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Customized Pedagogical Recommendation Using Automated Planning for Sequencing Based on Bloom's Taxonomy

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ABSTRACT

Personalized sequencing and recommendation of pedagogical actions in virtual learning environments are relevant aspects in promoting an effective learning process with computer-aided support. Hence, this work investigates the use of automated planning to sequence these actions according to student profiles. Actions are modeled to correspond to the cognitive process described by Bloom's taxonomy, and the student profile is set using the revised approaches to studying inventory. Both models share theoretical foundations linked to the cognitive process, and the mapping of these two theories is one of the contributions merged into this study. In planning, through use of a genetic algorithm, and the problem formulation as an optimization problem, one can correctly manage the search for good solutions, as demonstrated in this work. Through use of digital Bloom's taxonomy, one arrives at a recommend set of actions. Experiments were performed using 41 students. The results were promising and demonstrate the viability of the proposal.

KEYWORDS

ASSIST, Automated Planning, Bloom's Taxonomy, Genetic Algorithm, Pedagogical Recommendation, RASI, Sequencing of Pedagogical Actions, Taxonomy of Educational Objectives

1. INTRODUCTION

The Revised Bloom's Taxonomy[1] showed in Krathwohl (2002) and the Revised Approaches to Studying Inventory (RASI) discussed in Tait and Entwistle (1996) are appropriate for the proposal of a pedagogical recommender based on the student cognitive process. BT is a two-dimensional model for the learning process. One of these dimensions defines the cognitive process as six categories starting from the Lower Order Cognitive Skills (LOCS) to Higher-Order Cognitive Skills (HOCS). BT is related to the actions that can be used to develop student skills along the learning process. On the other hand, RASI defines the student cognitive profile employing the strengths of the student under three axes: *Surface*, *Strategic* and *Deep*. As in BT, the student cognitive process in RASI occurs from LOCS to HOCS. A relationship between RASI and BT was partially explored in Brown et al. (2015) and Shang (2019).

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The recommendation process assumes the determination of the recommendation itself, which in this case is a sequence of actions. Based on the aforementioned theories, these pedagogical actions (or sequence of pedagogical actions) can be determined by taking the student RASI profile and the BT actions. Searching for a sequence of pedagogical actions is reported in the literature as the well-known sequencing problem, with Automated Planning (AP) techniques in Artificial Intelligence being used to deal with it. Finding such a sequence is similar to planning the steps (actions) that a student should perform to reach a particular goal. Planning supposes an initial state that, in this case, is the initial student profile and the set of actions that allows for the advancing to other states from the current one. A goal state is also necessary to guide the search process.

The feasibility of modeling the teaching-learning process employing AP is presented in Caputi and Garrido (2015), Pireva and Kefalas (2018), and Nabizadeh et al. (2020), where AP is related to the fulfillment of learning objectives and the problem domain considers the restrictions to achieve these objectives. As AP is a difficult problem, bio-inspired algorithms for planning pedagogical sequences are an alternative, as can be seen in Ariyaratne and Fernando (2014) and Hssina and Erritali (2019).

Therefore, this work is driven by the following question: Can the pedagogical recommendations be independent of the curricular structure? This work proposes pedagogical recommendations based on the student cognitive process to answer this question. Additionally, it is assumed that these recommendations are automated and customized. Then, we propose a digital activity recommender based on personalized and automated pedagogical actions sequencing. The personalization is performed considering the RASI cognitive profile of the student. The sequencing of pedagogical actions uses automated planning supported by a GA. In addition, the pedagogical actions are modeled by the BT from the perspective of the student cognitive process.

In order to elaborate on the proposal presented herein, this paper is organized as follows: Section 2 shows an overview of studies that employ automated planning in pedagogical sequencing; Section 3 details the theoretical framework used, such as the RASI profile, the BT, and the GA technique, besides describing the proposed methodology; Section 4 presents the experiments and results obtained and the analysis of the findings of this research; Finally, Section 5 presents the conclusion and future work.

2. AUTOMATED PLANNING AND ACTION SEQUENCING

A systematic literature review described in da Costa et al. (2019) presented the AP application advances, limitations, and challenges in the pedagogical process and pointed to AP as an essential tool for interfacing the e-learning requirements and delivering personalized content. However, suppose there are many actions or parameters in the student profile, the state space of action sequences increases. In that case, the classical AP with Planning Domain Definition Language (PDDL) is impracticable when it comes to the search for a solution. Dwivedi et al. (2018) describe that in this case, GA is more suitable for dealing with this PA issue since it can minimize the computational effort.

GAs have been applied to optimize action sequences in the pedagogical context. Lin et al. (2016) presented learning map planning using a multi-objective GA, where the objective functions were learning time and student performance. In Dwivedi et al. (2018), GA was applied for curricular sequencing by considering learning styles, knowledge levels, and learning goals as parameters for optimizing learning paths. Curricular sequencing is also addressed in Agbonifo and Olanrewaju (2018), where the learning path optimization in an e-learning environment is performed by a GA, while taking into account the concept difficulty level and the relationship among concepts as objectives to be optimized.

Goyal and Rajalakshmi (2018) proposed a method that generates a set of evaluative activities according to BT learning levels, and a GA is used to create test sheets. Hence, the exams presented the degree of knowledge held by the student and optimized their performance. Hssina and Erritali (2019) developed an adaptive e-learning platform for generating learning paths appropriate to student profiles using a GA that considers pedagogical objectives set by the teacher and the student knowledge level. A GA for determining learning paths for student groups is addressed in de Miranda et al. (2019), where the optimization criteria were the maximization of student satisfaction and minimization of time to fulfill activities.

In the abovementioned studies, the optimization process is related to aspects linked to the curriculum, such as LO or activity restrictions and content requirements. Therefore, other research fronts that investigate the recommendation feasibility from the perspective of the student cognitive process are essential. Such a proposition can bring benefits, such as a recommendation process independent of curricular structures, besides focusing the learning control onto the student.

3. ACTION RECOMMENDER MODEL

da Costa and Fernandes (2021) proposed sequencing of pedagogical actions, which this work expands by including this sequencing in a recommendation model and evaluating the recommendation through experiments. This section presents the mapping proposal between BT and RASI theories, which is the foundation for the sequencing and the recommendation process.

3.1. Relationship BT and RASI

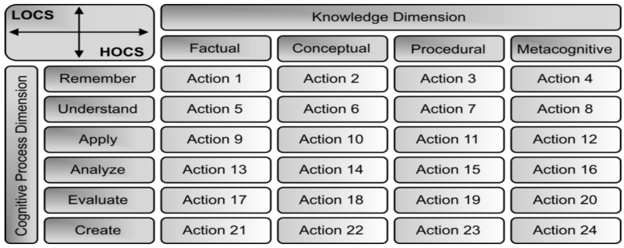
As mentioned previously, in many studies, customized pedagogical sequencing takes into account curriculum structures or learning objects, making these approaches dependent on a specific knowledge domain. By proposing independent sequencing on the domain, this work aims to sequence pedagogical actions rather than concepts or learning objects. Therefore, its use is more generalized, since it is possible to apply it to any domain.

3.1.1. Revised Bloom's Taxonomy

The BT showed in Krathwohl (2002) provides pedagogical actions for accomplishing the learning process since these actions are associated with some position of a two-dimensional framework, where the first dimension concerns the cognitive process dimension (CPD) and the second the knowledge dimension (KD). Figure 1 illustrates this framework, where CPD is divided into six categories (or cognitive states), namely: Remember, Understand, Apply, Analyze, Evaluate and Create. KD is divided into four categories (Factual, Conceptual, Procedural, and Metacognitive), according to a hierarchy from LOCS to HOCS.

BT's structure of educational objectives allows it to be employed in various scenarios, as in the work presented by Zhang et al. (2021), which classified assessment tasks in an automated manner through machine learning. Whereas in the work proposed by Callaghan-Koru and Aqil (2020), undergraduate public health courses were designed from the hierarchy of cognitive processes in BT. Prasad (2021) exploits BT to identify student performance in online classes by exploring the cognitive domain. Thus, we observe that it is possible to use the hierarchy of educational objectives provided by the BT in different scenarios. Therefore, in this work, we propose the use of the BT in a two-dimensional fashion (CBD x KD) by defining an action for each educational objective according to the matrix presented in Figure 1.

Figure 1. Pedagogical actions defined according to BT



Source: Adapted from da Costa and Fernandes (2021)

In Figure 1, there are 24 positions with pedagogical actions being associated to each. The general use of this framework implies attributing each educational objective to the positions that indicate which are the most appropriate actions to reach this objective. The most frequent use is manual, which is difficult and slow. Although there is a subjacent hierarchy in each dimension, and it is desirable that actions closer to LOCS (concrete actions) are sequenced before actions closer to HOCS (abstract actions). According to Figure 1, *Action 1* is the most concrete, and *Action 24* is the most abstract. The intermediate actions follow an increasing order of cognitive skills (LOCS to HOCS) required by the student. Positions (actions) can be suppressed according to the needs of the student (Krathwohl, 2002). In other words, it is not necessary to pass through each level, one by one. This leads to many action combinations and consequently to a significant number (2^{24}) of action sequences. Therefore, this study contributes to the automated selection of pedagogical action through planning and sequence customization.

3.1.2. Student RASI Profile

As one of the AP requirements is an initial state, in pedagogical sequencing problems, this state is or is related to the student profile, which can contain different attributes such as learning styles, time, and knowledge (Nabizadeh et al., 2020). In this work, the initial state is the tendency of the student to adopt specific learning and study approaches according to RASI defined in Tait and Entwistle (1996). This choice was made possible in order to establish an interface between the RASI profile of the student and the BT pedagogical actions.

In Entwistle (2018), RASI is a specific section that constitutes the Approaches and Study Skills Inventory for Students (ASSIST). This section has often been used as in Entwistle et al. (2013), and Fusilier et al. (2021). RASI is related to the description of strategies used by the student to learn and study through the mapping of their cognitive profile from the perspective of three axes, namely *Surface*, *Strategic* and *Deep*. These axes can be analyzed considering progress from LOCS to HOCS, similar to BT's hierarchy of educational objectives. The axes' indexes representing each dimension are obtained by a questionnaire consisting of 52 short statements (items). Students can express their agreement or disagreement on a five-point Likert[2] scale, as described in Entwistle (2018). From this, one can analyze the cognitive profile of each student described by the RASI, considering the variations of these indexes along the three dimensions.

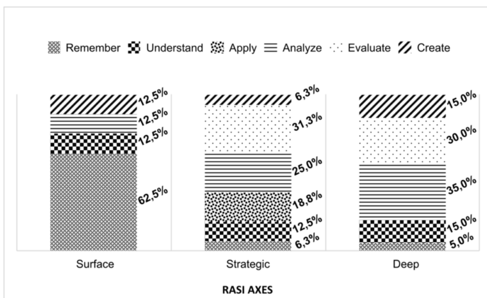
3.1.3. Mapping: BT to RASI

BT, as well as RASI, describe the student cognitive process from LOCS to HOCS. In other words, student progress is developed from concrete to abstract abilities. Due to this intersection, some studies have tried to understand and make this relationship evident. Brown et al. (2015) pointed out the convergence between these theories, identifying student cognitive state and possible pedagogical actions considering the *Surface* RASI axes. Shang (2019) established a relationship between the RASI sub-scales for *Deep* axes and the CPD categories. Inspired by this research, da Costa and Fernandes

(2021) determined how significant each CPD category for each RASI axes is by comparing the questions of RASI inventory with the definitions of the CPD subcategories. The 52 RASI questions were associated with the most compatible CPD category by comparing the key verbs and category definitions with the RASI questions. Consequently, the mapping (compatibility) between TB and RASI is obtained. In Figure 2, the result is the compatibility rate of each CPD category for each RASI axis.

In Figure 2, each column represents a RASI axis, and the pattern represents CPD categories. *Remember* is predominant for the *Surface*, *Evaluate* is prevailing for the *Strategic*, and *Analyze* is second most relevant. In respect to *Deep*, the predominant is *Analyze*, and the second most relevant is *Evaluate*. Note that for the *Deep*, the relevance of *Create* is greater than the other axes. This mapping uses a different methodology than the strategies presented in Brown et al. (2015) and Shang (2019). However, the similarity among these three mappings for the *Deep* axis was 58.3%, which shows some correlation between the strategy adopted by da Costa and Fernandes (2021) and Shang (2019).

Figure 2. Compatibility rate between profiles (RASI) and cognitive states (BT)



Source: Adapted from da Costa and Fernandes (2021)

Through the above mapping, one can sequence actions customized to the student RASI profile. However, it is necessary to associate each action in the sequence with a practical activity that students can perform. In addition, the intention here is that this activity is accomplished in virtual learning environments. The selection of these activities depends on a general attribution of activities digital to BT. Through such, Bloom's Digital Taxonomy (BDT), as proposed in Churches (2010), is suitable since it provides digital activities related to BT.

Table 1. Mapping of digital activities for the BT two dimensions

CPD[1]	KD[2]	A[3]	Digital Activity
Remember	Factual	**1**	Search for basic concepts on the Web or social networks.
	Conceptual	**2**	Read e-book.
	Procedural	**3**	Answer online quiz (quiz).
	Metacognitive	**4**	Post academic content on blogs or social networks.
CPD[1]	**KD[2]**	**A[3]**	**Digital Activity**

Table 1 continued on next page

Table 1 continued

CPD[1]	KD[2]	A[3]	Digital Activity
Understand	Factual	**5**	Perform an advanced search on the Web or in specific databases.
	Conceptual	**6**	Summarize or highlight excerpts in a digital document.
	Procedural	**7**	Laying out ideas, using Prezi, PowerPoint, etc.
	Metacognitive	**8**	Carry out a video or audio recording of the content.
Apply	Factual	**9**	Implement diagrams.
	Conceptual	**10**	Conduct demonstrations using graphic and/or audio/video tools.
	Procedural	**11**	Run simulation or interact with an educational game.
	Metacognitive	**12**	Participate in an interview or podcast.
Analyze	Factual	**13**	Organize mapping over the content.
	Conceptual	**14**	Structure database through lists and/or summaries.
	Procedural	**15**	Write reports with graphs and/or spreadsheets.
	Metacognitive	**16**	Draw diagrams with a relationship of ideas.
Evaluate	Factual	**17**	Participate in discussions using tools on the Web.
	Conceptual	**18**	Interact with the network using web tools.
	Procedural	**19**	Review group activities using web tools.
	Metacognitive	**20**	Evaluate content or moderate posts and comments from social networks.
Create	Factual	**21**	Present content using digital tools.
	Conceptual	**22**	Publish content to the Web.
	Procedural	**23**	Develop a project or model using digital tools.
	Metacognitive	**24**	Create digital media such as a game, a video, audio, or an image.

Subtitle: 1. Cognitive process dimension; 2. Knowledge dimension; 3. Action number

Churches (2010) presented BDT, a Bloom Taxonomy version composed by only a cognitive process dimension, where activities specified to each CPD category are digital activities. This study extends Churches (2010) proposal to the second dimension (KD) by ranking the BDT digital activities from concrete to abstract and assigning them to one of the four KD categories according to the rank order, as shown on Table 1. Noteworthy here is that extended mapping is a contribution of this study, as it allows the use of two-dimensional BT in virtual learning environments. In addition, a practical application of the approach for sequencing developed in this study becomes viable through the recommendation of digital activities. An example of an activity sequence and the use of Table 1 is shown in the following subsection.

3.2 Sequencing with a Genetic Algorithm

As the BT hierarchy can be changed according to the learning objectives, there are 24 possible pedagogical actions and 2^{24} different sequences of actions. Therefore, evolutionary algorithms, such as

GAs, are suitable for searching over a large search space. Recent studies demonstrated the GA ability for pedagogical sequencing. As such, this work proposes a GA to find the adequate sequence of BT actions for the student RASI profile. The GA specification consists of the individual representation, the objective function (optimization criterion), and genetic operators. The criterion definition for evaluating each sequence during the search process depends on the pedagogical aspects concerning sequencing. One then sees that this criterion is a research contribution since it is a proposal for analyzing and evaluating a specific combination of pedagogical features.

An individual is a problem solution, and a solution is a sequence of actions. An individual is a binary vector composed of 24 bits, where each bit represents a pedagogical action, as pictured on Table 2. Bits set to 1 indicate the corresponding actions are present at the sequence, otherwise not. As the goal is to find a more adequate sequence for the student RASI profile, the objective function measures how near the sequence is to the student RASI profile. Therefore it is necessary to determine the RASI indexes of the sequence which express the strength of each cognitive state (R*emember*, ..., *Create*) in the sequence weighted by the relevance of this state for each RASI axis (*Surface*, *Strategic* and *Deep*). Formally, these indices are given by the product between the cognitive state weight ($P_{cognitive\_state}$) and the RASI axis indices ($D_{category}$) in Figure 2, where $P_{cognitive\_state}$ is the product of the number of bits set to 1 in the cognitive state and 0.25.

Table 2. Individual Representation as a binary GA value

A[1]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
B[2]	1	1	0	1	1	1	1	1	0	0	0	0	0	0	1	0	1	1	1	1	0	1	0	1

Subtitle: 1. Action Number; 2. Bit value

Let's assume there is an individual described only by bits set to 1, *1–2–4–5–6–7–8–15–17–18–19–20–22–24*, the first cognitive state (*Remember*) presents 3 bits (1, 2 and 4) set to 1, the second presents 4 (5, 6, 7, 8) and so on. From the first to the sixth state, the number of bits set to 1 are 3, 4, 0, 1, 4 and 2, respectively, so the weights of cognitive states are 0.75, 1.0, 0, 0.25, 1.0 and 0.5. According to Figure 2, the *Surface* RASI indexes are 0.625 0.125 0.0 0.125 0.0 and 0.125, respectively, for each cognitive state. Therefore, the *Surface* RASI indexes for the individual are su = 0.75 x 0.625 + 1.0 x 0.125 +… + 0.5 x 0.125 = 0.6875. Likewise, *Strategic* and *Deep* indexes are calculated, resulting in I = (su = 0.6875; st = 0.09375; de = 0.2121). Now, it assumes the student RASI profile is given by S = (*su* = 0.34375; *st* = 0.5; *de* = 0.65), then the objective function (*fitness*) is given by Eq. 1, where *I* and *S* are as before, *dist(I, S)* is the Euclidean distance and *pnlt(I, S)* is a penalty.

$$fitness\left(I\right) = dist\left(I,S\right) + pnlt\left(I,S\right) \tag{1}$$

Note that only Euclidean distance does not allow for identification if the sequence is close to the student profile in respect to each RASI axis, then *pnlt(I, S)* adds to *fitness(I)* a penalty for each RASI axis that is violated. Table 3 presents an example where the *Deep* axis is more relevant for the student, and the *Surface* axis is more relevant for the sequence. To consider this relevance, weights are attributed to each axis, $W_1 = 1$ for the least relevant; $W_2 = 2$ for the intermediate axis; and $W_3 = 3$ for the most relevant. 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, as shown in Eq. 2. Thus, the penalty is at most the Euclidean distance and, consequently, the fitness is at most double the Euclidean distance. If there is no difference in the relevance order on any RASI axis, W_1, W_2, or W_3 are set to 0.

Table 3. Example of the order of relevance of RASI indexes

	RASI Indices			Relevance Order		
	su	st	de	**Weight 3**	**Weight 2**	**Weight 1**
Individual (I)	0.687500	0.578125	0.65000	su	de	st
Student (S)	0.343750	0.500000	0.65000	de	st	su

$$pnlt(I,S)=dist(I,S)/6\times W1+dist(I,S)/6\times W2+dist(I,S)/6\times W3 \tag{2}$$

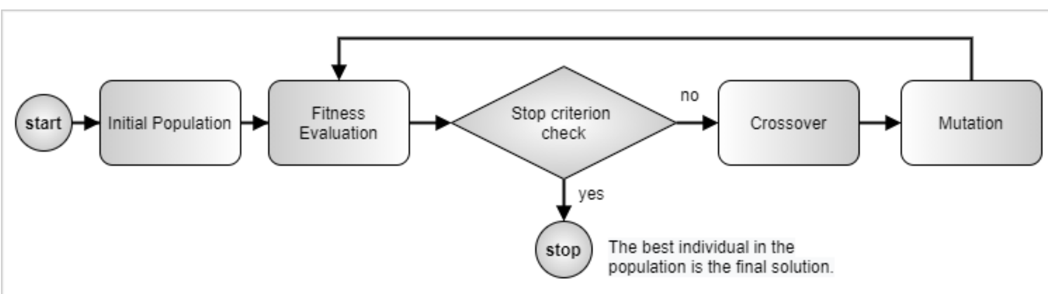
The penalty for the example of Table 3 considers the weights *3*, *2* and *1* since the relevance order for all axes is divergent, where *dist(I, S) = 0.352526*. Then *fitness (I) = 0.705032*.

$$pnlt(I,S)=\frac{dist(I,S)}{6\times 3}+\frac{dist(I,S)}{6\times 2}+\frac{dist(I,S)}{6\times 1}=0.352516$$

Finally, we present an example of a sequence of digital activities recommendations. Consider the individual on Table 2, and for each bit set to 1, the digital activity corresponding to this bit on Table 1 is one of the activities in the sequence. For example, on Table 2, the first bit set to 1 corresponds to the first row of Table 1. Therefore, the digital activity "*Search for basic concepts on the Web or social networks.*" is the first activity of the sequence, and so on. The complete sequence of digital activities corresponding to the individual on Table 2 is given by the activities in rows 1, 2, 4, 5, 6, 7, 8, 15, 17, 18, 19, 20, 22, and 24 on Table 1.

A flowchart for the GA is termed in Figure 3. We used in its implementation the parameters defined in Engelbrecht (2007) as having the following structure: i) Initial population generation; ii) Fitness evaluation; iii) Checking the stop criteria; iv) If the check of step *iii* is affirmative, the solution is returned, and algorithm execution stops; v) If the check of step *iii* is negative, crossover and mutation are performed, and the execution algorithm returns to step *ii*.

Figure 3. Genetic Algorithm Flowchart



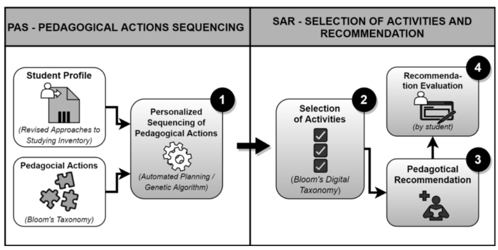
For the steps shown in Figure 3, parameters were set, as described in the following. The initial population is the size MAX_I. The maximum number of generations (MAX_G) is used as the stop criterion for the GA. The tournament method is used to select the individuals that will be part of the next generation. In this process, three individuals are randomly selected, and the best of these is chosen according to a probability rate P_T. The crossover is performed in adjacent 4-bit blocks, thus considering the six subcategories of CPD for BT. After the new individuals are ranked, the MAX_I best ranked will make up the next generation population. The mutation, performed randomly in the population and considering a P_M rate, inverts a random bit from an individual.

For the proposed GA, the population size $MAX_I = 1000$ and the number of generations $MAX_G = 100$ were defined. For the selection of individuals per tournament, the probability P_T was 60%, and the probability of mutation P_M, was 10%. These values were defined from exploratory tests. We observed that values different from those presented for the mentioned parameters did not cause significant changes or deteriorate the results.

3.3. Architecture Overview

In Figure 4, the pedagogical recommendation comprises of two modules: Pedagogical Actions Sequencing (PAS) and Activities Selection and Recommendation (SAR). The first module is responsible for the customized sequencing of pedagogical actions. The second is responsible for selecting activities, recommending, and evaluating the sequence of activities delivered to the student.

Figure 4. Recommendation model for the pedagogical actions



Process 1 in the PAS Module is responsible for sequencing pedagogical actions carried out by the GA specified in the previous section. Process 2 in the SAR module selects a digital activity for each action in the sequence, using the mapping BDT versus BT. Process 3 is responsible for delivering the sequence to the student, and in Process 4, the student evaluates the recommendation by answering a satisfaction questionnaire.

4. EXPERIMENTS, RESULTS, AND DISCUSSION

The sequencing and recommendation evaluation was performed by real experiments conducted during a degree course in computer science at a federal institute of education, science, and technology, located in the state of Minas Gerais, Brazil, to participate in the research. A total of 200 students over 18 years old were invited, of which 41 voluntarily participated in the experiments. The sampling was below the expected proportion for a homogeneous population (134 students for sampling error of 5%). Therefore, the expected margin of error in the responses is 11.41% and a confidence level of 90%.

The authors assured the students that their answers would be treated anonymously, using a random identifier and that no students' personal information would be disclosed under any circumstances. The experiments were developed in three stages:

i) Identification of the student RASI profiles, provided by Entwistle and Tait (2013).
ii) Sequencing of pedagogical actions for each student
iii) Recommendation of digital activity sequences for students and satisfaction analyses.

In step *i,* the students answered the RASI questionnaire[3], and their RASI profiles were calculated. In step *ii*, the sequences of activities were determined by the proposed GA and sent to the students. In step *iii,* the students answered an agreement questionnaire in accordance with their profiles and satisfaction questionnaire[4] concerning the received sequence of activities. The answers to these three questionnaires were formulated considering a 5-level Likert scale. All questionnaire links were sent to the students by email.

4.1 Identification of the Student RASI Profile

This first experiment stage consisted of collecting the RASI questionnaire answers of the 41 students. Each RASI student profile was determined using the questionnaire answers, resulting in 18 students with *Surface* as the predominant RASI profile, 17 were identified as *Strategic*, and 6 were *Deep*. These students received their respective profiles, along with another questionnaire to evaluate the degree of agreement with their RASI profiles. Only 24 students voluntarily answered this second questionnaire, and the degrees of agreement are seen in Figure 5. The 24 students evaluated whether each axis should be higher or lower in percentage points, according to the following Likert scale: *Very Low* - at least 7 points less; *Low* - between 3 and 6 points less; *Equal* - up to 2 points more or less; *High* - between 3 and 6 more points; *Very High* - at least 7 more points.

Figure 5. Degree of agreement with the RASI profile

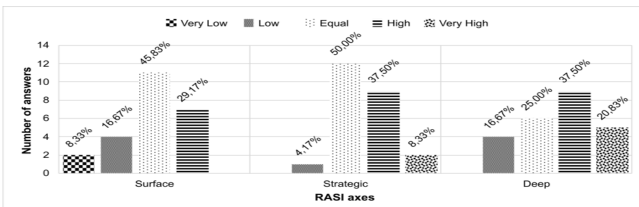


Figure 5 shows the degree of agreement with their cognitive profiles was satisfactory. However, 8.33% of participants consider the *Surface* axis should be much lower. Whereas, 8.33% of the students identified as *Strategic,* and 20.83% among the *Deep* students consider these axes should be much higher than that pointed out by the RASI profile calculus. These results demonstrated that the RASI profiles of the 24 students are, in general, their real profiles. The following steps of the experiments are sequencing and recommendation. Using such, the promising and expected result is the satisfaction of these students with the recommendation since it would indicate that this proposal can recommend suitable sequences for RASI profiles.

4.2 Action Sequencing

The student profiles, as previously calculated, were considered for sequencing pedagogical actions using GA (Process 1 in Figure 4), specifically in fitness function (Eq. 1). Next, one sequence was sent to each of the 41 students who responded to the RASI questionnaire, independent of their answering the second questionnaire. In this experiment stage, the sequences are expected to be in conformance with the predominant RASI axis. According to the mapping BT and RASI, sequences for students considered *Surface* should contain, preferentially, actions of *Remember*, which is the most relevant

CPD category for *Surface* axis. In order to analyze this sequence aspect, relevance degrees of the CPD categories for each RASI axis was defined and presented on Table 3.

Table 4. Relevance of CPD categories for each RASI axis

RASI Axis	Degree of Relevance		
	Low	Moderate	High
Surface	Apply, Evaluate	Understand, Analyze, Create	Remember
Strategic	Remember, Create	Understand, Apply	Analyze, Evaluate
Deep	Remember, Apply	Understand, Create	Analyze, Evaluate

The mapping defined in Figure 2 guided the definition of relevance degrees shown on Table 4. The categories with smaller indexes on each RASI axis were classified as *low relevance* to the profile. Those with the most relevant indexes were classified as *high relevance*. The remaining catergories were classified as *moderate relevance*. Based on Table 4, the classification of the sequences returned by GA for the 41 students was analyzed, as shown on Table 4. Noted from the mean (first row) among these 41 sequences, the GA was able to select principally the more relevant actions for *Deep* and *Surface* axis. Although the actions of high relevance for *Strategic* were not the most sequenced; moderate actions were. Noteworthy here is that this analysis aims to evaluate the proposed BT and RASI mapping, since the degrees of relevance are consequences of this mapping. Statistical tests were performed to verify the significance of the relationship expressed in this mapping. The Shapiro-Wilk Test [5] on Table 5 revealed that the data did not present a normal distribution for all relevance degrees, as there are p indexes greater than 0.05. At this point, the Kruskal-Wallis Test[6] was applied, as shown on Table 6.

Table 5. Analysis of GA sequences in relation to relevance degrees

	Relevance of the activities sequenced by profile			
	RASI Axis	Low	Moderate	High
Mean	deep	0.333	0.667	0.688
	strategic	0.507	0.897	0.625
	surface	0.757	0.500	0.903
Standard Deviation	deep	0.171	0.219	0.0685
	strategic	0.0934	0.173	0.133
	surface	0.289	0.167	0.125
Shapiro-Wilk W	deep	0.927	0.797	0.683
	strategic	0.787	0.667	0.922
	surface	0.812	0.937	0.624
Shapiro-Wilk p	deep	0.554	0.055	0.004
	strategic	0.001	< .001	0.159
	surface	0.002	0.255	< .001

Note that the p index was below 0.05, revealing the statistical significance of the sequenced actions when grouped by degree of relevance to each student profile. This means that the GA prioritizes sequencing activities that are more relevant to the cognitive profile of the student over less relevant activities, thus corroborating the effectiveness of the proposed algorithm. Noted here was that the proposed GA maintains expected technical objectives for a recommendation system, such as relevance, novelty, serendipity, and diversity, as described in Aggarwal et al. (2016). Although the most relevant actions were more recommended, there is a need for adjustments in GA to minimize the recommendation of less relevant actions to the student profile.

Table 6. Kruskal-Wallis Test for the relevance of sequenced actions

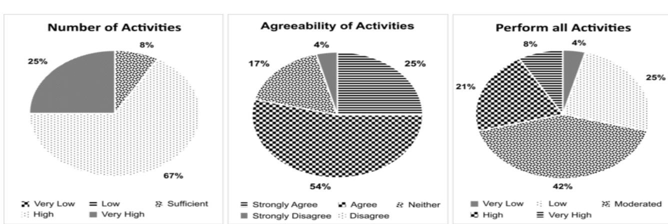
	χ^2	df	p
Moderate	23.0	2	<0.1%
High	22.6	2	<0.1%
Low	16.0	2	<0.1%

If the strata per RASI axis is analyzed separately, the *Surface* axis had the best recommendation rate of actions with high relevance to the cognitive profile. On the other hand, the *Strategic* axis had the worst recommendation rate of activities with high relevance. Given the analysis of the measures presented on Table 4, one is able to use this as a parameter to implement improvements to the proposed GA so that recommended actions are adjusted more effectively to the student profile.

4.3 Pedagogical Recommendations

According to student RASI profiles, each action in the sequences returned by GA represents a general view of what the students need to do in order to learn. However, these actions do not specify which activities they should perform. As such, before proceeding to this experiment stage, the recommendation itself (Process 3 in Figure 5), the digital activity corresponding to each action, based on Table 1, must be assigned to the sequences (Process 2 in Figure 4), building the sequences for the activities to be recommended. The student was presented with the sequence through an activity list on a web page. Once again, the results were evaluated by a satisfaction questionnaire, where the students evaluated the recommended sequences (Process 4 in Figure 4). Only 24 students responded to this third questionnaire regarding the respective pedagogical sequence received. The following criteria were used to evaluate the sequences: i) Number of recommended activities (sequence size) in Figure 6a; ii) Degree of agreeability with activities in Figure 6b; iii) Possibility of completing all activities in Figure 6c.

Figure 6. Evaluation of the recommended sequences



The performance criteria presented in Figure 6a consider evaluating the items offered to the students through the of these items. According to its use, Chen et al. (2020) state that this parameter may be desirable in recommender systems. In Figure 6a. The students presented their opinion on the number of activities received, whose answers could be:

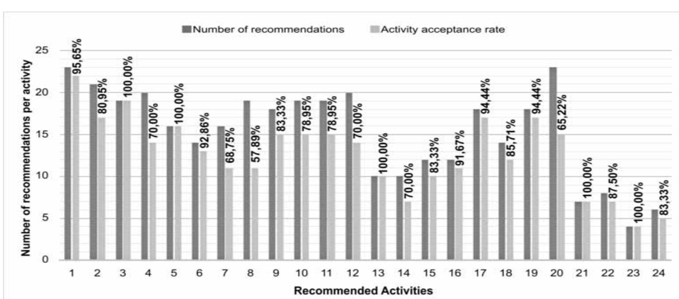
- *Very High* (has at least 6 activities more than considered ideal).
- *High* (has between 3 and 5 activities more than considered ideal).
- *Sufficient* (has 2 activities more or less what one would consider ideal).
- *Low* (has between 3 and 5 activities less than considered ideal).
- *Very Low* (has at least 6 activities less than considered ideal).

Note in Figure 6a that most students (92%) consider the number of activities *High*, or *Very High*. According to the proposed modeling, the maximum number of activities possible is 24, but on average 15 activities were recommended for each student. This represents almost $^2/_3$ of the maximum number of activities that can be recommended. The analysis of this evaluation can be used to improve the GA and adapt the number of sequenced activities to the cognitive profile of the student.

Figure 6b describes the analysis of agreeability. The students were questioned about how agreeable the sequences of activities received would be in terms of leading them toward learning new content. One notes that 79% of the students answered *Agree* or *Strongly Agree* that the sequence of activities would lead them to learn new content. Despite the satisfactory results, it is possible to use this evaluation to personalize the adequacy of the pedagogical recommendation to the student since 4% *Strongly Disagree* and 17% responded *Neither*.

In Figure 6c, the student was asked about the possibility of performing all the activities from the recommended sequence. The answer options were *Very High* (over 80%), *High* (between 61% and 80%), *Moderate* (between 41% and 60%), *Low* (between 20 and 40%), and *Very Low* (below 20%). Note that 29% of students consider *Low* or *Very Low* the possibility of performing all recommended pedagogical activities. Furthermore, 42% consider *Moderate,* and 29% consider *High* or *Very High* the possibility of completing all the activities. This result is related to the number of activities considered high by most students. Accordingly, this evaluation corroborates the need to adjust the number of activities to each student profile.

Figure 7. The acceptance rate for each recommended educational activity



Another factor analyzed was the acceptance rate of each pedagogical activity recommended. This rate was calculated from the responses of 16 students, who gave details concerning which activities they would not like to perform. In evaluating the sequence of activities, this question was optional for the students so that these answers may be of better quality. This analysis is seen in Figure 7. Note that the activities are recommended respecting the order of the most concrete (Activity 1) to the most abstract (Activity 24). In Figure 7, activities 1 and 20 were the most recommended (23 times), but Activity 1 had a higher acceptance rate (95.65%) by students. Nevertheless, one notes a slight predilection of the participants for the more abstract activities over the less abstract, since the average acceptance rate of the first 12 activities was 81.44% and the last 12 activities were 87.97%.

Overall, 24 students responded to the evaluation on the recommended pedagogical sequences. Regarding the RASI profile axis predominant to these students, 11 *Surface*, 9 *Strategic* and 4 *Deep* profiles were noted. The rejection rate of the activities by the grouping defined on Table 4 shows that most of the students who specified which activities they would not like to do, pointed out those that have a low or moderate degree of relevance to the respective predominant cognitive profile (*Deep* = 4 profiles; *Strategic* = 9 profiles; *Surface* = 11 profiles), as presented on Table 7.

Table 7. Activity rejection rate by RASI profile according to the relevance of the activities

	Activity rejection rate by RASI profile			
	RASI Axis	**Low**	**Moderate**	**High**
Mean	deep	0.00	0.182	0.175
	strategic	0.148	0.0900	0.0556
	surface	0.307	0.254	0.121
Standard deviation	deep	0.00	0.213	0.236
	strategic	0.190	0.130	0.167
	surface	0.277	0.347	0.141
Shapiro-Wilk W	deep	---	0.802	0.848
	strategic	0.784	0.749	0.390
	surface	0.915	0.770	0.719
Shapiro-Wilk p	deep	---	0.105	0.220
	strategic	0.13	0.5	< .001
	surface	0.277	0.4	< .001

On Table 7, the Shapiro-Wilk test shows that there is no normal distribution among all groups. Based on this, the Kruskal-Wallis test was applied, as shown on Table 8, to verify the statistical significance of the results found. Note that on Table 8, statistical significance was seen only for activities in the *Low* group. This means that one can state that the rejection rate observed for the RASI profiles concerning the *Moderate* and *High* groups follows a decreasing trend. Nevertheless, when looking at the average for activity rejection rates, according to Figure 8, one notes a greater tendency to reject activities with *Low* and *Moderate* relevance.

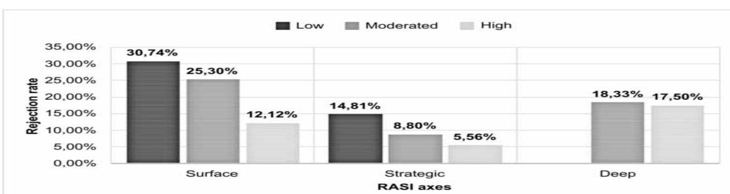
Table 8. Kruskal-Wallis *T*est for the activity rejection rate

	χ^2	df	p
Low	6.06	2	0.048
Moderate	1.19	2	0.550
High	2.28	2	0.320

From the results presented in Figure 8, the average rejection rate of the activities according to the relevance for the predominant axis of the RASI profile was *High* - 10.56%, *Moderate* - 17.95%, *Low* - 19.64%. This shows that, in general, the GA recommendation prioritizes activities closer to the needs of the student profile. In addition, students prefer activities more relevant to the profile over less relevant activities.

In Figure 8, one notes that the rejection rate was zero on the *Deep* axis for activities of low relevance. In this experiment, four students presented the predominant *Deep* axis, however, according to Table 8, the remaining students (who were not predominantly *Deep*) presented comparable indexes for *Deep* axis. Moreover, two of these four students presented *Surface* indexes near to *Deep* indexes. Note that some activities with high relevance for *Surface* are the opposite of the *Deep* profile. As such, the results presented in Figure 8 are coherent with the RASI theory. The reduced version of RASI inventory can increase accuracy in identifying the RASI profiles. Due to the smaller number of questions, the student will be more motivated to answer them. In employing this version, the expectation is that if there are a more significant number of responses, it will be possible to improve the RASI profile identification and, consequently, the other processes that pertain to the recommendation model.

Figure 8. The average rate of rejection of activities by the RASI axis according to relevance



Based on the aforementioned considerations, these results corroborate the degree of cohesion in the mapping between BT and RASI, as described in Subsection 3.1.3. Another finding was the classification of the digital activities from BDT under the perspective of the two-dimensional BT, as proposed in this work. On the other hand, such results can support improvements in both the proposed mapping and classification.

Table 9. RASI index averages, grouped by predominant axis

Predominant RASI Axis	Average per Axis		
	Surface	Strategic	Deep
Surface	0.7852	0.6918	0.5199
Strategic	0.7417	0.8090	0.4809
Deep	0.5875	0.4766	0.6797

The GA adapts a pedagogical sequence to the student profile during the sequencing process without considering the number of activities. This is an essential aspect for the student, according to the answers to the satisfaction questionnaire. Based on the results, it was noted that the number of activities influences student perception when it comes to the pedagogical recommendation. Thus, including other optimization objectives in the GA, such as the number of activities and student satisfaction, may bring benefits. This work and the suggestions for improvement present a recommendation perspective focused on the cognitive process, preferences, and goals of the student.

5. CONCLUSION AND FUTURE WORKS

This work presented an approach for automatizing and customizing the sequencing based on Revised Bloom's Taxonomy and student RASI profile. These cognitive theories allowed for the proposal of a model where the sequencing takes advantage of the cognitive aspects of the learning process instead of curricular structure. Therefore, it can be applied to any knowledge domain due to its independence of content to be learned. The sequences determined by a GA-based planner were recommended in the experiments, and a questionnaire evaluated student satisfaction.

The most important finding of this paper is related to the feasibility of personalized recommendations in digital activities to students by sequencing pedagogical actions prioritizing a cognitive domain. Consequently, the relationship between BT and RASI was confirmed as an interesting framework for solving this problem. In experiments, the authors observed that the number of activities is essential in terms of increasing or decreasing student satisfaction.

The relevant contributions were the mapping between BT and RASI, including the three axes, the mapping of digital activities into the two-dimensional BT, and a GA-based planner of pedagogical actions. As future studies, we propose to automate the recommendation process into a virtual learning environment, proceed with more experiments and specify other objective functions to model a multi-objective GA.

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ENDNOTES

[1] In this paper, we refer to the Revised Bloom's Taxonomy as BT, or Bloom's Taxonomy.
[2] Likert, R. (1932). A technique for the measurement of attitudes. Archives of psychology.
[3] Link to RASI questionnaire (used in a free translation from English to Portuguese): https://bit.ly/3l9S0xm
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