modularization is beneficial [62].

One critical factor that influences the effectiveness of modularization is the type of task at hand [62,51]. Modularized models inherently cause information to be fragmented across several modules, affecting readers' mental effort (i.e., cognitive load) and task performance (in terms of model comprehension) in a manner that varies with the task type [51]. Indeed, previous research [51] has shown that local tasks, which require information located within a single module, are generally unaffected by such fragmentation. In contrast, global tasks, which require information from multiple modules, suffer due to the increased effort imposed by the split attention effect and the need to cognitively integrate information from different locations [62,51]. However, these findings have been predominantly based on flow-based tasks [62,51]. These tasks (also called sequential tasks) require understanding the procedural aspects of the process [57,19,23,45]. A typical example of a flow-based comprehension task involves determining whether, in a given model, an activity can be executed before or after another one.

This paper broadens the scope of existing research [62,51] by incorporating circumstantial tasks in the investigation of fragmentation caused by modularization. Unlike flow-based tasks, circumstantial tasks require an understanding of the broader context associated with specific parts of the process. These tasks often involve rules or constraints that are not strictly sequential but are dependent on certain state changes within the process [57,19,23,45]. A typical example of a circumstantial comprehension task involves determining whether, in a given model, certain activities can only be executed when an object in the process gets into a specific state. Both flow-based and circumstantial tasks are needed in practice. Flow-based tasks are common to understand routine and procedural process operations, whereas circumstantial tasks are critical in comprehending the circumstances under which a particular process outcome can occur [57,19,23,45]. Moreover, our paper delves further into the investigation of the interplay between fragmentation and cognitive load as well as task performance by introducing cognitive integration (i.e., the collection and synthesis of information distributed over several locations [13]) as a mediating variable. Cognitive integration is thereby considered as a driver for readers' cognitive load and task performance. Furthermore, our work expands the research on flow-based and circumstantial tasks by integrating cognitive integration into the investigation of these tasks, which previous studies have not thoroughly explored [57,19,23,45]. Additionally, it contributes to the growing research stream that examines how distinct task characteristics affect process model comprehension [48,51,34,44].

Our research questions can be summarized as follows: **RQ1. How does fragmentation in modular process models impact readers' cognitive integration in flow-based and circumstantial comprehension tasks?** and **RQ2. How does cognitive integration affect readers' cognitive load and task performance?** To answer these questions, we designed and conducted an

eye-tracking experiment, aiming to obtain detailed insights into readers' cognitive integration through their visual behavior during different comprehension tasks. Also, this technology allows to objectively assess readers' cognitive load. In our experiment, we used horizontal modularization, a technique that involves breaking down a system into interconnected modules without imposing hierarchical constraints [33,59]. This approach facilitates the modeling of knowledge-intensive and flexible processes [1,26], and is frequently used to model case-based processes [1,26]. It has also been shown to enhance process model comprehension [59]. Specifically, we adopt the fragment-based approach [26] within the horizontal modularization paradigm. Our findings indicate that the fragmentation of information caused by modularization affects readers' cognitive integration differently in flow-based local and global tasks, whereas cognitive integration remains equally high in both circumstantial local and global tasks. The implications of this work extend to both research and practice. Especially, in research, our work provides a more detailed model that explains the effect of fragmentation on cognitive integration and its subsequent effect on cognitive load and task performance while considering both flow-based and circumstantial tasks. Practically, our findings raise the need for advanced tool support that can dynamically adjust their user interface to reduce readers' cognitive integration demands and thus lower their cognitive load and increase their performance.

The remainder of this paper is structured as follows. Sect. 2 presents the background and related work. Sect. 3 describes our empirical research method. Sect. 4 presents our findings. Then, Sect. 5 discusses these findings, relates them to the existing literature, and highlights the implications of our research and its threats. Finally, Sect. 6 concludes the paper and sets directions for future work.

2 Background and Related Work

This section presents the background and related work, Sect. 2.1 provides an overview of process model comprehension, Sect. 2.2 introduces the different facets of modularization and the associated effects. Sect. 2.3 introduces cognitive integration, cognitive load and process comprehension measures.

2.1 Process Model Comprehension

Existing research on process model comprehension can be organized into three key streams: (1) research focused on the *presentation* of process models, which can be further divided into those focused on presentation mediums and tools (e.g., [54,3]) and those investigating the syntax, semantics and pragmatics of process models (e.g., [36,49,59,21,52,58,60,22]). (2) Research focused on the *users* of process models, notably looking into domain knowledge, expertise and educational aspects (e.g., [47,37,8,32]). (3) Research exploring the characteristics of the *tasks* for which process models are used and their impact on process model comprehension (e.g., [48,50,51,34,62,16]). Therein, authors have, for instance, investigated the difference between schema-based tasks (i.e., requiring information

shown explicitly in the model) versus non-schema-based tasks (i.e., requiring knowledge beyond the explicit information provided by the model) [48], local tasks (i.e., addressing a single module of a modular process model) versus global tasks (i.e., addressing many modules of a modular process model) [62,50,51], and flow-based tasks (i.e., examining the procedural aspects of processes) versus circumstantial tasks (i.e., examining the rules and constraints within the process that are not strictly sequential but are dependent on certain state changes) [57,19,23,45]. Our work contributes to the stream of research focused on the task characteristics by examining the interplay between local and global tasks, both in flow-based and circumstantial contexts. To the best of our knowledge, such a combination has not yet been explored in the literature.

2.2 Modularization

Modularization in Process Models. Modularization refers to the technique of dividing a system into interconnected, self-contained modules [43]. The literature on process modeling identifies three distinct forms of modularization: vertical, horizontal, and orthogonal [33,59]. Vertical modularization organizes the process into hierarchical modules [33,59]. In contrast, horizontal modularization splits the process into various linked modules without imposing a hierarchical structure [33,59]. Orthogonal modularization organizes the process based on cross-cutting concerns such as privacy and security, spanning over several parts of the process [33,59]. Given that horizontal modularization facilitates the division of process modules without any restrictions on hierarchical relationships or cross-cutting concerns, it emerges as a more universally applicable method.

The Fragment-based Modeling Approach. This approach [26] is a representative for horizontal modularization. It is based on the Business Process Modeling and Notation (BPMN) [41]. At the design stage, complex processes are segmented into smaller, independently modeled modules (i.e., called *fragments*) that are interconnected through the use of data objects. These objects are linked to specific process activities and serve to define the pre- and post-conditions constraining their execution. Each data object is further associated with a specific data class and is assigned a state. The different states and their progression are organized into a structure known as a lifecycle, which is a labeled transition system. Transitions between states occur as a result of executing a process activity. At run time, the fragments can be executed in different orders. Therein, the interaction protocol between the different fragments, defining how they could possibly be combined, is handled through the data objects and their lifecycles. Since the connections among the fragments do not have to follow a hierarchical structure, the fragment-based approach reflects very well the core principle of horizontal modularization.

Figure 1 depicts an example of a logistics process modeled using the fragment-based approach. This figure shows 2 out of 6 fragments and one out of 3 lifecycles that we have actually used in our experiment (cf. Sect. 3.2). The fragments *F3_Store_Container* and *F4_Load_Container* use the data-object *Con-*

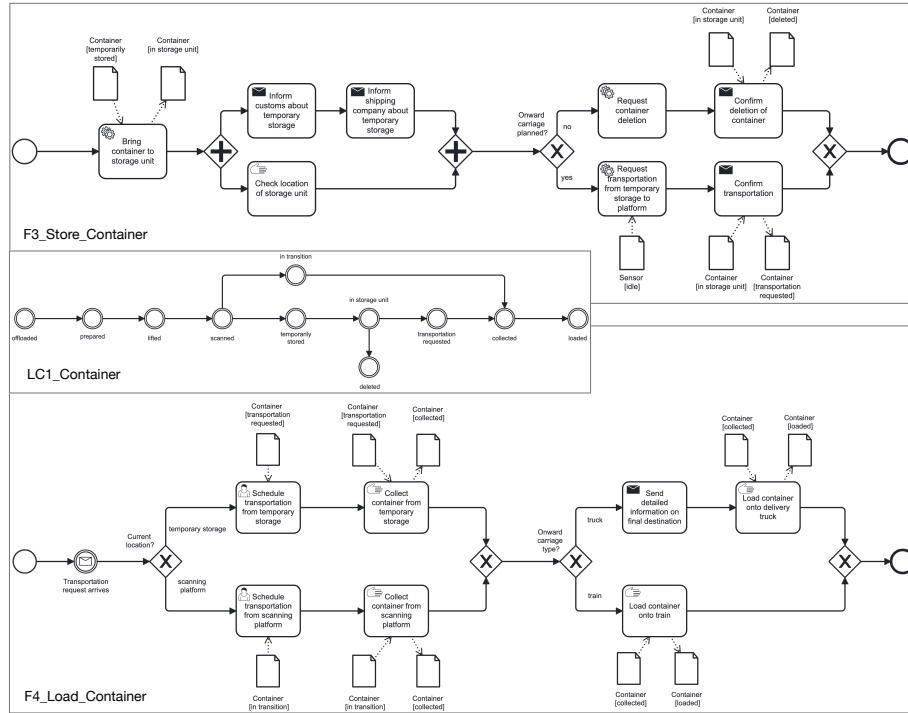


Fig. 1: Example of a process modeled using the fragment-based approach. A better resolution is available in our online appendix³.

tainer to interact with each other. The lifecycle of this data object is shown in *LC1.Container*. To demonstrate the interaction between the two fragments, in *F3.Store.Container*, when the activity *Confirm transportation* is executed, the state of the data object *Container* moves from *[in storage unit]* to *[transportation requested]*. Consequently, the execution of the activity *Schedule transportation from temporary storage* becomes enabled in *F4.Load.Container*.

Besides the fragment-based approach, various techniques have been suggested in the literature to decompose processes horizontally. For example, events have been used to connect process fragments (cf. overview in [31]). Our study, however, uses the fragment-based approach [26] because it is rooted in BPMN [41] – the process modeling language standard in the industry. Moreover, this approach has clear execution semantics driven by pre- and post-conditions, assigned as data objects to the process activities. These semantics enhance the expressiveness of the approach and enable capturing complex process behavior efficiently.

The Task-specific Effect of Fragmentation in Modular Process Models. Depending on the characteristics of the task at hand, modularization could have varying effects [62,50,51]. Indeed, modularization could lead to fragmentation when the task-relevant information span multiple modules [62,7,51]. This

hypothesis was specifically tested in [50,51], where the authors have found that global tasks, addressing several process modules, are more impeded by the effect fragmentation than local tasks, addressing a single module. This effect translated into higher cognitive load and lower task performance (in terms of model comprehension) in global tasks compared to the local ones. While the authors in [50,51], focused on flow-based tasks, our study broadens the scope to circumstantial tasks. Moreover, it uses cognitive integration [13] as a factor that mediates the relationship between fragmentation, and cognitive load as well as task performance.

2.3 Cognitive Integration, Cognitive Load and Comprehension

Cognitive Integration. This process involves merging information from various sources [13]. In process modeling research, eye-tracking data have indicated that visual associations act as a good indicator of cognitive integration [13]. The run count measure is a key metric for capturing readers’ visual associations as documented in [13]. It quantifies the number of times a reader enters and exits areas of interest (i.e., process model elements) that are relevant to solving a specific task. While the authors in [13] have linked this measure to task performance, its relationship with cognitive load still requires statistical evidence. Such evidence would establish the relationship between cognitive integration and cognitive load. Motivated by the goal to substantiate this relationship, our work first confirms the impact of cognitive integration on task performance, as reported in [13], and extends the investigation to also assess the effect of cognitive integration on cognitive load in the context of process comprehension tasks.

Cognitive Load. Cognitive load defines the strain imposed on the human working memory when executing a mental task [14,42]. The cognitive load theory (CLT) posits that human performance is constrained by their cognitive load [14,42]. When reaching high levels of cognitive load (also called cognitive overload), their performance is likely to drop [14,42], leading them to misinterpret the process behavior in the context of comprehension tasks. Cognitive load can be quantified using subjective and objective measures. The subjective measures rely on self-reporting where users are asked to subjectively assess the difficulty they perceived when solving a given task. In the literature [5,50,51,62], this is typically administrated using a 5-point Likert scale ([0: “very easy”, 4: “very difficult”). The objective measures, in turn, are usually based on users’ behavioral and physiological reactions to cognitive load. In this regard, eye-tracking technology can provide interesting insights [14,27,56]. Unlike the subjective assessment of perceived difficulty that is collected in a retrospective manner, eye-tracking continuously captures users’ visual behavioral and physiological reactions to cognitive load throughout the entire task, offering detailed temporal insights [27]. Central to eye-tracking is the notion of a fixation, which refers to the time period the human eyes remain still at a specific location in a stimulus [27]. According to the eye-mind hypothesis, our eyes fixate on what our minds are actively processing [30]. Based on that, the work by Glöckner and

Herbold [24] suggests that fixations longer than 250 ms are indicative of mental processing, which accentuates as the duration of the fixation increases, signifying progressively deeper levels of mental processing. Fixation-based measures have been applied in several studies to capture users' cognitive load [55,5,59,50,51]. The *low/high index of pupil activity* (LHIPA) [17] is another approach to objectively assess cognitive load. This index differentiates lower and higher oscillations in pupil frequencies, with lower values indicating higher levels of cognitive load. The LHIPA measure has been used in a set of studies as a robust indicator of cognitive load [6,50,51].

Task Performance in Terms of Process Comprehension. Users' performance has been assessed through various metrics (cf. overview in [20]). These metrics often evaluate both the correctness of the operations required by a task and the time needed to complete these operations. A particularly insightful metric that encapsulates both aspects is the comprehension efficiency measure. This measure, is calculated as the ratio of task correctness to the task duration [38]. Higher values indicate higher comprehension efficiency.

Overall, as outlined in Sect. 1, our study investigates the effect of fragmentation on cognitive integration and its subsequent influence on cognitive load and task performance, considering both flow-based and circumstantial tasks. Drawing on existing literature, we are capturing cognitive integration using the run count measure, cognitive load using a 5-point Likert scale of perceived difficulty, mental processing fixations, and LHIPA; and finally, task performance using the comprehension efficiency measure.

3 Research Method

3.1 Research Model

The Task-Dependent Effect of Fragmentation on Cognitive Integration. As specified in Sect. 2.2, modularization can lead to fragmentation [43,62,51]. Hence, when solving tasks that require information covering several modules, readers would engage in a complex process of collecting and synthesizing this information, known as cognitive integration [13]. We advance that this effect can be observed by contrasting local tasks confined to a single module with global tasks spanning several modules. This effect is, however, expected to occur only when the tasks address procedural aspects of the process (i.e., flow-based tasks). This is because, for flow-based local tasks, the procedural information needed to complete the task is readily available within a single, self-contained module, reducing the need for extensive cognitive integration. Whereas for flow-based global tasks, the procedural information is spread across multiple modules, necessitating a significant amount of cognitive integration as readers must trace the dependencies between process activities that are not immediately visible within a single module. When it comes to circumstantial tasks, we expect that the differentiation between local and global tasks in terms of cognitive integration would not be as pronounced as for flow-based tasks. Indeed for both circumstantial

local and global tasks, a substantial level of cognitive integration is required as readers need to understand the rules and constraints closely tied to the different process activities and how these integrate and affect the process behavior.

Based on these assumptions, we expect the relationship between fragmentation and cognitive integration to be moderated by the task perspective (i.e., flow-based or circumstantial). This is because the task perspective factor can affect the strength of the aforementioned relationship depending on its levels [25,40]. Hence, our first hypothesis can be formulated as follows: **H1: The effect of fragmentation on cognitive integration in process model comprehension is moderated by the task perspective.**

The Effects of Cognitive Integration on Cognitive Load and Task Performance. Cognitive integration involves the collection and synthesis of information from various sources [13]. Throughout this process, readers must identify each piece of information relevant to their task and temporarily store it in working memory until all the other corresponding pieces of information are located and assembled together. Considering the limited capacity of the working memory, the increased need for information intake occurring during cognitive integration is expected to yield high levels of cognitive load [14,39,53]. Higher demands for cognitive integration are also expected to yield lower task performance. Indeed, when task-relevant information is consolidated in one place and only low cognitive integration is needed, mapping this information to the reader’s existing mental scheme (i.e., mental structure capturing well-integrated chunks of knowledge) is simpler, than in cases where the information is dispersed over several places and high cognitive integration is needed [11,29]. In such scenarios, readers should combine and reorganize information before finding a fit with their mental scheme [11,29]. This process is expected to take longer and plausibly be more prone to errors, which would translate to reduced comprehension efficiency and thus low task performance.

Based on these assumptions, we formulate our second hypothesis as follows: **H2: Readers’ cognitive integration during process comprehension can explain their cognitive load and task performance.**

Research Model Overview. Overall our study aims to investigate the complex relationship between *fragmentation* in modular process models, denoting our independent variable, and readers’ *cognitive load* as well as *task performance*, both denoting our dependent variables. We use *task perspective* as a moderator and *cognitive integration* as a mediator [25,40]. An overview of our research model is depicted in Fig. 2. Fragmentation is operationalized with local and global tasks. Cognitive load is operationalized with both objective measures derived from fixation and pupil measurements (i.e., mental processing fixations above 250ms [24] and LHIPA [17]) and a subjective 5-point Likert scale of perceived difficulty. Task performance is operationalized with comprehension efficiency [38]. The task perspective, in turn, is operationalized with flow-based and circumstantial tasks [23]. Cognitive integration is operationalized through visual associations captured with the run count measure [13].

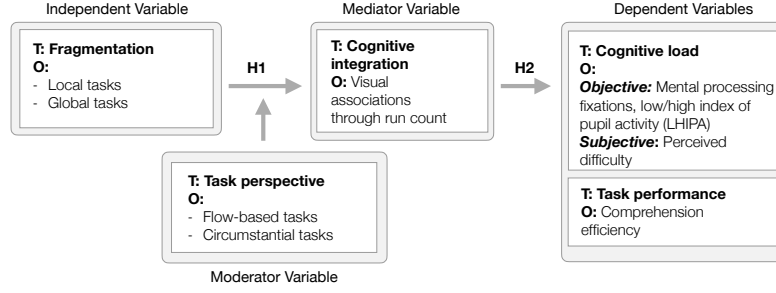


Fig. 2: Research model **T**: theoretical construct. **O**: Operationalization of construct.

3.2 Material and Participants

Material. The material designed for this experiment covers a large process model, capturing a logistics process, and a collection of tasks with different characteristics. Using the fragment-based approach [26], the logistics process is divided into six distinct fragments modeling (1) the offloading of a container upon its arrival at a port, (2) the scanning of the container, (3) the procedure for storing the container, (4) the loading of the container for delivery, (5) the management of information pertaining to the container, and (6) the analysis and reporting of any shakes that occur during the container’s handling at the port. The communication between these fragments is carried out through 3 data objects: i.e., container, sensor, and an enterprise resource planning (ERP) file. Throughout the process execution, each object can take a set of possible states which are represented in three respective object life cycles. A portion of this logistics process is depicted in Fig. 1, while the full process is available as part of the experiment material uploaded to our online appendix³. To avoid confounding factors, the process fragments were designed with similar essential and accidental complexity [2,9]. For the former, each fragment has 6 to 8 activities and 2 to 4 exclusive or parallel gateways. As for the latter, the layout of the models was carefully designed and all the activities were labeled using the verb-object naming convention [15,36]. Details specific to real logistic processes were removed from the models to avoid the impact of domain knowledge and the use of common sense.

The experiment includes a set of 8 *flow-based* and 6 *circumstantial* tasks, half of which (4 flow-based, 3 circumstantial) address *local* aspects that can be found within a single process fragment and the other half address *global* aspects that require information spread over two process fragments. The flow-based tasks address popular workflow patterns including sequencing, choice, concurrency, and iteration (e.g., for sequencing: “The activity X needs to be executed before the activity Y”); whereas the circumstantial tasks focus on the overall pre- and post-conditions governing the execution of the process activities [57,19,23,45] (e.g., pre-conditions: “The activities X and Y can only be executed if the object O is

³ See <https://github.com/aminobest/ER2024Fragmentation>

in the state [state1]”). All these tasks comprise a statement that readers need to validate, by selecting one of the following options: *true*, *false*, *I don’t know*, after checking the given set of process model fragments. To avoid task-related confounding factors, each pair of tasks compared according to our research model (i.e., flow-based local vs. flow-based global; circumstantial local vs. circumstantial global) comprises statements that are formulated exactly in the same way, addresses two process activities only and has the same answers (both true or both false). The material of this experiment including all the used tasks and process fragments is available in our online appendix³.

Participants. We recruited 46 participants for this experiment which took place at the University of St Gallen in Switzerland (22 participants), Karlsruhe Institute of Technology in Germany (17 participants), the research center Forschungszentrum für Informatik FZI in Karlsruhe (4 participants) and Promatis an IT-consulting company in Karlsruhe (3 participants). The participants ranged in age from 20 to 50 years, with the majority (63%) aged between 20 and 30 years. Their professional backgrounds fell into three primary categories: researchers with PhDs or higher (22 individuals), students (17 individuals), and those from an industry or IT-admin background (7 individuals). The participants had varying expertise in BPMN. To facilitate their involvement in the experiment, we conducted a standardized familiarization session and assessed their understanding through a quiz. Moreover, to minimize confounding effects due to differences in expertise, a within-subject design was used. Each participant repeatedly encountered flow-based local, flow-based global, circumstantial local and circumstantial global tasks. Although their background might influence the tasks’ outcome, the within-subject design ensures that all treatments are equally affected, allowing for reliable conclusions about their distinct effects. Detailed demographics are available in our online appendix³.

3.3 Experiment Procedure

Every participant attended a separate experiment session that lasted approximately one hour. The sessions were conducted in a controlled laboratory setting. The session’s procedure began by acquainting the participant with BPMN and the fragment-based modeling approach [26], followed by a brief quiz comprising two comprehension tasks to ensure good understanding of the modeling approach. During the quiz, participants were permitted to ask questions and receive feedback on their answers. All the participants passed the quiz and therefore could participate in the experiment. Prior to the main experiment’s part, participants had to fill out a demographic survey asking about their background and experience in process modeling and checking their physical ability to participate in an eye-tracking experiment. The experiment then proceeded with two test tasks designed to help participants become familiar with the experimental setup. These initial tasks were not included in the final data analysis to prevent any biases stemming from the participants’ unfamiliarity with the experimental setup. To counter any potential learning effect, the tasks were randomized

and presented in varying sequences to different participants. For each task, participants were given the 6 process model fragments of the logistic process (cf. Sect. 3.2) and were asked to validate a statement about this process. Following that, a 5-point Likert scale was administered to assess their perceived difficulty of that task.

3.4 Data Collection and Analysis Approaches

Data Collection. The first phase of data collection involved the gathering of demographic data as outlined in Sect. 3.3. The second phase involved eye-tracking. Therein, we used a Tobii X3-120 eye-tracker attached to a 24" monitor. To ensure consistent recording quality, lab lighting was adjusted according to established guidelines [27]. The open-source eye-tracking software EyeMind [6] was used to run the experiment protocol and to automatically link eye-tracking data with the underlying elements of the process model fragments.

Data Analysis. From the 46 participants, we collected a total of 644 data points per measure, distributed as follows: 184 data points for flow-based local and global tasks *each*, and 138 for circumstantial local and global tasks *each*. For one participant (SP11), the data for a flow-based local task and a flow-based global task were removed due to an issue during data collection, as the participant accidentally skipped these tasks.

We investigated the effect of fragmentation on readers' cognitive integration, considering the task perspective as a moderator variable (i.e., Hypothesis **H1**, cf. Sect. 3.1 and Fig. 2). As explained in Sect. 3.1 fragmentation was operationalized with local and global tasks, while cognitive integration was operationalized using the run count measure, which we calculated by counting the number of entries and exits to the process model elements relevant for each specific task (similar to [13]). The visits to these elements were automatically derived thanks to the automated mapping between eye-tracking data and the underlying process model elements granted by EyeMind [6]. The task perspective, in turn, was operationalized using flow-based and circumstantial tasks. At first, we computed the mean run count for flow-based local, flow-based global, circumstantial local and circumstantial global tasks. This allowed us to compare local vs global flow-based tasks as well as local vs global circumstantial tasks. These comparisons are shown on the left side of Table 1. For the inferential tests, to eliminate interdependencies between data points, we averaged the measurements to derive a single data point per participant, measure and condition (flow-based local, flow-based global, circumstantial local, and circumstantial global). Then, we used the MEMORE approach [40] to test for the moderating effect of the task perspective. MEMORE is adequate for repeated measures collected following a within-subject design. For this specific test, to meet the normal distribution assumption of MEMORE moderation analysis, we applied a log transformation to the run count measures and conducted the Shapiro-Wilk test to ensure that the data is normally distributed. As a second approach, we applied the non-parametric Wilcoxon Signed-Rank test (single-tailed) to compare the run count of flow-based local versus flow-based global tasks and the run count of circumstantial

local versus circumstantial global tasks separately. Wilcoxon Signed-Rank test is adequate for repeated measures collected following a within-subject design and does not impose assumptions on the normality of the data. Using MEMORE to test for the moderating effect along with splitting the data and running separate Wilcoxon tests enhances the certainty regarding the moderating effect of the task perspective. The inferential tests are shown on the right side of Table 1.

Following that, we investigated the effect of cognitive integration on cognitive load and task performance (i.e., Hypothesis **H2**, cf. Sect. 3.1 and Fig. 2). Herein, we conducted a regression analysis of cognitive integration, operationalized with the run count measure, against cognitive load and task performance, operationalized with the measures shown in Fig. 2. The mental processing fixations and the LHIPA measures were derived respectively considering the gaze data and pupil data collected throughout each task. The fixations were derived using the Identification by Velocity Threshold-Algorithm (IVT) [27] and a threshold was set to keep only fixations associated with mental processing operations (i.e., with a duration >250 ms) [24]. The LHIPA, in turn, was calculated after cleaning the pupil data using the Cheetah Pipeline [63] and applying the LHIPA algorithm documented in [17]. The perceived difficulty measure was obtained from the 5-point Likert scale survey that the participants had to fill in after each task. The comprehension efficiency measure was calculated by dividing the task correctness by the time taken to complete that task in milliseconds. To run the regression analysis, we used the Robust linear Model Regression (RLM) approach, which is less sensitive to the assumption of normally distributed data. To avoid interdependencies between the data points when using RLM, we averaged each used measure to derive one data point per participant and measure. Then, to check whether the relationship between the run count measure and the dependent variables holds under the different conditions, we repeated the regression analysis for each level of each condition. The results are reported in Table 2. Detailed documentation of our analysis approach can be found in the Python notebook provided as part of the online appendix³.

4 Findings

The Task-specific Effect of Fragmentation on Cognitive Integration.

The results summarized in Table 1 address **RQ1** (cf. Sect. 1). The left side of the table shows the descriptive statistics corresponding to the mean run count measured when solving flow-based local, flow-based global, circumstantial local, and circumstantial global tasks. Note that to investigate Hypothesis H1, the comparisons are done horizontally between local and global tasks (cf. Fig. 2). These statistics suggest that flow-based global tasks yield a higher run count than flow-based local tasks. However, for circumstantial global and local tasks, no clear difference in the means of run count is apparent. The inferential statistics shown on the right side of Table 1 confirm these observations as the mean difference of the former comparison is significant (both p-values of MEMORE and Wilcoxon tests $<.001$), while the mean difference of the latter comparison

Task perspective	Measure	Descriptive		Inferential	
		Local M	Global M	<i>p</i> -value MEMORE	<i>p</i> -value Wilcoxon
Flow-based	Run count	16.159	31.578	<.001	<.001
Circumstantial	Run count	20.962	20.379	0.690	0.667

Table 1: Analysis of readers’ cognitive integration when solving different types of tasks, via the run count measure. M: mean. *p*-value Wilcoxon is the result of the Wilcoxon Signed-Rank test. *p*-value MEMORE is the result of the MEMORE moderation analysis. Additional statistics provided by MEMORE (i.e., effect, standard error, t, confidence intervals) are provided in our online appendix as part of the analysis notebook³.

is not significant (*p*-value MEMORE=0.690, *p*-value Wilcoxon=0.667). Overall, these results support **H1** (*The effect of fragmentation on cognitive integration in process model comprehension is moderated by the task perspective*) as the task perspective (flow-based versus circumstantial) affects the relationship between fragmentation and cognitive integration. This finding is discussed in Sect. 5.

Effect of Cognitive Integration on Cognitive Load and Task Performance. The findings summarized in Table 2 address **RQ2** (cf. Sect. 1). The influence of cognitive integration on cognitive load and performance across different task types – whether flow-based, circumstantial, local, or global – is evident. The regression analysis results indicate a significant impact of run count on both the objective cognitive load measures (i.e., mental processing fixations and low/high index of pupil activity LHIPA) and the comprehension efficiency measure, as indicated by the respective *p*-values in Table 2. However, the effect of run count on subjective perceived difficulty across three task types (flow-based local, flow-based global, and circumstantial global) is not significant. Moreover, the signs of the coefficient measures in Table 2 show that for all the tests with a significant effect, increases in run count lead to higher mental processing fixations as well as lower LHIPA and comprehension efficiency. These trends suggest that increased run count yields higher cognitive load and lower task performance (cf. Sect. 2.3). These results support **H2** (*Readers’ cognitive integration during process comprehension can explain their cognitive load and task performance*) considering objective measures only. This finding is discussed in Sect. 5.

5 Discussion

This section synthesizes the findings presented in Sect. 4, discusses them in relation to existing literature and outlines their implications. Regarding our first hypothesis (i.e., **H1**, cf. Sect. 3.1), our results show a significant relationship between fragmentation in modular process models and readers’ cognitive integration when solving flow-based tasks. Indeed, for flow-based global tasks, fragmentation caused an increase in readers’ run count, which reflects higher visual associations and thus more cognitive integration [13], compared to flow-based local tasks. However, for circumstantial tasks, no significant differences were observed. The lack of a significant effect thereby aligns with our initial assumption

	Gr.	Indep. var.	Dep. var.	Coef.	p-value
Flow. local	Run count		Mental processing fixations	1.185	<.001
			Low/High Index of Pupil Activity	-0.009	0.038
			Perceived difficulty	0.006	0.561
			Comprehension efficiency	-4.89e-04	<.001
Flow. global	Run count		Mental processing fixations	1.966	<.001
			Low/High Index of Pupil Activity	-0.006	0.012
			Perceived difficulty	0.020	0.005
			Comprehension efficiency	-1.75e-04	<.001
Circms. local	Run count		Mental processing fixations	1.569	<.001
			Low/High Index of Pupil Activity	-0.011	0.009
			Perceived difficulty	0.008	0.518
			Comprehension efficiency	-2.79e-04	0.001
Circms. global	Run count		Mental processing fixations	1.456	0.025
			Low/High Index of Pupil Activity	-0.011	0.040
			Perceived difficulty	-0.016	0.414
			Comprehension efficiency	-2.54e-04	0.006

Table 2: Regression Analysis. Full statistics including the coef., standard error, z-score, and confidence intervals for the different regressions including the intercepts are provided in our online appendix as part of the analysis notebook³. Abbreviations: Gr.: Group, Dep.: Dependent, Indep.: Independent, Var.: Variable, Coef.: Coefficient, Flow.:Flow-based, Circms.:Circumstantial.

in Sect. 3.1, suggesting that cognitive integration demands are inherent to circumstantial tasks, regardless of the degree of fragmentation. This proposition is supported by the descriptive statistics in Table 1, where the run count was equally high in both local and global circumstantial tasks. Our findings align with those reported in [44], suggesting that difficulty increases proportionately with the size of the task-relevant region in the model. This can be interpreted within our context to mean that tasks involving larger portions of the model likely demand more cognitive integration. Circumstantial tasks inherently require synthesizing context beyond the explicit control-flow depicted in the model, which typically involves more extensive regions of the model compared to flow-based local tasks. This broader scope likely explains the consistently high demands for cognitive integration in circumstantial tasks. Similarly, when comparing flow-based local and global tasks, the latter span multiple process fragments, corresponding to a broader area of the overall process and thus yielding higher demands for cognitive integration. With respect to the second hypothesis (i.e., **H2**, cf. Sect. 3.1), our results demonstrate that changes in readers' cognitive load and task performance can be explained by their cognitive integration efforts as captured by the run count measure. Indeed, the impact of this measure on the number of mental processing fixations, LHIPA, and readers' comprehension efficiency was consistent across all task types (flow-based local, flow-based global, circumstantial local, and circumstantial global). In contrast, the subjec-

tive perceived difficulty measure, which relies on participants’ self-assessment using a Likert scale, was not significantly impacted by changes in run count in three out of the four task types. This discrepancy might be attributed to the nature of subjective measures, which are typically collected post-hoc (i.e., by the end of the task), thus failing to capture the continuous variations in cognitive load experienced throughout a task [14]. Moreover, subjective assessments are threatened by meta-cognitive biases where participants underestimate the difficulty of the task at hand or feel reluctance to report it [14]. Moreover, questionnaires used to capture users’ cognitive load subjectively may be prone to interpretation ambiguities in some circumstances [14].

Our research has implications for both research and practice. For the former, our findings contribute to the body of existing research investigating the comprehension of modular process models [59,12,46,54,62,50,51], specifically those focused on the cognitive effects of fragmentation [62,50,51]. Additionally, our results highlight the importance of potential moderating factors, such as the task perspective (flow-based or circumstantial), which could influence the degree to which different levels of fragmentation affect cognitive integration. This underscores the need to carefully interpret existing theories. Furthermore, as the previous studies [57,19,23,45] investigating flow-based and circumstantial tasks did not incorporate cognitive integration into their theoretical frameworks, our work enriches this stream of research by considering a key factor that turned out to be significantly impacting users’ cognitive load and task performance in our study. By considering the task perspective, our research further complements the insights on the impacts of cognitive integration in [13], which was rather focused on the model representation perspective. Also, our research expands the theoretical framework in [13] by delivering statistical evidence linking cognitive integration not only to users’ performance but also to cognitive load.

At a practical level, our findings raise the need for enhanced tool support to mitigate the negative impacts of cognitive integration on cognitive load and task performance. For example, guided simulations can assist readers in mentally offloading [62] the complex relationships and interplay between different parts of process models [10] — whether these parts are contained within the same file (e.g., the same process model fragment or sub-process) or distributed across multiple files. Several studies in the literature have recognized guided simulations for their effectiveness in enhancing process model comprehension (e.g., [10,8,35]). However, it remains to be seen whether the benefits of guided simulations extend beyond flow-based tasks to support circumstantial tasks as well, which may require more than a single or a few trace simulations to develop an overarching understanding of the model. Another proposal is to use natural language processing (NLP) techniques to automatically identify the task-relevant parts of the process model from the task prompt, then augmented with the capabilities of large language models (LLMs), generate coherent explanations of how the task-relevant parts of the process model are interlinked. Such technology could significantly reduce the cognitive integration burden on users during comprehension tasks.

Threats to Validity. Our study is subject to internal, construct, and external validity threats [61]. To mitigate the internal validity threats, we addressed potential learning effects by randomizing the experiment’s tasks, ensuring that these effects are spread uniformly across all tasks. Moreover, each task was designed to reference different combinations of activities within the process models, and tasks compared in a pairwise manner during the analysis were consistently formulated and have identical answers (either both true or both false). To mitigate the threats to construct validity, we selected measures that capture cognitive integration, cognitive load, and comprehension from studies that have successfully used them in their empirical studies (cf. Sect. 2.3). To mitigate the threats to external validity, despite the difficulty of organizing eye-tracking experiments, we recruited a large number of participants (46), making our study among the extensive ones in the process comprehension research involving eye-tracking. This relatively large sample enhances the generalizability of our findings. Moreover, the fragment-based approach [26] we used is based on BPMN [41], the de-facto process modeling language, and reflects the horizontal modularization approach which is commonly found in software engineering, particularly in architectures like microservices and service-oriented architectures. This relevance to current professional practices further supports the external validity of our research, suggesting that our findings can be applied outside lab environments and potentially beyond process modeling research.

6 Conclusion and Future Work

In this study, we examined the effects of fragmentation on readers’ cognitive integration across both flow-based and circumstantial comprehension tasks that address local and global aspects. Additionally, we investigated whether cognitive integration could explain variations in cognitive load and task performance. Our findings highlight a significant relationship between fragmentation and increased cognitive integration in flow-based global tasks, as opposed to local ones. However, in circumstantial tasks, fragmentation did not significantly impact cognitive integration, which remained high for both local and global tasks, indicating that such tasks inherently demand high levels of cognitive integration, regardless of fragmentation. Moreover, our results confirm that cognitive integration affects both readers’ cognitive load and their task performance.

An important direction for future work is to delve further into how to support circumstantial tasks on modular process models to reduce readers’ cognitive integration effort. Adapting these models to describe processes following a constraint-based declarative approach rather than an imperative one could be beneficial for circumstantial tasks, but may have the opposite effect on flow-based tasks [19]. Therefore, other alternatives that focus on augmenting existing process representations with additional artifacts would be more adequate [4]. Notably, one can investigate whether guided simulations could bring enhanced support to both local and global circumstantial tasks. Finally, the NLP and LLM-based approaches discussed in Sect. 6 are also worth evaluating.

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