A Framework to Personalise Open Learning Environments by Adapting to Learning Styles

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Abstract: This paper presents an adaptive framework to personalise open learning environments. The design of the framework has been grounded in cognitive science and learning principles. The theory of learning styles, and more specifically the model of Felder and Silverman, has been considered and applied. The developed framework has two main functions. First, it automatically identifies the learners' learning styles by tracking their behaviours and interactions with the provided learning objects. Secondly, it provides adaptive navigational support based on the identified learning styles. Sorting learning materials based on learners' preferences and hiding the least preferred materials are the two techniques of navigational support that have been applied in the proposed framework. Detailed descriptions of the framework functionalities and different components are presented in this paper. Future piloting and evaluation will test and verify this proposed framework.

1 INTRODUCTION

Online learning evolves to take advantage of continuous advancement of technology. Open learning is a form of online learning that allows learning materials to be freely available on the Internet for anyone who is interested.

Currently, several prestigious learning institutions, such as Harvard, MIT and Stanford, provide learning materials in an open approach. Coursera (Coursera, 2012), edX (edX, 2012), Udacity (Udacity, 2012) and Udemy (Udemy, 2014) are examples of open learning initiatives. Courses that are provided through these open learning environments are known as Massive Open Online Courses (MOOCs).

As with any new model for learning, MOOCs are still in their early stages of evolution. There are many areas and opportunities for improvement, such as teaching and learning methods; learning content; assessments; identity authentication; accreditation; and learners' varying needs, among others. The authors believe that considering cognitive science and learning principles has opportunity to enhance learning environments such as MOOCs (Fasihuddin et al., 2013b). This view is also supported by others (Williams, 2013).

This paper focuses on personalisation of open learning environments based on learning styles. Learning style refers to the way a learner receives and processes information; therefore, every learner has a different learning style (Felder and Silverman, 1988). Among the existing models of learning styles, Felder and Silverman Learning Style Model (FSLSM) was selected. This paper proposes an adaptive framework that identifies the learners' learning styles and consequently provides personalised navigational support. The literature-based approach (Graf, 2007) is used to automatically identify the learning style. This approach has been shown to have higher accuracy of results in detecting learning styles (Graf, 2007). It is mainly based on monitoring the learners' behaviours on determined patterns based on the FSLSM. These patterns are determined based on learning objects that are common in open learning environments, such as in edX, Coursera, Udemy and Udacity. Based on our knowledge, no previous study has attempted to personalise the open environment using learning styles, and this is what distinguishes this study and the proposed framework.

The rest of this paper is organised as follows: first, a background of the related concepts is presented in section 2; next, section 3 presents a review of previous work on adaptive systems based on learning styles; after that, the proposed adaptive framework and the development of the prototype are

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presented in sections 4 and 5 respectively; and finally, the paper is concluded in section 6 with a brief overview of future work.

2 BACKGROUND

2.1 Open Learning Environments

As mentioned, the evolution of technology leads to continual change and development in online learning approaches and, recently, open learning has emerged as a new form of online learning. In open learning, courses are freely available on the Internet to be accessed by anyone who is interested. These courses are provided by different learning providers who could be academics representing learning institutions or individuals who have appropriate knowledge and expertise. Recently many courses have been offered in this form by different prestigious institutions, such as Stanford and MIT. These courses have gradually refined into what are known as Massive Open Online Courses (MOOCs).

MOOCs offer free university-level courses online and have two key features – open access and scalability (Yuan and Powell, 2013). These two features allow MOOCs to be taken online by anyone and enable the courses to be designed to support an indefinite or even infinite number of participants. They are learner-centred courses so learners are able to work and learn at their own pace. The massive number of learners in MOOCs leads to significant variation in these learners' needs, preferences and even cognitive abilities. Therefore, personalisation of MOOCs is essential.

The development of open learning environments is a critical field due to the implications for learners, instructors and the learning process. Therefore, scientific principles for learning should be considered in the development of these environments in order to achieve the desired learning goals. It is stated by Williams (2013) that tailoring general learning principles and working with cognitive scientists is one approach that needs to be considered to enhance MOOCs and provide the best outcomes for learners. Based on this, the authors have considered the theory of learning styles (Felder and Silverman, 1988) to introduce an approach for personalising open learning environments. This should increase learners' satisfaction and lead to better learning outcomes. Following is an overview of this theory and its implications.

2.2 The Theory of Learning Styles

Learning style refers to the way a learner receives and processes information. Therefore, different learners will have different learning styles (Felder and Silverman, 1988). Considering learning styles in courseware design has been found to be effective and beneficial in learning. It has been shown that providing learners with learning materials and activities that suit their preferences and learning styles makes learning easier for them (Graf and Tzu-Chien, 2009). This has been shown by many studies that found that students can achieve better learning outcomes and higher scores (Bajraktarevic et al. 2003), and can also master the learning materials in less time (Graf and Kinshuk, 2007).

In literature, several models for learning styles were defined and found to be valid and reliable (Coffield et al., 2004). Felder and Silverman Learning Style Model (FSLSM) was selected as the most appropriate by the authors to be applied to personalise an open learning environment. A number of reasons led to this selection. The mechanism of the FSLSM Index of Learning Style (ILS) questionnaire (Soloman and Felder, nd) that identifies learning styles can be easily applied to adaptive systems. Furthermore, it has been shown that the FSLSM is the most appropriate and feasible model to be implemented in adaptive courseware (García et al., 2008; Carver et al., 1999). Moreover, a study that was conducted to compare the suitability of different learning style models to be applied to online learning also concluded that the FSLSM was the most appropriate model (Kuljis and Liu, 2005).

The FSLSM classifies learning styles into four dimensions and identifies two types of learners for each dimension. The dimensions are perception, input, processing and understanding. Firstly, the perception dimension defines the type of information that learners prefer to receive and learn by: intuitive learners prefer meaning and theories while sensory learners prefer learning by examples and practice. The second dimension is input which defines the approach the learners prefer to learn with: visual learners prefer pictures, diagrams and flowcharts while verbal learners prefer written or spoken explanations. The processing dimension indicates how learners prefer to process and practice their learning: active learners prefer working with others while reflective learners prefer thinking and working alone. Finally, the understanding dimension indicates how learners progress toward understanding: sequential learners learn in continual small steps while global learners learn holistically in large jumps. Table 1 represents these styles and their associated types.

Table 1: Felder and Silverman learning styles.

Dimension	Preferred Learning Styles	
Perception	Sensory	Intuitive
Input	Visual	Verbal
Processing	Active	Reflective
Understanding	Sequential	Global

2.3 Adaptive Systems with Respect to Learning Styles

Adaptive systems have been described as systems that are able to provide personalised learning support to the learner throughout their interaction based on the goals, preferences and knowledge of each individual learner (Brusilovsky, 2001). It has been found that adaptive learning systems lead to better learning outcomes, reduce time and effort required, and increase learners' satisfaction (Graf and Kinshuk, 2014). Adaptive systems can adapt to user data, usage data and environment data (Brusilovsky, 2001). User data refers to various characteristics of the user, such as learning styles and cognitive traits. Usage data refers to the user's interaction with the system. Environment data refers to the adaptation to the user context, including location or platform. Providing adaptability based on these considered factors has been classified into two different areas – adaptive presentation and adaptive navigation support (Brusilovsky, 2001). Adaptive presentation comprises text and multimedia adaptation technologies while adaptive navigation support comprises link sorting and hiding, and providing direct guidance.

Systems that are adaptive to learning styles need to identify the learner's learning style first and then adapt to the learner's preferences. Adaptation methods of adaptive systems have been classified into two different approaches – collaborative and automatic (Brusilovsky, 1996). In the collaborative approach, learners are asked to provide their preferences explicitly by taking a test or filling out a questionnaire, such as the ILS questionnaire (Soloman and Felder, nd), in order to build the adaptable models while in the automatic approach, the learners' adaptable model is built automatically by the adaptive system through intelligent and machine learning techniques that exploit learners' interactions and behaviours while they are using the system for learning.

In literature, two different methods for identifying learning styles based on the FSLSM were used – the data-driven method and the literature-based method (Graf, 2007). Both methods rely on some identified patterns to detect the learning style of the learner. These patterns are based on monitoring the provided learning objects in such a way that they adhere to the FSLSM. The data-driven method aims to build a model that imitates the ILS questionnaire and uses sample data to construct a model. Some of the techniques that have been used to apply this method are neural networks, decision tree, Hidden Markov Model, fuzzy clustering and Bayesian networks. The literature-based method uses the behaviour of students and their actions with the systems while they are learning in order to identify their learning style preferences. Patterns are identified based on findings of learners' preferences and behaviours for each specific learning style. This method uses simple rules to calculate learning styles. A study conducted to compare the efficiency of these two methods in detecting learning styles found that the literature-based method gives more accurate results than the data-driven method (Graf, 2007). Although the literature-based method has been found to be efficient, it has been claimed by Ahmad et al. (2013) that this method's point of weakness is embodied in the possibility of not considering all the potential patterns that could affect the detection of learning styles. Many studies have been conducted to automatically identify learning styles and the following section provides an overview.

3 RELATED WORK

Building adaptive systems that adapt to learners' learning styles has been a point of interest in research. Different studies have been conducted to provide adaptive learning based on learning styles. Some of these studies were based on the collaborative adaptive approach where students were asked to provide their preferences through answers to the ILS questionnaire while others were based on the automatic approach where their learning styles were detected automatically through their behaviours and interactions with the systems. In literature, a variety of methods and techniques were used. These methods differ based on the attributes that were used for detecting learning styles (personality factors, behaviour factors), the underlying technique (literature-based, data-driven) and the underlying infrastructure (Learning Management Systems, special user interface).

Various studies have considered the variety of learning styles and the importance of incorporating them into learning environments. Some of these studies were concerned with introducing models and approaches to incorporate FSLSM into adaptive systems based on the collaborative approach (Carver et al., 1999; Hong and Kinshuk, 2004; Gilbert and Han, 1999). Recently, studies have been more concerned with automatically detecting the learners' learning styles rather than using the collaborative approach. As stated, two main approaches are found in literature for learning style identification – the data-driven approach and the literature-based approach. In the data-driven approach, some data mining and machine learning algorithms were used to automatically identify the learners' learning styles. Some examples are: Bayesian networks (Carmona et al., 2008; García et al., 2007), neural networks (Cabada et al., 2009; Latham et al., 2013), decision tree, the Hidden Markov Model (Cha et al., 2006), NBTree (Özpolat and Akar, 2009), k-nearest neighbour algorithm along with genetic algorithm (Chang et al., 2009), and the AprioriAll mining algorithm (Klašnja-Milićević et al., 2011). Graf was the first to use the literature-based approach to automatically identify learning styles (Graf, 2007; Graf et al., 2008). She determined different patterns of learner behaviours and actions based on common learning objects in LMSs to identify learning styles. Other studies have also used this approach to identify some dimensions of the FSLSM (Ahmad et al., 2013; Şimşek et al., 2010; Atman et al., 2009).

4 THE PROPOSED FRAMEWORK FOR ADAPTIVE OPEN LEARNING

The objective of the framework is to perform two main functions: 1) identify the learners' learning style, and 2) recommend suitable learning materials and organise them in a way that the learner prefers. The recommendation and organisation of learning materials has been designed through providing navigational guidance and support based on the preferred learning style.

The adaptive engine consists of two main agents to perform the desired functionalities: 1) a learning style identification agent; and 2) a recommender agent. The identification agent is responsible for identifying the learning styles and storing them in the learners' profiles which is used by the recommender agent to provide the desired adaptability and navigational support to learners. An illustration of the proposed adaptive framework is provided in Figure 1.

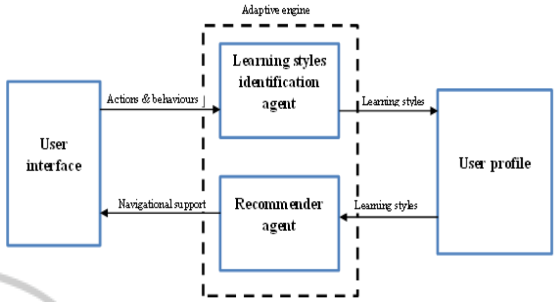

Figure 1: An illustration of the adaptive framework.

4.1 Learning Style Identification Agent

The design of the identification agent has been based on the literature-based method (Graf, 2007), which requires some determined patterns of learner interactions with the provided learning objects to be monitored in order to identify the learning styles. Graf was the first to use the literature-based method to automatically identify learning styles using the simple rule-based technique (Graf, 2007; Graf et al., 2008). She determined different patterns of learners' behaviours and actions based on common learning objects in LMSs that are used in blended learning. This approach has been shown to have higher accuracy of results in detecting learning styles (Graf, 2007).

As our study is looking at open learning environments, determining patterns for identifying learning styles should be based on the learning objects in these environments. For that, the authors have observed learning objects provided in well-known MOOCs, such as edX (edX, 2012), Coursera (Coursera, 2012), Udemy (Udemy, 2014) and Udacity (Udacity, 2012). The identified learning objects include course overviews, outlines, video lectures, a number of learning objects that vary between textual-based and visual-based, discussion forums, examples, exercises, quizzes with immediate feedback and additional reading materials.

The authors determined patterns to identify learning styles in open learning environments based on Felder and Silverman (Felder and Silverman, 1988) and others (Ahmad et al., 2013; Cha et al., 2006; Graf et al., 2008; Atman et al., 2009; Graf and Viola, 2009). These patterns consider the previously listed learning objects. In addition, knowledge maps have been considered as a learning object for organising learning concepts to support learners in open learning environments (Fasihuddin et al., 2013b; Fasihuddin et al., 2013a). Descriptions of the determined patterns of behaviours for each dimension of FSLSM are given below.

First, in terms of learner perceptions, sensory learners prefer facts, data and experimentation (i.e. concrete materials) while intuitive learners prefer principles and theories (i.e. abstract materials), so annotating the learning objects to specify their types (i.e. concrete or abstract) and examining the learners' access to these objects and the time spent on them can be used as a pattern. In addition, sensory learners like to solve problems by standard methods and do not like surprises, while intuitive learners like to invent new ways to solve problems. Based on this, sensory learners are expected to access more examples and spend more time on them, while intuitive learners spend more time on the learning materials. These can be considered among other patterns to distinguish between sensory and intuitive learners. Sensory learners are patient with details, careful but slow, while intuitive learners tend to be quick and careless; therefore sensory learners will spend more time on quizzes while intuitive learners spend less time. In regard to the input dimension, visual learners remember what they see better than what they hear while verbal learners remember more of what they hear than what they see. Visual learners learn better with diagrams, flowcharts and pictures while verbal learners prefer verbal explanations rather than visual demonstrations. Therefore, annotating the learning objects to distinguish whether they are visual or verbal and examining the access and time spent on them can reveal patterns.

In regard to the processing dimension, active learners like to try out and learn by practice while reflective learners prefer to think and reflect about what they learn so they learn better by observation. Based on this, active learners tend to access more exercises and spend more time on them. In addition, active learners like to work in groups while reflective learners prefer to learn alone; therefore, active learners tend to access the discussion forums and post more than reflective learners.

Finally, in regard to the understanding dimension, sequential learners like to learn in a sequential process and prefer learning materials to be organised and presented in a steady progression of complexity and difficulty. Global learners do not like the linear approach and might jump directly to the more complex materials. Based on this, the behaviour of accessing the learning materials can be considered as a pattern. In addition, global learners like to be provided with the overall picture of the

Active learners	Reflective learners
Exercise access (+) Exercise time (+) Example access (-) Example time (-) Additional reading access (-) Additional reading time (-)	Exercise access (-) Exercise time (-) Example access (+) Example time (+) Additional reading access (+) Additional reading time (+)
Sensing learners	**Intuitive learners**
Example access (+) Example time (+) Exercise access (+) Exercise time (+) Details and concrete LO time (+) Abstract learning object time (-) Quiz time (+)	Example access (-) Example time (-) Exercise access (-) Exercise time (-) Details and concrete LO time (-) Abstract learning object time (+) Quiz time (-)
Visual learners	**Verbal learners**
Visual LO access (+) Visual LO time (+) Additional reading material access (-) Verbal LO access (-) Verbal LO time (-)	Visual LO access (-) Visual LO time (-) Additional reading material access (+) Verbal LO access (+) Verbal LO time (+)
Sequential learner	**Global learners**
Outline access (-) Outline time (-) Concept maps access (-) Sequential access for LO (+)	Outline access (+) Outline time (+) Concept maps access (+) Sequential access for LO (-)

- While learner performs an action in the course, which represents a pattern:
  - oCalculate the hint values of the performed action ($h_{dim,i}$), where ($h_{dim,i}$) = {1,2,3}
  - oEnd While
- Calculate learning style for dimension LS_{dim} out of the collected hints $\frac{\sum_{i=1}^{P_{dim}} h_{dim,i}}{P_{dim}}$, where P_{dim} = number of patterns that are identified for a specific dimension

Figure 2: Pattern calculation method for identifying learning styles in open learning environments.

provided topic; therefore, they access and spend more time on the overview and outline. Moreover, global learners are expected to access the knowledge maps of the learning concepts more than sequential learners, so time spent accessing knowledge maps is another pattern. The table in Figure 2 summarises all the above mentioned patterns.

To identify the preferred learning style for each dimension, the specified patterns of behaviours need to be monitored in relation to pre-determined threshold values (Graf, 2007). For instance, if the expected time to spend on a certain example is 5 minutes, the time that a learner spends is recorded and then a ratio is calculated and compared to the pre-determined threshold values to give a hint ($h_{dim,i}$) for the corresponding dimension. The hint value is determined based on the ratio. If the ratio shows a strong preference for the corresponding dimension, then the hint value is 3. If the ratio lies between the thresholds then the hint value is 2. Finally, if the ratio shows a weak preference, then 1 is marked for the hint value. After that, the individual's learning style for the corresponding dimension is calculated by finding the mean value of the available hints. The resulting value, which will be between 1 and 3, indicates the learning style for the corresponding dimension. This calculation is computed for each of the four dimensions of FSLSM. The calculation method to determine learning styles is summarised in Figure 2.

In order to maintain any possible changes in learners' preferences, a dynamic adaptive approach should be considered in the framework design. This has been maintained by allowing learning styles to be re-calculated and updated in the learner's profile after each completed module in a provided course. The calculation of the updated learning style is done by finding the mean value of the previously stored learning styles in the learner's profile. This is an area of future extension of the study as more research still needs to be conducted in order to specify the optimal period of time or number of previous values that need to be considered in the calculation process.

4.2 Recommender Agent

After identifying the learning styles and storing them in the learners' profiles the recommender agent provides adaptive navigational support for learners. Every learner will be presented with learning objects organised in a way that suits their learning style or preferences. This organisation is based on the recommended teaching methods of Felder and Silverman for each learning style (Felder and Silverman, 1988). Other recommendations that have been provided by Graf and Kinshuk (2007) are also considered. More details about these recommendations and teaching methods for each style are provided below.

As mentioned, sensory learners prefer to learn from concrete materials, so these types of learning objects need to be shown before abstract materials. The opposite for intuitive learners – abstract materials need to be shown to them first. In addition, sensory learners prefer to learn by examples and real-life applications, so examples need to be shown to them before the explanation, while intuitive learners prefer the reverse. Moreover, sensory learners prefer more examples and exercises, so all available examples and exercises need to be recommended to them, while just some can be recommended to intuitive learners. In terms of the input dimensions, textual-based learning objects can be recommended to verbal-based learners, while the visual-based objects can be recommended to the visual learners. In addition, verbal learners may like to read over additional reading materials so these can be recommended for them. For the processing dimension, active learners prefer to learn by doing thus more exercises will be provided to them. They also like to invent their own approaches to solving problems, therefore, fewer examples will be shown to them. The reverse approach needs to be taken for reflective learners and more examples will be shown and less exercises. Also, additional reading materials will be shown to reflective learners. In regards to the understanding dimension, sequential learners prefer to learn with a linear approach, so learning objects involving examples and exercises need to be organised with a linear increase of complexity and the course conclusion and knowledge map are to be shown last. In contrast, the knowledge maps need to be presented first to global learners.

Providing learning objects in the above described organisation is believed to enhance learning experiences in open learning environments and consequently to enhance the learners' satisfaction and learning outcomes. This model will be evaluated in future implementation with learners.

5 PROTOTYPE DESIGN AND DEVELOPMENT

The proposed framework has been developed in a website termed CALC using ASP.net technology.

The website simulates the conditions of open learning, which is the focus of this study. First, CALC has the advantage of having a self-regulated learning approach where learners can learn at their own pace. Learners have personal profiles to keep their learning progress, interactions with the learning objects and their preferences. In addition, CALC provides self-assessment items with instant feedback so that learners can evaluate their own progress and knowledge gain. Furthermore, CALC has the advantage of media-technology enhanced learning as it provides learning objects in different formats in order to suit different preferences and needs.

CALC has been designed to conduct a pilot study at the University of Newcastle so that the adaptive framework can be evaluated. A course from the university has been selected and learning materials for that course have been developed and hosted on CALC to be learnt independently (as in MOOCs). More details about the development of learning materials are provided below.

5.1 Developing the Learning Materials

The development of learning materials has been conducted with consideration of the requirements of this study. Hence, various types of learning objects have been developed for the selected course - Systems and Network Administration. The learning objects for each module of the course include the module's overview, lecture slides, recorded videos, textual explanation documents, additional reading materials, examples, exercises, concept maps and quizzes. Each type of these learning objects has been annotated in CALC in order to be recognised by the adaptive engine and consequently patterns can be tracked and learning styles identified. Table 2 provides descriptions of these learning objects and their annotations in CALC.

5.2 Developing CALC

ASP.net technology has been used to develop CALC with consideration of different browser requirements. In CALC, every single learner has an account in order to allow the framework to track his/her interactions with the learning objects and store the resulting hints in his/her profile to calculate learning styles. Interactions that are tracked in CALC are based on the listed patterns in Figure 2. So time spent on learning objects is tracked to be compared with the expected time that is pre-assigned and saved in the database to calculate hints. Ajax technology has been used to implement this functionality. In addition, access to examples, exercises and other learning objects that need to be monitored are also tracked in order to find the total accessed number of these learning objects in each module and consequently to calculate hints that lead to identification of learning styles.

The adaptive framework that has been implemented in CALC is an automatic adaptive system. Therefore, it requires learners to use the system first to be able to collect data about their preferences and consequently provide the adaptive support. When a learner accesses the first module,

Table 2: Learning objects provided in CALC.

Learning Object	Description	Category	Annotation
Module overview	Provides an indication of the module contents and the main objective of learning it	Outline	OUT
Lecture slides	Presentation slides that provide the learning content in an abstracted form	Abstract	ABS
Recorded videos	Recorded videos of the lecturer's explanation to the lecture slides	Visual	VIS
Textual explanation documents	Textual documents that provide extended details about the learning content	Detailed Verbal	DET VER
Additional reading	Additional reading that is collected from different resources to provide additional information about the learning topic	Reading	READ
Examples	Provide more explanation of certain concepts or present some solved problems	Examples	EXP
Exercises	Multiple choice questions that allow learners to evaluate their level of understanding. Instant feedback is provided with an explanation of the right answer.	Exercises	EXER
Concept maps	A graphical representation of the module's different concepts that demonstrates how the concepts are related to each other.	Outline	OUT
Quizzes	Multiple choice questions with instant feedback and weighted results that specify whether a module has been successfully completed.	Quiz	QUIZ

the main page of that module will be represented in the standard organisation without any adaptive support. The standard presentation of a module has all the forms of learning objects shown (i.e. text, video and slides) as well as all the available examples and exercises. Also, in the standard presentation, the learning objects are organised as follows: course overview; learning concept materials in different forms; examples; exercises; and quizzes. A screen shot of the standard main page is provided in Figure 3.

For navigational support, hiding and sorting techniques have been applied in CALC. These techniques have been found to be efficient and improve user performance by significantly reducing navigation difficulty (Brusilovsky, 2003). Sorting in CALC has been implemented by sorting the different formats hiding of learning materials based on learners' preferences. Learning materials are sorted from the most preferred to the least preferred formats. For example, visual learners get the videos listed before the slides or the textual documents while verbal learners get the textual documents listed first. In addition, the order of showing examples and exercises are also based on the learner learning style. For instance, sensory learners prefer to have examples first while intuitive learners prefer to have exercises first.

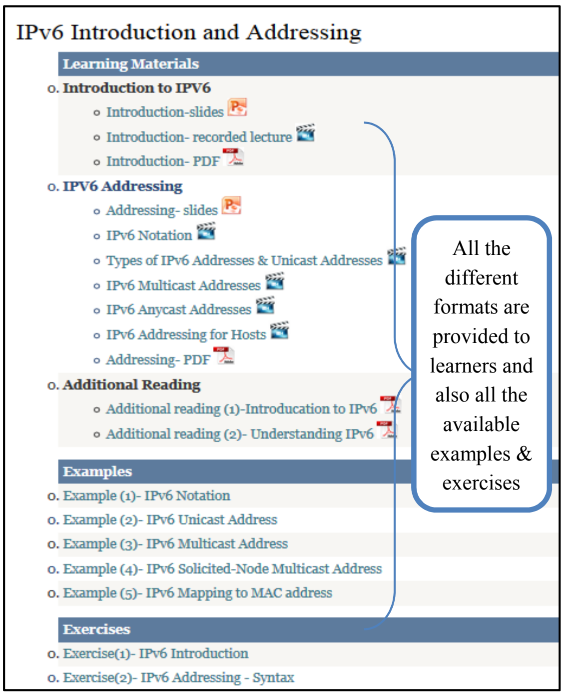

Figure 3: The standard main page in CALC.

In terms of, the least preferred format of learning materials are hidden from the list with the possibility to access them if required. If it is chosen to access the hidden materials, the list will still be sorted based on the learner's preferences. For instance, visual learners get the textual documents hidden or coming last in the case of the learner choosing to show the hidden materials. Moreover, the hiding technique is also applied to adapting the presentation of examples and exercises. In the case of learning styles that prefer to have less examples or exercises, just few are shown and the rest are hidden. Again, the hidden examples or exercises can be shown if the learner chooses that option. Finally, in the case of balanced learners, the standard organisation is shown to them. Some screenshots of CALC and how the adaptive navigational support is provided are shown in Figure 4.

6 DISCUSSION

This paper presents a framework for identifying learning style and adapting navigational support to learner's preferred learning styles. The proposed framework has been implemented using ASP.NET in a website termed CALC.

The automatic identification of learning styles in the proposed framework is mainly based on tracking students' behaviours and interactions with the determined patterns in the learning environments. The ILS questionnaire (Soloman and Felder, nd) is the standard approach for determining learning styles. One of the ways to benchmark the accuracy of the automatic learning style identification process is to benchmark the learning styles identified using the proposed automated method with ILS responses of the learner for a cohort of learners who use CALC.

In addition, the learners' satisfaction with regard to personalisation based on organisation and navigational support of learning materials can be measured by surveying the learners about their satisfaction level. Quantitative and qualitative analysis of survey responses as well as considering behaviour of learners (such as time spent on learning object, etc.) and analysis of learner's performance in assessments can provide an accurate evaluation of the personalisation based on learning styles.

In future, the authors intend to deploy the proposed framework and evaluate both learning style identification as well as personalisation impacts on learners.

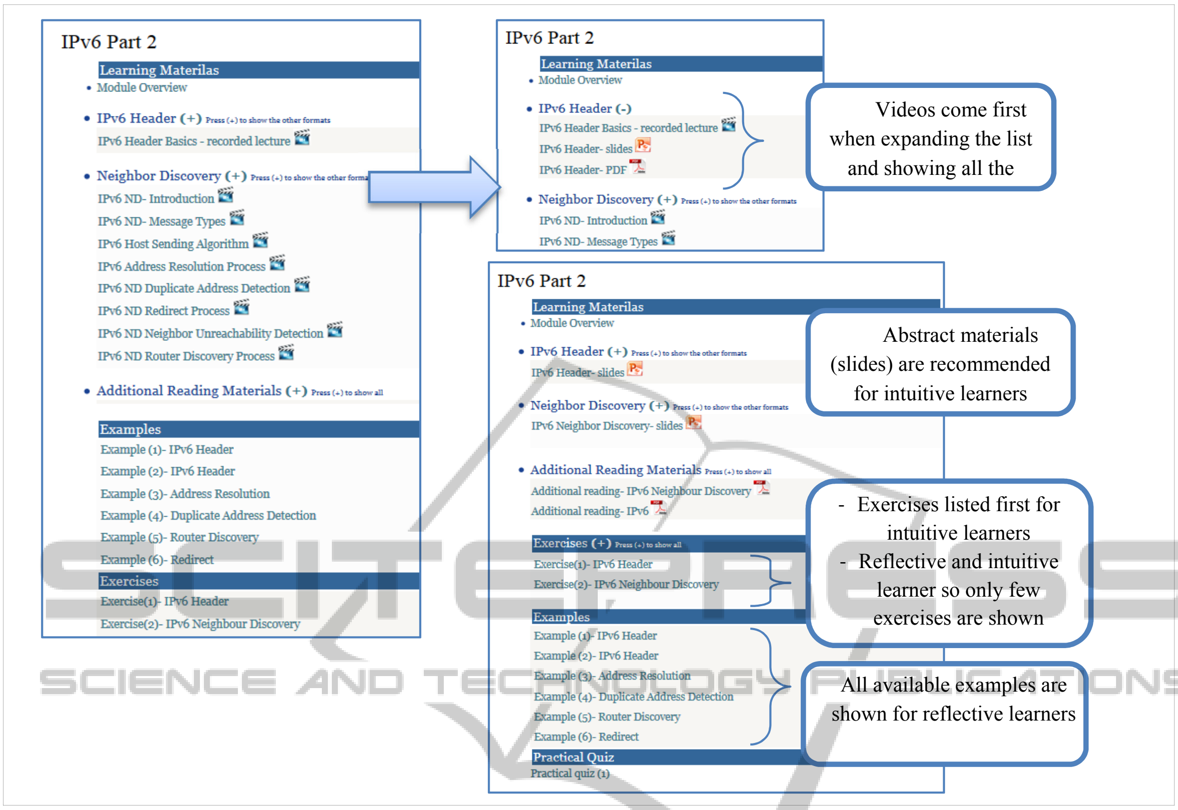

Figure 4: Some examples of the adaptive navigational support in CALC.

7 CONCLUSIONS

This paper introduces a framework to personalise open learning environments based on the theory of learning styles and particularly the Felder and Silverman Learning Style Model (FSLSM). A detailed description of the framework and its components along with the underlying functionalities is provided. The framework provides adaptive navigational support through sorting and hiding the learning materials based on learners' learning styles and the involved preferences.

A prototype that simulates an open learning environment in terms of offering open online courses has been developed and the proposed framework has been incorporated. In addition, learning materials have been developed in such a way that they fulfil the requirements of testing and evaluating the efficiency of the framework. Future work of this study involves piloting the developed prototype with a cohort of learners in order to evaluate the precision of identifying learning styles as well as the learners' satisfaction about the provided adaptability and navigational support.

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