Examining Learner Control in a Structured Inquiry Cycle Using Process Mining

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Abstract. High potential variation in prior knowledge, metacognitive skills, and motivation within learner populations can prompt design strategies that combine explicit structuring and scaffolding with increased learner control. We examine the use of such a strategy—a structured inquiry cycle—in a corpus of online modules (50) for adult informal learners using process mining. We apply process analysis techniques previously demonstrated by others to formative assessment data from the modules. We then use process modeling for mining module deliveries (N=5617) to investigate learner control within the inquiry cycle as a whole. Our experience suggests roles for these techniques beyond assessing conformity, both for design reflection and in preparation for deeper inquiry on self-regulation.

1 Introduction

Informal learning situations often exhibit high variability within the learner population, especially when learning experiences and environments offer broad availability, such as learning through the web. Varying school, work, and life experiences lead to differences in prior knowledge, learning skills, and learning styles among such learners. Disparate intrinsic and extrinsic motivations affect their engagement. Such variation presents interesting challenges for creating designs that are responsive to learners as individuals.

For over a decade, we have pursued design strategies that emphasize adaptive agency within computer-based environments for increasing responsiveness to individual learners. We have created and used a model-based design technology and adaptive learning platform [5] expressly for this purpose. But in designing a large corpus of online resources for adult informal learners (50 modules, each representing 4-8 contact hours) we chose to emphasize learner control as a primary strategy for individualization. Given research on learner control showing the positive *and* negative effects it can have on learning [8, 9, 14], we sought to strike a balance between the freedom of navigation afforded in cyberlearning environments and the need to scaffold learner experiences, particularly when prior domain knowledge or learning skills are weak.

This tension between self-direction and unambiguous instructional guidance is alleviated in environments where freedom of movement and explicit structuring can coexist within the same resource, such as in cyberlearning environments. To support learners who might otherwise make poor sequence or content choices within the environment, we present a well-formed structure—an inquiry cycle—in which to situate available learning activities.[11] Preserving navigational freedom, learners can follow a canonical path through the cycle and thus reduce cognitive load, or define their own unique pathway, exercising more control to create a more personalized learning experience. While the use of such a "loose-tight" design strategy is informed by prior work, it presents many new issues warranting analysis and reflection.

Earlier analyses of observational data from modules designed in this way [7] suggested value in putting observations of learner behavior into a process context. Two process mining directions were pursued: a process discovery approach using hidden Markov models [8] and a process analysis approach that we address here. In [12], the authors described process analysis techniques and applied them to online assessment data. Inspired by their work, we began by replicating the application of these techniques to similar formative assessment data from our modules. We then enlarged the scope of this application to examine issues of learner control within the modules as a whole.

We begin the paper with a description of the learning cycle employed by the modules and its influences from prior work. In Section 3, we describe the formative assessment aspects of the modules and present a process analysis of associated data. Section 4 presents and discusses the use of process mining to investigate issues of learner control for the modules overall. We conclude by briefly reflecting on our experience and highlighting directions for future work.

2 Anchored Inquiry and STAR Legacy

The inquiry cycle used as an instructional design pattern for the modules is an instance of the Software Technology for Assessment and Reflection (STAR) Legacy Cycle [13] that was developed in the course of work by the Cognition and Technology Group at Vanderbilt (CTGV) on anchored instruction [1] and situated cognition. STAR Legacy organizes a student's inquiry of a posed challenge around a set of activities. Among its central ideas is providing a structure that is both well-formed, including kinds of activities known to be beneficial to learner inquiry, and explicit, so that learners know where they are in the cycle, the intention of its activities, and therefore what it means to select and use them. STAR Legacy has been employed in many different educational settings, including a large corpus of classroom and blended instruction for undergraduate bioengineering education [2] and online continuing education for teachers [3].

Figure 1: STAR Legacy Inquiry Cycle

STAR Legacy arose from interest in "flexibly adaptive" instructional designs that are informed by research on effective learning experiences and easily tailored by educators to characteristics of particular learning situations. The original learning cycle consisted of six activities: The Challenge, Generate Ideas, Multiple Perspectives, Research and Revise, Test Your Mettle and Go Public.[13] In applying it to informal, asynchronous learning, the role of the original Multiple Perspectives activity was subsumed by Initial Thoughts, which guides the student's initial exploration of the challenge in ways echoing

Multiple Perspectives. Also, the original Go Public activity, used to scaffold synthesis, was replaced by a Wrap Up activity, where learners reflect on their initial thoughts in the presence of expert views and are provided an opportunity to apply what they've learned to a related situation. These adaptations reflect serious compromises, yet they allowed us to introduce extensive leaner control while preserving essential qualities of an explicit learning cycle and inquiry scaffolding afforded by its activities.

3 Formative Assessments

The *Assessment* activity in our adaptation of STAR Legacy provides a collection of questions that allow learners to confirm their understanding of learning materials presented in the cycle's *Resources* activity. Learners select questions from a menu organized around categories based on the module's terminal learning objectives. Each question's text is presented in the menu to facilitate selection. Questions can be used whenever, and as often as, learners choose.

The self-assessment questions support multiple attempts with feedback as shown in Figure 2. The feedback after an initial incorrect attempt (L1F) concerns clarifying the question by restatement. Following a second incorrect attempt, criticism of the learner's response is offered (L2F). This feedback takes the general form: "If X was true, as your answer indicates, then Y", where Y is some negative consequence. After the third and subsequent attempts, critiquing feedback is combined with a link back to related learning materials provided in the *Resources* activity (L3F).

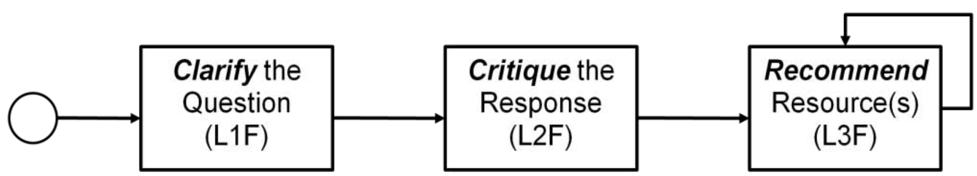

Figure 2: Feedback Progression in Module Self-Assessments

When a question is accessed, the feedback-giving process continues until either (1) the learner provides the correct response, at which time she is automatically returned to the question menu, or (2) the learner abandons the question, either by interface-supported navigation to another cycle activity or by selecting a resource link offered in the L3F. Successive accesses of a question restart the feedback process. On returning to the menu, an indication of success (or abandonment) for the most recent access is presented next to the question. The menu thus provides learners an "at a glance" view of their use of questions in the activity and the results.

3.1 Process Modeling

We began our process analysis of formative assessment data by constructing a Petri Net model of a question access, shown in Figure 3 below, which commences when a learner selects a question from the question menu. This model details the feedback process described above for consecutive attempts made during the access. Places in the Petri Net represent presentations of the question. Outbound transitions represent learner actions.

The CR and WR transitions represent the learner providing the correct or wrong response, respectively. WR transitions are labeled with the level of feedback incorporated into the subsequent question presentation. Two forms of question abandonment are modeled. The first (AR) occurs when the learner backtracks to a learning resource in the *Resources* activity immediately following question abandonment. The second (unlabelled) represents abandonment through other navigation supported by the interface without resource backtracking, such as continuing to a different question or transitioning to another activity.

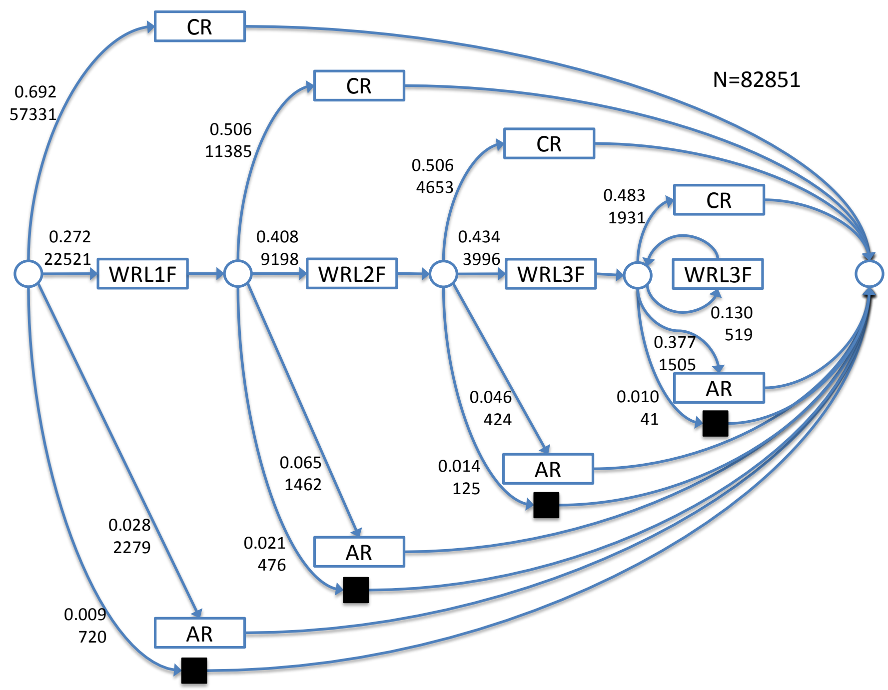

Figure 3: Petri Net Model of Accessing a Self-Assessment Question

The addition of the AR transitions represents modeling not solely for the purposes of fidelity, but also to address particular analysis interests. In this case, we wanted to examine prompted versus discretionary resource backtracking during a question access. The feedback provided on the third question attempt (L3F) and beyond includes remedial resource recommendations, so abandonment in this setting is prompted. In all earlier contexts, abandonment with resource backtracking is an unprompted discretionary move.

3.2 Discussion

The mining results, overlaid on the process model in Figure 3 above, detail 82,851 question accesses. 87% (72218) of these were first time accesses and the correct response was given 93% of the time over the sequence of attempts. Nearly 70% of the correct responses were given on the first attempt. The remaining question accesses were a combination of repetition following prior success (5%), suggesting review, and repetition following prior abandonment (8%).

One subject of our analysis was efficacy of the remediation scheme. The provided questions include a combination of multiple choice (MC) and fill-in-the-blank (FIB) types, skewed heavily towards the former for ease in constructing the critiquing (L2F) feedback. While the capability exists to provide response-specific FIB feedback, planned data mining and feedback preparation exceeded project constraints, so only non-specific feedback is given. Also different between the two question types is the falsification of alternatives that naturally occurs with MC questions over a series of attempts. We were interested in how these differences affected learner response to feedback.

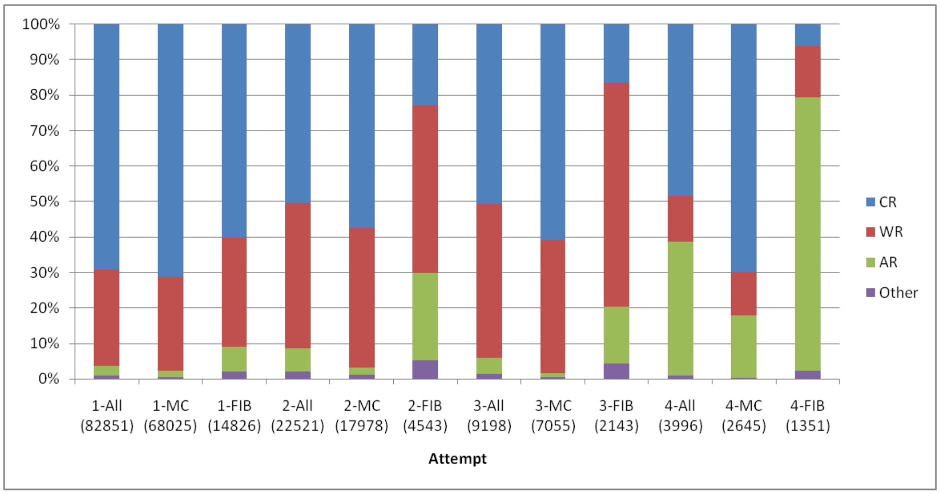

Figure 4: Question Accesses By Attempt Detailing Question Types

Figure 4 above provides a summary of results by attempt, both collectively and for each question type, which varied significantly. We will therefore present our discussion of the results by question type.

Overall, 95% of MC questions were correctly answered over the series of attempts. For 2nd MC attempts, with one choice falsified and the initial feedback, only 58% of learners provided the correct response, suggesting low efficacy for the question clarification feedback. With two choices falsified and specific criticism of the second response, correct responses on 3rd attempts improved marginally to 61%, a disappointing result for the much more labor-intensive response-specific feedback. On 4th attempts (where most questions provided just four choices) correct responses improved to just 70%. One possible explanation for results on later attempts (3+) is that a lack of penalty for incorrect responses, combined with benefits from specific formative feedback, lead some learners to explore, effectively using the questions as supplemental learning resources.

Only 70% of FIB questions were answered correctly over the sequence of attempts. Performance actually degraded, rather than improved, from 60% correct responses on the initial attempt to 23%, 17%, and 6% on subsequent attempts, respectively. Even the initial performance differed significantly from FIB questions on high-stakes assessments, where it was comparable to MC questions. On the formative assessments, the lack of penalty for attempts likely contributed to guessing or gaming to obtain more feedback, and non-specific feedback provided insufficient prompting.

Another analysis focus was to understand abandonment behavior. Figure 5 (at right) shows resource backtracking and other abandonment for each question type by attempt. Discretionary abandonment (attempts 1 thru 3) was clearly more pronounced for FIB questions, likely owing to weakness in feedback specificity and inability to proceed by falsifying choices, as with MC questions. Resource backtracking following abandonment predominated for both question types. While incidence of unprompted abandonment was low as an overall percentage, when viewed as a percentage of learners not making a correct response, between 1 and 2 in 10 made conscious decisions to remediate rather than (continue to) guess. For 4th attempts, abandonment without resource backtracking was practically non-existent, suggesting that the specific resource recommendations prompting abandonment were largely taken up by learners.

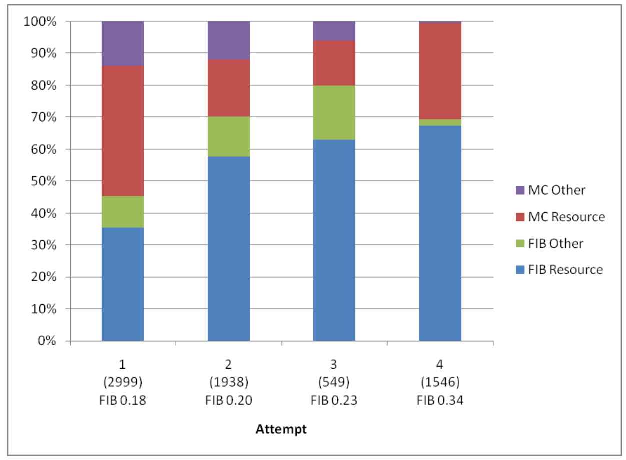

Figure 5: Question Abandonment By Attempt

An area for future work is to examine the effectiveness of self-remediation when backtracking to resources. An initial look showed that, on 88% of questions where learners backtracked to a resource following abandonment, a correct response was given on the 1st attempt when returning to the question. Comparative question evaluation, as in [10], might also help clarify performance differences between FIB and MC questions on self-assessments and on FIB questions between formative and summative assessments.

4 Examining Learner Control in STAR Legacy Modules

With this initial process mining, we turned our attention to issues of learner control within the modules as a whole. An initial area of interest concerned identifying the extent and nature of control that could be viewed as discretionary, as with unprompted question abandonment discussed earlier, versus ordinary forms of control, such as advancing to the next element in a sequence.

Discretionary navigation controls in the modules typically serve the dual purposes of affording action and informing status, as with the menu for self-assessment questions in the *Assessment* activity described earlier. The controls are not adaptive in the sense of controlling action through presentation, as typically found in adaptive hypermedia. A fixed navigation sidebar interface element continuously informs learners of where they are in the learning cycle and supports arbitrary transitions to any cycle activity at any time. Learners can decide for themselves when and how often to use the activities comprising the cycle. There is thus admitted a wide range of possible behavior. Such affordances for discretionary control are paired with traditional controls for advancing and backtracking, such that learners are not forced to choose direction, as a means of decreasing cognitive load [15].

4.1 Process Modeling

As before, we began by constructing a Petri Net model of navigation pathways within the inquiry cycle, shown in Figure 6 below. Places in the model represent the cycle activities and transitions are learner accesses of an activity. Transitions are labeled by the activity destination: “The Challenge” (C), “Initial Thoughts” (T), “Resources” (R), “Self-Assessment” (A) and “Wrap Up” (W). Unlabelled transitions represent leaving the module. Learners can freely move between a set of modules constituting a course, returning in-place to previously visited modules. Such “suspend-resume” decisions are not modeled here, so the exiting transitions represent final departures.

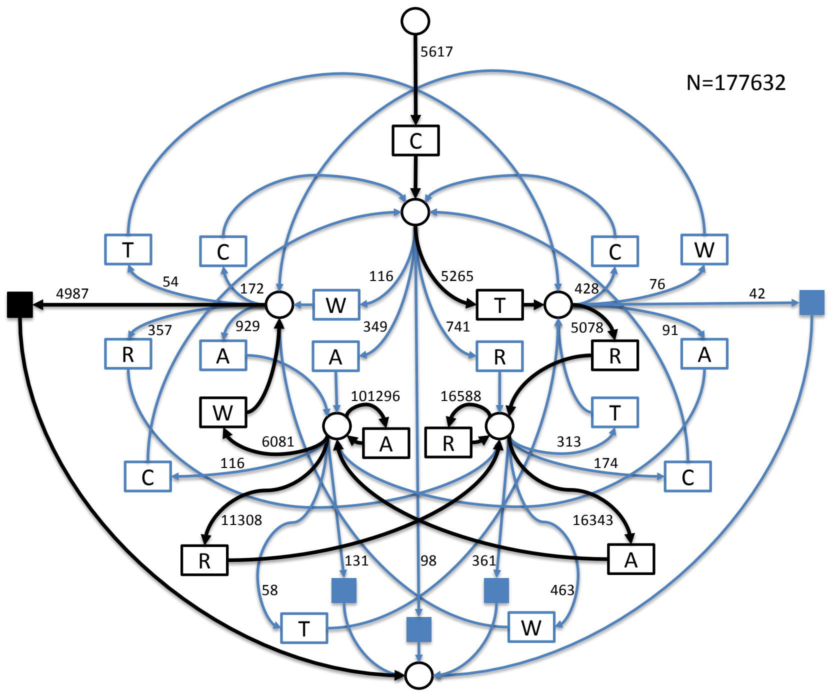

Figure 6: Petri Net Model of Learner Navigation in STAR Legacy

Annotating the transitions in this model with incidence data (177,632 observations from 5,617 individual module deliveries) showed that every possible navigation behavior was observed. The benefit of this exercise was that it yielded an “at a glance” view of learner control, allowing us to quickly compare relative transition incidences. Yet, to examine discretionary versus sequential control, we needed a more refined model. We began by marking the sequential pathway through STAR Legacy in Figure 6 (darkened edges.) From this we derived another process model, shown in Figure 7 below, to investigate deviation from sequential navigation. As before, places represent cycle activities. From each place is a transition (unlabelled) that represents deviation from the sequential path. For the *Resources* and *Assessment* activities, a cyclic transition was added (dashed edges) to differentiate just entering the activity's menu from use of its contained elements (resources or questions) prior to departure. Another incidental transition was included to identify any occurrence of backtracking by the learner from *Assessment* to *Resources*.

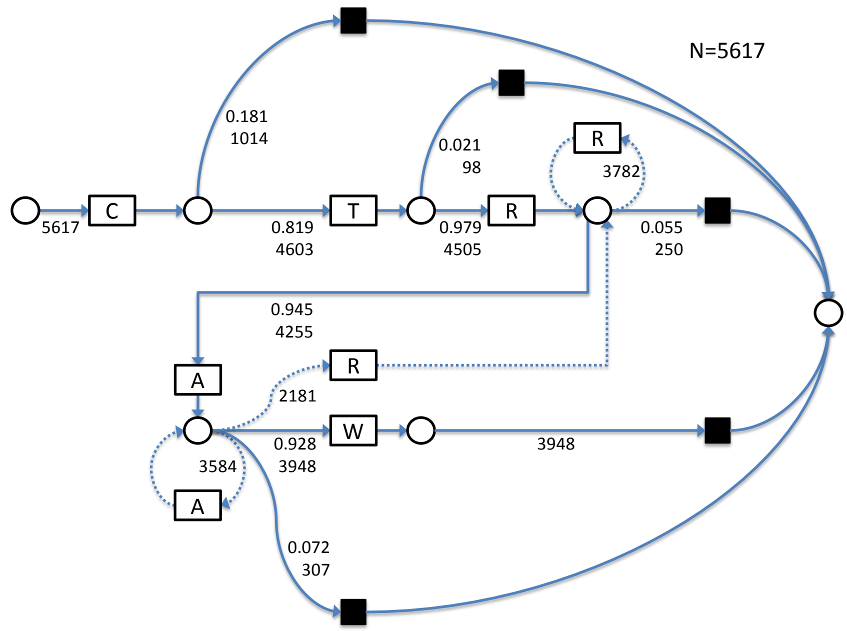

Figure 7: Petri Net Model of Linear Progression in STAR Legacy Cycle

4.2 Discussion

Results from data mining using the process model in Figure 7 are shown in annotations of the process model and summarized in Figure 8 below. The latter indicates cycle activities after which the learner deviated from the sequential process, both overall and for module progressions to examine changes over time. Overall, in 70% of the 5,617 modules examined learners stayed within the sequential pathway throughout the learning cycle. Only 51% of learners reaching the *Assessment* activity sequentially performed any resource backtracking. Curiously, 16% of learners reaching the *Resources* and *Assessment* activities linearly accessed no resource or question within the activity prior to transitioning or backtracking: a subject for future investigation.

The overall extent of sequential navigation agrees in some respects with earlier analyses performed using coded transition data, but process analysis clarified moments of deviation for further reflection. By-passing the *Thoughts* activity (that is, deviation immediately following the Challenge) was the most significant linear process deviation. This activity is intended to help learners consider what will be involved in addressing the challenge to highlight what they may already know and will need to learn in the course of their inquiry. In terms of self-regulation, it relates to the metacognitive task of strategic planning.[16] Typically an instructor-led discussion in classroom uses of STAR Legacy, with obvious social affordances, the online modules present open-ended questions that prompt learners to capture their initial thoughts. In feedback from course evaluations, some learners explicitly noted discomfort with this activity, regarding it as some form of evaluation prior to learning, even given guidance for the activity to the contrary.

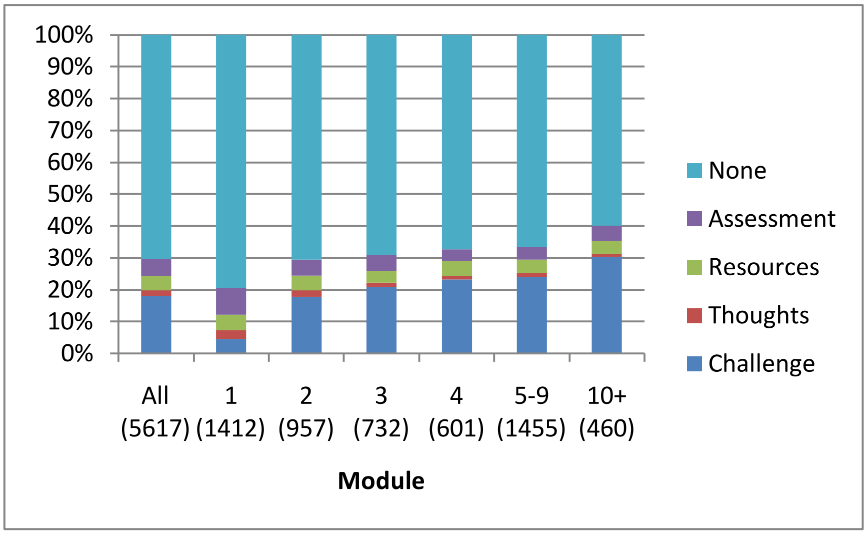

Figure 8: Changes in Deviation from Linear Pathway between Modules

One implication of greater learner control is that it allows avoidance of design elements intended to create ―cognitive dissonance" [4]. As shown in Figure 8, over consecutive modules the avoidance of the *Thoughts* activity increases to the point where it is three quarters of the total deviation, with the most significant increase immediately following the first module. Examination of summative assessment performance showed weak correlation between participation in the *Thoughts* activity and increased learning outcomes. These preliminary findings indicate weakness in our design of the activity that warrants further investigation to inform potential redesign efforts.

5 Conclusions and Future Work

Analysis approaches to process mining use models as *a priori* representations. In the presented analyses of formative assessments and learner control within a structured inquiry cycle, we incorporated elements into process models to disambiguate forms of control or address other control-related interests. These examples demonstrate use of process analysis not just to address conformity, but for other inquiry that involves putting data into ordered contexts. Petri Net process models, being both formal and visual, aided collaborative planning for such analyses and in reviewing results, where unshared, informal understandings can contribute hindrances. As discussed in [12], technology to support mining directly from process models would have been beneficial, and we are tracking progress towards this goal in frameworks such as ProM [14].

Whether using discovery or analysis approaches, the potential to assign meaning to observed behavior using process mining is limited. In an investigation of self-regulated learning, we plan to use more traditional, expensive, and invasive methods for attributing learner behavior in following-up our preliminary analyses. Understanding gained with such methods will be used to enhance the value of passively collected instrumentation as a primary data source. We hope this approach will enable richer accounts of learner behavior in environments for informal learning that afford both structure and freedom in addressing broad and diverse populations.

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