Sequencing and Recommending Pedagogical Activities from Bloom's Taxonomy using RASI and Multi-objective PSO

Denis José Almeida[1][a], Márcia Aparecida Fernandes[1][b] and Newarney Torrezão da Costa[2][c]
[1]*Department of Computing, Federal University of Uberlândia, Av. João Naves de Ávila, Uberlândia, Brazil*
[2]*Department of Computing, Federal Institute of Goiás, Iporá, Brazil*

Keywords: Sequencing of Pedagogical Activities, Pedagogical Recommendation, Bloom's Taxonomy, RASI, PSO, Multi-objective Optimization.

Abstract: According to student needs, learning can be supported and enhanced through structured and personalized instruction. This paper presents an approach to personalized pedagogical recommendations based on the student's cognitive profile, given by the Revised Approaches to Studying Inventory (RASI). The recommended pedagogical actions follow the hierarchy of Revised Bloom's Taxonomy. We model the sequencing of pedagogical actions as a multi-objective optimization problem. This problem solution was implemented using a Particle Swarm Optimization (PSO) algorithm. The optimized objectives in this problem are the similarity between the student's profile and the sequence of actions, and the number of actions appropriate to the student's profile. Experiments conducted with students in higher education institutions suggest that the proposed approach using PSO presents solutions that are better accepted by students than the randomized pedagogical recommendation.

1 INTRODUCTION

Learning is a continuous and natural process that occurs in both organized situations and everyday activities Huang et al. (2019). According to Brown et al. (2020), teaching and learning is a human effort carried out by people for the benefit of others, and Woolf (2010) argues that learning is more efficient when students are motivated to learn. In addition, Huang et al. (2019) state that learning, when intentional and defined in an institutional context with explicit goals and objectives, is generally supported by structured sequences of instructions designed to support, facilitate or improve learning and performance.

Traditional teaching models are dependent on course content and are teacher-centered; therefore, the teaching strategies are based on the teacher's understanding of the course. Because classes are heterogeneous, adjustments must be made to the content or pedagogical strategies to help students perform better and reach a different level in the learning process.

The student's cognitive profile is an example of an attribute that can be considered to make the learning process student-centered. With this type of information, teachers can plan learning activities that are more appropriate for students. Moreover, technology can play a crucial role in developing personalized and individualized learning activities (Huang et al., 2019), which largely determines student satisfaction and teaching efficiency.

Automation of the teaching process in formal learning can collaborate with teaching methodologies that put the student in a more active role in the learning process. Teaching can be customized in intelligent and adaptive virtual platforms by recommending tailored activities to students. This can be done by considering the student's cognitive profile or preferences to meet individual needs, providing stimuli that guide the student, and allowing everyone to learn in their own time (Sunaga and Carvalho, 2015).

Student performance in Virtual Learning Environments (VLEs) can be improved by recommending teaching strategies customized and individualized. With the support of these environments, it is possible to provide personalized and more appropriate sequences of pedagogical activities for each predominant learning style of students, which is impossible in mass or conventional education (Moran, 2015). The relevance of VLEs leads to the exploration and de-

[a] https://orcid.org/0000-0003-3224-8249
[b] https://orcid.org/0000-0003-3572-612X
[c] https://orcid.org/0000-0002-4954-176X

Almeida, D., Fernandes, M. and Torrezão da Costa, N.
Sequencing and Recommending Pedagogical Activities from Bloom's Taxonomy using RASI and Multi-objective PSO.
DOI: 10.5220/0011090000003182
In *Proceedings of the 14th International Conference on Computer Supported Education (CSEDU 2022) - Volume 2*, pages 105-116
ISBN: 978-989-758-562-3; ISSN: 2184-5026

velopment of new tools to adapt and respond to the student.

Considering the previous scenario, this work presents a proposal for sequencing pedagogical actions to be recommended to students. The sequencing problem is formulated as a multi-objective optimization problem, and the solution is obtained by a discrete binary approach of the Particle Swarm Optimization (PSO) algorithm. The pedagogical actions are those from Bloom's Taxonomy, and the student model is the cognitive profile of Revised Approaches to Studying Inventory (RASI). Experiments have been conducted and the results are promising in terms of student satisfaction and sequence quality.

The paper is organized as follows. Section 2 presents previous work that used PSO for pedagogical sequencing. Bloom's Taxonomy, RASI profiles, the relationships between both theories, and a general view of PSO are described in Section 3. The multi-objective optimization problem for sequencing and the search for a solution by a PSO algorithm are described in Section 4. Experiments and the analysis of the results are presented in Section 5. Section 6 contains the conclusion and further work.

2 RELATED WORKS

Meta-heuristics based on Evolutionary Computing (EC) have been used to cope with pedagogical sequencing since is a hard problem (Al-Muhaideb and Menai, 2011), especially when it considers some student characteristics to propose an adaptive sequencing. In this sense, Al-Muhaideb and Menai (2011) provide an overview of EC approaches — such as Ant Colony Optimization (ACO), Genetic Algorithm (GA), Parallel Memetic Algorithm, and Particle Swarm Optimization (PSO) — for solving the Curriculum Sequencing problem.

De-Marcos et al. (2009) proposed the automatic sequencing process of learning objects in the e-learning content creation. The sequencing problem was transformed into a constraint satisfaction problem, and two optimization agents were designed, developed, and tested: a discrete PSO and a GA. The results showed that both can solve the problem and PSO implementation outperforms GA.

In Chu et al. (2011), PC^{2}PSO was proposed to select appropriate e-learning materials for individual learners in a personalized e-course. In this approach, a binary multi-objective PSO was used, considering four different factors as optimization objectives: the learning concept covered, the difficulty level of the e-learning materials, the total learning time required, and the balance among the weighs of the learning concepts.

In Smaili et al. (2020), a solution was proposed to dynamically adapt the content offered in distance learning courses based on student profiles. Student profiles are generated from personal data collected in virtual learning environments, forums and social networks. Starting from the identification of the profiles, a PSO-based approach is used to select activities and recommend them in an order to be followed in the course.

The research conducted by Subiyantoro et al. (2021) proposed a model for recommending learning paths based on the cognitive classification of Revised Bloom's Taxonomy and an ontology of learning objects. To determine the most appropriate learning path for the student's cognitive abilities, the Hybrid PSO method was used, which consists of a Binary PSO to represent the cognitive classes and a Discrete PSO to

Table 1: Summary of researches using meta-heuristics to sequencing problem.

Paper	Metaheuristic algorithms	Student Model	Pedagogical Theories
De-Marcos et al. (2009)	Discrete PSO, GA	Competencies	-
Chu et al. (2011)	Binary PSO	Ability level, expected learning targets, expected learning time of an e-course	-
Smaili et al. (2020)	PSO	Objectives, preferences, level of knowledge, learning styles and academic motivations	-
Subiyantoro et al. (2021)	Hibrid PSO (Binary and Discrete)	Cognitive classes based on BT	BT
Martins et al. (2021)	AG, Binary PSO, Prey Predator Algorithm, Differential Evolution	Previous knowledge, time availability, learning preferences based on ILS	Learning Style and prior knowledge (ILS), Felder and Silverman Learning Style Model (FSLSM)

represent the learning objects of an ontology.

Martins et al. (2021) presented a procedure for generating synthetic data sets to evaluate approaches used in the Adaptive Curriculum Sequencing problem. The generated datasets were used to investigate the contribution of four metaheuristic techniques: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Prey Predator Algorithm, and a proposed technique based on Differential Evolution. The individual sequencing approach was modeled as a multi-objective problem using information from the students, the learning materials (difficulty, content, and style), and the course (target concepts).

Table 1 provides an overview of researches addressing the pedagogical sequencing problem using metaheuristics.

3 BACKGROUND

In this section, the Revised Approaches to Studying Inventory and Bloom's Taxonomy theories are introduced and the mapping created between them is presented. Such mapping is the basis for pedagogical sequencing and allows automatic sequencing of pedagogical actions in a way that is independent of the curriculum and takes into account the learning process. In addition, the metaheuristic approach used to determine optimal sequences of actions is described.

3.1 Student's RASI Profile

An essential requirement for customizing the sequencing of pedagogical actions is the student's profile. Several student characteristics can be used. In Pireva and Kefalas (2017), learning style and VLE's metadata were used to provide a personalized learning path for the student. In work proposed by Smaili et al. (2020), learning style and knowledge level were used to provide a course tailored to the student's needs.

Thus, the student is classified under the surface, strategic or deep dimensions. According to this study, the student classified in the surface category, presents a preference for directing the learning process to the requirements of the evaluation. The student whose category is defined as strategic is motivated by personal satisfaction, that is, he or she prioritizes achieving the best results by means of organized study and optimizing time. On the other hand, the student identified in the deep category directs his study toward challenging teaching activities, that is, that aim at researching the meaning of things.

The Revised Approaches to Studying Inventory (RASI) defines the student's cognitive profile from the perspective of three axes (*Surface*, *Strategic*, and *Deep*), as described by Tait and Entwistle (1996).
Thus, the student is classified under the surface, strategic or deep dimensions. According to this study, the student classified in the surface category, presents a preference for directing the learning process to the requirements of the evaluation. The student whose category is defined as strategic is motivated by personal satisfaction, that is, he or she prioritizes achieving the best results by means of organized study and optimizing time. On the other hand, the student identified in the deep category directs his study toward challenging teaching activities, that is, that aim at researching the meaning of things.

The RASI establishes a relationship with the BT since each axes presents an evolution in the student's cognitive profile, from Lower Order Cognitive Skills (LOCS) to Higher-Order Cognitive Skills (HOCS) just as occurs with the educational objectives in the BT. This characteristic led us to decide by using the RASI as a student model to provide the personalization of pedagogical actions based on the BT.

The RASI was developed for use with students in higher education. It is also widely used in several works, such as Entwistle (2018), in which the RASI is one of the dimensions of the Approaches and Study Skills Inventory for Students (ASSIST). Its use can also be seen in Fusilier et al. (2021), whose goal was to identify students' study approaches to suggest adaptations in the delivery of educational content. The RASI in its original version is composed of 52 objective questions, with answers on a 5-point Likert[1] scale. A short version of the RASI consisting of 18 questions is used in Entwistle and Tait (2013), which was also used in this work since the chance of student engagement and attention when answering this questionnaire may be increased.

3.2 Bloom's Taxonomy

In Krathwohl (2002), BT was extended by the introduction of a second dimension, defining a two-dimensional BT composed of Cognitive Process Dimension (CPD) and Knowledge Dimension (KD). Then the taxonomy's educational objectives are placed in a matrix. CPD has six levels (Remember, Understand, Apply, Analyze, Evaluate, Create) and KD into four levels (Factual, Conceptual, Procedural, and Metacognitive). As the flow through these levels follows a hierarchy from LOCS to HOCS, which is also observed in RASI, it is possible to define pedagogical actions from the BT and RASI perspectives.

[1]Likert, R. (1932). A technique for the measurement of attitudes. *Archives of psychology*.

Thus, we defined 24 pedagogical actions, as shown in Table 2.

Table 2: Pedagogical actions defined according to BT. Source: Adapted from da Costa and Fernandes (2021).

		KD			
		FA	**CO**	**PR**	**ME**
CPD	**Remember**	A1	A2	A3	A4
	Understand	A5	A6	A7	A8
	Apply	A9	A10	A11	A12
	Analyze	A13	A14	A15	A16
	Evaluate	A17	A18	A19	A20
	Create	A21	A22	A23	A24

Subtitle: FA. Factual; CO. Conceptual; PR. Procedural; ME. Metacognitive; A. Action.

On Table 2, 24 actions are arranged, one for each educational objective of the BT. These actions follow the hierarchy proposed in the BT in which they develop from actions close to LOCS (concrete actions) to actions close to HOCS (abstract actions), in the order A1, A2, ..., A24. Note also that such a hierarchy allows for supplanting actions according to the student's needs. In this way, a pedagogical sequence would not necessarily contemplate the 24 proposed actions. Thus, there are 2^{24} sequencing possibilities, which makes manual customization difficult. In this sense, a contribution of this work is the automation of this process, based on the student's RASI profile.

For the sequencing of pedagogical actions (educational objectives), as proposed in this work to be possible, it is essential to associate activities with pedagogical actions. Several works structure activities or digital tools to the educational objectives of the BT. In Schrock (2011), for each of the levels of CPD in BT, technologies capable of meeting such requirements are listed. In work proposed by Goštautaitė (2019), digital activities indexed by BT are used to select an optimal set of activities to enhance the learning of a group of students.

In Churches (2010), Bloom's Digital Taxonomy (BDT) was developed to index digital activities to CPD levels to make the pedagogical recommendation based on BT actions feasible. da Costa and Fernandes (2021) extended this indexing to the KD, making it feasible to use the BDT as support for the recommendation of digital activities from the pedagogical goals structured by the two dimensional BT. In this work, we have chosen to use such a framework because it enables the recommendation from the sequencing of pedagogical actions.

3.3 Relationship between RASI and BT

Both RASI and BT present a hierarchy based on the evolution of the student's cognitive level from LOCS to HOCS. da Costa and Fernandes (2021) proposed a mapping that establishes this relationship based on this principle. Figure 1 shows the influence of each CPD level on each RASI axis. The framework formulated according to Figure 1 is essential for developing this proposal since it allows comparisons between a sequence of actions based on the BT and the student's RASI profile. From this, our goal is to find, in an automated way, a sequence of actions that are as close as possible to the student's needs, considering his/her RASI profile.

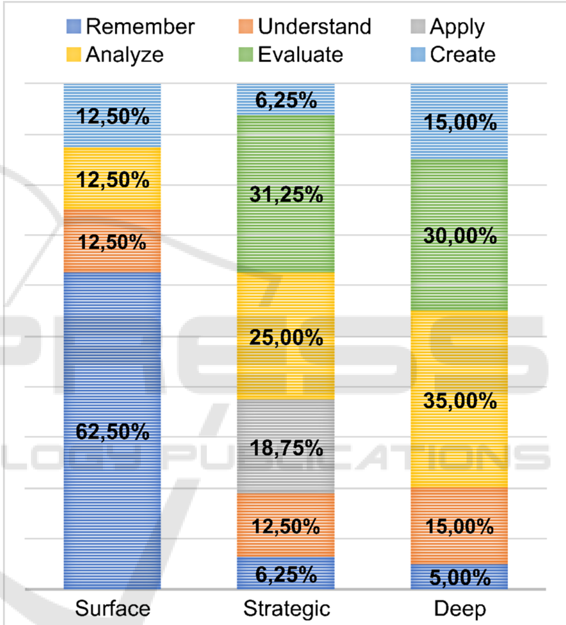


Figure 1: Mapping RASI versus BT. Source: Adapted from da Costa and Fernandes (2021).

3.4 Particle Swarm Optimization

Optimization problems can consider one or more objective functions, which represent the criteria to be optimized (minimized or maximized) and are directly related to the problem to be solved. These functions can be influenced by independent variables that affect the evaluation of the solutions.

An efficient stochastic optimization method is Particle Swarm Optimization (PSO), which is modeled from the emergent social behavior of a birds' flock. Then, each bird is represented by a particle and as the birds are changing their positions during the flight, the particle position is the information to be considered by PSO and the search process in the solution space is performed on a swarm of particles. Each particle position is associated with a candidate solution for the optimization problem and its representation is a vector d-dimensional where each dimension is a component of the solution.

The particles' positions are adjusted toward an optimal position (optimal solution) by the influence of their own particle experience (the cognitive component) and by the experience of their neighborhood in the swarm (the social component). These components enable the particles to move toward an optimal solution as they explore the space around the best solution found so far. The PSO algorithm was originally proposed by Kennedy and Eberhart (1995) as a robust approach to the optimization of problems characterized by nonlinearity and nondifferentiability, optimal multiples, and high dimensionality, and according to Kennedy et al. (2001) is highly resistant to being trapped in local optima.

During the optimization process, the PSO maintains a swarm of particles and iteratively updates their positions by adding a new velocity v_i^{t+1} to their current position x_i^t . The update of the position x_i of each particle i in the search space at time $t+1$ depends on the calculation of the velocity and is given by Eq. 1.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{1}$$

The optimization process is driven by the velocity vector, which reflects the particle's experiential knowledge and information exchanged with neighboring particles about promising areas in the search space. The particle velocity (v_i) update consists of the sum of three main terms and is calculated, by dimension d, according to Eq. 2:

$$v_{id}^{t+1} = wv_{id}^t + c_1 r_{1d}^t [p_{id}^t - x_{id}^t] + c_2 r_{2d}^t [g_{id}^t - x_{id}^t] \tag{2}$$

The previous velocity v_i^t represents the memory of the previous direction of the particle and prevents it from drastically changing its direction. This component is weighted by the inertia w, which determines how much it affects the new velocity. The cognitive component $c_1 r_{1d}^t [p_{id}^t - x_{id}^t]$ quantifies the particle's performance with respect to its previous performance, attracting it back to its personal best position p_{id} found since the first-time step. The social component quantifies the particle's performance with respect to the particles in its neighborhood, resulting in each particle also being attracted to the best position g_{id} found so far by that group of particles. The cognitive and social components are weighted by the positive acceleration coefficients c_1 and c_2 and the random values r_1 and r_2. The values of r_1 and r_2 control the stochastic influence of each component on the general velocity of the particles and are obtained for each time step from a uniform distribution $\in$ [0,1].

Since optimization problems with real-valued domains can easily be converted to binary domains (Engelbrecht, 2006), a discrete version was developed by Kennedy and Eberhart (1997) to work in binary search spaces. In this version, the particles represent positions in binary space, where each element of the position vector can take the values 0 and 1 (Engelbrecht, 2006). The position of the particle changes when any bit of the position vector flips its value from one value to another. In this way, the velocity of a particle can be interpreted as the Hamming distance between its previous and its current position.

The binary PSO is a binary decision model calculated as a function of social and personal factors Kennedy et al. (2001). The new velocity v_{id}^{t+1} is defined as the probability that a bit is in one state or the other, and its value represents the probability that the bit value is 1. The previous velocity v_{id}^t measures the predisposition (or current probability) to choose the next bit value 1.

In this probabilistic view, velocity must be normalized to be confined to the interval $[0,1]$. This normalization is achieved by using the sigmoid function presented in Eq. 3. The parameter $V_{max} = \pm 4$ was set to limit the particle velocity to the interval $[-4,4]$ to ensure that there is always the possibility of a bit changing state.

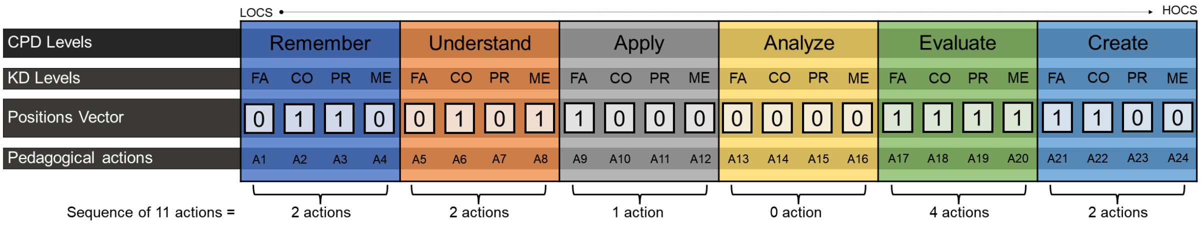
$$sig(v_{id}^{t+1}) = \frac{1}{1+e^{-v_{id}^t}} \tag{3}$$

The normalized velocity is now the probability with the d-th bit of position vector will be set to 1. The position x_{id}^{t+1} of the particle is changed stochastically by comparing, at each iteration, the result of $sig(v_{id}^{t+1})$ with a random number ρ from a uniform distribution $\in$ [0,1], according to Eq. 4. Due to the random number, the new bit position can be changed even if the velocity does not change.

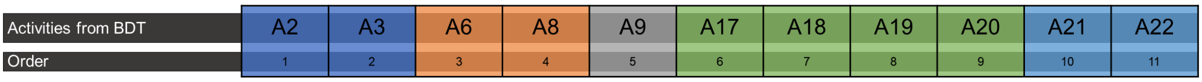
$$x_{id}^{t+1} = \begin{cases} 1, & \text{if } \rho_d < sig(v_{id}^{t+1}) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

4 PROPOSED METHOD

This section describes the pedagogical sequencing of actions which is formulated as a multi-objective optimization problem since the goal is to recommend a sequence of actions that best fit student's cognitive profile. As previously mentioned, metaheuristics such as PSO are suitable to a such problem. Hence, the



(a) Particle representation vector



(b) Recommended Sequence

Figure 2: Positions vector of a particle and corresponding recommendation sequence with 11 actions.

proposal consists of a multi-objective PSO for the sequencing.

In the proposed model, a particle is represented by a vector sized 24 as pictured in Figure 2a, where each position is associated with a pedagogical action according to Table 2. If an action is present in the sequence, the corresponding bit is set to 1, otherwise, 0. Formally, the problem is defined as the minimization of the objective function $f(x)$ as given by Eq. 5, where x is a sequence represented by a particle, F_1 measures the similarity between the sequence RASI index R_{RASI} and the student's RASI profile S_{RASI} and F_2 the sequence size. The weights ω_i were adopted to weigh the contribution of each criterium and then the multi-objective aspect was considered as the weighed sum of criteria. After simulations performed on the RASI profiles of 156 students, the weights were adjusted to $\omega_1 = 0.7$ and $\omega_2 = (1 - \omega_1)$ as the best values for minimizing f.

$$f(x) = \sum_{i=1}^{2} \omega_i F_i(x) \tag{5}$$

F_1 checks whether the sequence matches the RASI profile of the student. Therefore, the RASI indices of the sequence must be determined, expressing the strength of each CPD level (*Remember*, ..., *Create*) in the sequence weighted by the relevance of that level to each RASI axis (*Surface*, *Strategic* and *Deep*). Formally, the index of each RASI axis that makes up R_{RASI} is calculated by the product between the weight of the influence of each CPD level for the RASI axis (Figure 1) and the number of bits set to 1 in that BT level multiplied by 1/4. The S_{RASI} index is obtained from students' responses to the RASI questionnaire. Notice in Figure 1 that the *Apply* level does not influence the *Surface* and *Deep* axes, just as the *Evaluate* level has no influence on the *Deep* axis.

The R_{RASI} index of the sequence represented by the vector in Figure 2a is $[0.438, 0.484, 0.475]$, where the value for each axis is *Surface* = 0.438, *Strategic* = 0.484, and *Deep* = 0.475. To illustrate the calculation of the value of each axis, we can take the value for the *Surface* axis of this sequence, which is the result of the calculation of Equation 6.

$$\begin{aligned} R_{RASI}^{Surface} = \frac{2*0.625}{4} + \frac{2*0.125}{4} + \frac{1*0.000}{4} + \\ \frac{0*0.125}{4} + \frac{4*0.000}{4} + \frac{2*0.125}{4} \end{aligned} \tag{6}$$

Finally, the similarity between the RASI index of the sequence and the RASI profile of the student is given by the Euclidean distance D between R_{RASI} and S_{RASI}. Note that the Euclidean distance alone is not sufficient to determine whether the sequence is close to the student's profile with respect to each RASI axis. Then P adds a penalty to $F_1(x)$ for each RASI axis that is violated. Assume that the *Deep* axis is more relevant to the student and the *Surface* axis is more relevant to the sequence. This relevance is attributed to each axis according to $w_1 = 1$ for the least relevant axis, $w_2 = 2$ for the intermediate axis, and $w_3 = 3$ for the most relevant axis. At each RASI axis where there is a divergence of relevance between the student and the sequence, the corresponding weight is multiplied by 1/6 of the Euclidean distance. Thus, the penalty is at most the Euclidean distance and consequently, $F_1(x)$ is at most twice the Euclidean distance. If there is no difference in the order of relevance on any of the RASI axes, w_1, w_2, and w_3 are set to 0. The objective function F_1 and the penalty P are given by Eq. 7 and Eq. 8, respectively.

$$F_1(x) = D(S_{RASI}, R_{RASI}) + P \tag{7}$$

$$P = \sum_{i=1}^{3} w_i * \frac{D}{6} \tag{8}$$

Through experiments conducted by da Costa and Fernandes (2021), the appropriate number of actions for each predominant RASI profile was defined and it is used in this study as a reference value for the sequence size (ref): 9 for *Surface*, 13 for *Strategic*, and 11 for *Deep*. Thus, the objective function F_2 has the task of optimizing the number of activities that make up the sequence, minimizing the difference between the sequence size and the reference value. Eq. 9 defines F_2.

$$F_2(x) = \begin{cases} \frac{ref - size(x)}{ref - 1}, & \text{if } size(x) < ref \\ \frac{size(x) - ref}{24 - ref}, & \text{otherwise} \end{cases} \quad (9)$$

We can assume that the problem of sequencing pedagogical actions allows one to find more than one appropriate sequence for a student. Hence, some PSO properties were defined to make this metaheuristic more adherent to the sequencing problem. Then, a lbest PSO was developed using a ring social network topology, where the information exchange in the social component of the particle is realized with only a small neighborhood (two other particles). Updating the best particle positions is done asynchronously, as this is more suitable for the *lbest* PSO.

The recommended sequence is composed of digital activities according to the BDT. Then, for each bit set to 1 in the sequence returned by the PSO, a BDT activity is assigned (see Figure 2b). This attribution was performed according to the mapping presented by da Costa and Fernandes (2021) between BDT and BT. So, in effect, the recommendation is a sequence of digital activities.

5 RESULTS AND DISCUSSION

A total of 979 higher education students at three educational institutions were invited to participate in the experiments. Distance learning and presential course of a Federal Institute of Education, Science and Technology and Distance Learning Center of a Federal University are in Minas Gerais, Brazil. Also, a Federal Institute is in Goiás, Brazil. The experiments took place in the period from May to December 2021.

The experiments were divided into three phases: *i*) Application of the RASI questionnaire; *ii*) Sequencing of pedagogical actions; and *iii*) Recommendation of pedagogical activities. The research participants were divided into two groups: a control group, which received random sequences of activities; and the experimental group, that received sequenced activities through the PSO algorithm.

The student's participation in each phase was voluntary. In addition, they were informed that the collected data would be anonymized, and that no personal information would be disclosed under any circumstances. Thus, we had 182 participants in Phase *i*, and of these, 50 participated in Phase *iii*. In the next subsections, we will discuss the results obtained in the experiments.

The questions asked in the questionnaires of phases *i* and *iii* of the experiment are listed in Table 3, and the groups of response options are shown in Table 4.

5.1 Students' Profiles

We used a free translation of the short version of the RASI questionnaire into Portuguese in Phase *i* of the experiments. One hundred eighty-two students answered the RASI questionnaire. For each student, the values for the RASI axes were calculated according to the respective answer to the questionnaire. The distribution of the participants' profiles according to the predominant RASI axis was *Surface* = 9%, *Strategic* = 25%, and *Deep* = 66%.

In addition, 100 of these participants answered a questionnaire stating how much they agreed with the obtained RASI indices. For this, six objective questions with answer options on a 5-point Likert scale were asked, as shown in Figure 3.

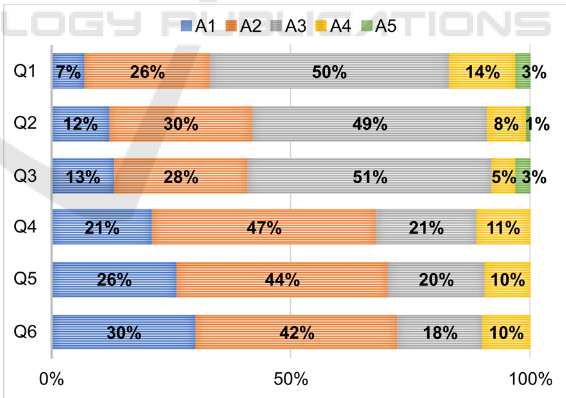


Figure 3: Students' perception of the indices obtained by the RASI profile.

In Figure 3, Q1 to Q6 questions are intended to know about the students' agreement with their RASI profile obtained from their questionnaire answers. Q1 to Q3 asked the student if the percentage for *Surface*, *Strategic*, and *Deep*, respectively, should be less or more significant. Q4 to Q6 intended to confirm the answers from Q1 to Q3. It was only asked if the student agreed with the percentual of each axis. Most of the answers for Q1 to Q3 were *Higher*, *Equal*, or

Table 3: Questionnaire questions and their answer groups.

QUESTION		AG*
Q1.	I consider that the percentage assigned to me on the SURFACE axis should be:	G1
Q2.	I consider that the percentage assigned to me on the STRATEGIC axis should be:	G1
Q3.	I believe that the percentage assigned to me on the DEEP axis should be:	G1
Q4.	I consider that the percentage assigned to me on the SURFACE axis is in line with my learning profile.	G2
Q5.	I consider that the percentage assigned to me on the STRATEGIC axis is in line with my learning profile.	G2
Q6.	I consider that the percentage assigned to me on the DEEP axis is in line with my learning profile.	G2
Q7.	Do you think the number of activities is:	G3
Q8.	The sequence of activities is comfortable to lead you in learning a new content or subject.	G2
Q9.	What is the probability that you will complete all the activities in this sequence?	G4
Q10.	The total number of recommended activities is too many.	G2

* Answer Group

Table 4: Questionnaire answer groups.

AN*	G1**	G2**	G3**	G4**
A1	Much higher (from 7% more)	Agree	Very High (at least 6 more than ideal)	Very High (above 80%)
A2	Higher (3% to 6% more)	Partially Agree	High (between 3 and 5 more than ideal)	High (between 61% and 80%)
A3	Equal (up to 2% more or less)	Indifferent	Sufficient (up to 2 more or fewer than ideal)	Moderated (between 41% and 60%)
A4	Smaller (from 3 to 6% less)	Partially Disagre	Low (between 3 and 5 less than ideal)	Low (between 20% and 40%)
A5	Much Smaller (from 7% less)	Disagree	Very Low (at least 6 fewer than ideal)	Very Low (below 20%)

* Answer Number; ** Answer Group

Smaller, with a higher concentration on the *Equal* answer. This result suggests a certain degree of student awareness while taking the RASI questionnaire. The results show that most of the answers from Q4 to Q6 focused on *Agree* and *Partially Agree*, confirming the students' attention to answer the RASI questionnaire and, therefore, the quality of this questionnaire's answers.

5.2 Sequencing Analysis Regarding the Student's Profile

The optimization process was performed for the participants of Phase i of the experiment. Based on the sequences generated in the process, the distribution of pedagogical actions was observed for each predominant RASI profile according to CPD levels.

Compared to the mapping RASI performed to TB, it can be seen in Figure 4 that the actions for the *Surface* profile were mostly distributed across the profile's preference levels, with recommendations for an unexpected level (*Evaluate*) and no recommendation for the Understand level; for the *Strategic* profile, no action was recommended for the Create level; and for the *Deep* profile, all recommendations were distributed across the assigned levels.

Table 5: Relevance of BT levels for each RASI axis.

	Surface	Strategic	Deep
High	Remember	Analyze Evaluate	Analyze Evaluate
Moderate	Understand Analyze Create	Understand Apply	Understand Create
Low	Apply Evaluate	Remember Create	Remember Apply

In F_1, the predominant RASI axis of the student's profile is used to calculate the penalty. However, the similarity between the sequence and the student's profile considers all the axes that make up the profile. In this sense, the analysis of the quality of the recommendation distribution can be performed by grouping

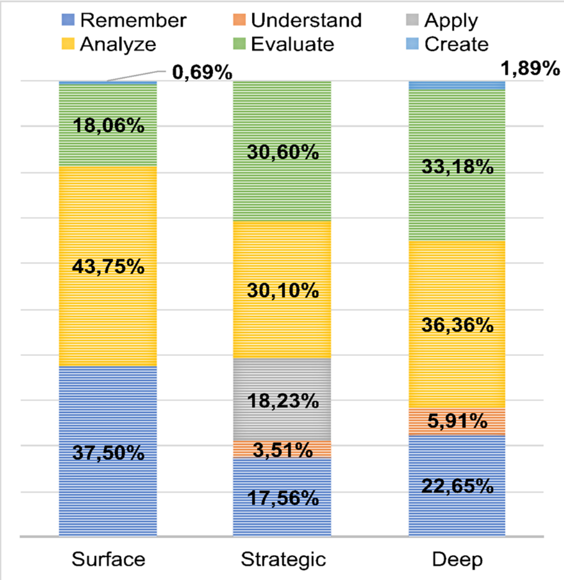


Figure 4: Recommended actions by CPD levels for each RASI profile.

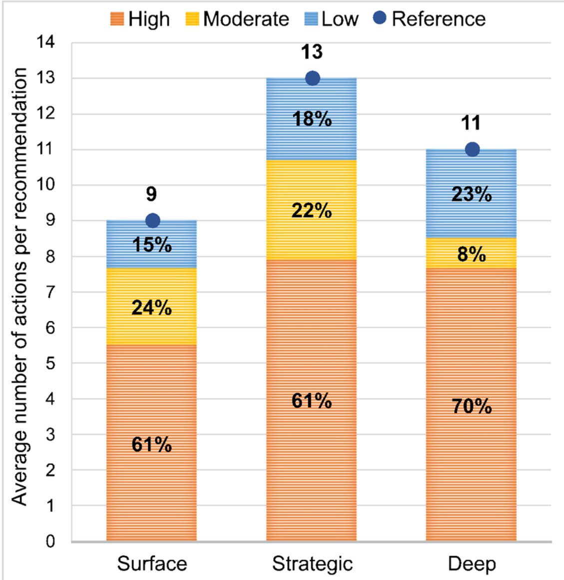


Figure 5: Recommended actions by the degree of relevance for each RASI profile.

the CPD levels according to the degree of relevance (*High*, *Moderate*, and *Low*) for each RASI profile. The relevance of the CPD levels for each RASI profile can be seen in Table 5.

Thus, Figure 5 shows the distribution of recommendations by the degree of relevance, the average number of recommended actions, and the reference values for each predominant profile. As can be seen, most of the recommended actions are concentrated at BT levels that are more relevant to the predominant profile, and the average of the number of recommended actions for each predominant profile is equal to the reference values, showing the convergence of the F_1 and F_2 functions, respectively.

5.3 Students' Perception about the Recommended Sequences of Activities

In Phase *iii* of the experiments, sequenced activities were recommended. Two groups received the pedagogical recommendations generated by different methods. The first group, with 41 participants, was presented with sequences of pedagogical activities generated using the PSO algorithm. The second group, called the control group, with 15 participants, was presented with randomly sequenced activities. Figures 6 and 7 show the students' perceptions regarding the pedagogical recommendations in each of these groups.

Q7 is related to the students' perception regarding the number of recommended activities. In Figure 6 (PSO), 7% of the participants consider the number of activities *Very High*, while in Figure 7 (random), 14% of the participants consider this number *Very High*. This item is directly related to the quality of the second objective of the PSO algorithm since it seeks to optimize the number of sequenced actions according to the student's profile. Compared to randomly sequenced activities, the results of Q7 for PSO are better since the percentage of participants who consider the number of answers *Sufficient* is higher than each other answers. Also, in the recommendation of randomly sequenced activities, the number of participants who consider the number of activities *Very high*

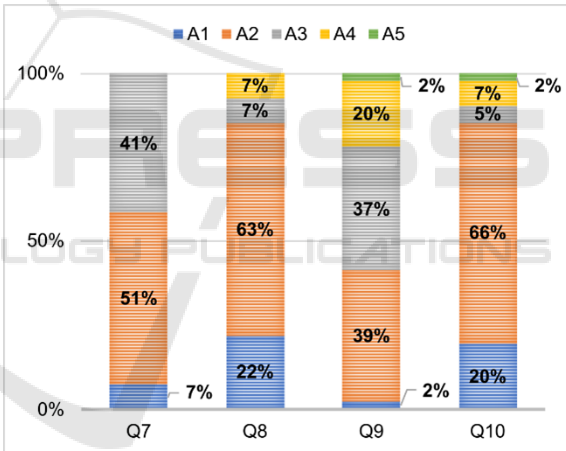


Figure 6: Satisfaction questionnaire for activities sequenced using the PSO algorithm (41 attendees).

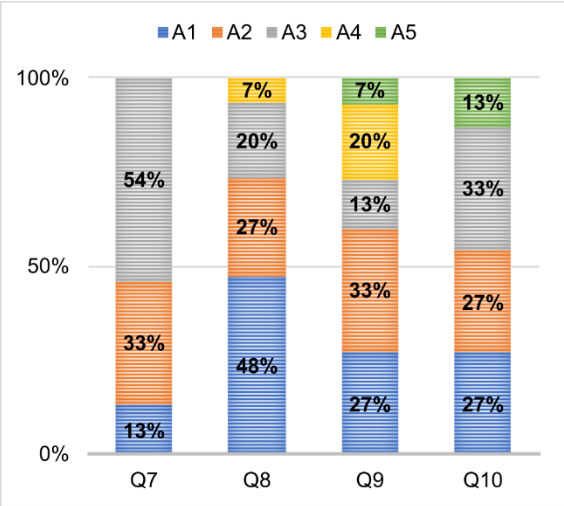


Figure 7: Satisfaction questionnaire for randomly sequenced activities (15 attendees).

is higher. We observe that the PSO algorithm fulfills the requirement of controlling the number of activities. However, a more detailed analysis of the results is necessary to adapt better the reference values of the number of activities for each student profile.

In figures 6 and 7, Q8 is related to the quality of the sequence of activities offered to the student since the student answers how comfortable he considers the pedagogical recommendation to be for learning new content. In Figure 6, 85% of the participants agreed or partially agreed with the statement of Q8 for the PSO algorithm. This result is better than that observed for randomly generated sequencing. This result directly evaluates the first objective of the PSO algorithm since this objective seeks to sequence pedagogical actions compatible with the student's RASI profile.

The Q9 in figures 6 and 7 mixed evaluate the quality of the recommendation and the number of sequenced activities. Most of the answers (78%) focused on *Very High*, *High*, or *Moderated* for the PSO Algorithm. Again, these results are better than those observed in the recommendation of randomly generated activities. Q10 presents a statement related to the high quantity of recommended activities. In this item, the percentage of *Agree* is lower for the PSO algorithm than for the randomly generated sequence. While noting the need for adjustments in the number of sequenced actions, these results confirm the effectiveness of the proposed algorithm.

In Figure 8, the results of the satisfaction questionnaire shown in Figure 6 are presented, that is, for the PSO algorithm, but grouped by the predominant RASI axis of the participant. The number of participants per profile was *Surface* = 5, *Strategic* = 7, and *Deep* = 29. Note that the results for the *Deep* group tend to resemble the results in Figure 6, as there is a significant number of participants with a predominant *Deep* profile.

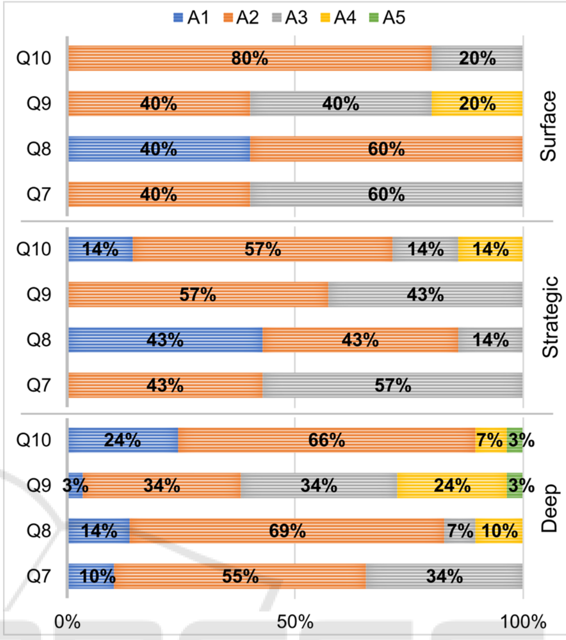


Figure 8: Satisfaction questionnaire layered by predominant RASI axis, for activities sequenced by the PSO algorithm (41 attendees).

Regarding question Q7, there is a lower tendency for participants with *Surface* and *Strategic* profiles to consider the number of actions *Very High*. Also, at this point, the low number of participants with *Surface* or *Strategic* profile may explain why this is these groups with the lowest rate of *Very High* answers. In question Q8, which analyzes how comfortable the students consider the sequence of activities received, we observed that the results were satisfactory, with a positive highlight for *Surface* and *Strategic* groups.

In question Q9, students in the *Strategic* group showed better results regarding the probability of performing all the recommended activities. Thus, we see better performance of the PSO algorithm concerning the quality of the pedagogical recommendation for the *Strategic* profile. In question Q10, we observe that 10% disagree or partially disagree that the quantity of activities is high for the *Deep* group. This result may suggest better adequacy of the algorithm to *Deep* profiles. However, it should be noted that the low number of participants with a *Surface* or *Strategic* profile may have distorted the results.

In general, we noticed that grouping the results allows us to better understand the PSO algorithm's behavior for each profile. In this sense, the proposal of this work satisfactorily meets the need and personalizes personalized pedagogical actions in an automated manner. From this, we understand that in future works, it is necessary to improve the adaptation functions (F_1 and F_2) to provide pedagogical sequences more adjusted to the students' profiles.

6 CONCLUSIONS

This paper presents an approach to automatically sequencing customized pedagogical actions to the student. Using two cognitive theories, such as the Revised Bloom Taxonomy and the student's RASI profile, it was possible to sequence actions in an independent way of the curriculum structure, considering the learning process. Using digital activities provided by Bloom's Digital Taxonomy, a satisfaction experiment was carried out in which sequences of activities were recommended for students from the sequences of actions generated by the PSO.

An important finding of this work concerns the feasibility of personalized pedagogical recommendations through digital activities that consider a student RASI profile. Thus, it was shown that the relationship established between the BT and the RASI is an effective approach to solve this problem. From the results of the experiment, it was concluded that students were satisfied with the quantity and quality of activities recommended by the PSO.

In this sense, the binary PSO developed from the proposed methodology proved to be an efficient approach to solve the sequencing problem. The optimization process was able to find sequences composed of actions that were relevant and in adequate quantity for each student. A limitation in this study is the discrepancy between the predominant profiles of the students who participated in the experiment, which requires a more in-depth statistical analysis of the data obtained. As future works, we intend to feedback the reference values of the optimization objectives from the satisfaction survey results and carry out the integration with a Virtual Learning Environment in order to automate the recommendation process.

ACKNOWLEDGMENT

The authors thank the Federal University of Uberlândia, the Goiano Federal Institute, and the Federal Institute of Triângulo Mineiro for supporting this research.

REFERENCES

Al-Muhaideb, S. and Menai, M. E. B. (2011). Evolutionary computation approaches to the curriculum sequencing problem. *Natural Computing*, 10(2):891–920.

Brown, M., McCormack, M., Reeves, J., Brook, D. C., Grajek, S., Alexander, B., Bali, M., Bulger, S., Dark, S., Engelbert, N., et al. (2020). 2020 educause horizon report teaching and learning edition. Technical report, EDUCAUSE.

Chu, C.-P., Chang, Y.-C., and Tsai, C.-C. (2011). Pc 2 pso: personalized e-course composition based on particle swarm optimization. *Applied Intelligence*, 34(1):141–154.

Churches, A. (2010). Bloom's digital taxonomy.

da Costa, N. T. and Fernandes, M. A. (2021). Sequenciamento de ações pedagógicas baseadas na taxonomia de bloom usando planejamento automatizado apoiado por algoritmo genético. *Revista Brasileira de Informática na Educação*, 29:485–501.

De-Marcos, L., Martínez, J. J., Gutiérrez, J. A., Barchino, R., and Gutiérrez, J. M. (2009). A new sequencing method in web-based education. In *2009 IEEE Congress on Evolutionary Computation*, pages 3219–3225. IEEE.

Engelbrecht, A. P. (2006). *Fundamentals of Computational Swarm Intelligence*. John Wiley & Sons, Inc., Hoboken, NJ, USA.

Entwistle, N. (2018). *Student learning and academic understanding: A research perspective with implications for teaching*. Academic Press.

Entwistle, N. and Tait, H. (2013). Approaches and study skills inventory for students (assist) (incorporating the revised approaches to studying inventory - rasi). *Edinburgh: Centre for Research on Learning and Instruction, University of Edinburgh*.

Fusilier, M., Bhuyan, R., Russell, J., Lin, S., and Yang, S. (2021). Studying approaches: samples in china, kuwait, and usa. *Journal of Applied Research in Higher Education*, ahead-of-print.

Goštautaitė, D. (2019). Principal component analysis and bloom taxonomy to personalise learning. In *EDULEARN19 Proceedings 11th International Conference on Education and New Learning Technologies: Palma, Spain. 1-3 July, 2019*, pages 2910–2920. IATED Academy.

Huang, R., Spector, J. M., and Yang, J. (2019). *Educational technology: a primer for the 21st century*. Springer.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks*, volume 4, pages 1942–1948 vol.4.

Kennedy, J. and Eberhart, R. C. (1997). A discrete binary version of the particle swarm algorithm. In *1997 IEEE International conference on systems, man, and cybernetics. Computational cybernetics and simulation*, volume 5, pages 4104–4108. IEEE.

Kennedy, J. F., Eberhart, R. C., and Shi, Y. (2001). *Swarm intelligence*. The Morgan Kaufmann series in evolutionary computation. Morgan Kaufmann Publishers, San Francisco.

Krathwohl, D. R. (2002). A revision of bloom's taxonomy: An overview. *Theory Into Practice*, 41(4):212–218.

Martins, A. F., Machado, M., Bernardino, H. S., and de Souza, J. F. (2021). A comparative analysis of metaheuristics applied to adaptive curriculum sequencing. *Soft Computing*, pages 1–16.

Moran, J. (2015). Educação híbrida: um conceito-chave para a educação, hoje. *Ensino híbrido: personalização e tecnologia na educação. Porto Alegre: Penso*, pages 27–45.

Pireva, K. and Kefalas, P. (2017). A recommender system based on hierarchical clustering for cloud e-learning. In *Intelligent Distributed Computing XI*, pages 235–245.

Schrock, K. (2011). Bloomin' Apps: Kathy Schrock's Guide to Everything.

Smaili, E. M., Khoudda, C., Sraidi, S., and Charaf, M. E. H. (2020). An optimized method for adaptive learning based on pso algorithm. In *2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*, pages 1–5. IEEE.

Subiyantoro, E., Ashari, A., and Suprapto, S. (2021). Learning Path Recommendation using Hybrid Particle Swarm Optimization. *Advances in Science, Technology and Engineering Systems Journal*, 6(1):570–576.

Sunaga, A. and Carvalho, C. S. (2015). As tecnologias digitais no ensino híbrido. In Bacich, L., Neto, A. T., and Trevisani, F. d. M., editors, *Ensino híbrido: personalização e tecnologia na educação*. Penso Editora. Capítulo 7.

Tait, H. and Entwistle, N. (1996). Identifying students at risk through ineffective study strategies. *Higher Education*, 31:97–116.

Woolf, B. P. (2010). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann.