The Influence of Automated Planning on the Task Performance of Process Modelers

Completed Research Paper

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Abstract

Constructing and adapting process models is highly relevant in today's business world, but time-consuming and error-prone. Several approaches address these issues by manual tasks or making use of automation in the past years. Especially the research field Automated Planning envisions a (semi-)automated construction of process models by using semantic annotations and planning techniques.
We aim at an empirical analysis of the influence of Automated Planning on the task performance of process modelers compared to the task performance when using common process modeling tools. We analyze the invested effort in terms of the required time for modeling tasks and the outcome in terms of the quality of the constructed process models by means of a laboratory experiment.
Our findings indicate that Automated Planning significantly improves the task performance. The quality of constructed process models is increased, and especially for larger process models, the required time for modeling tasks could be decreased.

Keywords: Business Process Management, Automated Planning, Experimental Evaluation, Task Performance

Introduction

Process models not only allow representing processes but are crucial instruments for decision-makers (Rosemann and vom Brocke 2015), support the alignment of companies' IT infrastructure with their business strategy (Branco et al. 2014) and are an essential tool in business reorganization projects (Becker et al. 2010a; Mendling et al. 2010). Formalized, imperative process models are commonly used as a basis for a semi-automated execution of processes (Ding et al. 2015; Paik et al. 2014; Wang et al. 2014) or their verification (e.g., Wetzstein et al. 2007). Additionally, a suitable representation of processes using process models is a crucial success factor for the development of service-oriented information systems (Aguilar-Savén 2004; Mendling et al. 2012a). However, today's process modeling projects are facing several issues in practice (i.e., in a business context). Process modeling and improving processes is time-consuming (Heinrich et al. 2015; Hornung et al. 2007; van der Aalst and Jablonski 2000) as it is not supported by algorithms mainly. A survey conducted by Becker et al. (2010b) among 60 banks underlines this: "over two thirds […] have a negative effort-utility-ratio concerning their process modeling initiatives". In a cooperative project, we analyzed over 600 core business processes as well as 1,500 support processes of a European bank. Several IT and business executives of the bank stated that today's process (re)design projects are more cost-intensive and time-consuming than ten years ago, due to higher complexity. This is particularly relevant as the know-how of representing business processes in a formal and syntactically as well as semantically correct way is completely missing (Becker et al. 2015) or in the responsibility of a few specialists in many organizations.

Hence, when talking about an effort-utility-ratio of business process modeling, assessing the required time (i.e., personnel costs) is not sufficient. With missing know-how, quality issues of process models are more likely (Becker et al. 2006; Kusiak et al. 1994; Mendling et al. 2007). Thus, the "value of business process modeling", seen as one of the leading challenges and issues for practitioners in the field of Business Process Management (BPM) by Indulska et al. (2009), could be decreased due to errors during process modeling. Empirical studies of Roy et al. (2014) and Fahland et al. (2011) show that up to 92.9 % of process models are erroneous in business contexts. Besides semantic errors like missing actions, in particular, syntactic errors (e.g., ambiguous gateways) are contained in these process models. Even though such errors do not render the models worthless, they make it very difficult to use them to apply, for instance, approaches for automated verification (Weber et al. 2008) and execution (Khan et al. 2010; Weber 2007) of service-oriented systems. As said, usually few specialists are responsible for process modeling by translating the input of process participants (e.g., staff from specialist departments) into formalized process models. If this translation fails, process modeling projects fail as well (Rosemann 2006).

On the other hand, employees' implicit knowledge is essential when constructing process models (cf. Seethamraju and Marjanovic 2009). Especially, when business processes span across different departments or companies, this is even more relevant as participants tend to have isolated views only on parts of processes within their organizational unit (cf. Gordijn et al. 2000). For instance, we were facing two significant challenges in a large-scale business process reengineering project of a German insurance in which the authors were involved: the retrieval of complete and correct information of how processes are executed in reality and a precise definition of conditions that regulate, when and by whom parts of processes may be executed. Hence, it is promising to deeply involve employees with strong explicit knowledge of how parts of processes are executed in process modeling projects (Rosemann 2006).

Thus, enabling process participants (novices regarding process modeling) to construct process models and allowing them to construct process models (cf. Scholtz et al. 2013) on their own is promising. It seems favorable to enable employees capturing their specific work tasks from an insider's perspective (Fleischmann et al. 2013) instead of specialists constructing process models with an outsider's perspective. Guidance for constructing formalized, imperative process models, using algorithms, especially for novices (Recker et al. 2012), may help to achieve this objective. The research strand of Automated Planning of Process Models (we refer to *Automated Planning* in the following) envisions to construct process models (semi-)automatically (Heinrich et al. 2012, 2015; Henneberger et al. 2008). A combination of semantic annotations, as envisioned in Semantic Business Process Management (Becker et al. 2015; Betz et al. 2006; Brockmans et al. 2006; Hepp et al. 2005; Hepp and Dumitri 2007; Thomas and Fellmann 2009), and existing planning techniques (Bertoli et al. 2006; Hoffmann and Brafman 2005) is used. Particularly, a planner generates a feasible process model based on a set of semantically annotated actions, an initial state that represents the starting point of a process and goal states representing the desired outcome of the process (see Related Work section). However, it is still to evaluate whether novices are able to specify such information and whether the resulting process models are less erroneous. Even though a higher degree of automation is envisioned, for instance, the efforts required for the (initial) annotation of actions are expected to be higher, compared to common process modeling approaches (cf., e.g., Heinrich et al. 2015; Krause et al. 2013). We, therefore, follow previous works and evaluate the "task performance of users" of Automated Planning, one of the most common evaluation criteria, according to Prat et al. (2015).

Research Objective & Context

We aim at evaluating whether Automated Planning influences the task performance of process modelers. Therefore, we conduct a laboratory experiment. Jedlitschka et al. (2008) propose a structured approach for conducting and reporting empirical research in the field of Information Systems, which strongly influences the structure and contents of this paper. In the next section, we briefly introduce the incorporated Automated Planning approach and outline the differences between common process modeling (particularly using ARIS Express) and Automated Planning. Thereafter, we introduce the plan of our experiment. In the main part of this paper, we describe the results of the experiment, interpret them, and discuss the validity of our findings. We close with limitations and an outlook on further research.

The study consists of one controlled experiment conducted with 70 students, who enrolled in the course "Programming in Practice" (not-mandatory part of the bachelor's in management of Information Systems curricula) at a German university. Students can be considered as novices in process modeling (cf. Recker et al. 2012) but, according to Kitchenham et al. (2002), using students "is not a major issue as long as you are interested in evaluating the use of a technique by novice[s] or nonexpert[s]", the primary goal of this study.

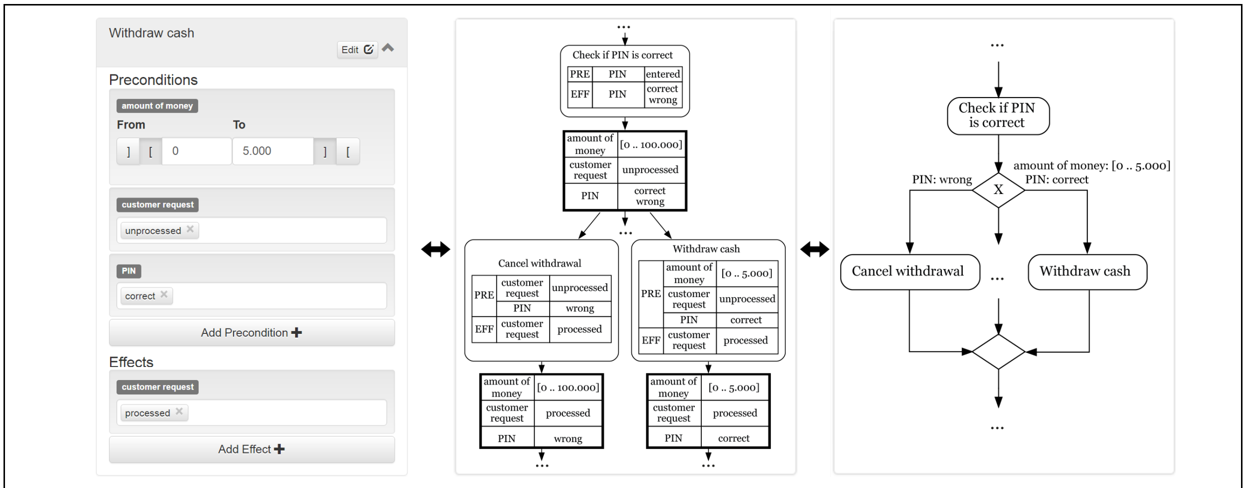

Figure 1. Basic steps of the Automated Planning approach (left: annotated action in web-based tool; center: excerpt of Action State Graph; right: excerpt of process model)

Related Work and Technology under Investigation

Several research fields along the BPM Lifecycle (Scheer and Brabänder 2010; van der Aalst 2013; zur Muehlen and Rosemann 2004) support modelers and business analysts via automatic techniques as "BPM should make opportune use of technology" (vom Brocke et al. 2014). It seems promising to provide guidance in constructing formalized, imperative process models, especially for novices (Recker et al. 2012). Plenty of these existing approaches rely on semantic annotations and integrate semantic technologies in process modeling and analysis (cf., e.g., Fellmann et al. 2015). In the process analysis phase, for instance, process mining, as well as process model verification and validation, assist analysts (e.g., Wetzstein et al. 2007). Automated (web) service selection and composition can be seen as part of the phases process implementation and process execution (Ding et al. 2015; Paik et al. 2014; Wang et al. 2014). In the process modeling phase the research strand of Automated Process Planning envisions the construction of process models by means of algorithms (cf., e.g., Heinrich et al. 2009; Heinrich et al. 2012; Henneberger et al. 2008; Hoffmann et al. 2012; Lautenbacher et al. 2009) and aims at increasing the "flexibility by definition" (van der Aalst 2013) of process models and to reduce the manual efforts when constructing process models (Heinrich et al. 2012, 2015; Henneberger et al. 2008). In the remainder, we describe Automated Planning, the technology under investigation, and present differences between process modeling, using Automated Planning and process modeling using common process modeling tools (i.e., alternative technologies).

Automated Planning constructs imperative process models consisting of actions and control-flow patterns (e.g., exclusive choice and parallelization) based on a formalized input of annotated actions, an initial state and one to many goal states. The annotation of actions consists of preconditions (criteria to conduct the action) and effects (how the action affects the state of the process) which are represented by variables (e.g., "amount of money"; cf. leftmost in Figure 1). Each variable depicts one specific aspect of the represented process. The approach abstracts the construction of (graphical) process models from ordering actions and control-flow patterns to specifying contentual information about the process and the actions the process comprises. This is the (evaluated) manual task, a modeler has to perform when constructing process models using Automated Planning. Based on this input, the annotated actions, an initial state as well as the goal states (sets of variables, too; input of the approach), a *planner* (i.e., a set of algorithms) automatically constructs feasible process models (output of the approach) in three automated phases A1) to A3):

A1) Retrieval of dependencies between actions: When the modeler finishes entering the information as mentioned above, he/she initiates the actual automated planning. First, the planner retrieves dependencies between actions. It analyzes the actions pairwise regarding their preconditions and effects. Thereby, it retrieves whether, for instance, preconditions or effects of an action are missing to construct the desired process model successfully. It further avoids repeated (redundant) analyses in subsequent steps and hence improves the overall performance of the planner. In this step, algorithms identify all actions that possibly "contribute" to reaching the goal state(s) of the desired process model.

A2) Planning feasible sequences of actions: A depth-first forward search determines predecessor-successor-relationships between actions. Starting with the initial state, A2i) actions that are applicable in this state are retrieved (i.e., are preconditions fulfilled?). Then, A2ii) the following state for each applicable action is constructed by applying the preconditions and effects of the action on the preceding state (the initial state in the first iteration). After that, the subphases A2i) and A2ii) are performed recursively in each created following state. The forward search stops if all possible sequences of actions leading from the initial state to the goal state(s) are found and a complete Action State Graph is constructed (cf. center of Figure 1).

A3) Construction of feasible process models with control-flow patterns: To construct feasible process models with control-flow patterns, determining sequences of actions is not sufficient. Therefore the planner constructs well-known control-flow patterns (Russell et al. 2006; Russell et al. 2016; van der Aalst et al. 2003) in the last step (cf., e.g., Heinrich et al. 2009; Heinrich et al. 2015). The approach relies on an abstract representation of process models. Thus, the construction of control-flow patterns is not restricted to a particular process modeling language.

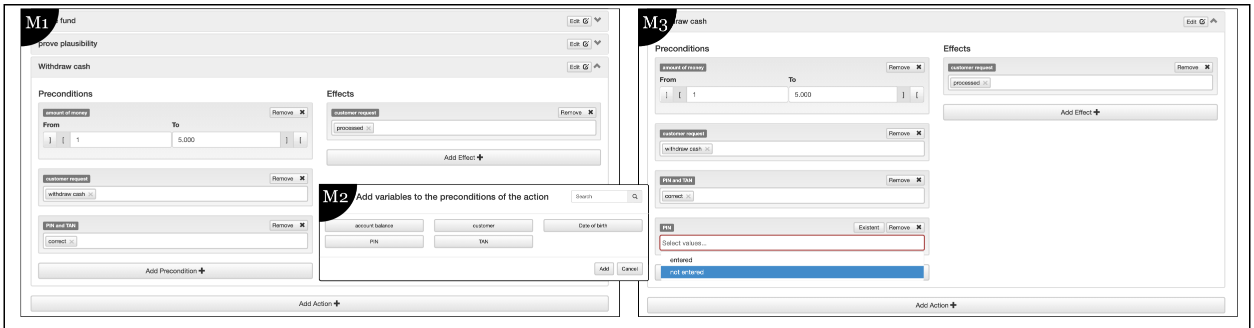

Figure 2. User interface of the Automated Planning tool when adding a precondition

The tool, used for this experiment (i.e., a scientific prototype), is able to generate UML Activity Diagrams (cf. rightmost area of Figure 1; Object Management Group 2015) but could be extended to generate other imperative process modeling languages (e.g., BPMN, eEPC, WS-BPEL). The algorithms are able to construct the most common control-flow patterns (e.g., exclusive choices, simple merges, parallelizations, and synchronizations) currently. It allows to define actions and annotations via a web-based user interface (see http://www-sempa.uni-regensburg.de for a public version of the prototype), Modelers define the preconditions and effects of actions in a formalized manner. This formal specification is the task under investigation. In particular, the tool allows defining one action after the other in a list-oriented way, regardless of the control-flow of the process which is constructed in an automated manner. Modelers define new actions by entering a unique name for the action and specifying its preconditions and effects by selecting variables as well as their possible values from lists. They select one to possibly many variables from a list and choose the according values in a second step. Figure 2 exemplarily illustrates the task of adding preconditions to the action "Withdraw cash" in the web-frontend. To conduct the action, the variable "amount of money" has to be between 1 and 5.000, "customer request" has to be "withdraw cash", "PIN and TAN" has to be "correct". The effect of the action is that "customer request" is set to "processed".

Additionally, the modeler adds the precondition that the variable "PIN" has to be "entered". To do this, in step M1 (see Figure 2), he/she clicks the "Add Precondition" button. After that, the tool presents possible variables (step M2). After choosing the according (here: "PIN"), the tool presents possible values for the variable (step M3) from which the modeler chooses. In addition to the annotated actions, the modeler has to define an initial state (representing the starting point of the process) and one or more goal states (representing the desired outcome of the process) similarly. In order to be able to determine possible sequences of actions manually, modelers using a common process modeling tool need to define (at least implicitly) preconditions and effects of actions as well as initial and goal states, too. However, for enabling the Automated Planning approach (phases A1) to A3)), they have to be formally and explicitly specified.

When constructing process models using a common process modeling tool, process modelers, on the other hand, need to arrange the actions of a process model in the appropriate order. Additionally, they have to construct control-flow patterns where necessary to create formalized process models in a particular process modeling language (e.g., eEPC, BPMN). From a modeler's perspective, common process modeling tools support constructing business process models "sequence-oriented". In particular, a modeler usually starts to define a start node of the process model. Then, the modeling tool presents a set of possible "next" node types (i.e., e.g., actions, control-flow patterns) to the modeler. He/she selects one of these and, in case of selecting an action, the modeler enters its name. After that, the modeling tool again presents a set of possible following node types. Hence, to be able to create an entire, feasible process model, a modeler has to construct an (at least vague) mental model of the entire process. Otherwise, he/she would not be able to incorporate such a "sequence-oriented" modeling approach.

To sum up, we presume the more formal specification of actions taking more time when using Automated Planning. On the other hand, modelers do not have to identify contributing actions as they are identified automatically during phase A1). Thereafter, the Automated Planning approach retrieves the feasible ordering of actions (phase A2)) as well as necessary control-flow patterns (phase A3)) automatically, based on the given set of annotated actions as well as initial and goal states, the modeler provides.

Experiment Planning

In this section, we describe the plan of the experiment that is used to perform it and to analyze the results.

Goals

Precisely, we state the overall experimental goal:

> Analyze an Automated Planning approach for (semi-) automatically constructing process models and a commonly used process modeling tool for the purpose of comparing them with respect to the task performance of process modelers from the point of view of the researcher in the context of a Management Information Systems lecture at a German university.

Performance is commonly defined as obtained outcome divided by invested resources. In the context of process modeling, this could be the quality (in terms of completeness and correctness) of the constructed process models (obtained outcome) divided by the time, needed for the modeling task (invested resources).

This leads us to formulate a different goal for each facet.

Goal G_A: Analyze an Automated Planning approach … and a commonly used process modeling tool for the purpose of comparing them with respect to the obtained outcome of modeling tasks …
Goal G_B: Analyze an Automated Planning approach … and a commonly used process modeling tool for the purpose of comparing them with respect to the required time of modeling tasks …

Overhage et al. (2012) propose the 3QM-Framework to determine the quality of process models systematically. They state that process models – amongst others – shall comply with the syntactical rules as well as semantically comply with the according real-world excerpt (in terms of completeness and correctness). In line with their approach, we divide Goal A into three sub-facets, each of which is covering one particular aspect of the obtained outcome of the modeling tasks:

Goal G_{A1}: … with respect to the syntactic correctness of constructed process models …
Goal G_{A2}: … with respect to the semantic correctness of constructed process models …
Goal G_{A3}: … with respect to the semantic completeness of constructed process models …

Participants

70 bachelor students in the field of Management of Information Systems participated in the experiment. It was part of courses, and the covered topic (i.e., the automated planning approach) was relevant for the exam. The experiment was part of the not mandatory practice lessons allowing the students to exercise for the final exams. Participating in the experiment was voluntary. Informed consent has been obtained by informing the students in advance about the experiment and stating that participation was voluntary. In advance of the actual experiment, coworkers of the authors (research assistants) participated in the pretest. We assigned participants randomly to one group whereas the groups differed in the selection of the process modeling tasks, their order (e.g., first the adaptation of the small process model, then modeling the large process model from scratch) and the tool the group had to use.

Table 1. Key figures of the process models, considered in the experiment

	P1 Mobile contract	*P2* Stationary internet contract	*P3* Cash with-drawal/deposit	*P4* Local electronics tore
Total num. of action / control-flow pattern occurrences	11 / 10	35 / 26	12 / 10	35 / 26
Total num. of variable occurrences	27	126	35	132

Experimental Material and Tasks

To analyze the influence of Automated Planning on the task performance of process modelers, we created textual descriptions of four processes. We aim at simulating real-world modeling projects, where system analysts and domain experts talk about to-be modeled processes in the first step (cf., e.g., Frederiks and van der Weide 2006; Hoppenbrouwers et al. 2005). Hence, we structured the textual descriptions in the form of interview transcripts. The processes are generally admitted, simplified versions of *enrollment of a mobile contract (P1)*, *enrollment of a stationary internet contract (P2)*, *cash withdrawal and deposit (P3)* as well as *shopping in a local electronics store (P4)*. These processes were derived from unstructured interviews with professionals in the according industries and simplified for the purpose of this experiment. We rely on these processes as each participant presumably has at least once experienced them and influences by *domain knowledge* could largely be alleviated. The process models differ in their size, i.e., the total number of action and control-flow pattern as well as variable occurrences. Table 1 summarizes these measures of the four "target process models", considered in our experiment. *P1* and *P2* have to be modeled from scratch. *P3* and *P4* have to be adapted significantly. In *P3*, security checks become obsolete in case of cash deposit and an account balance enquiry should be considered additionally in case of withdrawal. *P4* has to be extended: a customer has to be informed that ordered products are ready for collection and the subprocess of a customer collecting goods needs to be complemented. Further, options to use self-service terminals have to be included.

Hypotheses, Parameters, and Variables

As seen previously, constructing process models differs in several aspects when comparing the Automated Planning of process models and a common process modeling approach. Hence, we expect differences in the task performance of process modelers. We, therefore, chose the independent variable of our research model *Use of Automated Planning*, and the dependent variable *task performance of the process modeler*.

Therefore, we formulate the null hypothesis for our experiment
H_0: The use of Automated Planning does not *influence* the task performance of process modelers.

We divide the participants into two experimental groups concerning the treatment, the *use of Automated Planning*. One group uses the Automated Planning tool (i.e., a scientific prototype), the other uses ARIS Express, a common process modeling tool. To comprehensively investigate the performance of the process modeler, we rely on two facets of the performance. As mentioned in Section *Goals*, we aim at comparing two technologies with respect to the obtained outcomes of a task and the invested time for the task. We rely on the quality of the resulting process models as a measure for the obtained outcomes. In a literature review on quality issues of process models, conducted by Moreno-Montes de Oca et al. (2015), the semantic and syntactic quality belong to the most frequently referred. Becker et al. (2000) describe "syntactic correctness" as the consistency and completeness against the underlying metamodel of the according process model and semantic correctness as the consistency of a model with the real world. Leopold et al. (2016) state that, in about 77% of 585 process models (denoted in BPMN 2.0) data objects that are not linked to an existing glossary are used. Hence, the semantic quality, in particular, the consistency between different models representing the same process (Becker et al. 2000; Zamperoni and Löhr-Richter 1993), is threatened. Hence, we aim at evaluating how far the resulting process models are consistent with a given desired "target process model".

Previous works mathematically prove that the Automated Planning approach constructs correct, minimal and complete process models (cf., e.g., Bertoli et al. 2006; Heinrich et al. 2015). Thus, we especially expect increased syntactic correctness of the resulting process models when using Automated Planning. Though common process modeling tools support modelers to avoid syntactical errors by tooltips and hints, they do not prevent it. Further, Automated Planning enables modelers to specify one action after the other. This is due to the fact that in contrast to when using a common process modeling tool, a modeler does not have to cope with the whole process model at once. He/she has not to cope with dependencies between actions that may have consequences on other parts of a process model. Therefore, we assume that the semantic correctness could potentially be influenced as well. As previously mentioned, Automated Planning (in particular phase A1) of the approach) identifies actions that are necessary and relevant for a process model. Further, in phase A3), the approach identifies where to construct which control-flow pattern. These two capabilities of the approach let us assume that especially the semantic completeness of process models (i.e., all necessary actions and control-flow patterns are contained in the process model) could be increased.

To assess the influence of Automated Planning on the quality of process models, we aim at using objective metrics for assessing the quality of the resulting process models in our research. Overhage et al. (2012) propose the 3QM-Framework – a refinement of the SEQUAL framework, proposed by Lindland et al. (1994) and adapted for process modeling by Krogstie et al. (2006) – that provides specific quality metrics and measurements that allow "to systematically determine the quality of process models". Here, we focus on ❶ the syntactic correctness $corr_{syntactic}$, ❷ the semantic correctness $corr_{semantic}$ and ❸ the semantic completeness $comp_{semantic}$ of the process models. Overhage et al. (2012) propose to use a degree of correctly respectively consistently modeled elements (i.e., belief states, actions, control-flow patterns and edges). We slightly adapt the metrics to the context of our experimental setting and use the metrics, as seen in Table 2. Krogstie et al. (2006) propose several other "levels of quality" such as "pragmatic quality" that refers to the interpretation of process model. As we aim at an objective evaluation, we particularly focus on the semantic and syntactic quality for this experiment. To support the statistical validity of our findings (cf. Shadish et al. 2002), we operationalize the quality of resulting process models by the following first hypotheses:

Table 2. Variables, used in the experiment

Name of the variable	Type of the variable	Class	Entity	Type of attribute	Scale type	Unit	Range	Counting rule
use of Automated Planning (treatment)	independ.	method	used modeling approach	internal	nominal	boolean	"true" resp. "false"	true = technology under investigation is used; false = common process modeling tool is used
syntactic correctness ($corr_{syntactic}$)	dependent	product	resulting process model	internal	ratio	ratio of elements that are modeled syntactically correct	0 to 1	elements are syntactically correct if they are fully compliant to the according specification, to which the process model should comply
semantic correctness ($corr_{semantic}$)	dependent	product	resulting process model	internal	ratio	ratio of elements that are modeled semantically correct	0 to 1	elements are semantically correct, if they represent the desired semantics of the process (e.g., different naming does not lead to semantically incorrect elements)
semantic completeness ($comp_{semantic}$)	dependent	product	resulting process model	internal	ratio	1-(num. of superfluous elements + num. of missing elements) / num. of req. elements	0 to 1	elements are superfluous, if they are not required in the desired process model, but are contained in the resulting process model; elements are missing, if they are not contained but required
required time for modeling task	dependent	process	modeling task	internal	absolute	minutes	1 to infinity	difference between the time, when participant defines a task as "finished" and the time, when the participant started the task
type of the modeling task	moder.	process	modeling task	internal	nominal	n/a	"Modeling from scratch" resp. "Adapting an existing process model"	n/a
size of process model	moder.	product	desired process model	internal	ordinal	n/a	"small" resp. "large"	"small" = less than 50 actions and control-flow patterns; "large" = more or equal than 50

H$_A$: The use of Automated Planning *increases* the…
H$_{A1}$: …syntactic correctness of constructed process models.
H$_{A2}$: …semantic correctness of constructed process models.
H$_{A3}$: …semantic completeness of constructed process models.

Besides this, the invested time to construct the according process model is the second major factor influencing the task performance of a process modeler. According to Hornung et al. (2007), "manual process modeling is a time-consuming task and thus increases the total amount of modeling time." Over two-thirds of 60 banks surveyed complained about a negative effort-utility-ratio of their process modeling projects (cf. Becker et al. 2010b). Krause et al. (2013), as well as Bandara et al. (2006), refer to the "required person days" (resp. "invested person days of effort") as one of the key cost drivers for process redesign projects and process modeling in general. Hence, as the way of constructing process models is essentially different between the compared approaches, it has to be evaluated whether the required time for the overall task changes. When using the Automated Planning approach, modelers need to define the annotation of actions as well as the initial state and goal states of the to be constructed process models.

In particular, he/she has to explicitly formalize this information in contrast to a rather implicit consideration when constructing process models by means of a common process modeling tool. However, algorithms visualize the process model, as well as determine the correct order of actions and control-flow patterns, completely. Thus, we use ❹ the *required time for the modeling task* as a metric for the "invested resources" for process modeling tasks. The required time for the modeling task is derived from log entries (i.e., time between opening and saving the according modeling task) when using the Automated Planning approach. When using ARIS Express, the experimenters recorded the required time manually. We derive the hypothesis, evaluated by means of the following experiment:

H$_B$: The use of Automated Planning *decreases* the required time for the modeling task.

Besides the independent variable (using a common process modeling tool or an Automated Planning approach) and the dependent variables (❶ to ❹), we discuss the moderating variables in the following. We have to differentiate between "moderating factors" and "modeling related factors" affecting the task performance of process modelers (cf. Bandara et al. 2005; Rosemann et al. 2001; Sedera et al. 2002). Here, moderating factors refer to the process model that should be constructed and its characteristics (e.g., size and type of modeling task) and modeling related factors relate to, among others, *personal factors* of the modeler like his/her experience concerning process modeling. We build on this differentiation and consider *process model factors* and *personal factors* as moderating variables in our experiment.

It is proposed to consider established metrics for *process model factors*, such as the *size of process models* (cf. La Rosa et al. 2011b; Mendling et al. 2008). According to Mendling et al. (2008), especially larger (i.e., 40 actions and more) and complex process models contain more errors. We take this into account by the design of the materials as described in the previous section. Further, we consider the *type of the modeling task* (i.e., modeling from scratch or adapting existing process models) as moderating variable. We thereby aim at evaluating whether it influences the task performance (especially $corr_{syntactic}$) if a given process model is present for the according modeling task. If, for instance, unexperienced process modelers should adapt a given process model, they may align their changes to the existing process model. Without a given process model, they have no possibility to follow an already existing way of visualizing a process and hence may construct process models containing more syntactical errors. Regarding *personal factors* of the process modeler (cf. Recker et al. 2012), others differentiate between *modeling expertise* and *domain knowledge* (cf. Hornung et al. 2008; Moreno-Montes de Oca et al. 2015; Recker et al. 2012; Wang and Brooks 2007). Modeling expertise describes how familiar someone is regarding the construction of process models. Domain knowledge refers to the subject area of the according process. The participants have been questioned to self-assess their *modeling expertise*. However, all participants could be considered as novices. We renounced to question the domain knowledge but mitigated the influence of this personal factor by relying on generally admitted processes. Table 2 summarizes all variables used in our experiment.

Experimental Design

We conducted a laboratory experiment to investigate the influence of using an Automated Planning approach on the task performance of process modelers. In detail, we investigate differences in the metrics ❶ to ❹ for the task performance of process modelers between the construction of process models using a common modeling tool as well as an Automated Planning approach. We rely on a 2^k factorial design for our experiment. We aim at evaluating whether the treatment (i.e., using the technology under investigation) influences the task performance of process modelers in different scenarios. Hence, we consider the size of the process models and the type of the modeling task as additional factors. We further use a randomized complete block design as a participant has to solve different tasks in a given, randomized order. The experiment was conducted pursuant to the "Experiment Process" as shown by Wohlin et al. (2012). It was not conducted in an industrial modeling project. It did not focus on a particular modeling language and dealt with the construction of process models – a real problem encountered in BPM projects of every kind.

Procedure

All participants were familiar with the common process modeling tool. However, they had no experience in using Automated Planning and the tool at hand. Hence, we explained the Automated Planning approach and tool to the participants a week prior to the actual experiment and asked them to solve modeling tasks as homework to increase comparability. At the beginning of the experiment, we randomly assign each participant to a numbered desk. When all are seated, we give a brief introduction to the experiment and hand out the *Experimental Material*. After all participants have received the textual process descriptions, they are asked to start constructing the described processes in the given order. Hereby, each participant is assigned to one treatment. Participants at desks with even numbers use a common modeling tool, participants at desks with odd numbers use Automated Planning. The participants do not receive a visualization of the processes that should be modeled from scratch. The process models that should be adapted are prepared in both tools used. When a participant finishes the last task, he/she is asked to leave the room. The experimenters stay in the room for the whole experiment assuring there was no collaboration among the students. After the experiment, the constructed process models were compared to the desired target process models by the experimenters. Thereby, each element of the constructed process models is counted and, based on the counting rules (cf. Table 2), the dependent variables are calculated.

Analysis and Discussion

In this section, we at first present the results of our experiment, discuss them, and highlight implications for research as well as for practice. Thereafter, we discuss possible threats to the validity of our experiment.

Descriptive Statistics and Hypothesis Testing

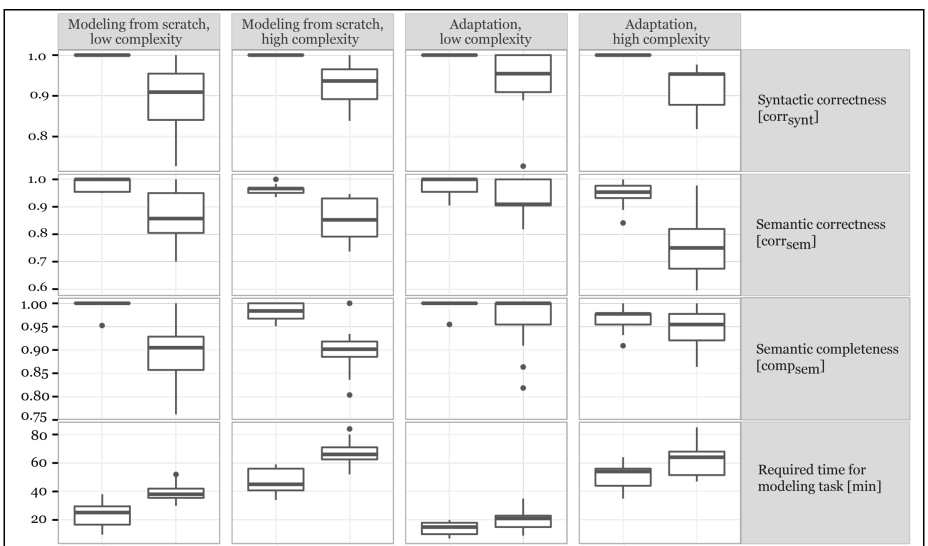

Figure 3. Box plots for all tested hypotheses

135 process models were constructed successfully. Another five modeling tasks had been canceled (i.e., the participants did not declare the tasks "finished" due to running out of time). The 135 valid samples spread across eight different groups based on the *use of Automated Planning* (Automated Planning vs. common

modeling tool), the *process model size* (small vs. larger, cf. Table 1), and the *type of the modeling task* (adaptation vs. modeling from scratch). The number of samples varied between 15 and 19 across the groups. As the dependent variables ❶-❸ are not normally distributed, a series of Wilcoxon rank-sum tests have been conducted, to evaluate the hypothesis H_A. As ❹ the required time for the modeling task follows a normal distribution in each class, we validated the results by means of t-tests. The tests have been executed using R version 3.2.3. In the following, we present the descriptive statistics as well as the results of the accordingly used test for each hypothesis. Figure 3 shows box plots for all tested hypotheses. Table 3 summarizes the descriptive statistics (M: mean; SD: standard deviation) for all hypotheses and the results of the Wilcoxon rank-sum test (W: rank-sum; p: p-value) respectively t-test.

H_{A1}: The use of Automated Planning increases the syntactic correctness of constructed process models. There is a highly significant difference in the syntactic correctness $corr_{synt}$ (cf. ❶) of process models constructed using a common process modeling tool ("com.") and automatically planned process models ("auto.") regardless of their size and the type of the modeling task ("Modeling from scratch" resp. "Adapting an existing process model"). These results suggest that when process modelers use Automated Planning, they construct process models with higher syntactic correctness in all cases. We, therefore, accept H_{A1}.

H_{A2}: The use of Automated Planning increases the semantic correctness of constructed process models. When modeling from scratch, there is a highly significant difference in the semantic correctness $corr_{sem}$ (cf. ❷) of process models between Automated Planning and using a common process modeling tool regardless of the size of the process models. For the adaptation of existing process models, using Automated Planning creates significantly better results for small process models. When comparing the results for larger process models, the differences are highly significant. These findings (cf. Table 3) support that Automated Planning improves the semantic correctness of the resulting process models. Although the semantic correctness of commonly constructed process models is rather high, too, Automated Planning significantly improved it across all cases. Thus, we can accept hypothesis H_{A2}.

H_{A3}: The use of Automated Planning increases the semantic completeness of constructed process models. The Wilcoxon rank-sum tests show that when adapting process models, Automated Planning does not lead

Table 3. The influence of Automated Planning on the task performance of process modelers
Significance codes: 0 '**' 0.001 '***' 0.01 '**' 0.05 '*' 0.1**

	Modeling from scratch				Adapting an existing process model			
	Small process model		Larger process model		Small process model		Larger process model	
***H_{A1}**: The use of Automated Planning increases the syntactic correctness of constructed process models.*								
Descriptive statistics [$corr_{synt}$]	com.	auto.	com.	auto.	com.	auto.	com.	auto.
	M=.897 SD=.088	M=1 SD=0	M=.931 SD=.052	M=1 SD=0	M=.947 SD=.069	M=1 SD=0	M=.920 SD=.053	M=1 SD=0
Res. of Wilc. rank-sum tests	W=332.5 p=0.000 ****		W=216.0 p=0.000 ****		W=229.5 p=0.000 ****		W=255.0 p=0.000 ****	
***H_{A2}**: The use of Automated Planning increases the semantic correctness of constructed process models.*								
Descriptive statistics [$corr_{sem}$]	com.	auto.	com.	auto.	com.	auto.	com.	auto.
	M=.866 SD=.089	M=.983 SD=.023	M=.849 SD=.078	M=.964 SD=.016	M=.937 SD=.062	M=.981 SD=.034	M=.755 SD=.104	M=.945 SD=.038
Res. of Wilc. rank-sum tests	W=325.5 p=0.000 ****		W=237.0 p=0.000 ****		W=201.0 p=0.034 **		W=237.5 p=0.000 ****	
***H_{A3}**: The use of Automated Planning increases the semantic completeness of constructed process models.*								
Descriptive statistics [$comp_{sem}$]	com.	auto.	com.	auto.	com.	auto.	com.	auto.
	M=.895 SD=.067	M=.992 SD=.018	M=.899 SD=.045	M=.984 SD=.016	M=.957 SD=.065	M=.989 SD=.020	M=.947 SD=.043	M=.968 SD=.027
Res. of Wilc. rank-sum tests	W=325.0 p=0.000 ****		W=227.0 p=0.000 ****		W=178.0 p=0.169		W=163.0 p=0.177	
***H_B**: The use of Automated Planning decreases the required time for the modeling task.*								
Descriptive statistics [minutes]	com.	auto.	com.	auto.	com.	auto.	com.	auto.
	M=39.0 SD=5.75	M=23.7 SD=8.68	M=67.5 SD=8.21	M=46.6 SD=8.13	M=19.6 SD=6.57	M=14.1 SD=4.2	M=61.8 SD=11.24	M=51.1 SD=8.4
Results of the t-tests	t=-6.387; df=31.3 p=0.000 ****		t=-7.119; df=28.8 p=0.000 ****		t=-2.894; df=27.2 p=0.004 ***		t=-3.013; df=25.7 p=0.003 ***	

to a significantly higher semantic completeness $comp_{sem}$ (cf. ❸; Table 3). However, Automated Planning creates highly significantly better results when constructing process models from scratch. We are able to accept hypothesis H_{A3} in these two groups. As process models in practice tend to be larger than the small and rather easy process models, considered in our research, the results support that Automated Planning allows process modelers to construct process models with higher semantic completeness.

***H_B:* *The use of Automated Planning decreases the required time for the modeling task*.** The analysis of the boxplots (cf. Figure 3) shows that the required time for modeling process models from scratch or adapting them (cf. ❹) is reduced by using Automated Planning. T-tests (cf. Table 3) show that using Automated Planning implies a highly significant difference in the required time to adapt or construct process models from scratch regardless of their size. Hypothesis H_B can, therefore, be accepted.

In summary, the results show a significant difference between constructing process models using a common process modeling tool and constructing process models with Automated Planning for all of our hypotheses and thus, $\mathbf{H_0}$ could be rejected.

Discussion of the Results

The results indicate that the task performance of process modelers (❶-❹) is positively influenced by using Automated Planning. We assume that process modelers may be able to focus on one action after the other in a sequential manner instead of having the control-flow of the complete, resulting process model in mind by using an Automated Planning approach. This assumption is supported by the findings of our research, particularly by the increase of ❷ the semantic correctness and ❸ the semantic completeness of resulting process models. This is of particular interest as especially the automated identification of issues regarding ❷ and ❸ is hard (cf. Soffer et al. 2012). Our findings support the initial assumption as the semantic quality (❷ and ❸) of small process models is at a rather high level, even when constructing process models with a common process modeling tool. Here, the consideration of the structure of the resulting process models is not that complex, so that process modelers are still able to focus on the semantics of the actions. Further, using an Automated Planning approach assures to construct syntactically correct process models (cf. ❶) by design of the incorporated algorithms. The required time for a modeling task ❹ could be significantly decreased by using Automated Planning. According to the findings of Krause et al. (2013) Automated Planning is especially beneficial for large process models and is not proposed to be used for small process models that are not required to be redesigned frequently due to higher initial setup cost. However, with our research, we have shown that not only the quality of the resulting, rather small process models (❶-❸) could be increased but also the required time for constructing the according modeling tasks could be decreased.

The participants are more experienced in using a common process modeling tool (i.e., ARIS Express) than in using Automated Planning as they used common process modeling tools in their prior studies. Thus, the results indicate that Automated Planning is advantageous compared to common process modeling tools.

Implications for Research and Practice

Our research illustrates the importance of research on the topic of how to support process modelers by means of algorithms. The approach at hand is mathematically proven to construct complete, correct, and minimal process models. However, the algorithms rely on a set of annotated actions. These annotations are not explicitly required when using a common process modeling approach. We have shown that using Automated Planning to construct process models from scratch or to adapt already annotated process models is beneficial. However, future work is required that enables annotating common process models as a basis for future adaptations by means of an Automated Planning approach. Some process mining works, for instance, already rely on rather similar formal foundations and are promising for further research. Verbeek et al. (2007) create variables from state spaces obtained through process mining by means of a Petri net synthesis technique based on so-called regions. Kindler et al. (2006) denote actions in terms of their input and output documents and describe states through the actions that were applied.

In practice, the efficiency of process modeling projects is a major issue. Our research shows that Automated Planning of process models has a positive influence on the task performance of process modelers. Hence, for transferring these findings into practical use, tool vendors can make use of our findings and the developed approaches. Further work has to be done to integrate the appropriate functionality in well-known process modeling tools. These features will enable modelers to avoid syntactic errors in process models. They further enable process modelers to construct semantically better process models in equal or less time.

Additionally, our findings indicate that novices are able to construct less erroneous process models in equal or less time. This opens plenty of chances from a managerial perspective. Most obviously, the number of required professional process modelers (and thus personnel costs) could potentially be reduced for business process modeling projects. Enabling novices to construct process models on their own further may lead to decentralized process modeling initiatives that could be conducted by one department or even employee solely, which further leads to an improved end to end performance for such initiatives.

Further, if less dedicated staff is required, the demand for coordination and communication within a process modeling project could potentially be reduced. With less communication between participants in a process modeling project, the chances for misunderstandings that lead to erroneous process models could be reduced as well. Such implicit consequences have, so far, not been part of our evaluation.

Threats to Validity

In this section, we want to discuss how far the results of our experiment support our claim about the influence of Automated Planning on the task performance of process modelers. Shadish et al. (2002) present different types of validity and common threats that we want to discuss regarding our research:

The **statistical conclusion validity** describes whether adequate statistical methods are used. We used Wilcoxon rank-sum tests which do not rely on normally distributed data. For the normally distributed classes, we relied on t-tests. Referring to literature (cf. Bandara et al. 2005, 2006; Mans et al. 2013; Overhage et al. 2012; Rosemann et al. 2001; Sedera et al. 2002), we expect having considered the relevant variables. However, as we described the Automated Planning approach in detail before the experiment, the way of the description might influence the results of the experiment. Further, the fact that all participants were aware of the other experimental group might be a confounding factor.

Internal validity refers to the question whether the difference in the task performance of process modelers is a consequence of using an Automated Planning approach or not. Here, the experiment was conducted once in one moment and place. Thus, threats caused by variance in implementation or selection of participants can be excluded. However, participants had to model two process models consecutively, which could cause learning or exhaustion effects. Thus, we randomized the order of the modeling tasks across the participants. Consequently, we could mitigate learning, maturation, exhaustion, and instrumentation effects. The modeling expertise of the participants was checked in the questionnaire.

Construct validity refers to the question, in how far our instruments reflect the constructs of the task performance of process modelers, personal factors, and process model factors correctly. We followed existing works and their proposals for using the quality of process models as "obtained outcomes" and required time for the modeling task as "invested resources" as factors for the task performance of process modelers (Bandara et al. 2006; Mans et al. 2013). However, due to the vague definition of "task performance of process modelers", the construct validity can hardly be assessed objectively. Nonetheless, to mitigate the most obvious pitfalls, our instrumentation referred to multiple methods of assessing constructs that were pretested and used by other authors before (cf., e.g., Mendling et al. 2012b).

External validity describes how far the causal relations discussed in this experiment can be generalized over different settings. As discussed before, a wide range of factors (e.g., modeling purpose, modeling language) can influence the task performance of process modelers. However, they are not part of our experimental setup. We intentionally chose the form of a laboratory experiment to analyze the effect of using Automated Planning in isolation. The isolated analysis allows an interpretation whether our results are caused by the treatment or result from an incidental combination of other factors (see internal validity). However, this isolated analysis limits the generalizability of our results. Obviously, it takes further research in the field to analyze how strong the influence of Automated Planning is in more general settings.

Summary, Limitations, and Outlook

To the best of our knowledge, our study is the first, evaluating the influence of Automated Planning on the task performance of process modelers by empirical analysis. After introducing the theoretical foundation and our experimental design, we evaluate the influence of Automated Planning on the task performance of process modelers in terms of the required modeling time as well as the semantic and syntactic correctness and the semantic completeness of the resulting process models. The results show that Automated Planning significantly influences the task performance of modelers. However, our work has several limitations, which we discuss in the following and address in future work.

First to mention, the use of students in a class setting. Students can be considered as novices in process modeling (cf. Recker et al. 2012), a target group where especially the correctness and completeness of process models is a well-known issue, which makes them eligible candidates for our experiment. The students in our experiment represent a rather homogenous group, whereas, among practitioners, there might be more variability, especially concerning "modeling expertise". Hence, the results might be different when considering experienced practitioners. In order to evaluate this, additional research is required. Further, we did not verify the self-assessed personal factor "modeling expertise" during the experiment. This could potentially be achieved by taking the quality of the preliminary homework into consideration as an indicator for their modeling expertise in a next experiment. However, our aim was to provide a first indication in how far Automated Planning influences process modelers and hence, this possibly confounding aspect should be evaluated in more detail in further research as well.

Second, comparing two specific approaches, namely one particular Automated Planning approach and one particular common process modeling tool threatens the generalizability of our findings. As the participants have been using ARIS Express in prior classes, we rely on it as a common process modeling tool. We expect a lower task performance when using a so far unknown tool. Hence, the results of our experiment serve as a lower bound, and we expect the differences between two unknown modeling tools to be even greater. In this context, the experiment should be repeated with different common process modeling tools like, for instance, Signavio or Camunda Modeler[1] as well as different Automated Planning tools. Additionally, common process modeling tools have been improved over time, whereas the Automated Planning tool is a scientific prototype. Thus, revising and improving its user interface may improve the results. This should be addressed by further research on the usability of the Automated Planning tool at hand.

Third, we relied on four particular processes, partly of moderate size and complexity, though well known for the participants. However, according to Mendling et al. (2008), especially larger (they refer to 40 actions and more) and more complex process models likely contain more errors. Thus, our findings should also be verified for larger processes, which is part of future research. Additionally, we rely on two processes for each of the two cases of constructing process models from scratch and adapting them. In both cases, the processes differ considerably regarding their size and complexity. Thus, it is likely that the participants of the experiment assess the complexity of the processes as considerably different as well. Hence, in a second experiment, additional processes of medium size and complexity should be taken into account as well.

Additionally, with the research of Krause et al. (2013) in mind, assessing the economic value of Automated Planning is still an open topic. With our research, we provided a first basis for further research, as we addressed some well-known factors that affect the economic value of business process management projects (i.e., the required time for modeling tasks, influencing the costs, and the syntactic and semantic quality of resulting process models, influencing the value contribution of process modeling). However, based on the research of Krause et al. (2013) and our research, further work is necessary in order to gain detailed insights into the business value of Automated Planning. For instance, one could possibly find lower thresholds for the estimated size and complexity of process models to assess the economic reasonability of Automated Planning for a modeling task at hand. Lastly, other levels of quality should be evaluated as well. In our research, we focused on the semantic and the syntactic quality of process models. However, it is still to evaluate, whether, for instance, the pragmatic quality (Krogstie et al. 2006) could be increased as well.

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