Coherence Over Time: Understanding Day-to-Day Changes in Students' Open-Ended Problem Solving Behaviors

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Abstract. Understanding students' self-regulated learning (SRL) behaviors in open-ended learning environments (OELEs) is an on-going area of research. Whereas OELEs facilitate use of SRL processes, measuring them reliably is difficult. In this paper, we employ *coherence analysis*, a recently-developed approach to analyzing students' problem solving behaviors in OELEs, to study how student behaviors change over time as they use an OELE called *Betty's Brain*. Results show interesting patterns in students' day-to-day transitions, and these results can be used to better understand the individual student's characteristics and the challenges they face when learning in OELEs.

Keywords: open-ended learning environments, coherence analysis, self-regulated learning, temporal analysis

1 Introduction

Open-ended computer-based learning environments (OELEs) [1-2] are learner-centered; they present students with a challenging problem-solving task, information resources, and tools for completing the task. Students must use the resources and tools to construct and verify problem solutions, and in this process learn about the problem domain and develop their general problem-solving abilities. In OELEs, students have to distribute their time and effort between exploring and organizing their knowledge, creating and testing hypotheses, and using their learned knowledge to create solutions. Since there are no prescribed solution steps, students may have to discover the solution process over several hours. For example, learners may be given the following:

> *Use the provided simulation software to investigate which properties relate to the distance that a ball will travel when rolled down a ramp, and then use what you learn to design a wheelchair ramp for a community center.*

Whereas OELEs support a constructivist approach to learning, they also place significant cognitive demands on learners. To solve the overall problem, students must simultaneously wrestle with their emerging understanding of a complex topic, devel-

adfa, p. 1, 2011.

op and utilize skills to support their learning, and employ *self-regulated learning* (SRL) processes to manage the open-ended nature of the task. SRL is a theory of learning that describes how learners actively set goals, create plans for achieving those goals, continually monitor their progress, and revise their plans when necessary to continue to make progress [3]. As such, OELEs can *prepare students for future learning* [4] by developing their ability to independently investigate and develop solutions for complex open-ended problems.

This strong connection between self-regulation and OELEs make these environments ideal for studying SRL, an important research topic in the educational technology research community (*e.g.*, [5]). The open-ended nature of the environment forces students to make choices about how to proceed, and these choices reveal information about students' understanding of: (i) the problem domain; (ii) the problem-solving task; and (iii) strategies for solving the problem. By studying these choices, we can gain a better understanding of how students regulate their learning and how best to design scaffolds to support students who struggle to succeed.

In this paper, we employ *coherence analysis* (CA) [6] to study students' problem-solving behaviors. CA analyzes learner behaviors in terms of their demonstrated ability to seek out, interpret, and apply information encountered while working in the OELE. By characterizing behaviors in this manner, CA provides insight into students' problem-solving strategies as well as the extent to which they understand the nuances of the learning and problem solving tasks they are currently completing. We extend our previous work by applying coherence analysis to study how students' behaviors change over time as they use an OELE called *Betty's Brain* [7]. Results show interesting patterns in students' day-to-day behavior transitions, and these results provide insight into how students regulate their learning over an extended period of time.

2 Background

A comprehensive approach to measuring students' self-regulation in real time is difficult; it requires detecting aspects of goal setting, planning, monitoring, and reflection from the actions students take in the learning environment. In OELEs, this involves assessing learners' skill proficiencies, interpreting their actions in terms of goals and learning strategies, and evaluating their success in accomplishing their tasks. The open-ended nature of OELEs further exacerbates the measurement problem: since OELEs are learner-centered, they typically do not restrict the approaches that learners take to solving their problems. Thus, interpreting and assessing students' learning behaviors is inherently complex; they may pursue, modify, and abandon any of a large number of approaches they adopt for completing their tasks.

Despite this complexity, researchers have developed several approaches to measuring aspects of self-regulation in OELEs. For example, several OELEs measure SRL by developing a predictive data-driven model for diagnosing constructs related to SRL in real time. In some OELEs, such as Crystal Island [8] and EcoMUVE [9], models have been created by first employing human coding to label students' log data with aspects of SRL and then using that labeled data to construct predictive models.

For example, Sabourin et al. [8] asked students to author "status updates" at regular intervals while using Crystal Island. These updates were later coded according to whether or not they included evaluations of the student's progress toward a goal, and this coded data was used to build a predictive model of good vs. poor self-regulation.

In other OELEs, researchers have developed theory-driven models of SRL and embedded those models into learning environments. For example, Snow, Jackson, & McNamara [10] measured the order and stability of students' behavior patterns as they used iSTART-ME, a science learning environment for helping students improve their science comprehension. In their model, lower levels of Shannon Entropy were interpreted as indicative of ordered and self-regulated behaviors.

Coherence analysis (CA) is also a theory-driven technique for modeling learning behaviors in OELEs. CA focuses on students' ability to seek, interpret, apply, and verify information within the OELE. In doing so, CA models aspects of students' problem-solving skills and metacognitive abilities. The approach is designed to be general, and should allow researchers to study the coherence aspect of SRL in multiple learning environments. A more in-depth presentation of coherence analysis appears in Section 4.1 and in [6].

3 Betty's Brain

Betty's Brain [6-7] presents the task of teaching a virtual agent, Betty, about a science phenomenon (e.g., climate change) by constructing a causal map that represents that phenomenon as a set of entities connected by directed links representing causal relationships. Once taught, Betty can use the map to answer causal questions. The goal for students is to construct a causal map that matches an expert model of the domain.

In *Betty's Brain*, students acquire domain knowledge by reading resources that include descriptions of scientific processes (*e.g.*, shivering) and information pertaining to each concept that appears in the expert map (*e.g.*, friction). As students read, they need to identify causal relations such as "*skeletal muscle contractions create friction in the body.*" Students can then apply this information by adding the entities to the map and creating a causal link between them (which "teaches" the information to Betty). Learners are provided with the list of concepts, and link definitions may be either increase (+) or decrease (-).

Learners can assess their causal map by asking Betty to answer questions and explain her answers. To answer questions, Betty applies qualitative reasoning to the causal map (*e.g., the question said that the hypothalamus response increases. This causes skin contraction to increase. The increase in skin contraction causes…*) [7]. After Betty answers a question, learners can ask Mr. Davis, another pedagogical agent that serves as the student's mentor, to evaluate her answer. If Betty's answer and explanation match the expert model (*i.e.*, in answering the question, both maps utilize the same causal links), then Betty's answer is correct.

Learners can also have Betty take *quizzes* (by answering sets of questions). Quiz questions are selected dynamically by comparing Betty's current causal map to the expert map such that a portion of the chosen questions, in proportion to the completeness of the current map, will be answered correctly by Betty. The rest of her quiz answers will be incorrect or incomplete, helping the student identify areas for correction or further exploration. When Betty answers a question correctly, students know that the links she used to answer that question are correct. Otherwise, they know that at least one of the links she used to answer the question is incorrect. Students may keep track of correct links by annotating them as such.

4 Classroom Study

The data presented in this paper comes from a study of students using *Betty's Brain* over a period of approximately six weeks covering two instructional units: climate change and thermoregulation. This paper focuses on the second unit only. Additional details of this study can be found in [6].

Ninety-nine 6th grade students from four middle Tennessee science classrooms participated in the study. However, one student was excused from the study due to an unrelated injury. Students used *Betty's Brain* to learn about human thermoregulation when exposed to cold temperatures. The expert map contained 13 concepts and 15 links representing cold detection and three bodily responses to cold: goose bumps, vasoconstriction, and shivering. The resources were organized into 15 pages (1,974 words) with a Flesch-Kincaid reading grade level of 9.0.

Betty's Brain generates event logs that capture every action taken by the student, Betty, and Mr. Davis. Actions correspond to atomic expressions of intent (*e.g.*, adding a causal link). In addition, the logs contain information on every view that was displayed while the system was running. A view captures the information visible to a user during a specific time interval. To analyze these logs, we first divided students' data into per-day sequences of actions and views, resulting in 395 student-days. We then removed all particularly short (< 30 minutes) and long (> 60 minutes) student-days to control for outliers, reducing the dataset to 332 student-days. For each student-day, we calculated a measure of task performance as the change in map score during the day. The *map score* at any point in time is calculated as the number of correct links (*i.e.*, links that appear in the expert map) minus the number of incorrect links in the student's map.

4.1 Learning Behavior Analysis

To analyze learners' behaviors in *Betty's Brain*, we employed our coherence analysis (CA) approach [6] that combines information from sequences of student actions to produce measures of *action coherence*. CA interprets student behaviors in terms of the information they encounter in the system and whether or not this information is utilized during subsequent actions. When students come into contact with information that can help them improve their current map, they have *generated potential* that should *motivate future actions*. The assumption is that if students can recognize relevant information in the resources and quiz results, then they should act on that information. Otherwise, CA assumes that they did not recognize or understand its relevance. This may stem from incomplete or incorrect understandings of the science topic, the learning task, and/or strategies for completing the learning task. Additionally, when students edit their map when they have not encountered information that could motivate the edit, CA assumes that they are guessing[1].

More formally, two ordered actions are *action coherent* if the second action is based on information generated by the first action. In this case, the first action *provides support* for the second action, and the second action is *supported* by the first action. Note that these two actions need not be consecutive. CA assumes that learners with higher levels of coherence possess stronger understandings of the problem-solving task and strategies for solving the problem. In studying students' coherence in *Betty's Brain*, we have focused on three primary action coherence relations: (1) accessing a resource page that discusses two concepts *provides support* for adding, removing, or editing a causal link that connects those concepts, *regardless* of whether or not these edits improve the causal map; (2) viewing assessment information (usually quiz results) that proves that a causal link is correct *provides support* for annotating that link as being correct; and (3) viewing assessment information (usually quiz results) that proves that a causal link is incorrect *provides support* for deleting it.

Student behaviors were described by the following CA-derived metrics, which are explained in more detail in [6]: (i) *edit frequency*, the number of causal link edits / annotations made by the student per minute; (ii) *unsupported edit percentage*, the percentage of unsupported causal link edits / annotations not supported by previous views within a five-minute window; (iii) *information viewing percentage*, the percentage of time the student spent viewing resources and quiz results; (iv) *potential generation percentage*, the percentage of the information viewing time spent viewing information that could support causal map edits that would improve the map score; (v) *used potential percentage*, the percentage of potential generation time associated with views that both occur within a five minute window of and also support an ensuing causal map edit; and (vi) *disengaged percentage*, the proportion of time students spent *not measurably engaged* with the system. *Disengaged time* is defined as the sum of all periods of time, at least five minutes long, during which the student neither viewed a source of information for at least 30 seconds nor edited the map. We have previously used these measures to study overall characteristics of students' problem-solving approaches in *Betty's Brain* [6]. In this paper, we extend our work to study how student behaviors (assessed by the coherence metrics) change on a day-by-day basis. We hypothesize that students' problem-solving approaches will fluctuate as they use the system, and that the nature of these fluctuations provides insight into how to develop adaptive supports for individual student learning.

To test these hypotheses, we characterize common behavior profiles exhibited during the student-days with an unsupervised machine learning approach. Specifically, we clustered student-days with a complete-link hierarchical clustering algorithm [11], where each student-day was described by the CA metrics. Euclidean distance between students' normalized CA metrics was used as the measure of dissimilarity among

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[1] Students may be applying their prior knowledge, but the assumption is that they are novices to the domain and should verify their prior knowledge during learning.

pairs of students. After characterizing student-days by these clusters, we reconstituted them into the specific sequence of days exhibited by each student. Using these day sequences, we calculated the number of transitions observed between each possible student-day characterization. In order to identify especially common and uncommon transitions in students' day-to-day problem solving behaviors, we compared the observed frequency of each possible transition to the expected frequency from a baseline independent random model of transitions. This random model assumes that the characterization of any student-day is independent from all others. Specifically, in this model the probability of any student-day being characterized as a specific cluster is the a priori probability of that cluster (approximated by the observed cluster frequency out of all student-days) without respect to previous (or future) days for the student. This allows us to identify the more important transitions characterizing day-to-day behavior by their deviation from the random model, analogous to the analysis of associations in other domains using the *lift* measure [12].

5 Results

The clustering analysis revealed four high level clusters among the 332 student-days, three of which split into two more specific clusters. Table 1 shows the CA metrics for all clusters. Cluster 1 student-days (n = 52) may be characterized as students who were strategic experimenters but struggling readers. On these days, students edited their maps often, but most of these edits were unsupported. They spent 1/3 of their time viewing information, but a majority of this time (67.6%) generated no potential. This cluster contained three student-days (Cluster 1-2) that corresponded to complete disengagement from the task. These students rarely viewed information, never generated any potential, and spent an average of 37.5% of their time in a disengaged state.

Cluster 2 student-days (n = 119) are characterized by engaged, effective, and strategic behaviors. Students on these days performed several supported map edits. They spent 1/3 of their time viewing sources of information, and most of this time generated potential (77.5%) that was later used (83.5%). These students were rarely disengaged from the task. Cluster 3 student-days (n = 74) may be characterized as researchers and careful editors. Students on these days spent large proportions of their time (46.4%) viewing sources of information but did not edit their maps very often. The edits these students made were usually supported (76.2%) and most of the information they viewed was useful for improving their causal maps (potential generation percentage = 64.2%). However, they often did not take advantage of this information (used potential percentage = 47.7%). A subset of these student-days (Cluster 3-1, n = 39) may be better characterized as inconsistently engaged students who spent less time viewing information but generated and used proportionally more potential compared to the rest of the student-days in Cluster 3 (*i.e.*, Cluster 3-2). Additionally, these student-days showed much higher levels of disengagement (25.3%).

Cluster 4 student-days (n = 83) are characterized by confusion and disengagement. Students on these days performed high proportions of unsupported edits (80.3%), used little of the potential they generated (28.7%), and spent a large proportion of their time disengaged (16.3%). Cluster 4-1 student-days (n = 65) are more characteristic of confused students, as students on these days were rarely disengaged from learning (7.3%), and Cluster 4-2 student-days (n = 18) are more characteristic of disengaged students.

Table 1. Means (and standard deviations) of CA-derived metrics by cluster

Cluster	Edit Freq.	Unsup. Edit %	Info. View %	Potential Gen. %	Used Potential %	Disengaged %
1. Strategic Experimenters / Struggling Readers (n = 52)	0.58 (0.29)	65.5% (20.4%)	35.6% (15.7%)	32.4% (15.4%)	78.9% (14.5%)	8.8% (11.7%)
1-1. Strategic Experimenters / Struggling Readers (n = 49)	0.60 (0.28)	64.2% (19.5%)	37.5% (14.0%)	34.3% (13.6%)	78.9% (14.5%)	7.0% (9.5%)
1-2. Disengaged (n = 3)	0.34 (0.25)	100.0% (0.0%)	4.4% (2.0%)	0.0% (0.0%)	-----	37.5% (4.9%)
2. Engaged, Effective, Strategic (n = 119)	0.86 (0.44)	45.3% (22.6%)	35.3% (13.7%)	77.5% (14.5%)	83.5% (12.3%)	4.2% (9.5%)
3. Researchers / Careful Editors (n = 74)	0.27 (0.19)	23.8% (21.3%)	46.4% (17.4%)	64.2% (17.5%)	47.7% (24.9%)	14.6% (14.4%)
3-1. Inconsistently Engaged (n = 39)	0.28 (0.18)	25.7% (21.0%)	34.9% (8.7%)	68.2% (17.2%)	57.3% (21.8%)	25.3% (11.0%)
3-2. Researchers / Careful Editors (n = 35)	0.25 (0.20)	21.6% (21.4%)	59.3% (15.5%)	59.7% (16.8%)	36.9% (23.7%)	2.6% (5.7%)
4. Confused / Disengaged (n = 83)	0.41 (0.30)	80.3% (15.9%)	34.4% (16.8%)	58.5% (23.3%)	28.7% (21.9%)	16.3% (20.1%)
4-1. Confused (n = 65)	0.45 (0.30)	78.8% (15.4%)	38.6% (15.7%)	58.6% (22.6%)	31.4% (21.8%)	7.3% (9.6%)
4-2. Disengaged (n = 18)	0.26 (0.22)	86.6% (16.0%)	19.1% (10.1%)	57.8% (25.6%)	18.4% (18.9%)	48.5% (14.1%)

Table 2 shows the change in map scores by cluster. In general, there are wide variations within each cluster, indicating that student-days within clusters resulted in varying levels of success. However, the days characterized as engaged, effective, and strategic resulted in much larger changes in map scores when compared to all other clusters. Because previous research has shown that map scores in *Betty's Brain* usually follow a non-normal distribution, we tested for differences in map score changes among the clusters using a Kruskal-Wallis H test. The test identified a statistically significant difference in map scores between the clusters (χ^2 = 40.15, p < 0.001). Follow-up Mann-Whitney tests between the groups showed that cluster 2 student-days resulted in significantly higher changes in map scores when compared to all other clusters except for cluster 1-2. No other significant differences were found between the remaining clusters. These results show that when students exhibited higher levels of coherence, they also made more progress in teaching Betty the correct map. It is important to remember that coherent behaviors are not always correct behaviors: an incorrect causal map edit is still coherent if it is supported by previous reading.

Table 2. Means (and standard deviations) of map scores by cluster

Cluster	1-1	1-2	2	3-1	3-2	4-1	4-2
Map Score Change	-0.57 (5.71)	-1.00 (5.57)	2.92 (4.73)	-0.13 (4.02)	-0.03 (2.91)	-0.63 (4.33)	-0.67 (3.34)

To understand how students' behaviors changed over time, we analyzed their day-to-day transitions by grouping student-days into sequences of days performed by individual students. These sequences show how students' problem-solving behaviors changed on a day-to-day basis. Table 3 shows the frequency of all day-to-day transitions made by students with the ratio (in brackets) of the observed frequency of that transition to the frequency expected from a baseline random transition model[2]. For example, the table shows that there were 14 instances of a student moving from cluster 1-1 to cluster 2, which is roughly the frequency predicted by the random transition model (a ratio of 1.1 : 1). Further, transitions to the same cluster are italicized and the five highest and five lowest transition ratios across different clusters (with respect to the random transition model) are shown in bold.

The results of this analysis show several interesting trends. First, transitions to the same cluster were more common than expected from a random transition model for all clusters. This suggests there is some stability to these characterizations of student activities that can persist from day to day. In particular, students characterized as engaged, effective, & strategic (cluster 2) were likely to exhibit similar behaviors the next day (45 out of 78, 150% vs. random) but were relatively less likely (with respect to the random transition model) to become confused (10 of 78, 60% vs. random) or any other characterization except inconsistently engaged (10 of 78, 100% vs. random). Further, all other clusters are less likely to transition to engaged, effective, & strategic, except the strategic experimenters / struggling readers (cluster 1-1).

At the opposite end of the spectrum, students who are characterized as confused or disengaged (clusters 4-1 and 4-2) were likely to remain confused or disengaged during the next day (22 of 55) and much less likely to become engaged, effective, and strategic (11 of 55, 50% vs. random from the confused cluster). Further, over one third of the days in which students were characterized as researchers / careful editors (cluster 3-2) were followed with a transition to the confused cluster (12 of 31, 250% vs. random) and also relatively more likely to transition to inconsistently engaged (6 of 31, 210% vs. random). These students were also the least likely to transition into the engaged, effective, and strategic cluster (4 of 31, 40% vs. random). This illustrates a behavior profile *at risk* for confusion and disengagement. Perhaps by properly scaffolding students exhibiting this behavior, we can prevent them from becoming con-

[2] Rare transitions that only occurred for 2 or fewer students are marked [NA] in Table 3.

fused or disengaging from the task. An important caveat of this analysis is the small number of instances of many transitions in Table 3. Additional data will be needed to further support these observations.

Table 3. Frequency of day-by-day cluster transitions [and ratio with respect to random].

Cluster	1-1	1-2	2	3-1	3-2	4-1	4-2
1-1. Strat. Experim. / Struggling Readers	*8* *[1.6]*	0 [NA]	14 [1.1]	2 [NA]	6 [1.6]	7 [1.0]	**4** **[2.1]**
2. Engaged, Effective, Strategic	**7** **[0.6]**	0 [NA]	*45* *[1.5]*	10 [1.0]	**5** **[0.6]**	**10** **[0.6]**	1 [NA]
3-1. Inconsistently Engaged	3 [0.7]	0 [NA]	7 [0.7]	*6* *[1.8]*	3 [1.0]	2 [NA]	**3** **[2.0]**
3-2. Researchers / Careful Editors	2 [NA]	0 [NA]	**4** **[0.4]**	**6** **[2.1]**	*6* *[2.3]*	**12** **[2.5]**	1 [NA]
4-1. Confused	8 [1.2]	0 [NA]	**9** **[0.5]**	5 [0.9]	5 [1.0]	*10* *[1.1]*	4 [1.6]
4-2. Disengaged	0 [NA]	3 [NA]	2 [NA]	1 [NA]	0 [NA]	**5** **[2.0]**	*3* *[NA]*

6 Discussion and Conclusions

In this paper, we presented an analysis of students' day-to-day problem solving approaches in *Betty's Brain* [7] using coherence analysis [6]. The results showed that, taken all together, students' day-to-day problem solving behaviors varied considerably, but in well-defined ways (when compared against random). By understanding these shifts, we may be able to identify opportunities to scaffold students in order to prevent them from transitioning into confusion and disengagement.

For example, the cluster transition analysis showed that students were more likely than expected to transition from researcher/careful editor behaviors to both confused and inconsistently engaged behaviors. This suggests a need to scaffold students who begin to exhibit the researcher/careful editor behavior profile for a sufficiently long period of time. Recognizing these behavior profiles based on problem solving activities will help us design better scaffolds that can be delivered at opportune moments to avoid extended confusion, disengagement, and frustration.

Our recent findings in [6] show the promise of coherence analysis by demonstrating possible links between coherent behavior, prior ability, learning, and success in *Betty's Brain* [6]. The findings in this paper further demonstrate the value of coherence analysis in *Betty's Brain*, but the approach is designed to be general; it should apply to OELEs beyond this one. Overall, these analyses help us understand nuances of how students approach open-ended problem solving. In Table 3, for example, we see 10 instances of students who transitioned from engaged, effective, and strategic one day to confused the next day. Similarly, there were 9 instances of students transitioning from confused one day to engaged, effective, and strategic the next day. The causes of these transitions and their relation to research on how students respond to confusion (*e.g.* [13]) needs further study. We hope this will lead to better understanding of SRL processes and how they can be developed in novice learners through proper scaffolding and support.

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References

1. Land, S., Hannafin, M., Oliver, K.: Student-centered learning environments: Foundations, assumptions and design. In: D. Jonassen & S. Land (eds.) Theoretical Foundations of Learning Environments, pp. 3-25. Routledge, New York, NY (2012)
2. Segedy, J.R., Biswas, G., Sulcer, B.: A model-based behavior analysis approach for open-ended environments. The Journal of Educational Technology & Society, 17(1), 272-282 (2014)
3. Zimmerman, B., Schunk, D. (eds.): Handbook of Self-Regulation of Learning and Performance. Routledge , New York, NY (2011)
4. Bransford, J., Schwartz, D.: Rethinking transfer: A simple proposal with multiple implications. Review of Research in Education, 24(1), 61-101 (1999)
5. Winters, F., Greene, J., Costich, C.: Self-regulation of learning within computer-based learning environments: A critical synthesis. Educational Psychology Review, 20(4), 429-444 (2008)
6. Segedy, J.R., Kinnebrew, J.S., Biswas, G.: Using coherence analysis to characterize self-regulated learning behaviours in open-ended learning environments. Journal of Learning Analytics (in press)
7. Leelawong, K., Biswas, G.: Designing learning by teaching agents: The Betty's Brain system. International Journal of Artificial Intelligence in Education, 18(3), 181-208 (2008)
8. Sabourin, J., Shores, L., Mott, B., Lester, J.: Understanding and predicting student self-regulated learning strategies in game-based environments. International Journal of Artificial Intelligence in Education, 23, 94-114 (2013)
9. Baker, R.S.J.d., Ocumpaugh, J., Gowda, S.M., Kamarainen, A.M., Metcalf, S.J.: Extending log-based affect detection to a multi-user virtual environment for science. In: Dimitrova, V., Kuflik, T., Chin, D., Ricci, F., Dolog, P, Houben, G. (eds.), UMAP 2014. LNCS, vol. 8538, pp. 290-300. Springer International Publishing (2014)
10. Snow, E.L., Jackson, G.T., McNamara, D.S.: Emergent behaviors in computer-based learning environments: Computational signals of catching up. Computers in Human Behavior, 41, 62-70 (2014)
11. Jain, A., Dubes, R.: Algorithms for clustering data. Prentice Hall, Upper Saddle River, NJ (1988)
12. Brin, S., Motwani, R., Ullman, J. D., & Tsur, S.: Dynamic itemset counting and implication rules for market basket data. In Proceedings of the ACM SIGMOD International Conference on Management of Data, 26(2), 255-264 (1997)
13. Lehman, B., D'Mello, S., Graesser, A.: Confusion and complex learning during interactions with computer learning environments. The Internet and Higher Education, 15(3), 184-194 (2013)