Detecting SMART Model Cognitive Operations in Mathematical Problem-Solving Process

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ABSTRACT

Self-regulated learning (SRL) is a critical component of mathematics problem solving. Students skilled in SRL are more likely to effectively set goals, search for information, and direct their attention and cognitive process so that they align their efforts with their objectives. An influential framework for SRL, the SMART model, proposes that five cognitive operations (i.e., searching, monitoring, assembling, rehearsing, and translating) play a key role in SRL. However, these categories encompass a wide range of behaviors, making measurement challenging – often involving observing individual students and recording their think-aloud activities or asking students to complete labor-intensive tagging activities as they work. In the current study, we develop machine-learned indicators of SMART operations, in order to achieve better scalability than other measurement approaches. We analyzed student's textual responses and interaction data collected from a mathematical learning platform where students are asked to thoroughly explain their solutions and are scaffolded in communicating their problem-solving process to their peers and teachers. We built detectors of four indicators of SMART operations (namely, assembling and translating operations). Our detectors are found to be reliable and generalizable, with AUC ROCs ranging from .76-.89. When applied to the full test set, the detectors are robust against algorithmic bias, performing well across different student populations.

Keywords

self-regulated learning, SMART model, automated detectors

1. INTRODUCTION

Work over the last two decades has developed automated detectors of a range of behaviors and constructs in students' interaction with computer-based learning environments [12]. These detectors utilize log data collected from these learning environments to infer the presence or absence of a complex behavior or a construct in student learning. For example, detectors have been built to identify student affect (e.g., [7, 21, 31]), engagement (e.g.,[6, 37]), and problem-solving strategies [43]. Such detectors can be split into two broad categories: detectors for post-hoc analysis and detectors for real-time adaptation. Post-hoc analysis allows researchers to detect constructs retrospectively and subsequently understand their prevalence (e.g., [32]) and conduct further analysis (e.g., [17, 41]). Detectors designed to be run in real-time facilitate adaptive experiences and real-time feedback [48], as well as reports to teachers[1].

In particular, considerable work has been devoted to detecting and understanding behaviors and strategies involved in self-regulated learning (SRL). By examining student behavior patterns, automated detectors have been developed for a range of SRL related constructs, including help avoidance [3], gaming the system [7], setting goals [5, 14], and planning and tracking progress [14]. However, the specific constructs being modeled often have not been clearly linked to any of the growing number of theoretical models of SRL (although [29] is an exception to this) and have mostly been operationalized in terms of high-level strategies that combine several of behaviors treated as separate in SRL theories, rather than the finer-grained behaviors used in those theories [cf. 46, 48]. Capturing fine-grained indicators of key aspects of SRL in terms of these theoretical models may yield a better understanding of the process of SRL and help EDM research make more direct theoretical contributions.

Self-regulation is a critical component of learning, and has been positively associated with learning outcomes [20, 34, 57]. In mathematics problem-solving, students who are skilled in SRL are able to effectively set goals, search for information, and direct their attention and cognitive resources to align their efforts with their objectives [56]. As a result, SRL facilitates the successful problem-solving process [20, 34, 57] and enables students to acquire a deep and conceptual understanding of the embedded knowledge [31]. Given its benefits, theory-based interventions have been developed to promote SRL [21]. However, current SRL assessments, such as self-reports and think-aloud activities, are not sufficient to provide measurement at scale; at the same time, existing scalable SRL assessments based on automated detection in log data are typically not connected back to theory, making it difficult to use them in theory-driven interventions. SRL assessments based on automated detectors have therefore been used in more ad-hoc, system-specific interventions, often with unintended consequences or unexpected patterns of findings [2, 35]

In the current study, we develop automated detectors that identify fine-grained evidence of SRL constructs drawn from theory. This study does so in the context of CueThink, a digital learning application that focuses on enhancing middle school student mathematics problem-solving skills. Through the lens of the SMART model of SRL (described in greater detail below) [53], we identify and operationalize five SRL indicators: numerical representation, contextual representation, strategy orientation, outcome orientation, and data transformation. We then build automated

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detectors for each indicator, evaluate their performance, and check them for algorithmic bias.

2. BACKGROUND

2.1 SRL and the SMART Model

Grounded in information processing theory, Winne and Hadwin [55] characterize the process of SRL as four interdependent and recursive stages, in which learners: 1) define the task, 2) set goals and form plans, 3) enact the plans, and 4) reflect and adapt strategies when goals are not met.

The SMART model of SRL [53] was later proposed to further elucidate the processes involved in these four tasks. Specifically, the model separates the "cognitive and behavioral actions applied to perform the task" into five categories: *searching*, *monitoring*, *assembling*, *rehearsing*, and *translating*. Each operation describes a way that learners cognitively engage and interact with information. For example, when working on a task, learners direct their attention to particular information (searching) and compare the information with a standard (monitoring), evaluating the relevance or the importance of the information. When relevant information is identified, students relate pieces of information to one another (assembling), in order to create a comprehensive understanding of the problem. When information does not fit into the current problem representation, learners manipulate the ways information is presented in order to find a solution (translating). Throughout the process, working memory is used to actively maintain and reinstate information (rehearsing).

These cognitive operations are an integral aspect of self-regulation: they help determine student success at completing each of the four SRL tasks, which, in turn, influences the progression of the problem-solving process [52]. However, despite the SMART categories' importance for SRL, they are often difficult to observe or measure, as most learning activities (whether online or offline) do not fully reify the cognitive process involved in their learning tasks. Further, these operations may occur non-linearly, and multiple operations can be employed when completing the same task– making the measurement of these constructs challenging.

2.2 Challenges in SRL Measurements

SRL has typically been measured using three common approaches: self-reports, think-aloud activities, and log data collected in computer-based learning environments [51]. With traditional self-report studies, students are asked about their SRL process either outside of a task (i.e., before or after completing a task) or while working on a task. In decontextualized self-report (outside of a task), students report on the SRL strategies they plan to use or recall on the strategies they used, using a pre- or post-task survey. Even though this approach is widely used, the nature of surveying cognitive processes outside of the task may lead to inaccuracies in the representation of cognition [51]. For example, when recalling a cognitive process retrospectively, students may aggregate the out-of-context, self-reported experience across numerous tasks, failing to demonstrate the relationship between the task and the corresponding SRL strategies. For this reason, several studies have adopted in-context self-report (e.g., [42, 47, 54]), in which students are asked to tag their SRL strategies as they occur.

Other research has leveraged think-aloud activities that ask students to verbalize their cognitive processes when solving a problem [28]. As with in-context self-reports, think-alouds give researchers an opportunity to identify processes that are contextualized in the problem-solving activity and are approximately concurrent with their occurrences. However, this process can suffer from an observation effect. Students being prompted to discuss their thinking process in real-time may alter that process and not provide an accurate representation of the processes they would engage in naturally [16, 44]. This, in turn, calls into question the validity of findings obtained using this type of measurement and whether they are generalizable to new students and contexts.

2.3 Use Log Data to Measure SRL in Computer-Based Learning Environments

Both self-report and think-aloud approaches are labor-intensive and time-consuming, which make them difficult to scale. As such, a third approach, analyzing log data collected from computer-based learning environments, has emerged as a promising way to measure SRL.

Aleven and colleagues [3] designed an exhaustive set of production rules to represent help-seeking behaviors within a geometry learning system, and then compared these rules to student problem-solving steps to determine whether those steps were warranted by the current situation. Similarly, Biswas et al. [14] used sequences of student behaviors to model a range of SRL behaviors, such as monitoring through explanation, self-assessment, tracking progress, and setting learning goals. Additionally, Segedy et al. [45] utilized log data and coherence analysis to assess students' ability to seek out, interpret, and apply information in an open-ended learning environment, examining if a student's subsequent action is coherent based on the information presented.

Researchers have also used textual responses within dialogue-based learning systems to measure SRL. Graesser and colleagues [27] used latent semantic analysis to study student conversations with animated pedagogical agents to assess and support SRL. Students who frequently use questions in a conversation can be interpreted as showing initiative, and engagement in monitoring can be inferred when students demonstrate in their responses that they feel they know the answer [26].

However, often the log data collected does not straightforwardly reflect a SRL construct [4]. Researchers must decide what data to use, what constructs to measure, and how to operationalize the constructs with the existing data [30]. SRL, as a process, covers a range of behaviors and strategies, so the constructs can vary depending on how SRL is conceptualized and also based on the design of the activity the learner is participating in. To ensure the validity of the operationalization, it is recommended that the operationalization should be conceptualized in terms of a SRL model and contextualized in the learning environment where the data is generated [51].

2.4 Algorithmic Bias

In order to use detectors at scale, we must ensure that they will be valid for the entire populations they are scaled to rather than only subgroups of students. Recent evidence suggests that many published detectors are prone to algorithmic bias, functioning better for some populations of learners than others [11]. However, there has been limited attention to algorithmic bias within the field of educational data mining, where analyses of algorithmic bias are rare and even overall population demographics are only reported in 15% of publications [38]. Verifying detector fairness is particularly pertinent to our study given the diverse student population who use CueThink, making it important to evaluate detector effectiveness across demographic groups before deploying and using the detectors at scale.

2.5 Current Study

In the current study, we address the challenges noted above by building automated detectors of SRL constructs from a theory-driven lens. Using a dataset of 79 students as they interacted with the online math learning platform CueThink, we first examine the learning environment understanding how students interact with the platform and the context of where the log data is generated. Based on the context and the log data available, we identify relevant theoretical constructs grounded in the SMART model. In particular, five SRL indicators relating to cognitive operations in the SMART model (in this case, all either *assembling* or *translating*) are identified for investigation.

We use text replay to code student interactions for each defined indicator. These labels are then used as ground truth for machine learning. We distill a variety of features from the log data to represent multiple aspects of a student's interaction, including the number of responses and the content in the responses. The ground truth and the features are then input into a machine learning process, training a model to emulate human coders' judgement, making predictions on the presence or absence of a SRL indicator.

We demonstrate that trained detectors provide accurate detection, suitable for real-time use. Finally, we also evaluate, through slicing analysis, the performance of our models across different demographic groups.

3. METHODS

3.1 Learning Environment

CueThink is a digital learning application that focuses on enhancing middle school student math problem-solving skills, by encouraging students to engage in self-regulated learning and to develop math language to communicate problem-solving processes. CueThink asks students both to solve a math problem and to create a shareable screen-cast video that provides the student's answer and also demonstrates their problem-solving process. As Figure 1 shows, CueThink structures a problem into a *Thinklet*, a process that includes four phases—*Understand, Plan, Solve,* and *Review*—that closely align with Winne & Hadwin's model of SRL [55].

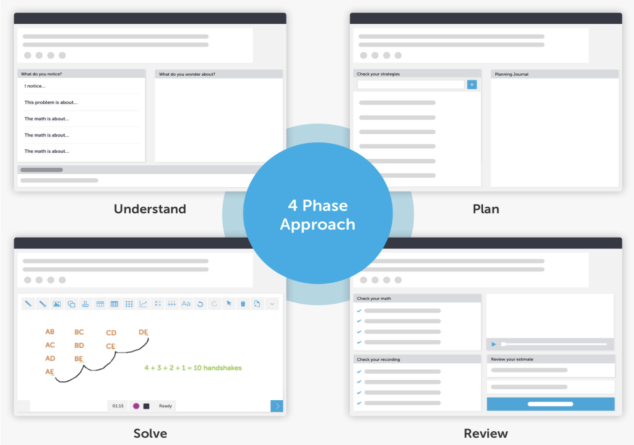


Figure 1. Screenshots of CueThink's 4 Phase Approach

Each phase of the *Thinklet* (outlined in Table 1 and described in more detail below), asks students to focus on a different part of the problem-solving process. While working on a *Thinklet*, students can move freely across the four phases, including going back to a previous phase or skipping phases.

Starting with the *Understand phase*, students read a problem and provide text-based responses to three questions: (1) "What do you notice?" (2) "What do you wonder?" and (3) "What is your estimated answer to the problem?" This phase encourages students to actively look for information in the problem and create a representation of the problem space. Thus, students demonstrate their understanding of what they know and what they need to know at this phase.

In the *Plan* phase, students build on what they have established in the *Understand* phase by planning how they will solve the problem. Students are first prompted to select what strategies they will use to solve the problem. They may choose from a predefined strategy list (i.e., draw a picture, model with an equation, work backwards, etc.) or define their own strategies. Once the student has selected which strategies they will use, the student is prompted to write a plan on how they will use the strategies to solve the problem.

In the *Solve* phase, students explain and present their answer. Specifically, they create a screen cast video using an interface that provides them with a whiteboard and mathematical tools (i.e., number lines, ruler, etc.).

In the *Review* phase, students provide the final answer to the math problem, but also reflect on whether the answer makes sense and whether their communication is clear, using checklists to scaffold their reflection.

Once students have completed the problem, they share their screencast explanation for *Peer Review*. In this phase, teachers and peers annotate both the textual responses and video, often asking the student for their underlying reasoning or why the student picked specific methods. These annotations are then sent back to the video's author for possible revision.

Table 1. Summary of Responses by *Thinklet* Phase

Phase	Tasks Description & Data Types
Understand	What I notice is (*textual response*) What I wonder is (*textual response*) Estimate your answer (*textual response*)
Plan	Choose your strategies (*select all that apply, textual response*) Planning journal (*textual response*)
Solve*	Video creation tools (*Whiteboard, math tools, and recording tools)*
Review	Check your math (*select all that apply*) Check your recoding (*select all that apply*) Review your estimate (*textual response*) Final answer (*textual response*)

* Student activity in the *Solve* phase is not used in this paper's analyses

3.2 Student Demographics

In this study, 79 students in grade 6 and 7 at a suburban school in the southwestern U.S. used CueThink during the 2020-21 school year. The school contains a diverse student population with around 40% Hispanic or Latino, 40% White, 15% African American, and 5% Asian students. Students' self-reported demographic information on gender and race/ethnicity was collected. For gender, students could choose to identify as male, female, non-binary, or leave the question blank. For race/ethnicity, options included African America, Hispanic/Latinx, White, Asian, Native American, two or more races, other, or prefer not to say. Students reporting "other" for their race/ethnicity were provided the option to give detail.

3.3 Log Data

CueThink was used in six classrooms over multiple weeks, with teachers assigning problems for students to complete in the application. We collected log files that reflect how students use the application and their problem-solving process. On average, students spent 5.2 hours in CueThink and 1.8 hours working on each *Thinklet*. Specifically, for each problem, encapsulated in a *Thinklet*, data generated during the problem-solving process that includes the questions students answered and their textual responses at each phase were collected. In this study, we analyzed textual and clickstream data, but did not analyze data from the videos. In total, we collected 349 *Thinklets* from 79 students working on 24 different problems. Of those 349 *Thinklets*, not all were first attempts. Students have the opportunity to revise their work, which creates another *Thinklet*. In those cases, it is possible that students do not go through the entire problem-solving process. Of the total number of *Thinklets*, 146 were duplicate attempts.

4. BUILDING DETECTORS

Building automated detectors of self-regulated behaviors was a multi-step process (detailed in the following subsections). First, we distilled human-readable text replays from log data. Using these text replays, we identified and operationalized qualitative categories that corresponded with SRL constructs, grounding the operationalization in Winne's SMART model. We then labeled the self-regulated behaviors, generating ground truth data. Feature engineering and feature distillation were conducted and used to train the predictive models. Lastly, we evaluated model performance and checked for algorithmic bias.

4.1 Text Replays of Interaction Logs

To facilitate inspection and exploration of the data, we used text replays. This method presents segments of interaction data (referred to as clips) in a human-readable presentation. This process facilitates both initial exploration of the data (such as in section 4.2) along with the final coding process (section 4.3). Clips are then viewed by human coders who label them accordingly [8]. Previous studies have used text replay coding to label student affect, disengagement, and learning strategies, such as gaming the system [10], confrustion [32], player goals [22], and SRL strategies such as whether a student is using a table to plan their analyses [43].This approach demonstrates a similar level of reliability as classroom observations and is 2-6 times faster compared to other methods of generating labels, such as classroom observations, screen replay, and retrospective think/emote-aloud protocols [8].

The length and the grain-size of text replay clips can vary depending on both the available data and the granularity of the predictions the researcher intends to make. Because this study seeks to detect cognitive SRL operations in the problem-solving process, which requires a comprehensive examination across questions and phases, the log files were delineated into clips on the level of entire *Thinklets*. Each clip contains a student's actions and text-based responses that were submitted as that student worked through the four phases to produce a single *Thinklet*. (Note that because video data was not available in these replays, our coders did not see information from the *Solve* phase.) The clips were distilled from log files and presented using a Python window, shown in Figure 2. As video data could not be trivially converted into a common text format (due to wide variability in the videos), video data was not included in the text replays at this time. Creating videos is the primary action in the *Solve* phase, thus the text replays did not contain any data from the *Solve* phase. Coding videos explicitly poses challenges to scalability of the work and is beyond the scope of this paper, but may be considered in future work.

4.2 Construct Operationalization

To identify constructs to detect, we first examined the clips containing student responses in *Thinklets* and coded student responses for indicators of SRL—qualitative categories that correspond with SRL constructs (we discuss the details of exactly how the data was coded in section 4.3). The definitions of the indicators we coded were developed through dialogue between the research team and system developers. This process followed the recursive, iterative process used in [49] that includes seven stages: conceptualization of codes, generation of codes, refinement of the first coding system, generation of the first codebook, continued revision and feedback, coding implementation, and continued revision of the codes [49]. The conceptualization of codes included a review of related literature, including several theoretical frameworks and perspectives [13, 15, 24], primarily focusing on the SMART model [53]. Using grounded theory [18], we identified common behaviors that were (1) indicative of SRL as characterized by Winne's SMART model [53] and (2) salient in the log files. A draft lexicon and multiple criteria were generated for a coding system to help identify these constructs.

Given the learning environment's design and the available data, our efforts focused on defining behaviors related to two categories of cognitive operations (the assembling and translating operations from the SMART model) as they are frequently employed in the initial stages of SRL as learners define tasks and set goals. Following the process used in [49], two coders (the first and second authors) coded a set of clips together, identified five SRL indicators (i.e., numerical representation, contextual representation, strategy orientation, outcome orientation, and data transformation), outlined the criteria for each indicator, and created a rubric.

The draft coding manual was discussed with all members of the research team and developers and designers at CueThink to build a common understanding of the criteria and constructs being examined as well as the features of the system to gain feedback for further refinement. This process was repeated until the entire team had reached a shared understanding of the criteria and constructs being examined by the codebook. The SRL indicators identified, the criteria, and alignment with the SMART model are included in Table 2.

Numerical and contextual representation consider a learner's process of creating a problem representation, which often occurs in the initial stage in the problem-solving process (i.e., define the task), outlined in the four-phase model of SRL [55]. In problem representation, learners create a problem space by identifying information they know and information they need to know. The two SRL indicators encode how learners represent and process information in math problems, denoting if numerical components and/or contextual details are noted. We consider both of these processes to reflect assembling in the SMART model as students are creating their representation of the data from the information provided. There may also be overlap with translating in some cases, especially if the question provides a different representation to the one the students use. However, as this is not always the case, we primarily consider both indicators to reflect assembling actions and tag translating actions in a different code (see below).

Strategy and outcome orientation also reflect student assembling behaviors. Both indicators consider how students set their goals and form plans for the problem-solving process. These two indicators demonstrate a difference in focuses (process vs. output).

Lastly, data transformation reflects behaviors that are associated with the translating operation, in which the learner manipulates the ways information is represented to them in the problem to find a solution.

Table 2. SRL Indicators Coded through Text Replays

SMART Category	SRL Indicator	Working Definition
Assembling	Numerical Representation (NR)	The learner's representation of the problems includes numerical components and demonstrates a level of understanding of how the numerical values are used in the math problem.
Assembling	Contextual Representation (CR)	The learner's representation of the problem includes contextual details relating to the setting/characters/situations within the given math problem.
Assembling	Strategy Orientation (SO)	Learners explicitly state a plan for how they will find the answer for the given math problem, decomposing information into a step-by-step process.
Assembling	Outcome Orientation (OO)	The learner provides only a numerical estimate of the final answer for the given math problem, suggesting that learners are focused on the output instead of the process itself.
Translating	Data Transformation (DT)	The learner manipulates the ways information is represented to them in the problem to find a solution. This suggests active problem solving.

4.3 Coding the Data

After constructs were operationalized and defined, we proceeded to code the remainder of the data. Two coders, (the same as in the previous section), completed the text replay coding in three phases: preliminary coding (discussed above), separate coding (two coders per clip; for establishing inter-rater reliability), and individual coding (one coder per clip; for completeness).

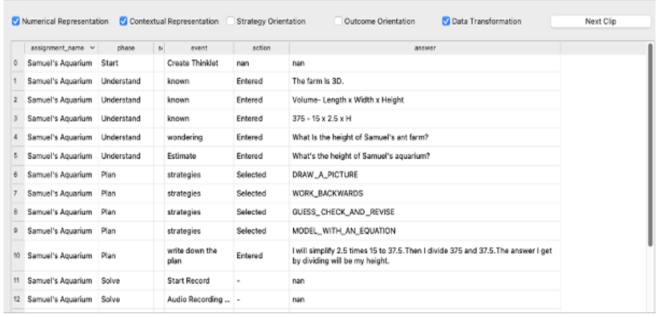
The two coders each used the codebook/rubric to code the same set of clips separately. They then compared the labels and computed the inter-rater reliability (IRR) kappa. For constructs with low kappa, the two coders discussed their differences in labeling and conducted another round of coding. This step of separate coding and comparing is repeated until an acceptable reliability is established. After two rounds of coding, as shown in Table 3, the two coders reached an acceptable IRR above 0.60 for all five SRL indicators (M=0.75).

Table 3. Inter-Rater Reliability in Separate Coding

SRL Indicator	IRR Kappa
Numerical Representation (NR)	0.83
Contextual Representation (CR)	0.63
Strategy Orientation (SO)	0.74
Outcome Orientation (OO)	0.78
Data Transformation (DT)	0.74

Once the reliability was established, the coders moved on to the individual coding where they split the rest of the clips and coded them individually.

Each construct was considered over the entire *thinklet*. Thus, in total, the two coders coded 349 clips. However, in order to consistently examine the entire problem-solving process, 167 clips that were marked incomplete because students stopped before completing the entire problem were excluded. Of the remaining 182 clips, coding resulted in the following distribution of labels: 64% numerical representation, 77% contextual representation, 8% strategy orientation, 72% outcome orientation, and 73% data transformation. These were produced by 72 students, who, on average, each contributed 3 clips (max=4, min=1, median=3).



☑ Numerical Representation ☑ Contextual Representation ☐ Strategy Orientation ☐ Outcome Orientation ☑ Data Transformation

	assignment_name	phase	event	action	answer
0	Samuel's Aquarium	Start	Create Thinklet	nan	nan
1	Samuel's Aquarium	Understand	known	Entered	The farm is 3D.
2	Samuel's Aquarium	Understand	known	Entered	Volume- Length x Width x Height
3	Samuel's Aquarium	Understand	known	Entered	375 - 15 x 2.5 x H
4	Samuel's Aquarium	Understand	wondering	Entered	What is the height of Samuel's ant farm?
5	Samuel's Aquarium	Understand	Estimate	Entered	What's the height of Samuel's aquarium?
6	Samuel's Aquarium	Plan	strategies	Selected	DRAW_A_PICTURE
7	Samuel's Aquarium	Plan	strategies	Selected	WORK_BACKWARDS
8	Samuel's Aquarium	Plan	strategies	Selected	GUESS_CHECK_AND_REVISE
9	Samuel's Aquarium	Plan	strategies	Selected	MODEL_WITH_AN_EQUATION
10	Samuel's Aquarium	Plan	write down the plan	Entered	I will simplify 2.5 times 15 to 37.5.Then I divide 375 and 37.5.The answer I get by dividing will be my height.
11	Samuel's Aquarium	Solve	Start Record	-	nan
12	Samuel's Aquarium	Solve	Audio Recording ...	-	nan

Figure 2. Screenshot of Text Replay Coding Window

4.4 Feature Distillation

Two sets of features were distilled to build the detectors. Both sets of features consist solely of features that can be extracted and used in real-time. The first set of features were designed to provide an overview of a *Thinklet* by examining the number of responses in a *Thinklet*. These features (N = 10) were distilled at the *Thinklet* level. For example, we distilled the number of questions students answered in a *Thinklet* and the number of responses in each phase. To understand the strategies that students select in the *Plan* phase, we also created a feature that counts the number of strategies a student selects among the top two strategies used by peers for the same problem.

The second set of features were designed to examine the content and the linguistic features of students' text-based responses. These features (N = 90) were first extracted at the response level and then aggregated to the phase level. These aggregations were calculated for the *Understand*, *Plan*, and *Review* phases. (No textual data was extracted from the *Solve* phase as there was no textual input in this phase.)

Specifically, we distilled whether each response: 1) contains a numerical value, 2) consists of only numerical values, 3) has mathematical operation signs, 4) contains a question (if it contains a question mark or uses keywords such as "wonder", "why", etc.), 5) uses language that indicates the formation of a plan (e.g., the use of keywords like "plan", "I will", "going to", etc.) , and 6) is the exact repetition of a previous answer. These criteria generate a set of binary variables for each response. We averaged these binary variables across the responses within a phase, creating 18 features for each *Thinklet*.

Additionally, in each response, we counted the number of 7) characters, 8) words, 9) numerical values, 10) verbs, 11) nouns, and 12) pronouns. Features 10-12 were counted using Udpipe, a natural language processing toolkit [50]. We also 13) counted the number of keywords used from a predefined list that provides the context of each problem; and 14) computed how similar each response is to the problem item using the Smith-Waterman algorithm [46]. For these continuous variables, we computed the mean, standard deviation, and max of the values for each phase, creating 72 features.

Features distilled from the two sets were combined. In total, 100 features were extracted from each *Thinklet* process and were then used to construct the automated detectors. Note that we did not extract any features from the video that students make in the current work. Similarly, we did not use any of the audio from the video (or transcription thereof) for any features.

4.5 Machine Learning Algorithms

We used the scikit-learn library [40] to implement commonly-used models, including Logistic Regression, Lasso, Decision Tree, Random Forest as well as Extreme Gradient Boosting (XGBoost) as implemented in the XGBoost library [19]. XGBoost outperformed other algorithms in all cases; we therefore only discuss the XGBoost results below.

XGBoost uses an ensemble technique that trains an initial, weak decision tree and calculates its prediction errors. It then iteratively trains subsequent decision trees to predict the error of the previous decision tree, with the final prediction representing the sum of the predictions of all the trees in the set. We tested the detectors with 10-fold student-level cross-validation. For this approach, the dataset was split into 10 student-level folds, meaning that in cases where students had multiple *Thinklets,* all of their data would be contained within the same fold and at no time could data from a student be included in both the training and testing set. Nine folds were used to train the model, and the trained model was used to make predictions for the 10th fold. Each fold acted as the test set once. Student-level cross-validation was conducted to verify generalizability to new students.

Models were evaluated using the area under the Receiver Operating Characteristic curve (AUC ROC), which indicates the probability that the model can correctly distinguish between an example of each class. An AUC ROC of 0.5 represents chance classification, while an AUC ROC of 1 represents perfect classification. Results were calculated for each fold and averaged to yield one AUC ROC score per detector.

5. RESULTS

5.1 Model Performance

Due to the rarity of strategy orientation (only 14 clips were labeled with this construct), a detector could not be built for this construct. Automated detectors were built for the other four constructs. As shown in Table 4, the average AUC ROC derived from 10-fold student-level cross-validation is 0.894 for numerical representation (NR), 0.813 for contextual representation (CR), 0.761 for outcome orientation (OO), and 0.815 for data transformation (DT). These findings suggest that the detectors were generally successful at capturing these four SRL constructs. We also calculated the standard deviations (SD) of the AUC ROCs across the 10 folds for each detector to investigate the variability across folds.

Table 4. Detector Performance Measured by AUC ROC

SRL Indicator	AUC ROC (SD)
Numerical Representation	0.894 (.078)
Contextual Representation	0.813 (.132)
Outcome Orientation	0.761 (.076)
Data Transformation	0.815 (.163)

5.2 Feature Importance

To better understand the detectors as well as to inform our understanding of how these features relate to the constructs, the SHapley Additive exPlanations (SHAP) [33] value, which reflects feature importance, was calculated for each feature within each test set.

These values were then averaged across the 10 testing sets and ranked based on their absolute values. Of the 100 features used, Table 5 reports the top five features with the highest absolute SHAP values for each detector. To understand the directionality, we examined the average SHAP values of the features listed. A positive average SHAP value was found for all the features listed (except for one, as indicated in the Contextual Representation section of Table 5). The positive values indicate that the features are positive predictors of the SRL indicators, suggesting that the higher the values in each feature, the more likely the model is to infer the presence of a SRL indicator.

Table 5. The Top Five Features from each Detector

Feature Phase	Feature
Numerical Representation	
Understand	Mean N of responses that give numerical values
Understand	Max value of the similarity feature which indicates how parallel a student's response is to the original problem
Understand	SD of the similarity feature
Understand	Total N of responses
Plan	Avg value of the similarity feature
Contextual Representation	
Understand	Is there a response to the "what do you notice" question?
Understand	Avg N of keywords used
Understand	SD of the N of characters used (Contextual Representation less likely)
Thinklet	Total N of responses
Plan	Max value of the N of characters used
Outcome Orientation	
Review	Avg N of keywords used
Review	Avg N of words used
Understand	SD of the N of numerical values used
Understand	Is there a response to the "what is your estimated answer" question?
Review	Avg N of nouns used
Data Transformation	
Plan	N of strategies selected that were among the most common strategies used by peers
Understand	SD of the similarity feature
Plan	SD of the N of characters used
Understand	SD of the N of nouns used
Plan	Max value of N of words used

We note that of the 20 features listed in Table 5, 11 are from the *Understand* phase, 5 are from the *Plan* Phase and 3 are from the *Review* phase. In other words, behaviors in the early phases

Table 6. Detector Performance by Gender and Racial/Ethnic Groups

			Gender			Race/Ethnicity					
	All Students (k-fold)	All Students (Pooled)	Male	Female	Left Blank	African American	Hispanic/ Latinx	White	Prefer Not to Say	Other	Two or more races
N. students	72	72	33	28	9	6	18	8	19	14	5
N. clips	182	182	81	73	24	20	38	19	50	37	12
NR	0.89	0.89	0.82	0.93	0.97	0.92	0.88	0.96	0.86	0.85	0.86
CR	0.81	0.80	0.74	0.75	0.94	0.75	0.72	0.80	0.90	0.65	0.78
OO	0.78	0.75	0.78	0.74	0.72	0.71	0.81	0.80	0.74	0.78	0.46
DT	0.82	0.86	0.88	0.87	0.78	0.92	0.91	0.83	0.84	0.82	0.86

contributed more heavily to the predictions. This finding aligns with how the *Thinklets* were initially coded. Specifically, the coders primarily examined student responses in the *Understand* phase for numerical and contextual representation as this phase contains information demonstrating how student assemble information and create a problem representation; the coders examined the *Thinklet* more broadly when coding for other SRL indicators, as they encompass behaviors that span across phases.

5.3 Algorithmic Bias

Algorithmic bias occurs when model performance is substantially better or worse across mutually exclusive groups separated by generally non-malleable factors [11]. To validate our detectors, we tested the model performance in different student populations, based on gender and race/ethnicity using slicing analysis [25]. Specifically, utilizing the predictions made in the testing sets, AUC was computed for each subgroup of students in the data for which we received data on group membership. However, due to sample size, comparisons were not possible for gender non-binary students (N=2), Asian students (N=2), or Native American students (N=0).

As Table 6 shows, the difference in model performance measured by AUC between male and female students is small, ranging from 0.01-0.11 for the four detectors. The detectors for numerical representation and contextual representation performed somewhat better for female students (AUC_{NR} = .93, AUC_{CR} = .75) than for male students (AUC_{NR} = .82, AUC_{CR} = .74), while detectors for outcome orientation and data transformation preformed somewhat better for male students (AUC_{OO} = .78, AUC_{DT} = .88) than for female students (AUC_{OO} = .74, AUC_{DT} = .87).

Table 6 also shows the analysis of algorithmic bias in terms of race/ethnicity, comparing the AUC between student racial/ethnic subgroups that had more than 5 students in our sample: African American, Hispanic/Latinx, and White. Small to moderate differences were observed across the three groups, though the differences were not consistent (i.e., no racial/ethnic group consistently had the best-performing detectors). However, performance remained acceptable for all four detectors across all groups. When detecting numerical representation and contextual representations, the detectors performed somewhat better for White students (AUC_{NR} = 0.96, AUC_{CR} = 0.80), than for African American (AUC_{NR} = 0.92, AUC_{CR} = 0.75) and Hispanic/Latinx (AUC_{NR} = 0.88, AUC_{CR} = 0.72) students. However, the outcome orientation detector had somewhat higher performance for Hispanic/Latinx students (AUC_{OO} = 0.81), than for White (AUC_{OO} = 0.80) and African American (AUC_{OO} = 0.71) students. The data transformation detector performed better for African American students (AUC_{DT} = 0.92) than for Hispanic/Latinx (AUC_{DT} = 0.91) and White (AUC_{DT} = 0.83) students. Performance was substantially lower for two constructs/group combinations: detecting contextual representation for students who identify race as other (AUC_{CR} = 0.65) and detecting outcome orientation for students who identify as belonging to two or more races (AUC_{OO} = 0.46). These more substantial differences may be due to the small sample size of these constructs within these subgroups; in future work, larger samples will be collected in order to validate performance in these groups.

Given the data collected, we noticed a considerable number of students who declined to report gender (N = 9) and race (N = 19). Both groups performed close to the average model performance, across groups and contexts.

6. CONCLUSION AND DISCUSSION

6.1 Main Findings

Given the importance of self-regulation in learning, specifically in the problem-solving process, an increasing number of studies have looked into ways to promote self-regulated learning. This first requires the ability to accurately measure SRL, so that interventions can be introduced to encourage and guide students to self-regulate effectively. However, the most common ways of measuring SRL in a fine-grained fashion – either through self-report and think-aloud protocols –are difficult to automate and scale, and they can also interrupt or interfere with the learning task. Log data collected from computer-based learning environments offers an unobtrusive and potentially scalable solution to help understand when and how students self-regulate within the problem-solving process, in order to inform decisions on intervention (e.g., [3]). However, previous automated detection of SRL constructs using log data has mostly not been explicitly connected to SRL theory. In the current work, we explored the possibility of detecting SRL constructs at a fine-grained level, focusing on detecting cognitive operations (i.e., assembling and translating), outlined in the SMART model [53]. Specifically, we detected the presence of four self-regulation indicators related to two categories of operations: numerical representation, contextual representation, outcome orientation, and data transformation. Evaluated using 10-fold student-level cross-validation, our detectors were found to be accurate and valid across demographic groups, with AUC ROC ranging from .76-.89.

To understand the detectors, feature importance was examined using SHAP values. The top five features with the highest absolute SHAP values were identified for each detector. With the features identified, we find that except for outcome orientation, the detectors primarily rely on features extracted from the *Understand* and *Plan* phases of the learning activity, the two phases where students assemble information and make plans. In particular, the numerical representation detector mainly relies on features that examine the numerical values used in the *Understand* phase as well as features that compare the similarity between student responses and the problem item. The numerical value feature makes sense, as the detector is operationalized to identify if numerical components are processed and represented when students assemble information.

However, the maximum similarity feature, a feature that takes both numerical values and text into account, also contributes to the NR indicator. This finding suggests that the NR detector not only examines if numbers are used in responses, but also how they are used in relation to the problem. As such, this finding validates the operationalization of this indicator, showing that the learner demonstrates a level of understanding of how numerical values are used in math problems, creating a representation of the problem space utilizing numbers.

The contextual representation detector looks at the keywords used in student responses in the *Understand* phase and the length of the responses in the *Plan* phase, which indicates the relationship that the longer the responses are when a student is forming a plan, the more likely it is for the student to contextually representing the problem. When predicting the presence of outcome orientation, the model utilizes features extracted in the *Understand* and the *Review* phases, understanding students' use of keywords, nouns, and numerical values in these two phases. At last, the data transformation detector checks the number of top strategies students select as well as the length and the variation in the length of the responses in the *Understand* and *Plan* phase.

Additionally, we examined model performance on different demographic subgroups of students, both in terms of gender and racial/ethnic groups, to verify their fairness and lack of algorithmic biases. Relatively small differences were observed in each comparison, and no student group (either gender or racial/ethnic group) consistently had the best-performing detectors.

6.2 Applications

The detectors built in the current study provide two advantages over previous SRL detectors. First, previous SRL detectors generally identify higher-level strategies and are not typically linked to theory; in contrast, we specifically based our detectors on a SRL model in order to identify theoretically-grounded SRL constructs at a finer-grain size. Having developed these fine-grained models of behavior associated with the assembling and translating operations of SMART, we can conduct analyses to further our understanding of the role that cognitive operations play in the broader process of SRL. For example, we can investigate questions about how often students use these cognitive operations in each of the four tasks outlined in the Winne and Hadwin's four-stage model, and how the engagement and the frequency of the engagement in these cognitive operations contributes to the success of completing the tasks. Results from future analyses will help expand the current theoretical understanding on SRL, adding specificity to the still high-level processes represented in contemporary SRL theory.

Second, given that most previous detectors are not connected back to SRL theory, it has been difficult to use them with theory-driven interventions. The detectors proposed in the current study are developed based on a theoretical model of SRL [46, 48] and are operationalized to capture key aspects of the cognitive operations in the model. These detectors can therefore be used to facilitate the development of adaptive learning environments that respond to student SRL, in a fashion connected to theory. For instance, a student demonstrating an outcome orientation could be encouraged to reflect further on their strategy. Similarly, these detectors could also provide theory-grounded information to teachers (e.g., through a dashboard), providing insight on how students are approaching problems. This data can inform teachers as they create and refine their problems, as well as informing how they support their students. As with any application of this nature, careful attention will be needed in design to ensure that data is presented in the most useful form for teachers and appropriately represents the uncertainty in the model (i.e., false positives or false negatives).

6.3 Limitations and Future Work

This work has five principal limitations that should be addressed in future work. First, when validating the fairness of the models, the sample size is small (less than five students) for several student groups. Reliable comparison of the model performance for these groups of students is therefore not possible. In future work, larger and more representative samples should be collected in order to validate model performance for a broader range of student groups.

Second, although our detectors are based on a theoretical model of SRL, the operationalization of our constructs is contextualized in the current learning environment, so our detectors may be platform-specific. Future work should study the transferability of the current detectors by examining their applicability and predictive performance, and explore how they can be adapted for use in other learning environments. To the extent that some of our detectors (such as the data transformation detector) apply across learning environments, we can investigate their performance within those contexts to evaluate their transferability (see, for instance, [39]).

Third, since the detectors are currently trained on complete *Thinklets*, they will have some limitations in the ways they can be used when being implemented in a learning platform. Specifically, the detectors will only be able to make predictions after a student has solved a problem, providing an indicator at that point on the student's use or lack of use of assembling and translating in the problem-solving process. As such, these detectors will not provide immediate detection of these strategies when students are working through a problem. However, they can still be used to inform teachers and direct their feedback after a problem has concluded, in between problems or for the next problem. To enable other uses, it may be relevant to examine ways of also making early predictions based on incomplete *Thinklets* in order to provide detection during the problem-solving process, enabling real-time interventions.

Future work should also consider additional methods for ground truth labelling. In this work we used a post-hoc tagging approach (through text replays), to identify indicators of SRL-related strategies. This approach has the potential to miss crucial "in-the-moment" events that are not evident from the log data alone. Future studies could examine how post-hoc tagging used in the current study align with in-the-moment tagging, reported by either student themselves or external observers/interviewers (e.g. [7]) to examine additional aspects of SRL.

Finally, future work should consider expanding the scope of this work. In the current study, five constructs were identified and four modeled. SRL as a process covers a much broader range of behaviors and strategies that elicit the use of various cognitive operations. Future studies should model and detect a broader range of cognitive operations throughout the four stages of self-regulated learning in the context of problem-solving.

6.4 Conclusions

To better understand and facilitate the use of self-regulation in problem-solving, the current study tested the possibility of scaling up SRL measurement by leveraging machine learning to automatically detect individual SRL indicators through the lens of the SMART model. We built automated detectors that identify four commonly used strategies in math problem solving, indicating assembling and translating operations. Our detectors were found to be reliable and generalizable. Additionally, the detectors were also tested on different student populations to verify their fairness and lack of algorithmic bias, addressing a previously overlooked issue in the field of educational data mining. Given these properties, we anticipate implementing the detectors in the learning environment to collect more fine-grained data and to leverage the detection to inform interventions, creating more positive experiences in mathematical problem-solving.

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