ULEARN: Personalised Learner's Profile Based On Dynamic Learning Style Questionnaire

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***Abstract*—E-Learning recommender system effectiveness relies upon their ability to recommend appropriate learning contents according to the learner learning style and preferences. An effective approach to handle the learner preferences is to build an efficient learner profile in order to gain adaptation and individualisation of the learning environment. It is usually necessary to know learning style and preferences of the learner on a domain before adapting the learning process and course content. This study focuses on identifying the learning styles of students in order to adapt the learning process and course content. ULEARN is an adaptive recommender learning system designed to provide learners with personalised learning environment such as course learning objects that match their adaptive profile. This paper presents the algorithm used in ULEARN to reduce dynamically the number of questions in Felder-Silverman learning style questionnaire used to initialise the adaptive learner profile. Firstly, the questionnaire is restructured into four groups, one for each learning style dimension; and a study is carried out to determine the order in which questions will be asked in each dimension. Then an algorithm is built upon this ranking of questions to calculate dynamically the initial learning style of the user as they go through the questionnaire.**

Keywords*—E-learning; adaptive-learning; algorithms; adaptive learner profile; learning style; felder-silverman model; questionnaire; profiler.

I. INTRODUCTION

Over the last few decades, the WWW has turned into a noteworthy source of information and a built up platform for education and entertainment. Nonetheless, this remarkable growth in the information available has led to information overload, as navigating through and finding relevant information has become more and more challenging. Personalisation has been widely used throughout the past few years to overcome this [1] [2]. Learners frequently find themselves overwhelmed by the huge amounts of information which may be associated with their interests. How to present the learning material (g.g. course learning objects) with respect to learning style is one of the key issues for recommender learning systems [3]. One approach to deal with this issue is to build the learner model, which is a core component in any intelligent or adaptive learning recommender system. The learner model represents many of the learner's features, such as knowledge and learning style, so as to be accessible for offering adaptation [4]. The learner must be set at the core of the instructional situation in order to encourage his/her integration into the learning process.

Adaptive learning uses techniques to interpret the activities of learners on the basis of domain-specific models, infers learner needs out of the interpreted activities, represents the needs in associated models appropriately, and acts upon adaptive learner profile in order to dynamically facilitate the learning process [5]. Actually, most courses tried to overcome one-size fits all approach. Adaptive learning systems can increase the individualisation of learners' learning [6] by changing content and delivery for a learner based on their learning profile as depicted in Figure 1. The learner profile includes

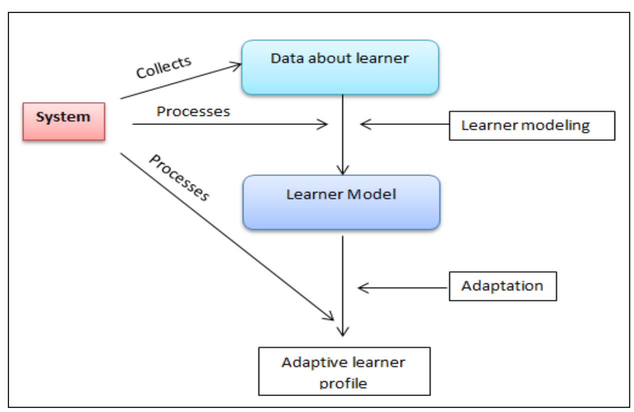

Fig. 1. Classic model of learner profile adaptation

several data such as personal information, knowledge and learning style. There are two main approaches to detect the learning styles: the *explicit modelling* (questionnaire based) and the *implicit modelling* (literature based).

The explicit modelling approach represents the learning characteristics and needs of each learners based on data obtained by requiring each learner to fill out a learning style questionnaire. Examples of systems that use this explicit modelling method are CS383 [55] INSPIRE [16] and iWeaver[51]. The implicit modelling approach means that an adaptive system continuously updates the learner model by monitoring interactions with the system; examples include Arthur system [10] and Protus 2.0 [56].

The proposed ULEARN recommender learning system combines the two approaches. The Felder-Silverman learning style questionnaire [35] is used to determine the initial learning style of the learner which is used together with the user preferences to initialise the learner profile. During the system usage, the learner profile is dynamically adapted based on the user behaviour (i.e. interactions with the system), knowledge and performance at learning. This paper focuses on the initialisation of the adaptive learner profile using a dynamic variant of the Felder-Silverman learning style questionnaire. The main contribution of this paper is threefold:

- An algorithm for constructing the adaptive learner profile during registration based on the Felder-Silverman learning style model (Sect. III)
- An empirical study to determine the order of questions for each of the four dimensions of the Felder-Silverman learning style questionnaire (Sect. IV)
- An algorithm, built upon this ranking of questions, to calculate dynamically the initial learning style of the user as they go through the questionnaire (Sect. V). The innovative feature of this algorithm is its ability to determine the learning style of the learner in each dimension from the users responses to just a few questions of the questionnaire; hence save the user time and effort from answering all the 44 questions of the Felder-Silverman learning style questionnaire.

II. Overview of the Felder-Silverman Learning Style model

The learning style of the learner has been identified as an important factor that impacts the learning process. Learning style is the most significant parameter for personalization. Learners differ in the ways of perceiving, processing and receiving the information. Based on the means of processing and organizing the information, learners are considered to possess their own style of learning. Figure 2 shows the four dimensions of the Felder-Silverman learning style model (FSLSM) [35] which are related to the processing, understanding, input, and perception of information. Each of these dimensions is characterised by a pair X/Y (i.e. active/reflective, sequential/global, visual/verbal, and sensing/intuitive) meaning that the learning style of a learner in that dimension is X or Y to some extent. For example, in the information processing dimension the learning style of a user is *active* or *reflective* to some extent. In the information input dimension a user can be *visual* or *verbal* to some extent. FSLSM is considered the most stable and appropriate learning style model for adaptive hypermedia learning systems [50].

According to this description, the Index of Learning Styles (ILS) questionnaire proposes a list of 44 questions (see Table I) effective in identifying the style of each learner. There are 11 questions for each dimension and each question has two possible answers: the answer “a” or the answer “b”. For a dimension characterised by the pair X/Y, the answer “a” corresponds to the preference for the learning style X, while the answer “b” indicates the preference for the learning style Y.

To determine the learning style of the learner in a dimension using the questionnaire of Felder-Silverman, it is

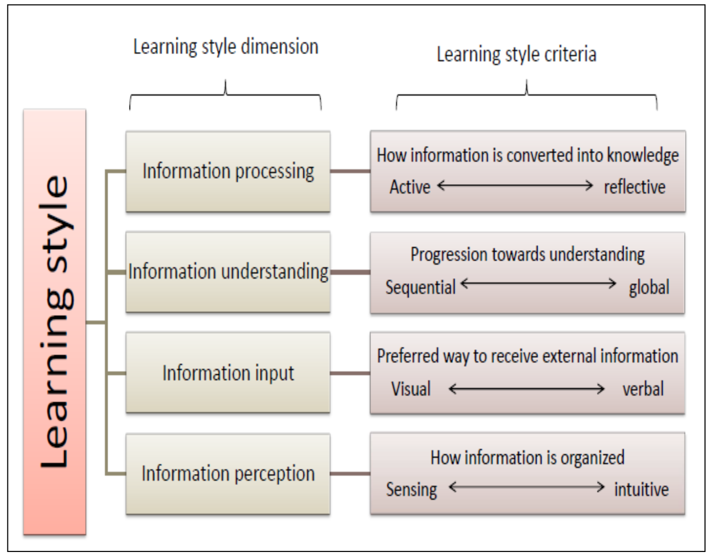

Fig. 2. FSLSM learning style model

sufficient to count the number of answers ”a” and the number of answers ”b” on the 11 questions corresponding to the dimension and calculate the difference between these two numbers. Obviously, this score is an odd number between 11 (all the answers of the learner are equal to “a”) and -11 (all responses are equal to “b”). A learner whose score is 1 or 3 (-1 or -3) has a mild preference for X (resp. for Y); yet is essentially well balanced to learn in a teaching environment that favours X or Y. For a score of 5 or 7 (-5 or -7), the learner has a moderate preference for X (resp. for Y) and will learn more easily in a teaching environment that favours X (resp. Y). Finally, a score of 9 or 11 (-9 or -11) indicates a strong preference for X (resp. for Y); and the learner may have real difficulty learning in an environment which does not support that preference.

III. Algorithm for Creating an Adaptive Learner Profile

The proposed method for initialising the learner adaptive profile based on dynamic learning style questionnaire is illustrated by the block diagram in Figure 3. The profile of the learner that includes the personal details of the learner is collected from the learner during the registration process. After the registration, student is asked to fill out ILS questionnaire described in the previous section. The algorithm includes the following basic steps:

- Step 1: (Registration) Student must register through ULEARN learning portal before using the system. During registration, personal data such as name, email address and password are collected.
- Step 2: (Fill out learning style questionnaire) After the registration step the student must take the ILS questionnaire. As the student answers the questionnaire, the system calculates dynamically the learning style of the student for each dimension by counting the number of answers “a” and the number of answers “b”. When the number of “a” (or “b”) reaches 7 (i.e. 60% of the 11 questions) in one dimension, the system skips the

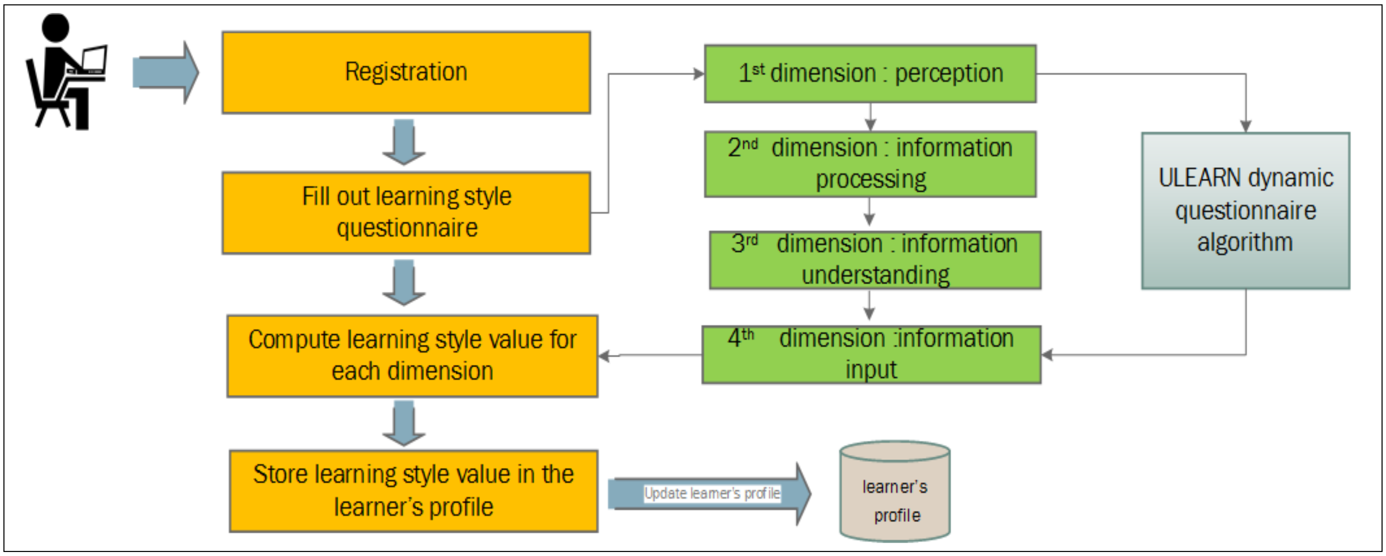

Fig. 3. Algorithm to create adaptive learner profile

rest of questions for that dimension and moves to the first question of the next dimension.

- Step 3: (Compute learning style value for each dimension) Calculate the learning style for each dimension as the percentages of "a" and "b". For example, in the dimension *information input*, one may have 60% *visual* and 40% *verbal*.
- Step 4: (Store learning style values in the student's profile) The initial learning style calculated through the ILS questionnaire is stored in the learner profile database.

IV. Ranking the Questionnaire Questions

The ILS questionnaire has 44 questions; this may be too long for some learners and may lead to undesired behaviours such as skipping questions, answering falsely, or giving up the questionnaire (and the system) all together. Therefore the ULEARN learning system proposes a dynamic questionnaire algorithm which does not need to go through all the 44 questions of the questionnaire to determine the learning style of the learner. In order to do that, the ILS questionnaire is restructured into 4 groups of 11 questions, one for each dimension of the FSLSM. Within a dimension, questions are ranked based on how easy it is to choose between answer "a" and answer "b". The easiest questions in that respect will come first, and the difficult ones last.

A study was carried out to determine the ranking of questions in each dimension. Participants to the study were asked to tell for each question of the ILS questionnaire how easy it is to choose between answer "a" and answer "b" using a 5-levels Likert scale: 1. Very easy, 2. Easy, 3. Intermediate, 4. difficult, and 5. Very difficult. Thirty-four responses were received from which 30 were used for the analysis and the other 4 not included because they were incomplete. The score for each question were added up and normalised; and the results for each dimension are depicted in Fig.4-7. The most difficult questions are highlighted in red. Based on this study, questions can be ranked in ascending order of difficulty levels in each dimension as shown in Table I. This ranking of questions is used as precondition for the algorithm to calculate a learner's initial learning style using the ILS questionnaire, presented in the following section.

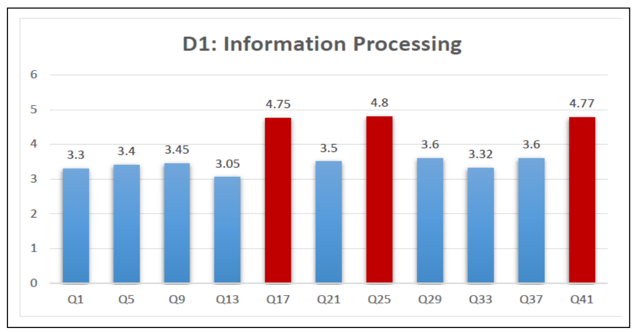

Fig. 4. Difficulty level of questions in Information Processing

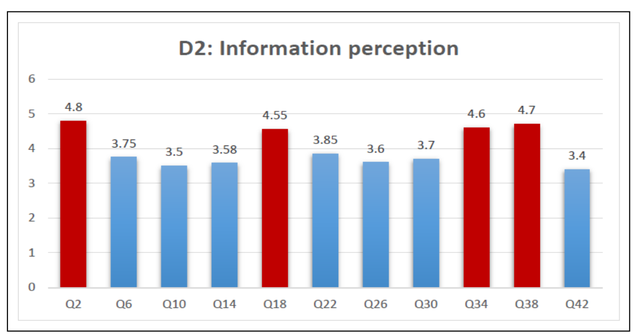

Fig. 5. Difficulty level of questions in Information Perception

V. Algorithm for Calculating Initial Learning Style

The algorithm `Initial_LS` described by the pseudo-code in Fig. 8 and the flowchart in Fig. 9 calculates the initial learning style of a learner using the ILS questionnaire given in Table I. The algorithm counts the number of answers "a" and

TABLE I. ORDER OF QUESTIONS IN EACH DIMENSION

D1: Information Processing			
Question	FSLSM question's Sequence	ULEARN Sequence	Difficulty level
In classes I have taken a) I have usually gotten to know many of the students. b) I have rarely gotten to know many of the students.	13	1	3.05
I understand something better after I a) try it out. b) think it through.	1	2	3.3
When I have to work on a group project, I first want to a) have group brainstorming where everyone contributes ideas.b) brainstorm individually and then come together as a group to compare ideas.	33	3	3.32
When I am learning something new, it helps me toa) talk about it. b) think about it.	5	4	3.4
In a study group working on difficult material, I am more likely to a) jump in and contribute ideas.b) sit back and listen.	9	5	3.45
I prefer to study a) in a study group.b) alone.	21	6	3.5
I more easily remember a) something I have done. b) something I have thought a lot about.	29	7	3.6
I am more likely to be considered a) outgoing. b) reserved.	37	8	3.6
When I start a homework problem, I am more likely to a) start working on the solution immediately.b) try to fully understand the problem first.	17	9	4.75
The idea of doing homework in groups, with one grade for the entire group, a) appeals to me. b) does not appeal to me.	41	10	4.77
I would rather first a) try things out. b) think about how Im going to do it.	25	11	4.8
D2: Information Perception			
When I am doing long calculations,a) I tend to repeat all my steps and check my work carefully. b) I find checking my work tiresome and have to force myself to do it.	42	1	3.4
I find it easier a) to learn facts. b) to learn concepts.	10	2	3.5
In reading nonfiction, I prefer a) something that teaches me new facts or tells me how to do something.b) something that gives me new ideas to think about.	14	3	3.58
When I am reading for enjoyment, I like writers to a) clearly say what they mean. b) say things in creative, interesting ways.	26	4	3.6
When I have to perform a task, I prefer to a) master one way of doing it. b) come up with new ways of doing it.	30	5	3.7
If I were a teacher, I would rather teach a course a) that deals with facts and real life situations. b) that deals with ideas and theories.	6	6	3.75
I am more likely to be considered a) careful about the details of my work. b) creative about how to do my work.	22	7	3.85
I prefer the idea of a) certainty. b) theory.	18	8	4.55
I consider it higher praise to call someone a) sensible. b) imaginative.	34	9	4.6
I prefer courses that emphasize a) concrete material (facts, data). b) abstract material (concepts, theories).	38	10	4.7
I would rather be considered a) realistic. b) innovative.	2	11	4.8
D3: Information Input			
When I am learning a new subject, I prefer to a) stay focused on that subject, learning as much about it as I can. b) try to make connections between that subject and related subjects	36	1	3.4
I tend to a) understand details of a subject but may be fuzzy about its overall structure. b) understand the overall structure but may be fuzzy about details.	4	2	3.45
It is more important to me that an instructor a) lay out the material in clear sequential steps. b) give me an overall picture and relate the material to other subjects.	20	3	3.45
When solving problems in a group, I would be more likely to a) think of the steps in the solution process. b) think of possible consequences or applications of the solution in a wide range of area	44	4	3.55
When considering a body of information, I am more likely to a) focus on details and miss the big picture. b) try to understand the big picture before getting into the details	28	5	3.6
Some teachers start their lectures with an outline of what they will cover. Such outlines are a) somewhat helpful to me. b) very helpful to me.	40	6	3.6
When I am analyzing a story or a novel a) I think of the incidents and try to put them together to figure out the themes. b) I just know what the themes are when,I finish reading and then I have to go back and find the incidents that demonstrate them.	16	7	3.65
When I solve math problems a) I usually work my way to the solutions one step at a time. b) I often just see the solutions but then have to struggle to figure out the steps to get to them.	12	8	3.75
I learn a) at a fairly regular pace. If I study hard, Ill get it. b) in fits and starts., Ill be totally confused and then suddenly it all clicks.	24	9	4.5
When writing a paper, I am more likely to a) work on (think about or write) the beginning of the paper and progress forward. b) work on (think about or write) different parts of the paper and then order them.	32	10	4.65
Once I understand a) all the parts, I understand the whole thing. b) the whole thing, I see how the parts fit.	8	11	4.7
D4: Information Understanding			
When I think about what I did yesterday, I am most likely to get a) a picture. b) words	3	1	3.15
When I meet people at a party, I am more likely to remember a) what they looked like. b) what they said about themselves	35	2	3.2
When I see a diagram or sketch in class, I am most likely to remember a) the picture. b) what the instructor said about it.	27	3	3.3
I prefer to get new information in a) pictures, diagrams, graphs, or maps. b) written directions or verbal information.	7	4	3.5
When I get directions to a new place, I prefer a) a map. b) written instructions	23	5	3.6
In a book with lots of pictures and charts, I am likely to a) look over the pictures and charts carefully. b) focus on the written text.	11	6	3.7
I remember best a) what I see. b) what I hear.	19	7	3.75
I tend to picture places I have been a) easily and fairly accurately. b) with difficulty and without much detail.	43	8	4.5
I like teachers a) who put a lot of diagrams on the board. b) who spend a lot of time explaining.	15	9	4.65
When someone is showing me data, I prefer a) charts or graphs. b) text summarizing the results	31	10	4.8
For entertainment, I would rather a) watch television. b) read a book.	39	11	4.85

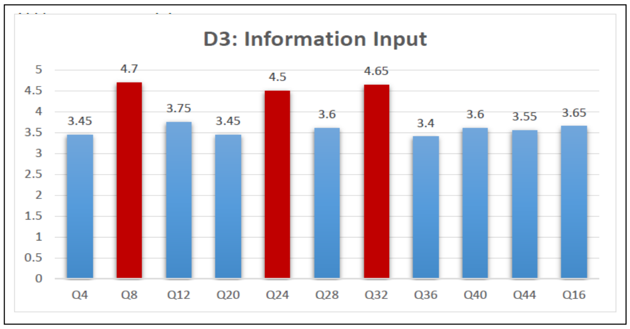

Fig. 6. Difficulty level of questions in Information Input

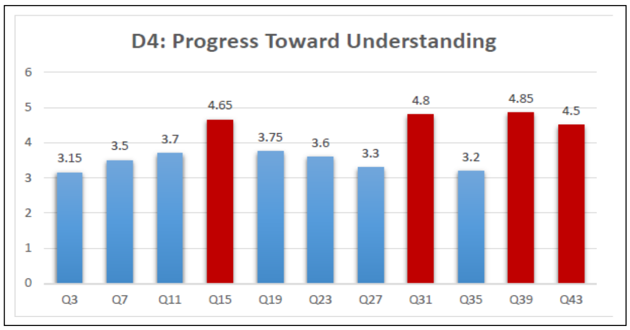

Fig. 7. Difficulty level of questions in Information Understanding

the number of answers “b” in each dimension. If the number of answers “a” or the number of answers “b” reaches 7, the rest of questions in that dimension will be skipped. In this way, only learners with mild preferences will take all the 11 questions of the dimension. This is based on the assumption that if 60% of a learner’s answers are in favour of one preference (X or Y) in a dimension, then that learner will likely be fine in a teaching environment that favours that preference. However, this threshold of 60% may be revised for some courses as appropriate during the validation of the system in real-word settings.

In the flowchart in Fig. 9, the variable i ranges over the 4 dimensions of the FSLSM and the variable j refers to the current question being processed within a dimension. Thus, j ranges over the 11 questions of a dimension. The number of answers “a” (answers “b”) in the dimension i is calculated in the variable A_i (resp. B_i), for $1 \leq i \leq 4$. The algorithm ends when all the 4 dimensions have been processed. To illustrate how this algorithm works, Table II shows the execution outputs for 5 different learners who have taken the ILS questionnaire. The notation #a means the number of answer “a”. The learner Clara, in each dimension chooses the same answer for the first 7 questions. She demonstrates the best case scenario where the smallest (28) number of questions are taken.

Fatima and Bob represent the worst case scenarios where all the 44 questions are taken; these are the only situations where this happens. For Fatima the difference #a - #b in each dimension is either 1 or -1, while that difference is either 3 or -3 for Bob. They both have *mild* learning style preferences (see Sect. II) in each dimension and so are well balanced to learn in any teaching environment. The other learners learning styles are *moderate* at least.

```
Algorithm Initial_LS
Input: the ILS questionnaire structured
       as in Table I
Output: an array A[1..4] of number of
        answer "a" in each dimension and
        an array B[1..4] of number of
        answer "b" in each dimension
Begin
/* i ranges over the 4 dimensions */
/* j ranges over the 11 questions in i */
 for i = 1 to 4 do
   A[i] = 0;
   B[i] = 0;
   j = 1;
   while (A[i]<7 and B[i]<7 and j<=11) do
       read answer to question j
                of dimension i;
       if (answer is "a") then
           A[i] = A[i] + 1;
       else
           B[i] = B[i] + 1;
       fi
       j = j+1;
   od
 od
End
```

Fig. 8. Pseudo-code of the algorithm for calculating initial learning style

TABLE II. EXAMPLES OF EXECUTION OUTPUT OF THE ALGORITHM INITIAL_LS

	Learning Style Dimensions								
	Processing		Perception		Input		Understanding		
	#a	#b	#a	#b	#a	#b	#a	#b	Total
Tom	2	7	1	7	7	3	0	7	34
Clara	0	7	7	0	0	7	0	7	28
Fatima	5	6	6	5	5	6	6	5	44
Bob	7	4	4	7	4	7	7	4	44
Alice	1	7	1	7	7	0	0	7	30

VI. IMPLEMENTATION

Our proposed framework ULEARN is an adaptive learning management system to provide adaptive course content based on personalised student profile. ULEARN has been implemented in java and SQL sever. The main purpose of system is to recommend useful and personalised materials prepared based on learner preferences in e-learning context. ULEARN supports three main roles:

1) Learners: attend courses and use the system in order to gain certain knowledge.
2) instructors: add course lessons and learning objects in different format as well as assignments.
3) administrator: assigns learners and instructors to specific courses and manages system database.

Hence, the system provides separate user interfaces for these roles. Instructor’s interface helps managing data about learners and course materials. The work-through of the learner interface is given in Fig. 10. An existing user logs in the system by entering a valid username and password as shown in Fig. 11. A new user needs to register with the system and will be

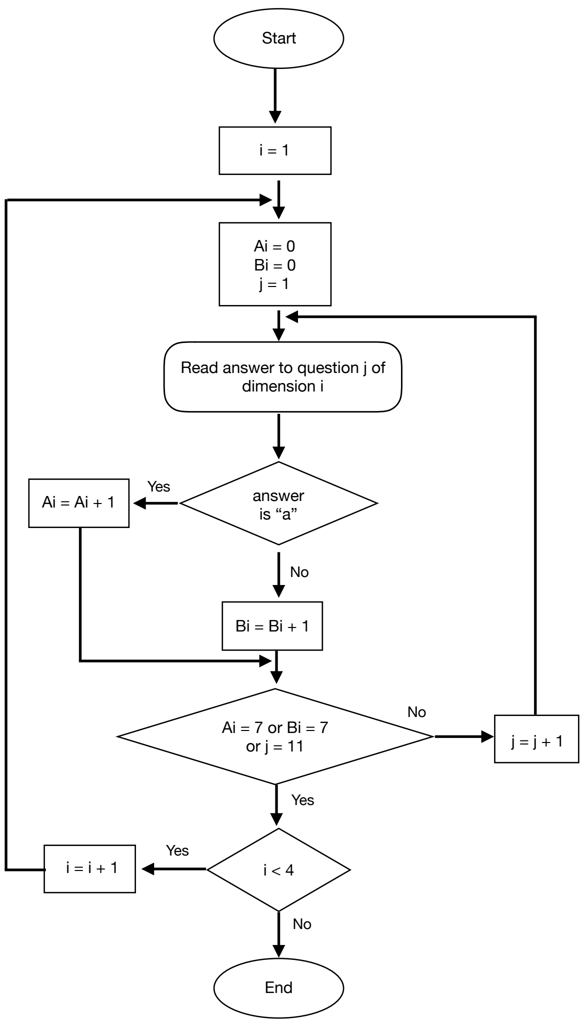

Fig. 9. Flowchart of the algorithm for calculating initial learning style

required to enter personal information as depicted in Fig. 12; and then answer the ILS questionnaire as explained above. The questionnaire interface looks like in Fig. 13.

VII. Related Work

This section presents a review of the existing literature relevant to this study with a focus on a brief overview of common techniques used to adapt personalized learner profile and previous related review studies. Table III presents a comparative study between the most known personalised e-learning systems. In addition, we give some examples of e-learning systems that implement these methods for modelling the learner's individual differences and highlight their limitations.

VIII. Conclusion

Personalised learner profile has emerged as core area in adaptive e-learning applications in which each learner's interests, preferences and contextual information were studied precisely. Characteristics of learning style play crucial role in identifying their learning style preferences. It helps to provide adaptive learning experiences in personalisation of learning materials based on the interactions with the learners. This paper proposes an algorithm for constructing the adaptive learner profile during registration based on the Felder-Silverman learning style model. An empirical study was undertaken to determine the order of questions for each of the four dimensions of the Felder-Silverman learning style questionnaire. This ranking of questions was used to build an algorithm that calculates dynamically the initial learning style of the user as they go through the questionnaire. This algorithm can infer the learning style of the learner in each dimension from the users responses to just a few questions of the questionnaire; hence save the user time and effort from answering all the 44 questions of the Felder-Silverman learning style questionnaire. In future work, an adaptive engine will be developed to adapt the user profile based on the learner behaviour, knowledge and performances.

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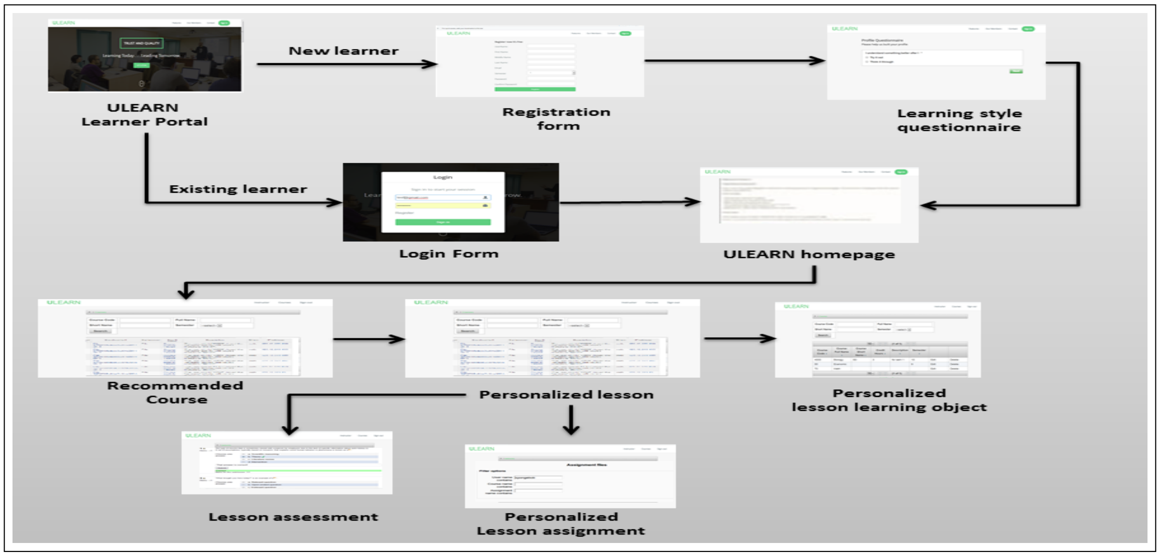

Fig. 10. ULEARN interface map

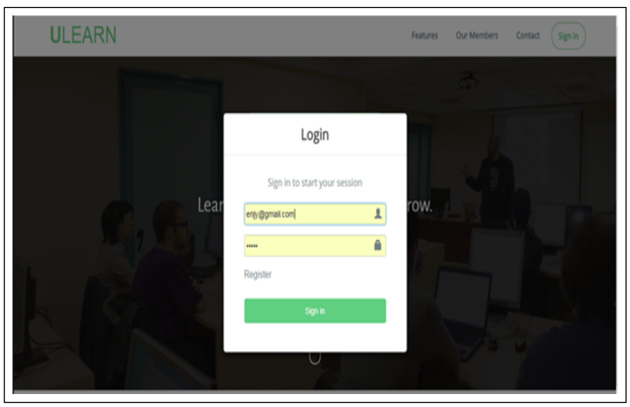

Fig. 11. Student login page

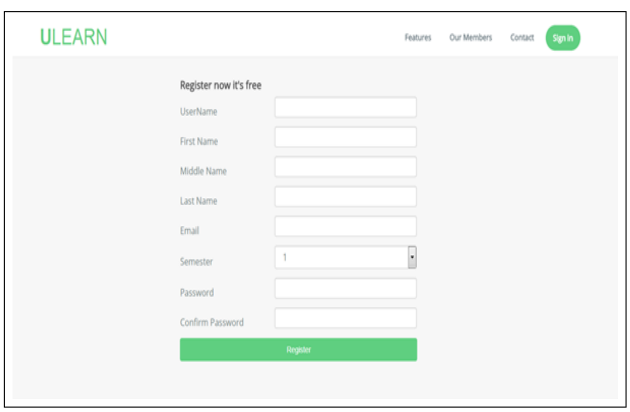

Fig. 12. Registration page

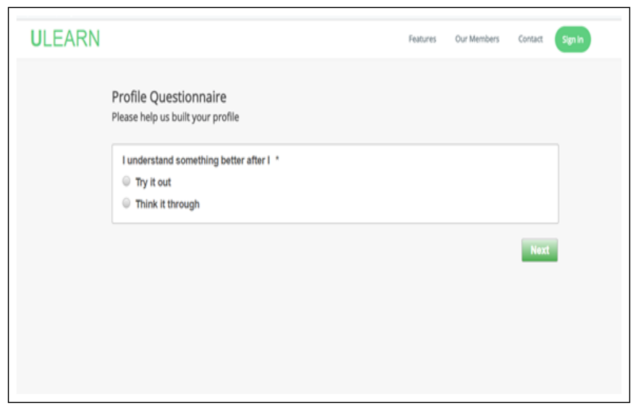

Fig. 13. Questionnaire interface

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TABLE III. SYSTEMS ADAPTATION AND USER MODELLING

System	Web based	Description	learning style model	Data Source	dynamic user modeling	limitations
[53]	yes	The system can categorise students according to FSLSM dimensions through case based reasoning inference.	FSLSM	questionnaire, student behaviour	No	system recommendation based on static user profile. That is the reason why highly personalized recommendation cannot achieve
[46]	Yes	system adapts Chapter, sections, sub-sections, and learning objects	Unified Learning Style Model	Student behaviour	Yes	could be extended by adding variety of adaptation actions, collaboration level adaptation
[52]	Yes	system generates teaching tasks and teaching rules	FSLSM understanding and perception	questionnaire	No	system adaptation rules defined by a teacher which decrease the recommendation accuracy
[44]	——	system generates learning resource ordering according entry dimension	FSLSM	questionnaire	No	recommendation based on static user profile.
[54]	Yes	The system generates Course, unit, topics and reading materials	perception, processing and understanding	questionnaire behaviour	Yes	the system cannot distinguish between visual and verbal learners also it cannot provide them assistance accordingly.
[51]	Yes	the system adapt learning strategies which generate media experiences	Dunn & Dunn Model	questionnaire	No	the course recommendation based on static student profile.Bayesian Networks can enhance by the combination of content-based and collaborative approaches
[56]	Yes	system adapt course, Topics, lessons, and educational materials	FSLSM	questionnaire behaviour	Yes	the system is used for learning Java programming language only I do recommend if it can be used in other domains
[48]	Yes	Adapt teaching activates based on knowledge and learning abilities.	———	behaviour	Yes	the system should be extended with an adaptive mechanism that will monitor the student during the interaction, and adapt the level of feedback automatically

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