Towards Hybrid Human-System Regulation: Understanding Children' SRL Support Needs in Blended Classrooms

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ABSTRACT

This paper proposes a new approach to translate learner data into self-regulated learning support. Learning phases in blended classrooms place unique requirements on students' self-regulated learning (SRL). Learning path graphs merge moment-by-moment learning curves and learning phase data to understand student' SRL support needs. Results indicate 4 groups with different SRL support needs. Students in the *self-regulated learning group* are capable of learning without external regulation. In the *teacher regulation group* students need initial teacher regulation but rely on SRL thereafter. Students in the *system regulation group* require teacher and system regulation to learn. Finally, the *advanced system support group* is in need of support beyond the current level of system regulation. Based on these insights, the application of personalized dashboards and hybrid human-system regulation is further specified.

CCS CONCEPTS

• CCS → Human-centered computing → Visualization → Visualization design and evaluation methods
•CCS → Applied computing → Education → E-learning

KEYWORDS

Hybrid Human-System Intelligence; Self-Regulated Learning; Adaptive Learning Technologies; Blended Classrooms

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1 INTRODUCTION

In the Netherlands alone, over 250,000 students in primary education learn Mathematics, Dutch and English using adaptive learning technologies (ALTs) such as Snappet, Muiswerk, Taalzee/Rekentuin, Got it, and PulseOn on a daily basis [37]. These technologies capture rich data about students' performance during learning [23, 38]. Often a distinction is made between two main approaches for using learner data: i) extracted analytics in which data is reported directly to stakeholders and ii) embedded analytics in which systems automatically process data [45]. The combination of extracted and embedded analytics in the same instructional context gives rise to systems that do not intend to take the place of human teachers, but instead aim to optimize student learning with hybrid human-system interaction in blended classrooms [26, 35].

In blended classrooms, human instruction is combined with adaptive practice on ALTs to leverage the distinct strengths of human teachers and learning technologies. Teachers use extracted analytics in the form of dashboards to consult learners' data and adjust instruction and feedback accordingly. ALTs adjust problems to students' knowledge level based on their performance data during individual practice [15, 29]. Consequently, learning in blended classrooms is adjusted to individual students' needs; several studies have shown the effectiveness of hybrid human-systems in edcuational contexts [20, 26, 28, 40]. Suprisingly, learner-faced learning analytics have so far been largely ignored in blended classrooms. The important role of self-regulated learning (SRL) has been emphasized in the field of learning analytics, but few tools to support SRL have been developed so far [44] – although some SRL tools for blended learning do exist [1, 3, 12]. The relative rarity of SRL support is due to challenges related to understanding what student data reveal about SRL. The contribution of this paper is the examination of what student data tell us about student' SRL in blended classrooms. Moreover, these insights are translated into new learning analytics informed types of SRL support. Thus this paper takes a step towards translating learner data into SRL support using learning analytics techniques.

1.1 SRL in Blended Classrooms

SRL theory defines learning as a goal-oriented process, in which students work consciously toward one or more learning goals [46]. Self-regulating learners use cognitive activities (reading, practicing and elaboration) to study a topic, control and monitor their learning with metacognitive activities (orientation, planning, monitoring and evaluation) and motivate themselves to engage in an appropriate level of effort [21]. Accuracy can be conceptualized a function of a student' knowledge and effort. Hence effective self-regulating learners adjust their effort to ensure that planned learning goals are achieved and control their learning to ensure a productive level of accuracy [24]. Students continuously monitor their accuracy to determine whether their actions lead to progress towards their learning goals [22, 43]. Consequently, the control and monitoring loop support the level of effort needed in relation to students current knowledge to ensure accuracy and consequent progress to their learning goals. In this light, alignment between learning goals and learner actions, allocation of learner effort, and how students uphold their accuracy are all elements that student data can reveal.

This is especially important because the majority of learners do not regulate their learning sufficiently, leading to less efficient and effective learning [5]. Students are faced with a "utilization deficiency", the failure to adequately activate the control and monitor loop during learning [8]. In primary education, students develop SRL skills with teacher guidance [17, 18]. There is an ongoing transition from teacher regulation to shared- and eventually self-regulated learning [16–18]. This gradual transfer of control to students is expected to enhance students' SRL [5, 18]. Hence in students' development of self-regulated learning skills, teachers' modeling, guidance and gradual transfer of control plays an important role [42].

In blended classrooms teachers naturally embed this transitional process to support SRL [36]. Teacher consistently apply the direct instruction model to orchestrate blended classrooms [32, 11]. Hence distinct learning phase are followed, namely instruction, guided practice under teacher supervision and individual practice. In blended classrooms ALTs are used for guided and individual practice. The later phase is divided in a non-adaptive practice phase in which all students make the same problems and an adaptive practice phase in which students receive problems adjusted to their current knowledge level [32]. As in traditional classrooms the learning phases in these classrooms are characterized by different levels of external regulation by the teacher and additionally during adaptive problems solving by the system.

Teacher regulation is high during instruction and guided practice. During instruction, teachers explain new knowledge and model to how to apply this new knowledge. Modeling is effective for a wide range of subjects, from applying grammar rules and performing a mathematical calculation to the application of self-regulated learning [11]. Effective teachers model not only how to solve problems, but also explicitly discuss how to control and monitor effort and accuracy during problem solving [18, 42]. During guided practice, teachers assess students' understanding of the new topics through class-wide practice. This phase is also typified by the teacher executing part of the control and monitoring loops for students. Namely, teachers control the selection of problems and explicitly monitor and discuss accuracy of answers.

After guided practice students continue to practice individually and move towards self-regulated learning. Students are responsible adjust their effort to uphold accuracy during practice themselves. Thus, in this learning phase both effort control and accuracy monitoring are controlled by the student. Teachers' abilities to provide additional support during individual practice are limited due to the differential needs of students in larger classes [16, 41].

During adaptive practice, ALTs support students by adjusting problems to the needs of the individual student. ALTs select new problems based on an estimate of the students' current knowledge and the probability that a problem will be solved correctly by the student [15, 29]. Even though adaptive problem selection is developed as cognitive support for students, the execution also supports students' regulation. In fact, some ALTs now execute elements of the control and monitoring loop which are otherwise performed by learners themselves. In the control loop, these ALTs select instructional events that are aligned with the students' learning goal and adjusted to students' current knowledge. This reduces the need for learners to adjustment their effort. In the monitoring loop, ALTs overtake the part of students accuracy monitoring. When a learner does not make sufficient progress, many ALTs automatically reduce the difficultly of the problems. This reduces the dependency of a student's own monitoring of accuracy. Research has indicated that the accuracy monitoring of students in primary education is often imperfect, leading to consequences for their learning efficiency [31, 39]. Therefore, adaptive problem selection in ALTs, could overcome students' reduced ability to control and monitor their learning.

Based on the above, we can conclude that learning phases in the blended classrooms are characterized by unique configurations of teacher, student and system regulation. On the one hand, students receive external regulation during both guided practice and adaptive practice. During guided practice, the teacher takes over part of the regulation and during adaptive practice the system does. On the other hand, during non-adaptive practice, students are reliant on self-regulated learning and have to control and monitor their effort and accuracy themselves. Accordingly, the learning phrase in which students experience problems to regulate their learning provides insights into students' needs for regulation support in blended classrooms.

1.2 UNDERSTANDING HUMAN-SYSTEM REGULATION

It is important to understand how students' learning enacts regulation of effort and accuracy during learning in order to understand students' needs for SRL support [34]. Moment-by-moment learning curves (MbMLC) are a way to visualize a student's learning over time. First developed in the context of intelligent tutoring systems, these curves visualize the probability that a student learned a specific skill at the time a particular problem is solved [6]. Baker and colleagues showed that the spikiness of the probability of learning at each time point was associated with increased learning. This finding has been replicated in several studies [7]. Moreover, visualizing this probability revealed seven relatively stable patterns which were differently related to learning [6]. For example, immediate drops, where the probability of learning was high initially and rapidly reduced, were found to be correlated with longer-term retention of learning. Immediate peaks, with a peak of the probability of learning early on during problem solving, were associated with higher immediate post-test scores.

Recently, authors (under review) showed that four patterns were found in the context of blended classrooms. These patterns were not only predictors of students' learning, but also were informative as to how students regulate their accuracy. The immediate drop pattern was associated with high accuracy on problem solving attempts, whereas the immediate peak pattern was linked to moderate accuracy. Particularly complex curves, such as close multiple spikes and separated multiple spikes, that show multiple fluctuations of the probability just learned, were associated with lower accuracy and moderate learning. Hence moment-by-moment learning curves seem to be valuable indicators of regulation during learning in ALTs and could potentially be used in interventions to support SRL.

We postulate that to further understand how students regulate their learning, it is important to better understand the students' needs for SRL support. Combining MbMLC with information on the student's current learning phase in blended classrooms provides insights into how different levels of external regulation by the teacher and the system support students. We refer to the combination of MbMLC and learning phases as learning phase graphs. These graphs have the power to indicate in which learning phase a student learns and when a student experiences trouble regulating her/his learning. Moreover, it provides information on whether a student is dependent on teacher regulation, can effectively self-regulate, or is in need of advanced system regulation. New types of support for regulation can be developed that either take an extracted analytics approach and provide information back to the learner in personalized visualizations or take an embedded approach by fluctuating control of regulation between the system and the learner in intelligent hybrid human-system regulation.

1.3 NEW FORMS OF REGULATION SUPPORT

Existing support for self-regulated learning relies on students as agents that enact the support given. A range of techniques (e.g., prompts [9], scaffolding [33], intelligent tutor systems [4]) are used to assist learners' in regulating their learning. There are two main drawbacks of these techniques. First, they generally do not help learners to make explicit inferences about how their actions relate to progress towards their learning goals. As Winne states: "*Without reliable, revealing and relevant data that support learners to make valid inferences about how they control and monitor their learning learners are handicapped*" [44]. A possible solution can be found in personalized visualizations that provide learners with a continuous reference to understand the relation between their learning actions, accuracy and progress towards their learning goal. As such, the newly developed "learning path graphs" could be powerful tools to support learners to efficiently control their effort and monitor their accuracy, to help them make progress toward their goals. Hence, these graphs could constitute a promising way to overcome learners' inadequate regulation of their learning. In particular, learners need to be able to make inferences about how their learning actions are related to their progress and achievements [18]. Learners require continuous, personalized feedback to understand how progress toward learning goals is related to their actions.

Learner faced dashboards have recently become a more prominent way of providing SRL support through learning analytics [e.g. 23], although visualizations on students' progress towards their goals have been used in some learning systems for some time [2, 30]. However, a recent review by Jivet and colleagues indicates that most dashboards do not provide actionable information for students to improve their regulation. Students are frequently in need of additional feedback to be able to act on the provided data. Similarly, a meta-review on learning diaries recently indicated that these interventions are more effective when students are provided with feedback on their reflections [18].

Second, another drawback of traditional SRL support is that it only functions well when students comply with systems' advice and research indicates that students often do not act upon the suggestions given. Students ignore help or actively choose not to follow the advice given [10, 14, 25]. In contrast, when other actors, such as teachers or systems, take over part of the student's regulation, the costs of student non-compliance is likely to be reduced. As such, we envision hybrid human-system regulation with fluctuating boundaries between student and system control. Beyond educational contexts, there is an on-going "fusion" between human and system control, for example in aviation systems and self-driving cars. A defining characteristic of hybrid human-systems is that the boundaries between human and system decision making fluctuate [13]. In line with this, embedded learning analytics techniques can support a new generation of SRL support that adjusts external regulation based on insights gained from data. Transitions between internal student and external system control according to the students' needs becomes feasible. Consequently, insights into students' functioning in blended classrooms helps us define such a support system.

Therefore, this paper examines student' needs for SRL support in blended classrooms. Learning phases in blended classrooms place unique requirements on student' regulation and can hence be viewed as a natural context to investigate student' need for SRL support. During guided practice, teachers regulate students learning. In non-adaptive practice, students are reliant on SRL and during adaptive practice the system partially regulates the learner. This paper explores how learning phase graphs can be indicative of student' SRL support needs. One the one hand, when MbMLC consistently show peaks in learning phase, this may indicate a particular SRL support need for students showing a form of MbMLC. On the other hand, when peaks of a form of MbMLC are shown in different learning phases, this may indicate different support needs. Therefore we explore i) how peaks in particular learning phases are related to different forms of MbMLC and ii) how the positioning of peaks implies the need for SLR support. Last design implications for SRL support are derived based on findings.

2 METHOD

2.1 Participants

98 students in grade five of primary school, divided between four schools, participated in this study. The schools were located in the south and west of the Netherlands and had a diverse population. The inclusion criterion was that students had to participate in at least 3 lessons; 3 students were excluded from analysis. 51 boys (53%) and 44 girls (47%) were therefore included in the analyses of this study. The students were between 10 and 12 years old with a mean of 10.87 (sd=.45). 5 students missed the pre-test and 4 students did not participate in the post-test and transfer test.

2.2 Design

This study was conducted with a pre-test/post-test design. All students worked on 3 arithmetic skills in 4 lessons of 45 minutes each. The lessons follow the blended classroom direct instruction model with teacher instruction and individual practice in the ALT. The measurements took place prior to the first lesson (pre-test) and after the completion of all lessons (post-test and transfer test). Next, students received direct instruction and practiced the three skills during 3 lessons of 45 minutes each on three consecutive days. In the fourth lesson students were instructed to practice those skills for which they had not yet received their proficiency level. Figure 1 shows the design of this study.

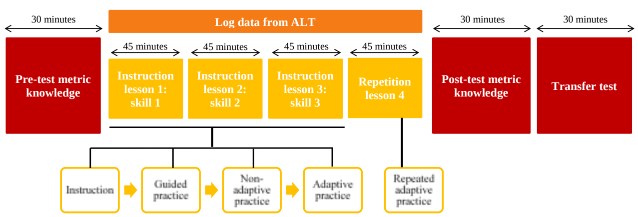

Figure 1. Study design

2.3 Materials

The adaptive learning technology used in this study runs on tablet computers and is widely used for arithmetic and spelling across schools in the Netherlands. Students practiced the skills in the ALT after teacher instruction. Guided and non-adaptive practice problems were the same for all students in the class. Adaptive problems were adjusted to the knowledge of the student by an adaptive mechanism that selected a new problem after completion of the previous item, based on the estimated student knowledge. A derivative of the ELO algorithm adapted problems to the current knowledge of an individual student [19, 29]; The algorithm worked with a student's knowledge score, which is the representation of a student's current knowledge on a particular skill. The knowledge score was calculated based on all the problems that a student had answered related to that specific skill. Every problem in the system had a difficulty level which was automatically generated and updated by the system based on all of the students' answers. The student's knowledge level was used by the system to select the next problem. Based on a student's knowledge level, the system attempted to select problems where there was a probability of 75% that the student would solve the problem correctly.

The skills. The three skills all included different aspects of measurements of capacity. The skills increased in difficulty. The first skill "Calculate capacity using the formula: 'capacity = length x width x height" is relatively easy, because students were given a formula to solve the problem. Also, in this skill, examples were used to support students' problem solving. The second skill "Convert between common cubic capacity units" has an intermediate difficulty. Students were asked to convert from common capacity units into cubic meters (cm3, dm3, m3). Finally, the third skill is "Convert cubic meters units to liter units" is hard. Students were asked to convert cubic meters (cm3, dm3, m3) into cubic liter units (cl3, dl3, l3) without a formula.

2.4 Measurements

Learning indicators. The pre- and post-test consisted of 24 items, 8 items per skill. The items in the pre- and post-test were structurally similar, but different digits were used. The difficulty level of the items, as indicated by the ALT, was used to balance the tests. The transfer test consisted of 15 items that tested students' understanding of the relations between meter units and liter units. The Cronbach's alpha for all tests indicated acceptable reliability from .73 to .94.

Effort and accuracy indicators. The logs of the ALT stored data of students' practice activities, including a date and time stamp, student identifier, problem identifier, learning objective identifier, knowledge score after the problem and correctness of the answer given. Based on this information the following indicators of effort and efficiency were calculated, see table 1.

Table 1: Overview of learning, effort and accuracy indicators.

Indicator	Definition
Prior knowledge	Pre-test score per skill
Post Knowledge	Post-test score per skill
Gain	Post-test minus pre-test per skill
Transfer score	Transfer test score
Effort: Unique problems	Number of unique problems made per skill
Effort: Problem solving attempts	Number of unique problem solving attempts per skill
Accuracy of unique problems	Correct problems / total unique problems
Accuracy of problem solving attempts	Correct problems / total problem solving attempts

2.5 Moment-by-moment learning curves

The moment-by-moment learning curves were derived based on an algorithm developed by Baker et al. (2013) that calculates the probability that the student has just learned the skill. This probability is plotted across the student's problem solving attempts on a single skill over time, to derive the MbMLC. We developed a Python script to automatically classify the form MbMLC (based on Baker et al., 2014), following the rules in table 2. Peaks were defined as points that more than .015 higher than the point before and after. The script found that two peaks that follow each other was a common pattern, so this pattern was added to the list of curves as "double spike".

Table 2: Coding rules for classifying moment-by-moment learning curves.

Curve	Rules
Immediate drop	The curve starts high, drops quickly after solving problems and remains low afterwards.
Immediate peak	The curve starts low, peaks within the first 10 problems and remains low afterwards.
Double spikes	The curve starts low and shows 2 peaks over the course of problem solving.
Close multiple spikes	The curve starts low and shows more than 2 peaks within the first 25 problems and remains low afterwards.
Separated multiple spikes	This curve starts low and continues to show multiple peaks, even after 25 problems

2. 6 Learning phases

To identify different learning phases (LP), all student activities were assigned to a learning phase as described below in table 2

Table 3: Description of the learning phases.

Learning phase	Description
Pre-test	Measurement of students' prior knowledge on the three skills
Guided practice	Problems modeled by the teacher and solved together with the teacher
Non-adaptive practice	Problems that are pre-selected and given in the same order to all students.
Adaptive practice	Problems which adapt to the knowledge level of the student, directly following guided and non-adaptive practice
Repeated adaptive practice	Problems which adapt to the knowledge level of the student, made during the fourth "rehearsal" lesson
Post-test	Measurement of students' knowledge after the lessons

2.7 Learning Path Graph

The learning path graphs were plotted by superimposing the moment-by-moment learning curves over the learning phases, as shown in figure 2.

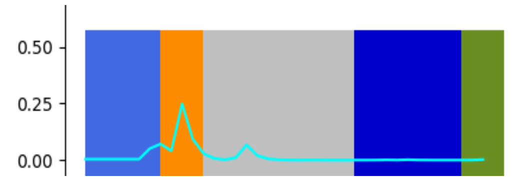

Figure 2: Learning Path Graph

The vertical axis displays the probability just learned, with values ranging from 0 to .5. The horizontal axis indicates how many problems the student has completed so far. The line in the graph depicts the probability the student just learned the skill at each opportunity to do so, and how this probability evolves across the set of problems. The color blocks in the background indicate the learning phases. Cyan indicated the pre-test, orange was guided practice, gray indicated the non-adaptive practice phase, yellow was adaptive practice, dark blue repeated adaptive practice and green indicated the post-test.

4 RESULTS

4.1 Peaks in learning phases and forms of MbMLC

First, we describe the mean and standard deviation of effort, accuracy and learning indicators (Table 4) for different forms of MbMLC .

Table 4: Effort and accuracy indicators per MbMLC form.

Effort	Unique problems solved	Problem solving attempts
Immediate drop	53.55 (18.35)	60.77 (23.13)
Immediate peak	57.84 (19.03)	70.60 (24.34)
Double spikes	54.57 (19.65)	71.04 (25.62)
Close multiple spikes	57.38 (24.96)	76.64 (33.96)
Separated multiple spikes	52.34 (19.21)	79.78 (28.02)
Accuracy	Problems solved	Problem solving attempts
Immediate drop	0.968 (0.098)	0.865 (0.103)
Immediate peak	0.847 0.1398)	0.699 (0.129)
Double spikes	0.791 (0.173)	0.616 (0.163)
Close multiple spikes	0.749 (0.152)	0.603 (0.149)
Separated multiple spikes	0.749 (0.097)	0.4936 (0.090)
learning	Pre-test	Post-test
Immediate drop	7.31 (1.56)	7.31 (1.22)
Immediate peak	2.06 (2.54)	6.33 (2.06)
Double spikes	1.18 (1.68)	4.92 (2.71)
Close multiple spikes	1.49 (1.56)	4.26 (2.67)
Separated multiple spikes	1.16 (1.59)	3.84 (2.59)
	Learning gain	Transfer test
Immediate drop	0.05 (1.68)	11.11 (4.23)
Immediate peak	4.39 (2.96)	10.73 (3.69)
Double spikes	3.76 (2.94)	10.48 (3.93)
Close multiple spikes	3.06 (2.49)	10.40 (3.78)
Separated multiple spikes	2.90 (2.79)	7.09 (3.10)

Below, we describe how the occurrence of peaks in particular learning phases was related to different forms of MbMLC.

Immediate drops. Immediate drop curves start high, drop quickly as the student solves problems and afterwards they remain low, as shown in figure 3. Baker and his colleagues (2014) indicated that this pattern reflects a student who already knows the skill at the beginning (which the system lacks the information to know, so this comes across as an initial high learning rate that drops off).

We found 65 immediate drop curves. There were 56 curves for the easy skill, 8 for the intermediate skill and 1 for the hard skill. This indicates an interaction with skill difficulty. In all cases, the drop occurred in the pre-test for all curves and remained low afterwards. This indicates that indeed these students were able to self-regulate their learning.

Figure 3. Immediate drop learning phase graph

Immediate peak. This curve starts low and peaks within the first 10 problems that are solved and remains low afterwards; see figure 4. This curve is characterized by one peak. We found 74 immediate peaks, of which 26 were found for the easy skill, 42 for the intermediate skill and 6 for the hard skill. Again there was an interaction with skill difficulty.

Figure 4. Immediate peak learning phase graph

The peaks of this curve occurred during pre-test or guided practice. The easy skill showed 3 peaks during the pre-test and 23 during guided practice. The intermediate skill displayed 12 peaks during pre-test, 27 during guided practice and 3 during repeated adaptive practice. The difficult skill demonstrated 4 peaks during pre-test, 2 during guided-practice.

We expect that students who appeared to learn during pre-test are not in need of teacher regulation whereas those that learned during guide practice are. Independent sample t-tests indeed showed that the immediate peak pre-test group is significantly different from the immediate peak guided practice group on prior knowledge $t(78)= 4.55$, $p=.001$, the number of problems solved $t(81)= -2.39$, $p=.019$ and the accuracy on problems solved $t(81)= 1.03$, $p=.023$ and number of problem solving attempts $t(81)= 4.03$, $p=.001$. The immediate peak pre-test group showed higher pre-test ($M=7.31$ $SE=1.56$) than the immediate peak guided practice group($M=5.53$ $SE=1.21$), they made less problems ($M=53.55$ $SE=18.35$) vs. ($M=65.05$ $SE=18.55$) and showed higher accuracy both on problems solved ($M=.96$ $SE=.09$) vs ($M=.94$ $SE=.04$) and problem solving attempts ($M=.86$ $SE=.11$) vs ($M=.76$ $SE=.07$). Hence indeed although students in both groups are capable of self-regulated learning these groups have differential needs for SRL support.

Double Spikes. This curve starts low and shows 2 peaks over the course of problem solving, as shown in figure 5. We found 54 double peaks, 4 for the easy skill, 25 for the intermediate and 25

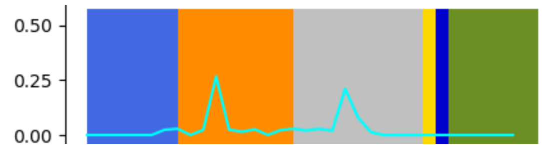

Figure 5. Double spikes learning phase graph

For the hard skill. For the easy skill, the 4 peaks that were found had diverse patterns of peaks during pre-test, guided practice and non-adaptive practice. For the intermediate skill, 2 curves had two peaks during the pre-test and 17 curves had a first peak during the pre-test and the second peak during guided practice. Moreover, 6 curves had 2 peaks during guided practice. For the difficult skill we found 2 curves with a first peak during the pre-test and a second peak during guided practice, and 11 curves with 2 peaks during guided practice. Moreover, 4 curves with peaks in guided practice and non-adaptive practice and 4 curves combining peaks in guided and adaptive practice were found.

Hence students showing double spikes showed their peaks early on during learning. The majority of the students (n=19) showed a first peak during pre-test and a second peak during guided practice. Another 17 students showed both peaks during guided practice. The remaining students showed diverse patterns, but only 4 students continued to show peaks during adaptive practice. This indicates that most students were in need of teacher regulation.

Close multiple spikes. The curve starts low, shows more than 2 peaks within the first 25 problems and remains low afterwards, as shown in figure 6. We found 50 close multiple spikes in total,

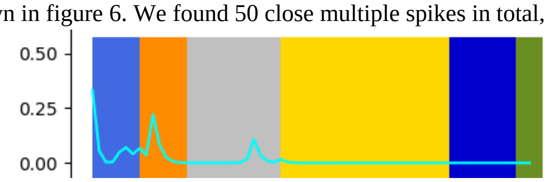

Figure 6. Close multiple spikes learning phase graph

5 for the easy skill, 6 for the intermediate skill and 39 for the hard skill. There was significant variation in where peaks occurred among students showing this curve, yet all students experienced multiple moments of learning: 29 students showed 3 peaks, 14 students had 4 peaks and 5 students had 5 peaks. 25 students showed multiple peaks during the pre-test and guided practice and for 16 students multiple peaks continued during non-adaptive practice. Only a small proportion of the students (n=5) continued to show peaks during adaptive practice.

These results indicate that not all students were in need of system support. Two groups can be distinguished, those that only show peaks in the lesson phases before non-adaptive practice, and those that continue to show peaks during non-adaptive practice.

Students who appeared to learn during guided practice are not in need of system regulation whereas those that continue to show peaks during non-adaptive practice are likely to benefit from system regulation. Independent sample t-tests showed that the close multiple spikes guided practice group is significantly different from the close multiple spike non-adaptive practice group on prior knowledge $t(43)= 2.51$, $p=.016$, and the accuracy on problems solved $t(45)= 2.07$, $p=.009$ and number of problem solving attempts $t(45)= 2.93$, $p=.005$. The close multiple spikes guided practice showed higher pre-test ($M=1.96$ $SE=1.58$) than the close multiple spike non-adaptive practice group($M=.84$ $SE=1.30$), and showed higher accuracy both on problems solved ($M=.85$ $SE=.09$) vs ($M=.76$ $SE=.14$) and problem solving attempts ($M=.66$ $SE=.10$) vs ($M=.56$ $SE=.14$). This supports the claim that although, students in both groups are showing similar MbMLC these groups do have differential needs for SRL support.

Separate multiple spikes. This curve starts low and continues to show multiple peaks even after 25 problems, as shown in figure 7. We found 34 separate multiple spikes in total: 2 for the easy skill, 12 for the intermediate skill and 20 for the hard skill.

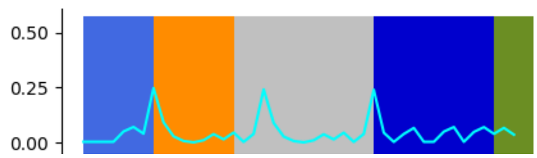

Figure 7. Separate multiple spikes learning phase graph

The number of peaks ranged from 3 peaks to 17 peaks. 7 students showed peaks until adaptive practice, 18 had peaks during adaptive and repeated adaptive practice and 10 students continued to show peaks even during the post-test. As such, these students continue to show difficulties during all lesson phases and some even seemed to improve during the post-test. Investigating the properties of the separate multiple spike adaptive practice group versus the separate multiple spike posttest group showed no clear difference on the learning, effort or accuracy indicators. Hence, students showing separate multiple spikes appear to be experiencing problems regulating their learning in all learning phases.

We can conclude that although the occurrence of curves is different for different skills, the distribution of peaks does not seem to be impacted systematically by skill difficulty. Figure 8 shows when the last peak occurred for each MbMLC (3 curves per student). For immediate drop, we see that all students have their drop right at the start during pre-test. Students showing immediate peaks show the last peak either during the pre-test or guided practice, with implications for their SRL support needs. Double peaks occur mostly during mostly guided practice but also occur during other learning phases. For close multiple spikes, the last peak is divided over two groups, with some students encountering their last peak during guided practice and others encountering it during non-adaptive practice. These groups are in need of different SRL support. Lastly, peaks in separated multiple spikes occur mostly during adaptive practice but can even occur during the post-test.

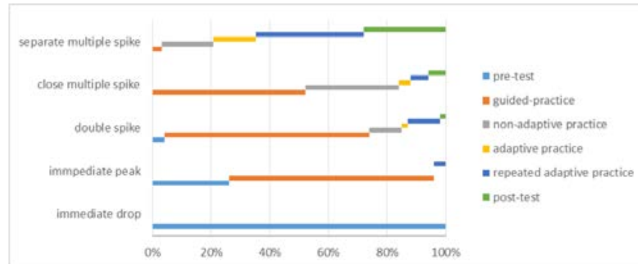

Figure 8: Last peaks in MbMLC

4.2 Groups with different SRL support needs

Based on the results above, the explore how the positioning of peaks implies the need for SLR support. We distinguish 4 groups with differential needs for SRL support. Below we describe the groups, their classification based on learning path graphs and associations with learning, effort and accuracy indicators.

Self-regulated learning (SRL) group. This group consists of students showing immediate drops and immediate peaks during the pre-test. For students showing immediate drops, the graphs indicated that students already knew the skill at pre-test, which is in line with high prior knowledge. Accordingly, accuracy was high and students' number of problem solving attempts was low. These indicators also confirm that there is little need for external regulation by the teacher or the system for these students. For students showing an immediate peak during pre-test, the graphs indicated that these students learned on their own without support from the teacher. Although both groups of students learned quickly, there are indeed differences between these groups on the pre-test, in terms of the number of problems solved and accuracy. Hence this indicates the groups regulate their learning differently and may require a slightly different support.

The teacher regulation group. This group includes students showing immediate peaks during guided practice, double spikes and close multiple spikes during guided practice. The majority of immediate peak curves showed a peak during guided practice. These students learned quickly and showed high to moderate post-test scores and transfer scores. The immediate peak was associated with low prior knowledge (pre-test scores) indicating that students did not know the skill in advance, and high post-test knowledge, learning gains and transfer scores, indicating effective learning. This curve was associated with relatively high accuracy, students were able to regulate their learning to maintain reasonably high performance within the system. This suggests these students benefitted from the teachers' regulation and learned successfully thereafter.

Within students showing double spikes there was variation in when peaks occurred, including during guided practice, non-adaptive, adaptive and repeated adaptive practice. The majority of the graphs indicated that students quickly learned the skill during guided practice. These curves were associated with low prior knowledge, moderate post-test knowledge, relatively high transfer and moderate learning gains. At the same time, the accuracy was moderate. This is in line with the view that these students are dependent on the teachers' regulation and that they learned during practice.

A proportion of students showing close multiple spikes students also fall in the teacher regulation group, as their multiple peaks also occurred during guided practice. Although close multiple spikes were associated with low prior knowledge, moderate post-knowledge, relatively high transfer and moderate learning gain and accuracy, this group showed higher pre-test and accuracy than students who continued to show spikes during non-adaptive practice. These students also appeared to benefit from the teachers' instruction and practice to master the skill.

System regulation group. This group constitutes of the second group showing close multiple spikes, who continue to have peaks during non-adaptive practice. The pattern seems to indicate that these students were in need of extensive practice. Close multiple spikes were associated with low prior knowledge, moderate post-test knowledge, relatively high transfer and moderate learning gain and accuracy. These students appeared to need both teacher regulation and system regulation to learn the skill. Contrary to our expectations, system regulation only appeared to support some of the students showing close multiple spikes. Hence, practice is key for all students showing close multiple spikes, but system regulation is not always useful. Our earlier hypothesis that these students tend to benefit from system regulation is only partially supported.

Advanced system regulation group. All students showing separated multiple spikes fit in this group. These students only partially learn the skill, indicated by moderate to low post-knowledge, moderate to low learning gain and low transfer. These students' peaks occurred during all phases and even during and after adaptive practice, which indicates that most students continue to face challenges even with system support. These students show multiple fluctuations in performance, low accuracy and an increased number of problem solving attempts. Students showing separated multiple spikes relied heavily on external regulation both by the teacher and the system. Most of these students need additional support. Our earlier hypothesis that these students tend not to benefit from system regulation is mostly supported.

4.3 Implications for SRL support

Personal visualizations function as a reference for students to better understand how they regulate their learning. The relation between learning actions and accuracy serves as a reference for students to understand their progress toward learning goals. In order for students to understand how to act on these personal visualizations it is important to provide feedback. In table 5, we provide potential feedback for each of the groups.

Table 5. Potential actionable feedback for students based on their learning path graphs

Groups		**Feedback**
SRL group	Immediate drop	You already know this skill. Please practice a different skill.
	Immediate peak	You have learned this skill quickly. You can practice until you have reached proficiency and then continue on the next skill.
Teacher regulation group	Immediate peak	You have learned this skill quickly. You can practice until you have reached proficiency and then continue on the next skill.
	Double Spikes	You have learned this skill in two stages. Please monitor your accuracy and practice until you have reached proficiency.
	Close multiple spikes	You are learning this skill somewhat slowly. Please monitor your accuracy and continue to practice until you have reached proficiency.
System regulation group	Close multiple spikes	You are learning this skill somewhat slowly. Please continue to practice in adaptive mode until you have reached proficiency.
Advanced system regulation group	Separate multiple spikes	You are learning this skill somewhat slowly. Please continue to practice in adaptive mode and if you cannot master this skill please notify your teacher.

We expect that personal visualizations will positively affect students in the SRL and Teacher regulation group. For students in the system and the advanced system regulation group, the translation of feedback into appropriate learner actions might be too demanding. For this group we propose a more integrated type of support that is less dependent on student' own actions and compliance. For these students we envision hybrid human-system regulation, which is typified by fluctuating boundaries between student and system control. System regulation can take over a large part of the regulation until the student is ready to self-regulate. One way to implement this additional system regulation is by selecting easier problems; within this system, this goal can be accomplished by increasing the desired probability that a student will solve the problem correctly. When this is set at 85% as opposed to the current 75% this automatically further reduces the difficulty of the problems given to the student which is likely to improve performance. After a number of success experiences, the difficulty level can be increased to see if students are able to maintain their higher performance.

5 CONCLUSIONS

This paper examined students' needs for self-regulated learning (SRL) support and defined design elements for new SRL support based on student data. Learning phases in blended classrooms place unique requirements on students' regulation and hence can be studied in order to better understand students' needs for SRL support. In order to analyze students' needs, learning path graphs were introduced, combining MbMLC and learning phase data. The results suggested that students showing immediate drops probably already knew the skill at the pre-test. Students with immediate peaks mostly showed the peak during guided practice and were able to regulate their accuracy after initial teacher regulation. Students with double spike graphs showed two peaks, mostly during guided practice and non-adaptive practice. These students needed teacher regulation and additional practice to acquire the skill, but are mostly able to regulate their learning to a reasonable level. Students showing close multiple spikes were divided in two groups: those that showed several fluctuations during guided practice only and those that continued to show fluctuations during non-adaptive practice. Whereas the first group only needed teacher regulation and practice opportunities, the second group benefited from system regulation. Finally, separate multiple spikes indicate continued fluctuations throughout all learning phases. These students were in need of more support than the current level of system regulation.

For immediate drop, double spikes and separate multiple spikes the student' SRL support needs were indicated by the form of MbMLC. Immediate peaks and close multiple spikes showed more complex interactions between the learning phases and in these cases learning path graphs provided additional information about the support needs of students. This indicates that the integration of MbMLC and learning phases into a single visualization can be considered a fruitful approach to further understand student' learning and needs for regulatory support in these technology enhanced learning contexts.

These insights helped to specify four groups with distinct SRL support needs. The SRL group seemed to over-practice and can optimize their learning efficiency by earlier transition to the next skill. The teacher regulation groups were able to self-regulate, but appeared to contain three independent groups that need increasing amounts of attention to maintain high performance. The system regulation group was clearly in need of additional system regulation and should aim to transition to adaptive problem solving quickly. Finally the advanced system regulation group needed high levels of system regulation, perhaps more than is currently available in the system.

Two new types of regulation support based on learner data are specified with additional design requirements for the four different groups. The first type is classified as an extracted learning analytics approach and proposes to use learning path graphs as personalized visualizations to support students' SRL. Actionable feedback for different groups of students was further specified based on the insights of this study. The second type takes an embedded approach by using the learning groups to adjust system regulation in ALTs to the specific needs of students. This hybrid human-system regulation appears to be especially needed for the advance system regulation group, but other groups may also benefit from using learning path graph indicators to govern transfers of control between system and human control of regulation.

To conclude, we proposed that personalized visualizations with feedback appear to have the potential to enhance outcomes for both the SRL and Teacher regulation groups. By contrast, the two system regulation groups are expected to benefit from human-system regulation that takes over parts of the regulation until the student is ready to exert more control over their learning. By tailoring feedback and support to learner needs, we can help learners who are ready to develop their self-regulated learning skills, and help all learners to develop their understanding of key mathematics skills.

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