Toward the selection of the appropriate e-learning personalization strategy

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Abstract. Many recent studies have proposed several e-learning personalization systems that could be used in the learning field. In particular, the divergence of the personalization parameters used in the literature makes the selection of the appropriate personalization strategy to apply for a given course complicated. Therefore, this paper presents a web-based system which aims to help teachers select the appropriate combination of personalization parameters for a personalization strategy for a given course. The selection process made by the system is based on Dynamic Programming. Thirty one student-teachers participated in evaluating the system using Technology Acceptance Model (TAM) questionnaire. The obtained results were very promising where the student-teachers revealed a high perceived ease of use and usefulness toward the system. Besides, they reported that they are willing to use the system in the future to select the appropriate personalization strategy of a given course.

Keywords. e-learning, adaptive learning, dynamic programming, Personalization.

1 Introduction

Traditional learning has usually followed one size fits all approach without taking into consideration the differences between learners [1]. This can affect negatively the learning process and its results. With the Advances of Technology Enhanced learning (TEL), researchers have thought of using personalized learning systems where the learners' individual needs are considered [2]. According to the National Academy of Engineering [1], advance personalized learning is one of the 14 most important challenges of the 21st Century.

However, many personalization parameters are proposed in the literature which can be used during learning personalization. For instance, Essalmi et al. identified

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19 personalization parameters in [3, 4]. These parameters include fifty nine learner characteristics. Thus, each concept of a course should be represented in fifty nine ways (learning objects) in order to satisfy all learner characteristics. This is time consuming and not motivating, since learners have to answer different questionnaires related to each personalization parameter which are long. For example, to know the personality of a learner, he/she has to answer the Big Five Inventory (BFI) questionnaire [5] which contains forty four questions. Besides, teachers have to spend a lot of time creating the required fifty nine Learning Objects (LO) which is very hard and complicated. Therefore, the main research question that this paper aims to answer is *How to select the appropriate e-learning personalization strategy for a specific course?*

In this context, this paper presents a new approach for the analysis and selection of the appropriate personalization strategy. It is based on the Dynamic Programming method which is widely used in the operations research field to find the optimal solution of a given problem. The proposed approach takes into consideration two criteria which are as follows:

- Maximize the availability of LOs, based on the learner characteristics for a particular personalization parameter, of a given course.
- Minimize the time spent by learners answering questionnaires related to a particular personalization parameter.

The rest of the paper explores the proposed research question as follows: section 2 presents a literature review regarding personalized learning systems and the available metrics for the analysis of the personalization strategies. Section 3 presents the proposed approach and the implemented system used to select the appropriate personalization strategy. Section 4 presents the conducted experiment to validate the proposed system. Finally, section 5 concludes the paper with a summary of the findings, the limits and potential research directions.

2 Literature Review

Applying one size fits all strategy in learning can affect negatively learners' learning motivation and performance. Therefore, learning experiences should be personalized according to each learner's profile. This profile contains the characteristics of a learner. This section presents examples of developed personalized systems in the literature. Besides, it investigates the proposed approaches or methods to select the appropriate personalization strategies.

2.1 Personalized Learning Systems

Personalized learning systems aim to identify the learners' needs and apply the learning strategies that best fits them. Uniform learning approaches can make learners perform poorer academically [6]. Various personalized systems are developed based on different personalization parameters. For example, ML-Tutor [7] is an adaptive web-based information system which uses learning goals as a personalization parameter. Interbook [8] uses the learner's level of knowledge to serve a personalized learning experience. There are also several e-learning personalization systems which use a combination of personalization parameters. For instance, EDUCE [9] allows the personalization of the course according to the learning goals and Gardner's multiple intelligences [10]. In DCG [11], the personalization of learning is based on the learner's level of knowledge and learning goals. AST [12] is a system which is based on a conceptual model of the domain of introductory statistics adapted to the learner's level of knowledge, media preferences and learning goals. Other studies have attempted to integrate learning styles as a personalization parameter of learning scenarios. In this context, Oscar CITS [13] is an adaptive educational system which provides learners with personalized course according to the Felder–Silverman learning style and the learner's level of knowledge.

Table 1 summarizes this section by presenting the six personalized learning systems described above. In particular, the second column presents the personalization parameters that each system used.

Table 1. **E**xamples of personalized learning systems.

Personalized e-learning systems	Personalization parameters
MLTutor [7]	Learning goals
Interbook [8]	Learner's Level of knowledge
EDUCE [9]	Learning goals, Gardner's multiple intelligences
DCG [11]	Learner's level of knowledge, learning goals
AST [12]	Learner's Level of knowledge, Media preferences, learning goals
Oscar CITS [13]	Learner's level of knowledge, dimensions of the Felder-Silverman learning style

As shown in table 1, the presented systems combine at most three personalization parameters to serve a personalized learning strategy. However, there are several combinations of personalization parameters which have not been applied yet on a given course. Therefore, the next section investigates the proposed methods to select the appropriate personalization strategy for a given course.

2.2 Personalization Strategies

Before applying a personalization strategy for a particular course, the teacher has to select the combination of personalization parameters to use. There are 524287 $=\sum_{i=1}^{19} C_1^{19}$ possible combinations when considering the subset of personalization parameters generated from the 19 personalization parameters presented in [4]. Thus, the selection of the personalization strategy to apply for a particular course could be based on the personalization parameters that require less creation of extra LO by the teacher. In this context, some research works, in the literature, proposed some techniques for rating the personalization parameters according to the available LOs in a given course. For example, Essalmi et al. presented in [14] four metrics for evaluating the personalization parameters according to the available LO, namely CRCH, CRP, CRCHDegree and CRPDegree. In particular, CRCH and CRP are based on Boolean logic. However, CRCHDegree and CRPDegree are based on fuzzy logic. Furthermore, Essalmi et al. presented metrics which aim to evaluate the personalization strategies composed of more than one personalization parameter [4].

The next section presents a new system which analyzes the given personalization parameters and select the appropriate combination of parameters to use in a personalization learning strategy.

3 MSPSS System

To simplify the task of a teacher when it comes to selecting the appropriate personalization strategy for a given course, a web-based system called Most Suitable Personalization Strategy Selector (MSPSS) is developed. The main objective of this system is to guide the teacher's decision regarding the appropriate combination of personalization parameters to use in personalization strategy of a course. The proposed system is based on Dynamic Programming which is an algorithmic method formalized by the mathematician Richard Bellman in the 1950s [15] for solving complex optimization problems by breaking them down into a number of overlapping sub-problems. This method is used in many domains, such as image processing [16] and bioinformatics [17, 18]. MSPSS uses two values which are as follows:

Satisfaction value: It is calculated based on the availability of LOs of a given course according to a personalization parameter. This value ranges from 0 (no LO available for the learner characters) to 1 (each learner character has a LO). In this context, Essalmi et al. proposed in [14] a CRCH metric which calculates the satisfaction value of six personalization parameters within the Microsoft Excel course. These values are presented in table 2.

Table 2. Satisfaction value of the personalization parameters in the Microsoft Excel course.

Personalization parameters	**Satisfaction value**
Learner's level of knowledge	0.37
Media preference	0.87
Honey & Mumford learning style	0.27
Active/reflective dimension of Felder– Silverman learning style	0.87
Sequential/Global dimension of Felder– Silverman learning style	0
Visual/verbal dimension of Felder– Silverman learning style	0.56

Assessment time value: It is the time that a learner could spend answering a questionnaire regarding a personalization parameter. This value could vary from a questionnaire (or test) to another. To define each assessment time value within MSPSS, 35 learners (25 girls, 10 boys) from a public university in Tunisia have participated in an experiment where they answered different assessment questionnaires regarding the different personalization parameters presented in table 2. Then, for each questionnaire, the average assessment time value is calculated. These values are presented in table 3.

Table 3. Assessment time value of the personalization parameters.

Personalization parameters	**Assessment tests**	**Assessment Time value**
Learner's level of knowledge	Microsoft Excel test	6
Media preference	Affective profile questionnaire [21]	1
Honey & Mumford learning style	Learning style questionnaire [20]	15
Active/reflective dimension of Felder– Silverman learning style	Index of learning style questionnaire [19]	3
Sequential/Global dimension of Felder– Silverman learning style	Index of learning style questionnaire [19]	3
Visual/verbal dimension of Felder– Silverman learning style	Index of learning style questionnaire [19]	3

To select the most appropriate personalization strategy, MSPSS chooses the personalization parameters which have the highest satisfaction value within a course and also the lowest assessment time. Table 4 presents an example of an input, using the six personalization parameters (i), which is given to MSPSS regarding Microsoft Excel course.

Table 4. Example of an MSPSS input according to the Microsoft Excel course.

i	Personalization parameters	Satisfaction value (vi)	Assessment time value (wi)
1	Learner's level of knowledge	0.37	6
2	Media preference	0.87	1
3	Honey & Mumford learning style	0.27	15
4	Active/reflective dimension of Felder– Silverman learning style	0.87	3
5	Sequential/Global dimension of Felder– Silverman learning style	0	3
6	Visual/verbal dimension of Felder– Silverman learning style	0.56	3

Using the dynamic programming, this optimization problem will be solved as follows: the teacher starts by fixing the maximum assessment time that the learner should not pass (for example, W = 7 minutes), then, the dynamic programming matrix will be filled using the recursive definition [22] as shown in (1) bellow, from left to right, up to bottom.

$$m[i,w] = \begin{cases} 0 & if\ i = 0 \\ m(i-1,w) & if\ w_i > w \\ \max\{\ m(i-1,w), m(i-1,w-w_i) + v_i\} & if\ w_i \le w \end{cases} \qquad (1)$$

i: It is the number of each personalization parameter (as shown in table 4, i ranges from 1 to 6).
w_i: It is the satisfaction value of the personalization parameter i.
v_i: It is the assessment time value of the personalization parameter i.
w: It is the maximum assessment time given by a teacher (in this case 7min).

Table 5 presents the obtained Dynamic Programming matrix of the example presented in table 4. The personalization parameters are presented, in rows, numerated from 0 (initialization) to 6 while, the remaining time (w) is presented in columns. Finally, the optimal result is obtained with a recursive trace-back of the matrix starting from the last cell (Repeat for i = n to 1; if m [i, w] > m [i - 1, w] then the parameter i is included in the strategy, w= w - w_i; else i is not included).

Table 5. The obtained dynamic programming matrix**.**

i\w	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0.37	0.37
2	0	0.87	0.87	0.87	0.87	0.87	0.87	1.24
3	0	0.87	0.87	0.87	0.87	0.87	0.87	1.24
4	0	0.87	0.87	0.87	1.74	1.74	1.74	1.74
5	0	0.87	0.87	0.87	1.74	1.74	1.74	1.74
6	0	0.87	0.87	0.87	1.74	1.74	1.74	2.3

As shown in Table 5, the selected personalization parameters after applying the proposed method are: Media preference (i= 2), Active/reflective dimension of Felder–Silverman learning style (i= 4), Visual/verbal dimension of Felder–Silverman learning style (i= 6). Figure 1 presents the obtained results using MSPSS. The three appropriate personalization parameters (media preference, Active/reflective dimension of Felder–Silverman learning style and Visual/verbal dimension of Felder–Silverman learning style) are highlighted in green.

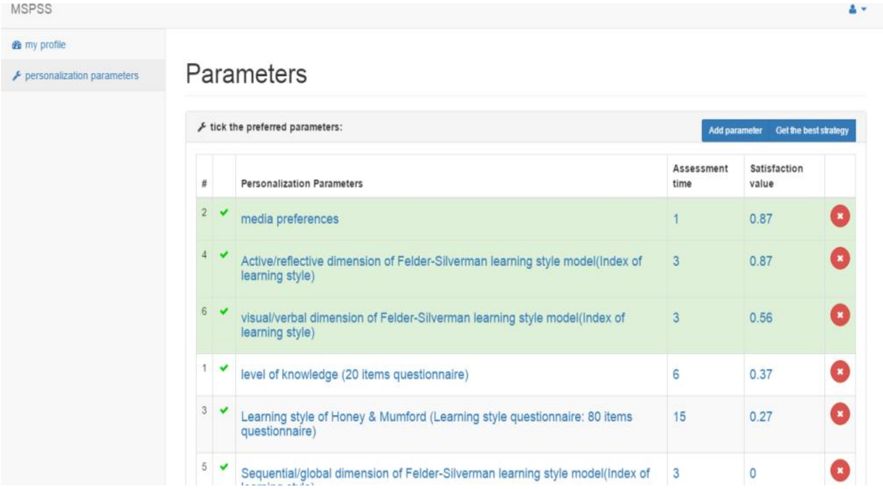

Fig. 1. Screenshot of the obtained result using MSPSS system.

4 Experiment

This section validates the proposed system MSPSS. In particular, section 4.1 introduces the participants of the conducted experiment and presents the followed procedure. Section 4.2 presents the used research instrument to validate the system. Finally, section 4.3 lists the obtained results.

4.1 Participants

Thirty one computer science student-teachers from a public university in Tunisia participated in validating MSPSS. They are all familiar with e-learning and personalized learning research areas. At first, these student-teachers took an overview about the main objective of this experiment. Then, they all used the MSPSS to select an appropriate personalization strategy for a given course. Finally, their level of satisfaction toward the system was evaluated. The next section presents the used instrument to evaluate the participants' level of satisfaction towards MSPSS.

4.2 Instrument

To evaluate the student-teachers' level of satisfaction after using MSPSS, they were asked to answer a Technology Acceptance Model (TAM) questionnaire. They had to answer by giving points which range from 1: Strongly agree to 5: Strongly disagree. TAM is a widely used model in information science [23]. Besides, it has been used to validate different application such as electronic courseware [24] and multimedia learning environment [25]. The questionnaire covers the four variables of TAM which are [26]: (1) Ease of use (EOU) which defines the degree to which the student-teachers find the system easy to use and free of effort, (2) Usefulness (U) which defines the degree to which the student-teachers think that the system will help them select the best personalization strategy for a given course, (3) Attitude towards using the system (ATT) which defines the degree to which the student-teachers report a favorable and positive attitude towards the system after using it and, (4) Intention to use the system (INT) which defines the degree to which the student-teachers are willing to use the system again in the future to select the suitable personalization strategy for a given course.

4.3 Results

The medians and averages of the student-teachers' answers to the questionnaire are calculated. In general, an average and median near 1 indicate that they are satisfied with MSPSS. However, an average and median near 5 indicate that the student-teachers are dissatisfied with MSPSS. Table 6 lists the values of medians and averages for the variables EOU, U, ATT and INT.

Table 6. Average and medians of user's satisfaction while using the MSPSS system.

	U	EOU	ATT	INT
Average	1.58	1.95	1.66	2.17
Median	1.00	2.00	1.00	2.00

As shown in table 6, the student-teachers were satisfied while using MSPSS since the averages and medians are far from 5 and range between 1 and 2. For instance, the average of the student-teachers' attitude toward using the system is equal to 1.66, while the median is equal to 1.

5 Conclusion, Limits and Future directions

This paper presented a new system called MSPSS which can help teachers select the appropriate personalization strategy for a particular course. The proposed system is based on the dynamic programming method which is widely used in the operations research field for solving complex optimization problems. In particular, MSPSS chooses the personalization parameters which have the highest satisfaction value within a course and also the lowest assessment time.

MSPSS was evaluated by thirty one student-teachers using TAM questionnaire. The obtained results were very promising. In particular, they found the system, useful and easy to use. Besides, they reported that they have a favorable attitude toward the system and they are willing to use it in the future to select the appropriate personalization strategy of a given course.

On the other hand, some limitations which may limit the generalizability of the results are found. For example, the selected personalization strategy using MSPSS of the given course Microsoft Excel was not evaluated with students. Consequently, their feedback regarding the effectiveness of the proposed personalization learning strategy was not collected.

Future directions focus on evaluating the personalized learning strategy selected by the system MSPSS. This allows investigating the effectiveness of the proposed system when it comes to the selection of the appropriate personalization strategy. Besides, further metrics which allow calculating the satisfaction value will be implemented within MSPSS. Consequently, compare the obtained personalization strategies using different metrics.

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