Chapter 5
Improving Learning Style Identification by Considering Different Weights of Behavior Patterns Using Particle Swarm Optimization

Jason Bernard, Ting-Wen Chang, Elvira Popescu and Sabine Graf

Abstract Matching the course content to students' learning style has been shown to benefit students by improving their learning outcome, increasing satisfaction, and reducing the time needed to learn. Consequently, an accurate method for identifying these learning styles is of a high importance. Up to the present, there have been proposed several such methods that use students' behavior in online courses to automatically identify their learning style. However, the precision of existing approaches peaks at approximately 80 %, thus leaving room for improvement. This paper introduces a novel approach, which combines the advantages of artificial/computational intelligence and rule-based techniques. More specifically, a rule-based method is extended to consider the different weights of behavior patterns using a particle swarm optimization algorithm. The approach has been evaluated with 75 students, and results show improved performance over similar state-of-the-art methods. By identifying learning styles with higher precision, students can benefit from adaptive courses that are tailored more precisely to their actual learning styles and teacher can benefit by being able to provide students with more helpful interventions.

Keywords Particle swarm optimization · Felder-Silverman learning style model · Identification of learning styles · Learning management systems

J. Bernard (✉) · S. Graf
Athabasca University, Edmonton, Canada
e-mail: c.j.bernard@ieee.org

S. Graf
e-mail: sabineg@athabascau.ca

T.-W. Chang
Beijing Normal University, Beijing, China
e-mail: tingwenchang@bnu.edu.cn

E. Popescu
University of Craiova, Craiova, Romania
e-mail: popescu_elvira@software.ucv.ro

Y. Li et al. (eds.), *State-of-the-Art and Future Directions of Smart Learning*,
Lecture Notes in Educational Technology, DOI 10.1007/978-981-287-868-7_5

5.1 Introduction

Adapting the educational experience to students' preferences and needs is an important objective of current technology-enhanced learning systems. Learning style is one of the individual characteristics which need to be taken into account, as it encompasses the strategies and preferences used by a student to approach the learning process [1]. While there have been some controversy and open questions around this concept [2], numerous studies have shown that matching the course content to students' learning styles leads to benefits such as better performance, higher learning satisfaction and a reduction in the time needed to learn [3–5].

For example, Popescu [3] found that students' perceived learning satisfaction was higher in case they followed a course which matched their learning styles (as compared to a course that did not match their learning styles). In another study, Ford and Chen [4] obtained an absolute gain in quiz scores by matching learning materials to students' learning styles. Furthermore, Graf et al. [5] reported a decrease in the study time for active and sequential learners, when provided with a course that matched their learning styles.

In this context, in the current paper we focus on the identification of learning styles, as the first step toward providing the required adaptation. Among the many learning style models proposed in the literature, we selected the Felder-Silverman model (FSLSM) [1], due to several reasons. FSLSM uses four learning style dimensions: active/reflective (A/R), sensing/intuitive (S/I), visual/verbal (V/V), and sequential/global (S/G), with the assumption that each learner has a preference on each of the four dimensions. By using dimensions rather than types (as done in many other learning style models), students' preferences can be described more accurately and in more detail. Additionally, FSLSM treats learning styles as tendencies, rather than immovable characteristics. Another advantage of this model is the existence of a reliable measuring instrument, called Index of Learning Styles Questionnaire (ILS) [6]. As a result of the questionnaire, the learning style of the student is described on a scale between -11 and $+11$ (with steps of ± 2) for each FSLSM dimension; hence, the strength of the preference is determined as well. For all these reasons, FSLSM seems to be one of the most often used learning style models in technology-enhanced learning and some researchers have argued that this model is one of the best or even the best model to use in adaptive systems [7, 8].

While the ILS questionnaire has been found to be a reliable and valid instrument to identify learning styles [9], there are some significant drawbacks of using questionnaires in general. For example, filling in the questionnaire requires a supplementary amount of work from the part of the students and it may be difficult to motivate them to answer it carefully, without skipping questions or giving wrong answers on purpose. Besides being intrusive, the student's mood or perceived importance of the questionnaire may influence the outcome. Finally, since the same questionnaire cannot be repeatedly applied, the student model is created only once at the beginning of the course, without the possibility to be updated later on [10].

In order to avoid these drawbacks, research has been conducted on automatically identifying students' learning styles by analyzing their behavior in online or blended courses [11–17]. However, there is still room for improvement with respect to the precision of the modeling methods. Therefore, in this paper we propose a novel approach called Learning Style Identifier based on Particle Swarm Optimization (LSID-PSO), which aims to outperform existing methods. LSID-PSO is designed to be used in any learning system since it is based on generic student behavior data as input.

The remainder of the paper is structured as follows: Sect. 5.2 presents other automatic approaches used to identify learning styles. Section 5.3 provides a brief introduction into particle swarm optimization. Section 5.4 explains the performance metrics used to assess LSID-PSO. Section 5.5 provides details on how LSID-PSO is used to identify learning styles and the methodology employed to evaluate it. Section 5.6 reports and discusses the results of the evaluation and compares them to other studies. Lastly, Sect. 5.7 concludes the paper.

5.2 Related Work

Recently much research has been done on automatic approaches to identify students' learning styles from their behavior in a course. The approaches can be broadly classified into two categories: artificial/computational intelligence (AI/CI) and rule-based. With respect to the AI/CI category, Dorça et al. [11] proposed the use of a reinforcement learning algorithm to dynamically identify learning styles but only evaluated their approach with simulated data. Garcia et al. [12] introduced a Bayesian approach which considered three of the four FSLSM dimensions and resulted in precision values between 58 and 77 %. Cha et al. [13] evaluated a decision tree and hidden Markov model and found error rates between 0 and 33 %. However, they only used data indicating a strong preference on a specific learning style dimension rather than including all data, and therefore, their approach can only classify a subset of learners. Özpolat and Akar [14] used data mining to extract training data from student behavior logs and construct decision trees. Their evaluation showed accuracy rates between 53 and 73 %. Furthermore, in our previous work [15], we used artificial neural networks considering a set of behavior patterns which are general to any learning system. This approach showed a range of precision from 79 to 84 %.

The rule-based approaches work by using predefined rules extracted from the literature to compute learning styles based on behavior patterns. The advantage of these approaches over AI/CI ones is that the rules are encoded prior to data collection, so no training of the approach is necessary. An example of such rule-based system is DeLeS, developed by Graf et al. [16], which is able to identify FSLSM dimensions with precision from 73 to 79 %. Another rule-based approach, WELSA, for the unified learning styles model (ULSM) obtained precision between 64 and 84 % [10]. The Oscar conversational intelligent tutoring system [17] also uses a rule-based approach. However, it employs data from a natural language dialog between the student and the system instead of behavior data, making the approach quite uniquely applicable to the respective system. Based on an evaluation, accuracy values of 72–86 % were achieved.

While rule-based approaches are very successful, a major drawback is that they assume that all behavior patterns are equally important. Relative importance may be implemented by weighting the patterns [10]; however, such weights are not easily extracted from the literature. LSID-PSO aims at addressing this issue by extending a rule-based approach with artificial/computational intelligence features to search for optimal weights of behavior patterns, using particle swarm optimization.

5.3 Particle Swarm Optimization

Particle swarm optimization (PSO) [18] is an algorithm, inspired by the movement of flocks of birds, designed to efficiently search an n-dimensional hyperspace, or hypershape when the space is bounded, for optimal solutions. PSO uses search by social intelligence as the population of particles share information as they fly through the space and adjust their trajectories to focus on promising areas. The n-dimensional location of a particle represents a solution to a problem and the particles' movement through the space represents their search for optimal solutions. Each coordinate of a particle's location represents a component of the solution although the decoding of the coordinate to the solution component is problem specific.

PSO is highly parameter driven as with many AI/CI algorithms. Without proper parameter selection, particle swarm optimization can suffer from inefficient trajectories that may prevent convergence to the optimal solution [19]. The parameters in particle swarm optimization are: population size, individual and global acceleration rates (c_1 and c_2), inertia (w), and maximum velocity ($V_{\max}$). The parameters and their effects, as described below, come from the original [18] and follow-up works [19, 20]. The population size is the number of particles in the swarm. The global acceleration rate encourages the particles to turn toward the global best solution, while the individual best acceleration rate causes the particles to turn toward their individual best. Inertia causes the particle to continue in the same direction so a higher inertia encourages global exploration. The maximum velocity prevents the particles from flying too far from promising areas; however, if it is set too low the particles will not be able to search very globally for promising areas to begin with. In each generation, each particle's velocity is updated using Formula 5.1, where V_0 is the previous generations velocity, rand is a random real value from 0 to 1, X_{curr} is the particle's current position, X_{pbest} is the individual's best position so far, and X_{gbest} is the global best position so far.

$$V = w \times V_0 + c1 \times \mathrm{rand} \times \left(X_{\mathrm{curr}} - X_{\mathrm{pbest}}\right) + c2 \times \mathrm{rand} \times \left(X_{\mathrm{curr}} - X_{\mathrm{gbest}}\right) \quad (5.1)$$

5.4 Performance Metrics

Four metrics are used to demonstrate the performance of LSID-PSO and compare its results to results from the literature. The first metric is SIM, which is commonly used for measuring the performance of learning style identification [12, 14–16]. A normalized range from 0 to 1 is used to describe each dimension of the students' learning style. Thus, values higher than 0.5 represent a tendency toward an active, sensing, visual, or sequential learning style and values lower than 0.5 represent the opposite preference (i.e., reflective, intuitive, verbal, or global). The SIM function divides the learning style range into a high region (>0.75), a low region (<0.25), and a balanced region (0.25–0.75). SIM returns 1 when the actual and identified learning style values are in the same region, 0.5 when they are in adjacent regions, and 0 when they are in opposite regions. SIM values are calculated for each student and then an average SIM value is built to measure the accuracy of the learning style identification approach.

While SIM is commonly used in the literature, it has a drawback of reduced accuracy due to classifying results into regions. While some identification approaches return learning style regions as results (e.g., Bayesian networks), LSID-PSO is capable of returning precise learning style values. Accordingly, we are able to measure the exact difference between the results from LSID-PSO and the actual learning style value, leading to a more accurate performance metric, which we call ACC. As with SIM, ACC is calculated for each student and an average ACC is built. ACC can measure the performance more accurately than SIM, especially when the actual and/or identified learning style values are near the region edges.

While the above-mentioned performance metrics provide details on how accurate the proposed approach is on average, in the current research we aim to also investigate the accuracy of learning style identification for each single student. To further investigate this "fairness problem," two additional metrics are introduced: (i) LACC is the lowest ACC value within a set of students; (ii) %Match measures the percentage of students which are identified with ACC > 0.5, showing how many students have been identified with reasonable accuracy. Both of these metrics provide deeper insights into whether some of the students are identified with significantly low accuracy.

5.5 Methodology

In order to evaluate LSID-PSO, data from 127 information system/computer science undergraduate students were collected, including their behavior data in a university course as well as their results on the ILS questionnaire. Only students who submitted more than half of the assignments, and attended the final exam were considered for this study. In addition, only data from students who spent more than 5 min on the ILS questionnaire were used. This led to a dataset of 75 students. It should be noted that this dataset is, in comparison with related studies, one of the largest datasets (e.g., Garcia et al. used 27 students [12] and Özpolat and Akar used 30 students [14]).

This research treats each FSLSM dimension as a separate problem, and therefore, a separate LSID-PSO algorithm is developed and applied for each dimension. The first step in developing LSID-PSO is to determine the behavior patterns related to that learning style dimension. As LSID-PSO aims at being applicable in different learning systems, it was important to use generic behavior patterns so that data can be collected in various systems. Therefore, we decided to use the same behavior patterns employed by DeLeS [16], as shown in Table 5.1. These patterns were retrieved from the learning styles literature [1] and, while a short description of the most relevant patterns is provided in the next paragraph, a more detailed discussion is provided in the study by Graf et al. [16]. While in DeLeS, each behavior pattern is considered equally important, LSID-PSO starts from the hypothesis that learning style identification may be improved by weighting the behavior patterns.

The patterns are based on different types of learning objects including outlines, content, examples, self-assessment quizzes, exercises, and forums; students' navigation sequence through the course is also taken into account. Patterns consider how long a student stayed on a certain type of learning object (e.g., *content_stay*) and how often a student visited a certain type of learning object (e.g., *content_visit*). Furthermore, questions of self-assessment quizzes were classified based on whether they are about facts or concepts, require details or overview knowledge, include graphics or text only, and deal with developing or interpreting solutions. Patterns then consider how well students performed on such types of questions (e.g., *question_concepts*).

LSID-PSO needs a solution space to search, so a hypercube is created with n-dimensions, each bounded from 0.01 to 1.0, where n is the number of behavior

Table 5.1 Behavior patterns for learning style identification [16]

Active/reflective	Sensing/intuitive	Visual/verbal	Sequential/global
content_stay	content_stay	content_visit	outline_stay
content_visit	content_visit	forum_post	outline_visit
example_stay	example_stay	forum_stay	question_detail
exercise_stay	example_visit	forum_visit	question_develop
exercise_visit	exercise_visit	question_graphics	question_interpret
forum_post	question_concepts	question_text	question_overview
forum_visit	question_details		navigation_overview_stay
outline_stay	question_develop		navigation_overview_visit
quiz_stay_results	question_facts		navigation_skip
self_assess_stay	quiz_revisions		
self_assess_twice_wrong	quiz_results_stay		
self_assess_visit	self_assess_stay		
	self_assess_visit		

patterns in the learning styles dimension. Each hypercube dimension represents a weight from 0.01 to 1.0, with zero excluded as the effectiveness of DeLeS suggests that the behavior patterns identified for each learning style dimension have at least some impact. From this, a particle's location can be decoded as a set of weights for patterns corresponding to a learning style dimension.

In order to operate effectively, PSO's parameters must be properly set and although some general principles [18–20] are known and used for the suggested values below, optimal parameterization is problem specific. Accordingly, the following parameters were optimized in the given order by experimentation: population size, acceleration rates, inertia, and maximum velocity. Although population size is generally less than 100 [18–20], in order to maximize the chance of optimization the range of values assessed was extended to (25, 50, 75, 100, 200, 400). The individual acceleration parameter (*c1*) was tested with values from the set (0.0, 0.25, 0.5, 0.75, 1.0) and the global acceleration parameter (*c2*) from the set (0.25, 0.5, 0.75, 1.0). As the global best must always be considered, *c2* is not assigned a value of zero. Although the suggested inertia range is 0.9–1.2 [20], to allow for the greatest chance of optimization the set was expanded to (0.75, 0.9, 1.0, 1.1, 1.2). It is recommended that V_{max} be made equal to the size of the hypershape bounds (X_{max}) [19]. In the current research, the bounds are the weight minimum (0.01) and maximum (1.0) values, hence $X_{max} = 0.99$. Values of $V_{max} > X_{max}$ were not assessed, as if a particle's velocity (v) is greater than X_{max}, it has the same effect as $v = X_{max}$, the particle will hit the hypershape boundary. In addition to assessing $V_{max} = X_{max}$, values smaller than X_{max} were assessed. Accordingly, possible V_{max} values were obtained by multiplying X_{max} by a factor from the set (0.05, 0.10, 0.25, 0.50, 1.00) giving a final set of V_{max} values of (0.0495, 0.099, 0.2475, 0.495, 0.990). Table 5.2 shows the optimal parameters obtained for each dimension.

With AI/CI algorithms there often exists the potential for overfitting, where solutions are fit to noise of the training data and so the found solution is not a general one. There exist numerous techniques for reducing overfitting; in case of LSID-PSO, we used stratification [21] which ensures that the training set and assessment set have a similar distribution of data, thus causing the solution to be more general toward future samples. After parameter optimization, the use of stratification was investigated. Stratification was found to improve the results for each learning styles dimension and therefore was used to produce the final results.

Table 5.2 Optimal parameter settings

FSLSM dimension	Population	Acceleration		Inertia	V_{max}
		Global	Individual		
A/R	400	1.00	1.00	0.75	0.990
S/I	100	1.00	0.25	1.20	0.990
V/V	400	1.00	0.50	1.00	0.099
S/G	50	1.00	1.00	0.90	0.495

A 10-fold cross-validation approach was used to ensure that the results are generalizable to other datasets. This approach was employed for parameter optimization, investigations on the overfitting reduction techniques and to calculate the final results.

5.6 Results and Discussion

In this section, we discuss the results of LSID-PSO and compare them to similar approaches (as identified in Sect. 5.2). While there are several other works that introduced approaches to identify learning styles, it was difficult to compare some of these approaches to ours. A comparison with the approach by Cha et al. [13] is not possible as their approach is only tailored to students with a strong preference on a learning style dimension rather than identifying learning styles from every student. Comparing results to Oscar [17] is not applicable as this approach focuses on identifying learning styles from natural language dialogs, whereas LSID-PSO (and most other works) focuses on identifying learning styles from behavior patterns in courses.

Table 5.3 shows a comparison of the SIM results between LSID-PSO and other approaches in the literature which use SIM. We can notice that LSID-PSO performs well compared to the other approaches: it achieved the second best results for the A/R, V/V, and S/G dimensions and the third best result for the S/I dimension.

Since the SIM metric is not as accurate as ACC and we also aim at investigating the mismatches of single learners, raw results from DeLeS and LSID-ANN were obtained to calculate ACC, LACC, and %Match (as these two approaches achieved the best results in two dimensions each and therefore seem to be the leading approaches). By comparing results from LSID-PSO with results from DeLeS and LSID-ANN based on the ACC, LACC, and %Match metrics, more accurate information can be provided on how well LSID-PSO performs. Table 5.4 shows these results.

In the A/R dimension, LSID-PSO achieved the best results with respect to ACC and %Match, while it obtained rank 2 for LACC. For S/I, LSID-PSO also achieved the highest ACC and %Match values, and again rank 2 for LACC. For V/V,

Table 5.3 Comparison of SIM results (with ranks in parentheses and top result bolded)

Approach	A/R	S/I	V/V	S/G
LSID-PSO	0.801 (2)	0.755 (3)	0.756 (2)	0.810 (2)
LSID-ANN [15]	**0.802 (1)**	0.741 (4)	0.727 (3)	**0.825 (1)**
DeLeS [16]	0.793 (3)	**0.773 (1)**	**0.767 (1)**	0.733 (3)
Bayesian [12]	0.580 (5)	0.770 (2)	–	0.630 (4)
NBTree [14]	0.700 (4)	0.733 (5)	0.533 (4)	0.733 (3)

Table 5.4 Comparison of ACC, LACC, and %Match metrics between LSID-ANN [15], DeLeS [16], and LSID-PSO

Dimension	Approach	ACC	LACC	%Match
A/R	LSID-PSO	**0.805 (1)**	0.596 (2)	**0.988 (1)**
	LSID-ANN	0.802 (2)	**0.610 (1)**	0.986 (3)
	DeLeS	0.799 (3)	0.435 (3)	0.987 (2)
S/I	LSID-PSO	**0.794 (1)**	0.551 (2)	**0.971 (1)**
	LSID-ANN	0.790 (2)	**0.575 (1)**	0.961 (2)
	DeLeS	0.790 (2)	0.389 (3)	0.960 (3)
V/V	LSID-PSO	0.796 (2)	0.482 (2)	0.909 (3)
	LSID-ANN	**0.840 (1)**	**0.656 (1)**	0.986 (2)
	DeLeS	0.788 (3)	0.226 (3)	**0.987 (1)**
S/G	LSID-PSO	0.768 (2)	0.524 (2)	0.943 (2)
	LSID-ANN	**0.797 (1)**	**0.613 (1)**	**0.986 (1)**
	DeLeS	0.702 (3)	0.134 (3)	0.880 (3)

LSID-PSO produced overall lower values, with rank 2 for ACC and LACC and rank 3 for %Match. In S/G, LSID-PSO was constantly on rank 2 for all metrics. Overall, it can be seen that LSID-PSO performed better than other approaches for A/R and for S/I: it reached the best ACC results and the best %Match results, however, for LACC, it performed better than DeLeS but not as well as LSID-ANN. For V/V and S/G dimensions, LSID-PSO performed better than DeLeS (apart from the %Match metric in V/V) but not as well as LSID-ANN. As the hypothesis is that weighting the behavior patterns would ameliorate results over no weighting, the comparison to DeLeS confirms it: weighting did improve results in every dimension for every metric, with the exception of %Match for V/V.

In order to understand the lower %Match value for V/V dimension, the individual mismatches were examined. We discovered that all of the mismatched students had a verbal learning style. It seems that LSID-PSO tend to correctly match the more numerous visual students (85 % of the total), at the cost of less precision with verbal students, in order to obtain a better average ACC.

Although LSID-PSO confirmed the hypothesis, it converged very quickly, often in less than 100 generations, raising the concern that it may not be searching very well. To address this concern, the particle trajectories were examined and two observations were made. When the global and individual best were distant, a flat oscillation was observed between the two points. When the individual and global best were close, the particles orbited a center between the global and individual best. Although the center did shift considerably, rarely would the particles pass close to the global or individual best. So although LSID-PSO performed well, a different optimizer could be considered for the problem to see whether it can search the solution space better.

5.7 Conclusions

In this paper, an approach (LSID-PSO) for automatically identifying students' learning styles based on Felder-Silverman Learning Style Model is introduced. LSID-PSO was assessed using different performance metrics and evaluated with real data from 75 students. The results were compared to other approaches in the literature and based on the most accurate performance metric (ACC), LSID-PSO produced the highest precision values for the A/R and S/I dimensions. In addition to measuring the average precision of the approaches, this study investigated how often single students are significantly misidentified via the two metrics LACC and %Match. In this regard, for LSID-PSO, the results are mixed: although it mostly did not provide an improvement compared to LSID-ANN (except for %Match for A/R and S/I), it did outperform DeLeS, except for %Match for V/V. Overall, the results from LSID-PSO confirm that extending the rule-based approach by considering weights for behavior patterns provides an improvement in the learning style identification.

In future work, other optimizers such as ant colony system will be investigated to see whether they can search more effectively and find a more optimal set of weights. Hybrid AI algorithms can also overcome weaknesses in mono-AI algorithms and will be investigated to see whether they can find better solutions than PSO alone.

Acknowledgements The authors acknowledge the support of Athabasca University, Alberta Innovates—Technology Futures, Alberta Innovation & Advanced Education and NSERC.

References

1. Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*, 674–681.
2. Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). *Learning styles and pedagogy in post-16 learning: A systematic and critical review*. London: Learning & Skills Research Centre.
3. Popescu, E. (2010). Adaptation provisioning with respect to learning styles in a Web-based educational system: an experimental study. *Journal of Computer Assisted Learning, 26*, 243–257.
4. Ford, N., & Chen, S. (2001). Matching/mismatching revisited: an empirical study of learning and teaching styles. *British Journal of Educational Technology, 32*, 5–22.
5. Graf, S., Chung, H.-L., Liu, T.-C., & Kinshuk. (2009). Investigations about the effects and effectiveness of adaptivity for students with different learning styles. In: A. Ignacio, N.-S. Chen, Kinshuk, D. Sampson, L. Zaitseva (Eds.), *Ninth IEEE International Conference on Advanced Learning Technologies, 2009*. ICALT 2009 (pp. 415–419). IEEE.
6. Soloman, B., & Felder, R. M. (1998). Index of learning styles questionnaire. http://www.engr.ncsu.edu/learningstyles/ilsweb.html
7. Kuljis, J., & Liu, F. (2005). A comparison of learning style theories on the suitability for eLearning. In: M. H. Hamza (Ed.), *Web Technologies, Applications, and Services* (pp. 191–197).

8. Carver, C. A., Jr., Howard, R. A., & Lane, W. D. (1999). Addressing different learning styles through course hypermedia. *IEEE Transactions on Education, 42*, 33–38.
9. Felder, R., & Spurlin, J. (2005). Applications, reliability and validity of the index of learning styles. *International Journal of Engineering Education, 21*, 103–112.
10. Popescu, E. (2009). Diagnosing students' learning style in an educational hypermedia system. In: *Cognitive and Emotional Processes in Web-based Education: Integrating Human Factors and Personalization, Advances in Web-Based Learning Book Series*, IGI Global (pp. 187–208).
11. Dorça, F. A., Lima, L. V., Fernandes, M. A., & Lopes, C. R. (2013). Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis. *Expert Systems with Applications, 40*, 2092–2101.
12. García, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers and Education, 49*, 794–808.
13. Cha, H. J., Kim, Y. S., Park, S. H., Yoon, T. B., Jung, Y. M., & Lee, J.-H. (2006). Learning styles diagnosis based on user interface behaviors for the customization of learning interfaces in an intelligent tutoring system. In M. Ikeda, K. D. Ashley, & T.-W. Chan (Eds.), *Intelligent tutoring systems* (pp. 513–524). Berlin: Springer.
14. Özpolat, E., & Akar, G. B. (2009). Automatic detection of learning styles for an e-learning system. *Computers and Education, 53*, 355–367.
15. Bernard, J., Ting-Wen, C., Popescu, E., & Graf, S. (2015). Using artificial neural networks to identify learning styles. In: Artificial intelligence in education (pp. 541–544) Berlin: Springer.
16. Graf, S., Kinshuk, Liu, T.-C. (2009). Supporting teachers in identifying students' learning styles in learning management systems: An automatic student modelling approach. *Educational Technology and Society*, *12*, 3–14.
17. Latham, A., Crockett, K., McLean, D., & Edmonds, B. (2012). A conversational intelligent tutoring system to automatically predict learning styles. *Computers and Education, 59*, 95–109.
18. Eberhart, R. C., & Kennedy, J. (1998). A new optimizer using particle swarm theory. In *Sixth International Symposium on Micro Machine and Human Science* (pp. 39–43).
19. Clerc, M., & Kennedy, J. (2002). The particle swarm-explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation, 6*(1), 58–73.
20. Shi, Y., & Eberhart, R. C. (1998). Parameter selection in particle swarm optimization. In *Evolutionary Programming VII* (pp. 591–600). Springer.
21. Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In C. S. Mellish (Ed.), *International joint conference on artificial intelligence* (pp. 1137–1145). Morgan Kaufmann Publishers Inc.