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Analyzing temporal data for understanding the learning process induced by metacognitive prompts

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1. Introduction

Self-regulated learning (SRL) is a crucial skill in lifelong learning (Ifenthaler, 2012). However, self-regulating their learning process can cause difficulties for students, particularly over multiple settings (Azevedo, Moos, Johnson, & Chauncey, 2010; Bannert, 2009; Bjork, Dunlosky, & Kornell, 2013; Winne, 2010). Empirical evidence shows that e.g. metacognitive prompts can successfully address these difficulties (Zheng, 2016). Yet, there is less empirical evidence giving insights into the SRL-process and more specifically, showing how SRL is influenced by metacognitive prompts. A rising approach to address this question is the application of educational data mining tools (Baker & Yacef, 2009). Educational data mining and more specifically process mining provides a new, emerging approach to investigate learning processes (with or without instructional scaffolds) more deeply (Bannert, Reimann, & Sonnenberg, 2014; Reimann, Markauskaite, & Bannert, 2014). Combining research in the areas of metacognitive prompts in SRL and educational process mining will give us new insights into understanding SRL processes that are supported by prompts. Moreover, it will help to improve design and timing of instructional interventions such as metacognitive prompts.

The aim of this paper is to combine two highly relevant research areas – metacognitive prompts in SRL and process mining. Process mining will give advanced insights into the SRL process because it provides a more comprehensive and detailed picture of the structure of events that occur during a learning process instead of having to aggregate process data into frequencies or probabilities of events. Consequently, the study reported in this paper will investigate the effects of metacognitive prompts on SRL processes. This research contributes to the existing literature in the field of educational psychology in providing a deeper insight into SRL processes as well as further supporting the growing discussion in the applicability of educational data mining techniques in educational research.

2. Supporting self-regulated learning with metacognitive prompts

One common learning goal in education is to enable students to learn self-regulation – even beyond formal education. SRL has been conceptualized from many different perspectives (Panadero, 2017). This research is built on an *event*-based (Van Laer & Elen, 2018) approach to SRL, conceptualizing it as a cyclical process with phases and sub-processes (Zimmerman, 2000). Thus, the SRL process can be described as an order of events that unfold during the learning process. Zimmerman (2000) organized the SRL process in three major phases (forethought, performance, and self-reflection) that will not play a role in this research. Nevertheless, these phases include a number of sub-processes (Zimmerman, 2000) or events such as goal setting, planning, monitoring, and evaluation.

Research shows that one important aspect of SRL are metacognitive strategies and knowledge (Boekaerts, Pintrich, & Zeidner, 2000), and students need self-regulation to optimize their learning process in computer-based learning environments (CBLEs) (Winne, 2011; Winne & Hadwin, 1998; Zimmerman, 2008). Unfortunately, many students struggle to learn self-regulated in CBLEs (Azevedo et al., 2010; Bannert, 2009; Bannert, Sonnenberg, Mengelkamp, & Pieger, 2015). These difficulties are associated with suboptimal learning outcomes (Land & Greene, 2000). One possibility to tackle these difficulties are metacognitive prompts. Empirical evidence demonstrates that metacognitive prompts could support students in SRL and improve learning (Azevedo & Hadwin, 2005; Dori, Avargil, Kohen, & Saar, 2018; Müller & Seufert, 2018).

Generally, instructional prompts are used to facilitate cognitive, metacognitive, motivational, and volitional activities while learning (Bannert, 2009). Metacognitive prompts are a specific type of prompt that remind students to enact metacognitive strategies or instruct specific metacognitive activities, such as orientation, goal-specification, planning, monitoring, and evaluation (Bannert, 2009) and thus foster the events of SRL processes mentioned above.

A review and meta-analysis (Belland, Walker, Olsen, & Leary, 2015; Zheng, 2016) showed that (metacognitive) support facilitates SRL and learning outcomes. Support of SRL is found to have a significant, medium-sized positive effect on academic performance. Moreover, metacognitive scaffolds prove to be the only function of scaffolds that lead significantly to increased learning outcomes (Zheng, 2016). A closer look at individual studies reveals quite a range of effects, or lack thereof. While some studies found metacognitive prompts to increase

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learning outcomes (e.g. Bannert et al., 2015; Bannert & Mengelkamp, 2013; Bannert & Reimann, 2011; Lin & Lehman, 1999; Zhang, Hsu, Wang, & Ho, 2015), there is also research in which metacognitive support failed to show a significant effect on learning outcomes (e.g. Mäeots et al., 2016; Reid, Morrison, & Bol, 2017; Van den Boom, Paas, van Merriënboer, & van Gog, 2004).

One possible reason for the incoherent effects of metacognitive prompts is the potential variance in students' SRL during the learning process. Most studies so far did not analyze the learning process supported by metacognitive prompts. Thus, this potential factor has not been investigated thoroughly.

In the last 10 years, there has been some progress in starting to analyze the sequences of SRL events in learning. As summarized by Van Laer and Elen (2018), these approaches of adapting process analysis in learning also vary substantially, including theory-driven methods (e.g., Roll & Winne, 2015; Winne, 2010) and data-driven methods (e.g., Beheshitha, Gasevic, & Hatala, 2015; Sonnenberg & Bannert, 2015, 2016). Most of the approaches work with log files as the basis of the process analysis (e.g., Azevedo, Taub, & Mudrick, 2015; Bannert et al., 2015; Roll & Winne, 2015). Yet, some researchers also investigated other data such as talk between students (Molenaar & Chiu, 2014) or think-aloud data (Sonnenberg & Bannert, 2015, 2016).

Molenaar and Chiu (2014) used statistical discourse analysis on sequences of talk between primary school students that were supported by scaffolds, to evaluate the probability of sequences of cognitive and metacognitive statements. Kinnebrew, Segedy, and Biswas (2014) evaluated log data that was categorized into actions (such as reading, searching) and then coded as relevant or irrelevant. A sequence mining algorithm was used to find frequent behavior sequences in students learning in an online learning environment supported by scaffolds. Sonnenberg and Bannert (2015) investigated the effect of metacognitive prompts in comparison to learning without prompts on the SRL process. In the study, the learning process was coded using think-aloud protocols and then operationalized in an event log of SRL events. Process mining using a heuristic miner indicated different learning sequences of students supported by metacognitive prompts, which corresponds with better transfer performance, in comparison to sequences of students learning without prompts (Sonnenberg & Bannert, 2015).

These studies show that process data can give important insights into the SRL process and potentially explain the success of instructional support in learning. Particular the study investigating think-aloud protocols (Sonnenberg & Bannert, 2015) shows that SRL events can be traced during the learning process and gives an insight into the effect of metacognitive prompts. Yet, the wide range of methodological approaches and the limited number of studies complicate the interpretation of these results. More importantly, none of the studies systematically investigated the extent to which metacognitive prompts affect the learning process more deeply by means of process mining techniques.

3. Understanding the process of self-regulated learning with process mining

Recent research became more interested in analyzing the learning process and the metacognitive and cognitive activities during SRL (Azevedo, 2014). The analysis of trace data that occurs during the learning process, for example coded think-aloud data, can potentially lead to a deeper understanding of learning processes and the evaluation of SRL on a more fine-grained level (Reimann et al., 2014; Sonnenberg & Bannert, 2015). Current research on metacognitive prompting and SRL relies on aggregated coded learning events to understand the learning process. An interpretation of all individual learning events is not possible in most cases, thus, process data is usually aggregated into descriptive values such as the frequency of events. Process mining can add meaning to the coded learning events by providing an alternative aggregation in order to interpret the learning events. Process mining takes (usually a high number of) the learning events and provides a different "form of aggregation" in the shape of process models. These models also aggregate the data of the learning process. Nevertheless, we would argue that the aggregation in process models is more meaningful. Process models do not just take the number of events into consideration, but additionally include their temporal structure and relation to each other.

3.1. Self-regulated learning as a regulatory process

Events of SRL can be understood to be the core of learning activities, particularly in CBLEs (Boekaerts et al., 2000). Most models share the view on SRL as a cyclical process that includes several phases, which themselves include several processes (Panadero, 2017). While the phases and processes vary between models, metacognitive events play a role in almost all conceptualizations. The model by Zimmerman (2000) includes metacognitive activities such as goal-setting, planning, self-control, self-judgment, and self-evaluation as central events in SRL. Moreover, metacognitive events are the core of the model by Winne and Hadwin (1998) as they consider metacognitive monitoring to be "the gateway to self-regulating one's learning" (Winne & Perry, 2000, p. 540).

Empirical research has shown that a learning process with metacognitive events can foster more successful learning (e.g., Azevedo, Guthrie, & Seibert, 2004; Bannert, 2009; Johnson, Azevedo, & D'Mello, 2011; Moos & Azevedo, 2009). The learning process, here conceptualized as a process of self-regulation events, is an important object to be investigated by educational researchers. Process analysis in educational settings makes it possible to investigate processes of learning behavior (Molenaar & Järvelä, 2014). Recent literature has shown that process mining can add interesting new insights into understanding SRL (Bannert et al., 2014; Sonnenberg & Bannert, 2015, 2018), Computer-Supported Collaborative Learning (Malmberg, Järvelä, Järvenoja, & Panadero, 2015; Reimann, Frerejean, & Thompson, 2009; Schoor & Bannert, 2012), and workplace learning (Siadaty, Gašević, & Hatala, 2016a; 2016b). This research starts to investigate rich data from verbal reports, eye tracking, computer log files, or even physiological measurement to operationalize SRL processes (Azevedo, 2009; Sonnenberg & Bannert, 2015, 2018; Trevors, Feyzi-Behnagh, Azevedo, & Bouchet, 2016). These approaches enable valuable insights into understanding learning processes and outcomes. This study aims to build on these new research methods by expanding the investigation of process mining of SRL processes.

3.2. Process mining to investigate self-regulated learning

Process mining is one application of educational data mining that induces process models from data, and these models could help to understand students' SRL processes (Roll & Winne, 2015). Process mining provides three main operations (Trčka, Pechenizkiy, & van der Aalst, 2010): (a) process model discovery, (b) conformance checking, and (c) process model extension. In understanding the SRL processes of learning, the first two approaches are of particular interest: (a) Process model discovery can reveal the most relevant temporal structure of the SRL events during the learning process and provide a visualization. (b) Conformance checking would make it possible to compare the processes of two groups, such as the students in an experimental and control condition in an experiment.

(a) The approach to investigate SRL process with process mining is promising because process mining considers all learning events to create a process model. These process models then give meaningful insights into the sequence of events and thus an insight into the sequential relationship between the metacognitive and cognitive events during the learning process. (For a more comprehensive comparison of process mining with other education data mining techniques in SRL, see Sonnenberg & Bannert, 2018, and Van Laer & Elen, 2018).

(b) Apart from the induction of process models, process mining can also test the conformance between a process model and process data and operationalize the conformance in metrics such as fitness and appropriateness (Rozinat & van der Aalst, 2008; Van der Aalst, Adriansyah, & van Dongen, 2012). In conformance analyses, a process model is compared to an event log. The results of the analysis show the degree to which the event log differs from the model (Van der Aalst et al., 2012). After inducing a process model for SRL events in the experimental as well as the control condition of an educational intervention, a conformance check could operationalize to what extent the process models represent the SRL learning process of the other condition. This data can give insight into the conformance between the SRL processes of different conditions, thereby showing how the educational intervention might influence the SRL process.

4. Research questions

Metacognitive prompts are considered to support learning (Zheng, 2016) by prompting SRL events during learning. However, a closer look at individual studies shows quite a range of effects, or lack thereof (e.g., Lin & Lehman, 1999; Bannert & Mengelkamp, 2013; Van den Boom, Paas, Van Merrienboer, & Van Gog, 2004; Mäeots et al., 2016; Zhang et al., 2015; Bannert et al., 2015; Bannert & Reimann, 2011; Reid et al., 2017). Metacognitive prompts supporting SRL have shown to support transfer learning (e.g., Bannert et al., 2015; Müller & Seufert, 2018) and we are building on this strand of literature. Some studies show that process mining can analyze and visualize the SRL process (e.g., Kinnebrew et al., 2014; Molenaar & Chiu, 2014; Sonnenberg & Bannert, 2015). Particularly the study by Sonnenberg and Bannert (2015) showed how the analysis of think-aloud data can give a visual insight into the learning process and explain learning outcomes.

This study builds on these results and expands the investigation of process mining of SRL processes. In a first step, we aim at replicating the descriptive results of the study by Sonnenberg and Bannert (2015) by investigating to which degree metacognitive prompts affect the learning processes. The investigation by Sonnenberg and Bannert (2015) suggested that the frequency of metacognitive events is significantly higher if students are supported by metacognitive prompts in comparison to not being supported by prompts. Thus, we hypothesize to find this pattern in this study, too.

1. To what extent do metacognitive prompts affect metacognitive and cognitive events during learning?

In the next step, this study utilizes process mining to explore the temporal structure of metacognitive and cognitive events during the students' SRL process. While there has been some development in adapting process mining into the investigation of learning processes (Van Laer & Elen, 2018), the limited number of studies precludes us from stating a hypothesis regarding the outcome of this research question. This question needs to be addressed with process model discovery because this approach reveals the most relevant temporal structure of (in this case metacognitive and cognitive) events during the learning process (Trčka et al., 2010).

2. What is the temporal structure of metacognitive and cognitive events during learning with or without metacognitive prompts?

In a third step, this study utilizes conformance checking. This method makes it possible to compare the learning process of students learning with and without prompts by comparing the process data from one group of students to the temporal structure of the other group of students (and vice versa). The results of this research question can give a deeper insight into understanding the learning process of learners with and without metacognitive prompts. The results would be interesting in both cases, whether the manipulation of metacognitive prompts yields an influence on the learning outcome or not. In both cases, it would be interesting to discover if the learning process between the two conditions differs because we assume the learning process to mediate between metacognitive prompts and learning outcome. Even if the learning outcome is not affected, the metacognitive prompts might influence the learning process.

3. To what extent does the temporal structure of metacognitive and cognitive events differ between students learning with or without metacognitive prompts?

5. Method

The study presented in this paper was conducted in a research project investigating the effect of metacognitive prompts on performance in computer-based learning environments. A comprehensive report of these results can be found in Engelmann and Bannert (2019). In this paper, we will focus on in-depth analyses of the metacognitive and cognitive processes during the learning phase.

5.1. Sample and design

The total sample of this study consisted of 66 German-speaking undergraduate university students (M_{age} = 19.9 years, SD = 1.58; 72% female). We excluded nine participants from the sample who did not follow the instructions or showed high prior knowledge. The final sample for all data reported in this article comprised of n = 57.

The data was collected in an experimental study with a between-subject design. The independent variable was manipulated with two conditions randomly assigned: participants learned with metacognitive prompts in the experimental condition (EG, n = 28) and participants learned without prompts in the control condition (CG, n = 29).

5.2. Learning environment

We presented the learning content in a CBLE taken from successfully published studies (e.g., Bannert, 2007; Bannert et al., 2015). The hypermedia learning environment was a closed environment that included over 50 subpages, including a page summarizing the learning goal for the participants, overviews, and summaries. Most of the CBLE consisted of text, as well as pictures and tables. The participants had various options of navigating the environment: a menu bar, hyperlinks, the next page or the previous page button, and the browser buttons.

5.3. Procedure

The experiment was conducted in a laboratory of a German university over three sessions (total time ~ 5 h). In the first session, learner characteristics were measured, the learning session took place during the second session, and the third session contained a follow-up. In this article, we will focus on the second session.

The second session contained three phases that took a total of approximately 2 h. The participants were introduced to the hypermedia learning environment and got a 15 min training about prompts or an alternative topic (depending on the experimental condition) during the first phase. The second phase contained a 40 min learning process during which the participants navigated a CBLE while thinking aloud. The participants studied about basic concepts of operant conditioning in the learning phase. Transfer performance as well as other performance measures were tested in the third phase.

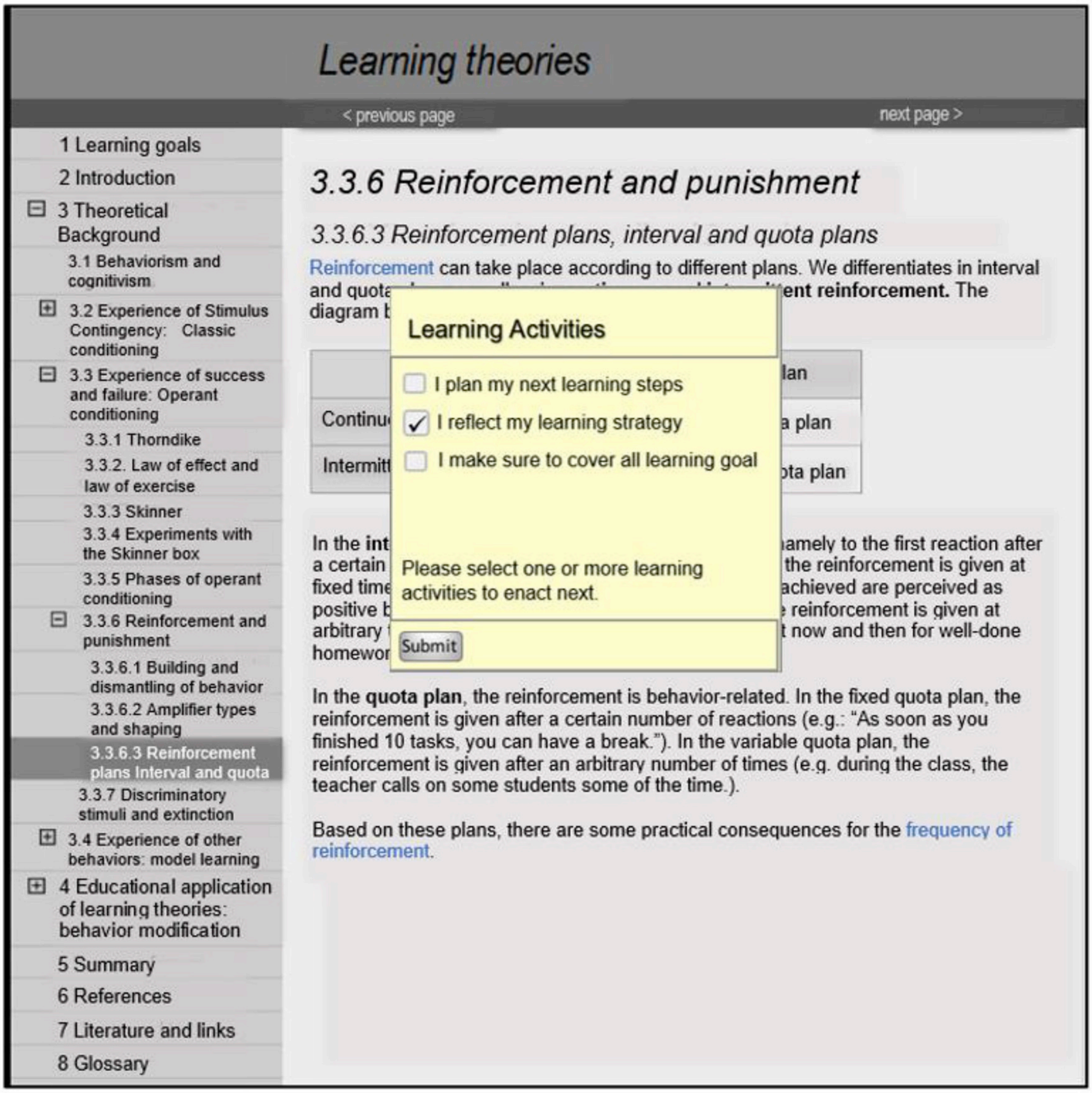

Fig. 1. Screenshot from the learning environment including a pop-up window displaying a metacognitive prompt.

5.4. Manipulation of the independent variable

The experimental and control condition differed in two aspects: (a) the instruction and creation of prompts as well as (b) the presence of prompts during the learning phase.

(a) During the instruction, participants in the experimental condition were introduced to prompts and it was explained to them, how to create metacognitive prompts. In the next step, the participants created their own prompts and determined the timing of the prompts. Participants of the control condition participated in an alternative, irrelevant training of the same workload and duration (see Engelmann and Bannert, 2019, for a more comprehensive description and analysis of different prompts).
(b) During the learning phase, participants in the experimental condition were presented with their own prompts at the times determined by the participants themselves. The prompts were shown as a list of activities in a pop-up window (see Fig. 1). Participants could select one or more activities and close the window to continue with learning in the CBLE. Participants of the control condition learned in the same CBLE without prompts.

5.5. Dependent variables

5.5.1. Learning process

During the entire learning phase, the verbal protocols and the screen were recorded in a video file. This file was coded in a 2-step procedure. First, the data was segmented based on meaning. Second, each segment was assigned one code. Two trained, independent research assistants coded the verbal protocols, based on the procedure suggested by Chi (1997) with sufficient interrater reliability ($\kappa = 0.80$), an example is shown in Table 1.

The coding was conducted using a coding scheme based on self-regulated hypermedia learning (Bannert, 2007) that has been successfully applied to data from similar studies (e.g. Bannert et al., 2015). Here, activities in hypermedia learning are categorized into *Cognition*, *Metacognition*, and *Motivation*. Thus, the main categories for the coding scheme are *Metacognition*, *Cognition*, *Motivation*, and *Other*. Metacognition is further divided into the sub-categories *Orientation*, *Goal specification*, *Planning*, *Searching for information*, *Judgment*, *Evaluating*, *Monitoring*, and *Regulation*. Similarly, Cognition is further divided into *Reading*, *Repeating information*, *Elaboration,* and *Organization of information*. The category of *Motivation* was used to code all motivational

Table 1
Example of an event log section and the underlying think-aloud protocol.

Case ID	Timestamp	Coded occurrence (event)	Transcript of the think-aloud protocol
012	18:10.098	ORGANIZATION	“Yes, as it was said previously … Of course, we need theses terms again, positive reinforcement, negative reinforcement, perhaps the punishment and extinction.”
012	18:47.291	MONITOR	“And now, yes, I would go into the text and read that section … to understand theses terms.”
012	18:55.937	READ	Reading from the text: „Generally, positive reinforcement means to […] The peadgogical use of punishment is controversial.”
012	19:33.647	MONITOR	„Yes.“
012	19:34.251	ELABORATE	„So, positive reinforcment means to get a desired reaction after a behavior. And this increases the likelihood of occurrence.”
012	19:47.861	MONITOR	“Yes, I'll note that down.”
012	19:51.539	ORGANIZATION	Noting down: „So, positive reinforcement increases the likelihood of occurrence of behavior.“
012	20:28.285	MONITOR	„Correct.“
012	20:29.154	REPEAT	„Punishment will suppress the behavior … So the behavior will occurred less often.”
012	20:37.991	MONITOR	„I'll note that down, too.”

aspects of the task, the situation, or oneself. The code *Other* was used to combine all irrelevant utterances or utterances that could not be categorized in the formerly mentioned categories.

To analyze the temporal structure of metacognitive and cognitive events, we simplified the coding scheme to keep the output model comparable to other studies with process analysis (e.g., Sonnenberg & Bannert, 2015; 2018). In the resulting categorization, the codes *orientation*, *planning*, and *goal specification* were combined to *analyze*, the category *judgment* was included into *monitoring*, and the categories *elaboration* and *organization* were combined in the category (deeper learning) *process*. Furthermore, the categories *motivation* and *other* were excluded from the analysis. In sum, seven categories (*analyze*/ANALYSIS, *search*/SEARCH, *evaluation*/EVAL, *monitoring*/MONITOR, *reading*/READ, *repeating*/REPEAT, *process*/PROCESS) were included in the process analysis. Table 1 shows a section of how the coded data looks like in the final event log that was used as process data for this study. Table 2 depicts the coding scheme with descriptions and examples for each category.

5.5.2. *Learning performance*

Transfer knowledge is one of the performance tests that were measured because it showed to be a relevant outcomes variable in similar investigations (e.g., Bannert et al., 2015; Müller & Seufert, 2018). The test for transfer consisted of open questions, asking the participants to apply knowledge of operant conditioning in order to solve eight unknown problems set in educational backgrounds (Cronbach's a = 0.54). The answers were rated by two research assistants (Cohens Kappa = .84) based on a scale of zero to five developed by Bannert (2007).

5.6. *Statistical analysis*

For this paper, we used three approaches to analyze the data. In order to investigate the first research question, we used descriptive analysis and multivariate analysis of variance (alpha set to 0.05). In order to investigate the second research question, we used process model discovery, more specifically, the *Heuristic Miner* (Weijters, van

Table 2
Coding scheme for analyzing students‘ metacognitive and cognitive events (cf. Sonnenberg & Bannert, 2015).

Initial Coding Category	Initial Code	Final Coding Category	Final Code	Description and Examples
Metacognition				
Orientation	ORIENT	Task Analysis	ANALYSIS	Task clarification, overview of material *I will sketch the menu first. I get a rough overview.*
Goal specification	SETGOAL			Goal setting and sub-goaling *I have to learn the basic concepts of operant conditioning.*
Planning	PLAN			Planning how to proceed *First I will decide in which sequence I have to learn and which pages to read.*
Search	SEARCH	Search	SEARCH	Searching for information *Where is the page with the information about reinforcement?*
Evaluation	EVAL	Evaluation	EVAL	Checking and evaluating *Did I process all the topics? Now I'll take a look at the examples, if I understood everything.*
Judgment	EVALUATE	Monitoring	MONITOR	Judgments about the relevance of information *Skinner's Vita is not relevant for my learning task.*
Monitoring	MONITOR			Monitoring one's own learning *Ah, now I understand the principle. The rule is hard.*
Cognition				
Reading	READ	Reading	READ	Reading out loud *I skim over the material. I look at the structure.*
Repeating	REPEAT	Repeating	REPEAT	Repeating *I memorize technical terms. I repeat the material that I just read to recognize it.*
Elaboration	ELABORATE	Deep Processing	PROCESS	Deeper processing, *paraphrasing, connecting, inferring. I summarize the topic in my own words.*
Organization	ORGANIZATION			Organization *Drawing a map, writing down major concepts*
Motivation				
Motivation	MOT	–	–	Positive, negative, neutral motivational utterances regarding a task, person or situation *The task is too difficult. I am good at this. I'm curious what else is coming.*
Other				
Other	REST	–	–	Off-topic statements, comments on technique, not interpretable statements, pauses *May I make notes? The mouse doesn't work well.*

Table 3
Frequencies of cognitive and metacognitive occurencies as well as inferential t-statistics regarding differences between students supported by metacognitive prompts (EG) and students learning without prompts (CG).

	Students supported by metacognitive prompts (EG, n = 28)					Students learning without prompts (CG, n = 29)					*F*	*p*	*d*
	Min	*Max*	*Sum*	*M*	*SD*	*Min*	*Max*	*Sum*	*M*	*SD*			
Metacognition	36	263	3956	141.29	51.51	28	199	3010	103.79	40.26	9.41	.01	0.83
Orientation (ORIENT)	5	44	631	22.54	10.15	3	41	544	18.76	10.07	1.99	.16	0.38
Planning (PLAN)	0	8	47	1.68	2.31	0	4	18	0.62	0.90	5.25	.03	0.62
Goal specification (SETGOAL)	0	4	30	1.07	1.30	0	4	13	0.45	1.06	3.95	.05	0.54
Search (SEARCH)	0	18	182	6.5	5.07	0	23	182	6.28	6.54	0.02	.89	0.04
Judgement (EVALUATE)	0	30	249	8.89	8.55	1	16	185	6.38	4.96	1.86	.18	0.37
Evaluation (EVAL)	0	8	93	3.32	2.82	0	6	42	1.45	1.80	9.01	.01	0.81
Monitoring (MONITOR)	22	186	2724	97.29	40.29	13	136	2026	69.86	28.45	8.86	.01	0.80
Cognition	50	177	3005	107.32	33.22	24	250	3428	118.21	59.44	0.72	.40	0.23
Reading (READ)	17	90	1327	47.39	17.64	19	117	1649	56.86	27.61	2.36	.13	0.41
Repeating (REPEAT)	0	39	438	15.64	10.31	0	56	322	11.10	13.00	2.13	.15	0.39
Elaboration (ELABORATE)	1	67	662	23.64	16.18	0	78	692	23.86	19.12	0.00	.96	0.00
Organization (ORGANIZATION)	0	47	578	20.64	13.03	0	81	765	26.38	21.11	1.51	.22	0.33
Motivation	0	18	65	2.32	3.53	0	7	54	1.86	2.12	0.36	.55	0.16

Der Aalst, & De Medeiros, 2006). Process model discovery makes it possible to analyze the temporal structure of metacognitive and cognitive events (see below for a more detailed description). In order to investigate the third research question, we applied the *Conformance Checker* (Rozinat & van der Aalst, 2008). The conformance checker is the only approach that can be used to explore the degree of conformance between the SRL processes we found in this study.

5.6.1. Process mining using the HeuristicsMiner algorithm

The process mining was applied to the event log data of the metacognitive and cognitive events (for an example of the data set in this study, see Table 1) after uploading the data set into the ProM framework version 5.2 (Verbeek, Buijs, Van Dongen, & Van Der Aalst, 2010, pp. 60–75).

For the analyses presented in this paper, we used the HeuristicsMiner algorithm (Weijters et al., 2006) to induce a model of the temporal structure of metacognitive and cognitive events during the learning process. The HeuristicMiner algorithm is a well applicable miner for educational data mining because it can deal with noise that can often be found in educational data and presents the main behavior found in an event log without paying too much attention to specifics and exceptions (Weijters et al., 2006).

During the mining procedure, the HeuristicsMiner algorithm generates a heuristic net as a visual representation of the dependencies among all events of the underlying event log (i.e. the metacognitive and cognitive events). The HeuristicsMiner algorithm has a number of underlying parameters that are applied for the creation of the output model and can be used in interpreting the model: *Frequency* stands for the number of links between two events. *Dependency* stands for the certainty of this link between two events (Weijters et al., 2006). For the analysis presented in this paper, were kept the threshold values at their default values (dependency threshold = 90, relative-to-best-threshold = 5). Sonnenberg and Bannert (2015) give a more detailed description of the application of the HeuristicsMiner algorithm in this type of data. The output of these analyses are two process models, one for all participants learning with metacognitive prompts, one for all participants learning without prompts.

5.6.2. Conformance checking

In a preparatory step, the process models induced by the HeuristicMiner algorithm were converted into Petri nets, the format necessary for the conformance analysis. In order to investigate the degree of conformance between the SRL processes we found in this study, we applied the *Conformance Checker* (Rozinat & van der Aalst, 2008).

The conformance checker compares an event log to a process model and gives a fitness value for their fit. It is not possible to directly compare process models with each other. Thus, for this study, we compare the fitness values for each model (students learning with metacognitive prompts and students learning without prompts, respectively) in comparison to the event log for both learning processes, the process that was used to discover the model as well as the process from students from the other condition.

Since there are no clear guidelines on the interpretation of the fitness value in educational science (Sonnenberg & Bannert, 2018; Van Laer & Elen, 2018), we will descriptively compare the results. The fitness value quantifies the degree to which an existing model can "play" the data in an event log file (ranging from 0 to 1). A model with high fitness allows most of the events in the log data to "replay". However, fitness provides no information on the precision of the model. A high fitness value could still mean that a model allows for trances different from the event log that it is compared to (Van der Aalst et al., 2012). For this study, the higher the fitness value is, the better does the model include a learning process (SRL event log), without evaluating the specificity of the model.

6. Results

6.1. Prior analysis on performance

A first analysis (Engelmann and Bannert, 2019), investigated the effect of metacognitive prompts on performance measures in this data set. Contrary to our hypothesis, metacognitive prompts did not significantly improve the transfer performance ($t(55) = 0.88$, $p = .19$). Consequently, the analyses of this paper does not only intend to discover the learning process of students supported with or without metacognitive prompts but also aims at investigating the inconclusive results of metacognitive prompts as elaborated above.

6.2. The effect of metacognitive prompts on metacognitive and cognitive events during learning

Regarding the first research question, we were expecting to find an advantage for the students learning with metacognitive prompts with respect to their frequency of metacognitive events during the learning process.

As shown in Table 3, there are descriptive differences in many metacognitive events. A multivariate analysis of variance showed a significant difference in metacognitive and cognitive events between

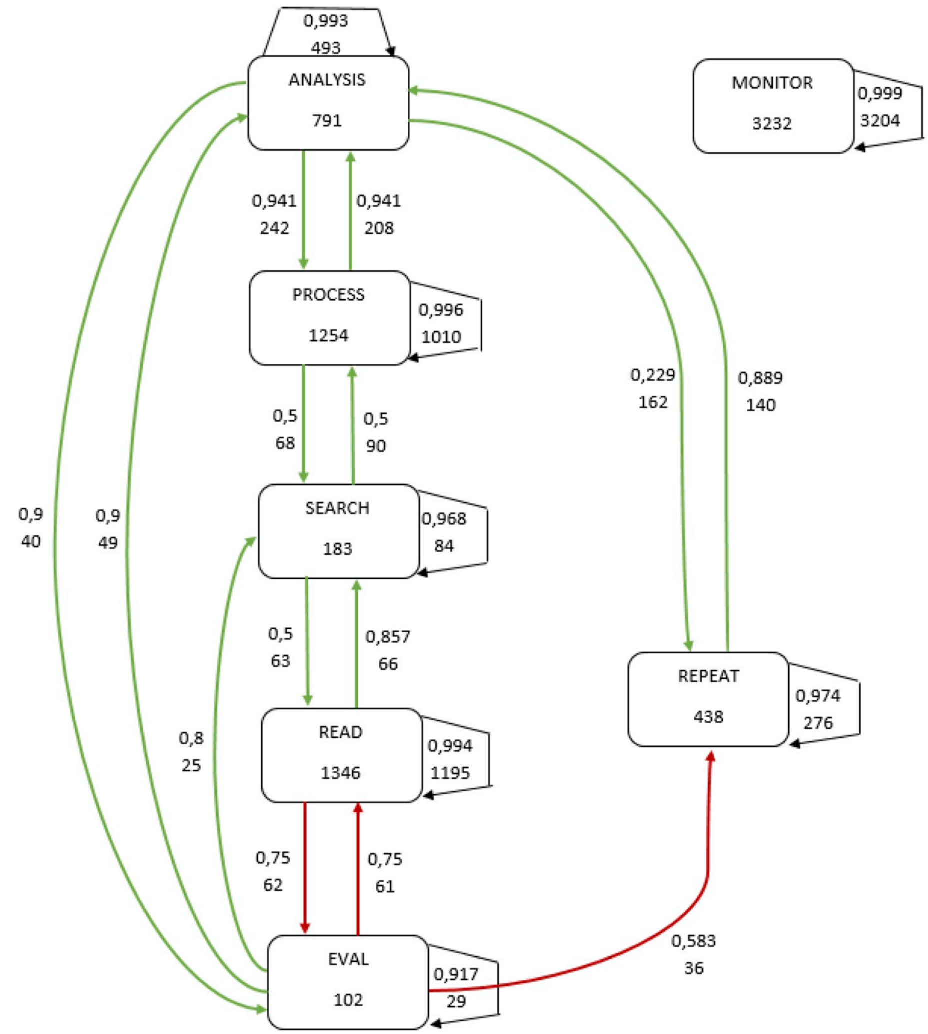

Fig. 2. Temporal model of metacognitive and cognitive events during the learning phase of students supported by metacognitive prompts (EG; n = 28). The green lines indicate links that are present in the process models of students in both conditions, the red lines indicate links that are only present in this model of students in the experimental condition. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

learning with and without metacognitive prompts (F (13, 43) = 2.31, Wilk's Λ = 0.59, p = .02). The metacognitive prompts had a significant effect on five of the events, i.e. students learning with prompts articulated more often about planning, monitoring, evaluating, and metacognition in general, as well as the other category (p < .05, d = [0.62; 0.83]). We found no significant differences for any of the cognitive events (Table 3).

In sum, the data support our hypothesis that the frequency of metacognitive events is significantly higher if students are supported by metacognitive prompts in comparison to not being supported by prompts.

6.3. Process discovery using the HeuristicsMiner

Regarding the second research question, we did not expect a specific temporal structure of metacognitive and cognitive events because the theoretical model (Zimmerman, 2000) underlying this research does not specify the relation between individual events. The output model for the condition with metacognitive prompts and the output model for the condition without prompts induced by the HeuristicsMiner algorithm are displayed in Figs. 2 and 3, respectively. In the figures, the boxes represent the metacognitive and cognitive events and the arrows represent links between events. Moreover, the dependency (ranging between 0 and 1) and the frequency of the events and links are displayed. The dependency stands for the certainty of this link between two events and the frequency stands for the number of links between two events (Weijters et al., 2006).

The coloring of the links shows whether a link is present in both models, thus a substantial path for students with and without prompts, or just one model. The green links can be found in both models and account for the majority of paths. The red links are only found in the models for students learning with metacognitive prompts or without prompts, respectively. Both models start with the event of ANALYSIS; in both models, the ANALYSIS and SEARCH are very connected events, while EVAL also belongs to this category for the students learning with metacognitive prompts and PROCESS belongs to this category for the students learning without prompts; both models do not integrate MONOTOR, even though it is the most frequent event. In both models, there are two substantial paths that are similar: (a) ANALYSIS → PROCESS → SEARCH → READ and (b) ANALYIS → EVAL → SEARCH → READ. The models for students supported by metacognitive prompts and students learning without prompts show similar patterns, ANALYSIS seems to be an important SRL event at the beginning of a learning process and is (together with SEARCH) well connected in the learning process. On the contrary, MONITOR has a very high frequency in the learning process but is not systematically connected to other SRL events.

In sum, the models show some interesting patterns such as the close

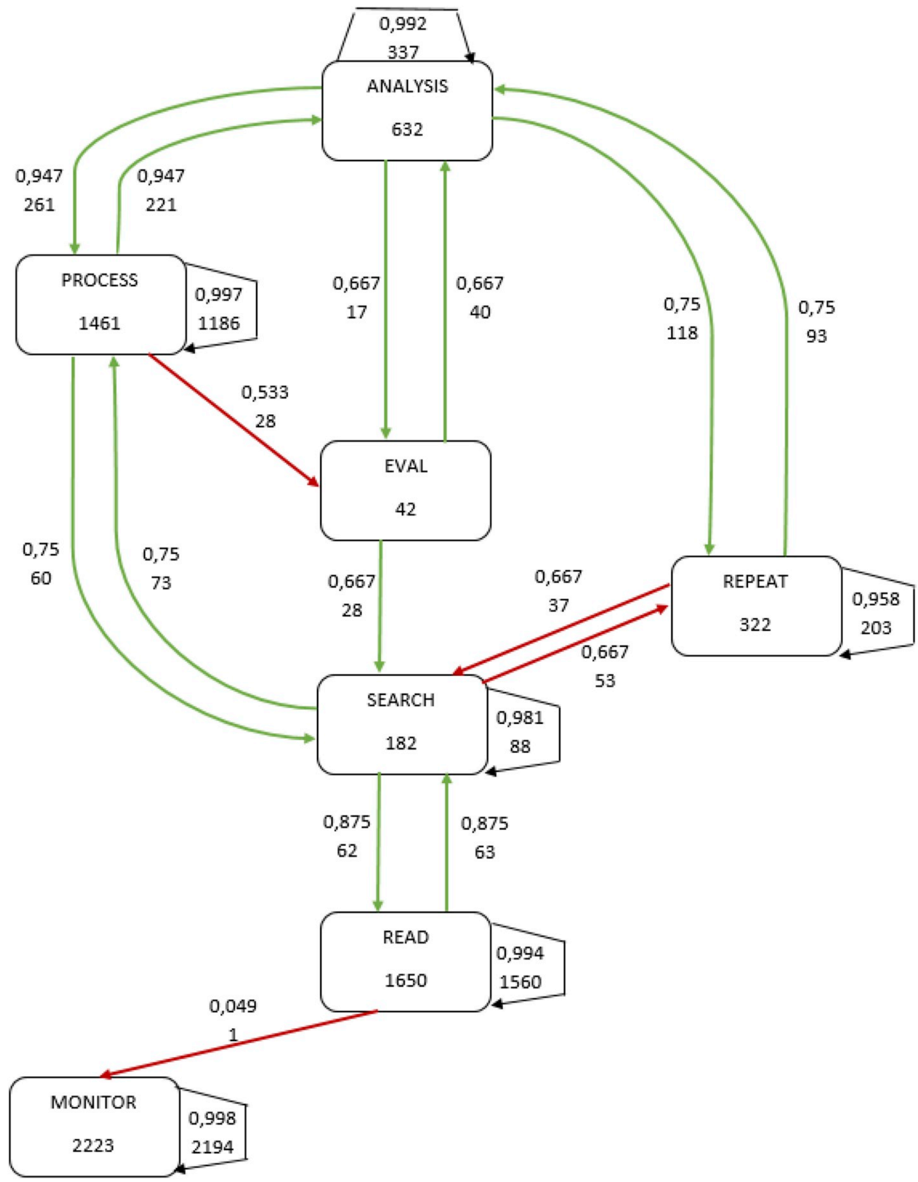

Fig. 3. Temporal model of metacognitive and cognitive events during the learning phase of students learning without prompts (CG; n = 29). The green lines indicate links that are present in the process models of students in both conditions, the red lines indicate links that are only present in this model of students in the control condition. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

connectedness of ANALYIS and SEARCH and the difficulty to connect MONITOR to the other events in the learning process.

6.4. Comparison of the learning process using conformance analyses

Regarding the third research question, we did not expect a certain degree of difference between the learning processes of students learning with metacognitive prompts or without prompts, but were rather interested in exploring to which degree the models display the learning process in the different conditions of this experiment.

For the comparisons between the conformance of the condition with metacognitive prompts and the condition without prompts, we compared the fitness for both process models (Figs. 2 and 3) with the event logs of the metacognitive and cognitive events in each condition. Fig. 4 displays the fitness values (f) for each of the comparisons. While the individual interpretation of the fitness values is impossible at this stage, the comparison shows that the fitness values for the process model for students' learning without prompts is higher for both event logs. Moreover, the fitness value is the highest for the event log for students learning with metacognitive prompts in the process model for students without prompts.

While it is unclear at which point the difference in fitness value is meaningful, these results indicate that the learning processes for students learning with metacognitive prompts and the students learning without prompts in this experiment are quite similar. If this was not the case, we would expect the fitness values for the corresponding process model and event log (i.e. the process model and event log for students with metacognitive prompts vs. the process model and event log for students without prompts) to be much higher than the fitness values for the different condition (e.g. the process model for students learning with metacognitive prompts and the event log for students learning without prompts).

7. Discussion

In the study presented in this paper, we aimed at investigating the effect of metacognitive prompts on metacognitive and cognitive learning processes as well as discovering a deeper insight into the SRL

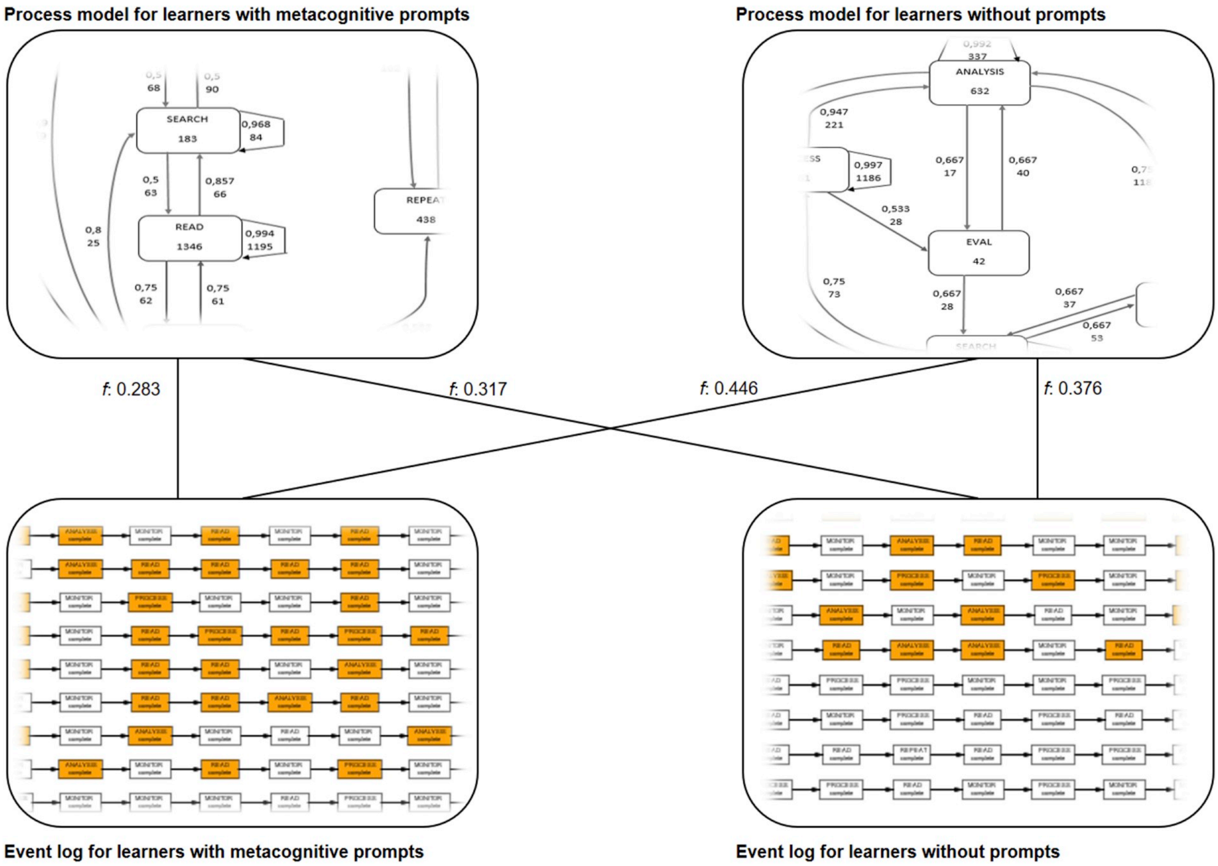

Fig. 4. Grafical presentation of the fitness values for the comparision of the inducted models and the event log data from students supported by metacognitive prompts (EG, n = 28) and students learning without prompts (CG, n = 29).

process itself.

Regarding the effect of metacognitive prompts on learning outcomes, we found no significant differences in transfer performance (Engelmann and Bannert, 2019). A result that contradicts prior findings (Zheng, 2016). However, as shown in the results regarding the first research question, students learning with metacognitive prompts did verbalize more metacognitive events during the learning process than students learning without prompts. This pattern of results is similar to prior findings in process analyses (Sonnenberg & Bannert, 2015; Bannert et al. 2015).

We argue that these incoherent results might point toward the central assumption that the frequency of cognitive and metacognitive events are less meaningful than the sequential process in which the cognitive and metacognitive events come about. The pattern of results in this study in comparison to prior research suggests that descriptive results such as the frequency of metacognitive and cognitive events are less significant in understanding the SRL process than a deeper analysis of the learning process. While a higher frequency of metacognitive events might *be necessary* for a beneficial SRL process (coherent with research finding that metacognitive support is beneficial for learning outcomes, e.g., Azevedo & Hadwin, 2005; Bannert et al., 2015; Bannert & Mengelkamp, 2013; Bannert & Reimann, 2011; Dori et al., 2018; Lin & Lehman, 1999; Müller & Seufert, 2018; Zhang et al., 2015), a higher frequencies of metacognitive events might *not be a sufficient* indicator for a beneficial SRL process; thus, some research (such as this study and e.g., Mäeots et al., 2016; Reid et al., 2017; Van den Boom, Paas, van Merriënboer, & van Gog, 2004) find no beneficial effect of supporting metacognitive events.

The results regarding the second and third research question show that there are few differences between the learning processes of students supported with metacognitive prompts and without prompts. Both models share a rather weak integration of one main metacognitive event: monitoring. These results stand in contrast to many theoretical SRL models in which metacognitive events are on the core of the learning process (e.g. Winne & Hadwin, 1998; Zimmerman, 2000). The weak interconnection of monitoring could point out that monitoring is similarly weak connected to almost all other events, therefore does not appear in one specific place of the SRL process but in many. However, the results could also indicate that the theoretical understanding underlying our coding scheme for metacognitive and cognitive events is not sufficient enough to depict these events.

Moreover, task analysis and search are well integrated into both process models, showing that several metacognitive events are relevant in the SRL process. Yet, evaluation is better integrated for students learning with metacognitive prompts. This finding could be a result of the metacognitive prompts. The metacognitive prompts were aimed at cueing the students to integrate more metacognitive events in their learning process (Bannert, 2009). While we do not know how significant the difference in the integration of evaluation between the two conditions of this study is, the results suggest that the prompts may have affected the integration of evaluation in the learning process. However, in order for the prompts to significantly affect the learning outcome, deeper integration of monitoring might also be necessary. This was not the case for this study (see also Engelmann and Bannert, 2019).

Current studies investigating data mining processes in SRL advance the field (Ben-Eliyahu & Bernacki, 2015; Molenaar & Järvelä, 2014; Roll & Winne, 2015; Sonnenberg & Bannert, 2018; Winne & Baker, 2013) but are still mainly exploratory (Sonnenberg & Bannert, 2018). The conclusions that can be drawn from the process mining analyses are based on exploratory analyses and are therefore hypothesis generating. We can hypothesize from the process models that the students often start with task analysis – which is coherent with conceptual models (e.g. Zimmerman, 2000). Moreover, the models also suggest that monitoring is not well connected in the process model – in contrast to theoretical concepts in which monitoring plays a central role (e.g. Winne & Hadwin, 1998; Zimmerman, 2000). In contrast, poor integration of monitoring in the process models while monitoring was the most often coded event could also point toward the hypothesis that monitoring is (less frequently) connected to many or all events and thus the process model cannot connect monitoring more stable to a selection of events. This hypothesis would not be in contrast to SRL conceptualizations (e.g. Winne & Hadwin, 1998; Zimmerman, 2000).

7.1. Limitations

It is important to notice the application of process mining in educational settings is still in its infancy (cf. Sonnenberg & Bannert, 2015, 2018; Van Laer & Elen, 2018). We need more process data that is evaluated with the methods applied in this paper to understand the range of (a) process models generated by a heuristic miner for SRL processes in an CBLE, (b) process models generated by a heuristic miner in other comparable learning setting, (c) fitness values for comparisons between learning settings. So far, we can provide descriptive results and compare the fitness values with each other. However, due to our limited experience with the range of results that can be obtained, even within the restricted area of SRL, and no clear guidelines on the significance of fitness values, it is very difficult to generalize the results presented in this paper. So far, we would consider the process mining results presented in this paper to be specific for our learning setting and the sample of students in this study.

Moreover, the setting of parameters and calibration of the process mining was kept similar to prior studies (e.g. Sonnenberg & Bannert, 2015, 2018) in order to enable us to make comparisons. Yet, the settings are not grounded in any theoretical conceptualization while making a considerable difference in the outcomes (Van Laer & Elen, 2018). We would recommend for future research to provide more examples of applying process mining to SRL processes. Once a solid research basis is created, reviews and meta-analyses could give a better insight into the effect of the application of different process mining techniques, settings, as well as the generalization of the findings of single studies.

While we regard the process mining results presented in this paper to be specific for our learning setting and the sample of students in this study, we would consider them to be a basis for more precise hypotheses in further analysis. Further research could test more specifically, how SRL events that play a prominent or anomalous role in the models discovered in this study (such as ANALYSIS, SEARCH, or MONITOR), are integrated into the learning process by targeting these specific events in instructional support.

7.2. Conclusion

In conclusion, the process models give a more meaningful insight into the learning process than descriptive values for metacognitive and cognitive events because they allow for a visual comparison of students' SRL processes in the study and theoretical models (e.g. Zimmerman, 2000) and might, therefore, explain the influencing role of metacognitive prompts on learning outcomes, or the lack thereof. The conformance check supports the inferences from the visual inspection of the process models; students learning with metacognitive prompts and learning without prompts did not differ much in their learning process in this study. It would be interesting to advance process analyses of SRL processes into two directions: a qualitative, inductive approach as well as a more theory-driven quantitative approach of comparing learning processes to conceptual models of SRL (e.g. Winne & Hadwin, 1998; Zimmerman, 2000). The question for the latter quantitative approach would be whether the conceptual models are fine-grained enough to be compared to descriptive, empirical models and learning processes as found in this study.

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