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Towards adaptive open learning environments: Evaluating the precision of identifying learning styles by tracking learners' behaviours

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Abstract Open learning represents a new form of online learning where courses are provided freely online for large numbers of learners. MOOCs are examples of this form of learning. The authors see an opportunity for personalising open learning environments by adapting to learners' learning styles and providing adaptive support to meet individual learner needs and preferences. Identifying learning styles of learners in open learning environments is crucial to providing adaptive support. Learning styles refer to the manner in which learners receive and perceive information. In the literature, a number of learning style models have been proposed. The Felder and Silverman Learning Styles Model (FSLSM) has been selected as the most appropriate model for open learning. In previous studies two approaches have been used to automatically identify learning styles based on the FSLSM. These approaches are known as the data-driven method and the literature-based method. In the literature, the literature-based method has been shown to be more accurate in identifying learning styles. This method relies on tracking learners' interactions with the provided learning objects based on a set of pre-determined patterns that help in inferring learning styles. The patterns are monitored based on pre-identified threshold values. This paper aims to apply the literature-based method to open learning environments and introduce the optimal patterns and threshold values for identifying learning styles based on the FSLSM. To achieve this aim, a study was conducted whereby a prototype that simulates the open learning environment was developed and piloted on an undergraduate IT course so that learner behaviour could be tracked and data could be collected. Next, different sets of

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threshold values from the literature were considered along with some updated threshold values considering the context of open learning environments, and the precision of identifying learning styles was calculated. Eighty-three students participated in the study and used the developed prototype. Precision results from different threshold values presented in the literature along with customised threshold values for this study are reported and analysed in this paper. It is shown that threshold values derived from literature and customised to suit open learning environments provide a high level of accuracy in identifying learning styles. The paper presents the first study of its kind in evaluating threshold values and precision in identifying learning styles based on the FSLSM in open learning environments. The results are promising and indicate that the proposed methodology is efficient in detecting learning styles in open learning environments and useful for developing an adaptive framework.

Keywords Adaptive learning · Felder and Silverman model · Learning styles identification · MOOCs · Open learning · Web-based learning

1 Introduction

Online learning, as with almost every other field, is influenced by advances in technology and keeps evolving to take advantage of these advancements. The ubiquitous nature of the Internet has provided tremendous opportunities for online learning and leads to new models and approaches in this field. Open learning is a form of online learning that allows learning materials to be freely available on the Internet for any interested learner, providing the flexibility for learners to learn at their own pace (Fasihuddin et al. 2013). It relies on ubiquitous networks and cloud computing technologies which provide scalable and broad access computing environments allowing on-demand access to data and infrastructure. Currently, several prestigious learning institutions, such as Harvard, MIT and Stanford, provide learning materials using this open approach. Coursera (2012), edX (2012), Udacity (2012) and Udemy (2014) are examples of open learning initiatives. Courses that are provided through these open learning environments are popularly known as Massive Open Online Courses (MOOCs).

Open learning environments, including MOOCs, are still in their early stages of evolution with different concerns and challenges (Fasihuddin et al. 2013). These challenges are related to different aspects such as: teaching and learning methods; learning content; assessments; identity authentication; accreditation; personalisation; and addressing learners' varying needs, among others. These challenges have led to a renewed interest in research into open learning environments and supporting technologies. The authors see many research opportunities to address these challenges and support open learning environments. One such area of research is developing personalised learning environments catering to varying learner needs and preferences. The open nature of MOOCs and other open learning environments attract large numbers of learners and so there is a need to deal with learners with significant variations in their needs, preferences and even cognitive abilities. Therefore, the ability to identify and cater to various learners' needs is crucial for successful delivery of courses.

The authors believe that one such way to improve open learning environments is to apply cognitive science and learning principles (Fasihuddin et al. 2013). This view is also supported by others in the literature (Williams 2013). In this study theories and models of learning styles have been considered to personalise open learning environments and provide adaptive support. The possssibility of identifying learning styles by tracking learner behaviour in open learning environments is also evaluated. Learning style refers to the way a learner receives and processes information (Felder and Silverman 1988). Considering learning styles in courseware design has been found to be effective and beneficial for learning. Different studies have mainly investigated the impacts of providing learning materials that suit learners' learning styles and have found that this positively impacts learners and learning in various ways. For example, 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). Also many studies have found that students can achieve better learning outcomes and higher scores (Bajraktarevic et al. 2003) and can master the learning materials in less time (Graf and Kinshuk 2007). Based on these findings, the author hypothesised that personalisation based on learning styles will increase learners' satisfaction and lead to a richer learning experience in open learning environments.

The first step to personalise open learning environments based on learning styles is to identify the learning styles of individual learners. Once the learner's learning style is identified to an acceptable precision level, learning environments can be personalised to suit the individual learner's needs and preferences. In Fasihuddin et al. (2015a) a framework was proposed to identify learning styles and personalise open learning environments. In this paper, we present a study which attempts to evaluate the precision of identifying learning styles of learners in open learning environments. Firstly, a literature review of existing learning models and theory is considered. Next, an appropriate learning style model for open learning environments is selected. An approach to identifying a learning style automatically is considered and applied to an open learning environment. Next, the methodology for identifying learning styles is evaluated based on the accuracy of the identified learning style and by comparing the results with other studies in the literature. To the authors' knowledge, this is the first study of its kind to evaluate the accuracy of identifying learning styles in open learning environments.

The rest of this paper is organised as follows: first, an overview of the theory of learning styles and the related work are presented in section 2; the research design of this study is provided in section 3; section 4 presents the proposed method for identifying learning styles and the determined patterns of behaviour; the determined threshold values are presented in section 5; overviews of the prototype development and piloting are provided in section 6; the results and discussion are given in section 7; and finally the paper is concluded in section 8.

2 Background and related work

Learning style refers to the way a learner receives and processes information. Therefore, different learners will have different learning styles (Felder and Silverman 1988). In the literature, different definitions can be found for learning styles. Pritchard

(2013) defined learning style as “a particular way in which an individual learner learns”. Another widely cited definition of learning style was given in Keefe (1988) as “characteristic cognitive, affective, and psychological behaviours that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment”. In addition, Moran (1991) defined it as “the consistent approaches of perceiving and processing information that students usually employ during their learning”.

Learning styles can be used to guide learners to the most suitable approach for them to learn or to assist instructors in selecting the most suitable teaching approaches. Incompatible teaching approaches and learning styles may lead to disappointing learning experiences and learning outcomes (Pritchard 2013). Therefore, learning styles should be taken into consideration and teaching approaches should cater to different learning styles. In the literature, several models for learning styles have been proposed and found to be valid and reliable (Coffield et al. 2004). Some of these learning style models have been found more appropriate for online learning than others (Kuljis and Liu 2005). These models include: Field-independence and Field-dependence (Witkin et al. 1977), Kolb’s learning style (Kolb 1984), the Honey and Mumford learning style (Honey and Mumford 1992), the Myers-Briggs personality dimensions (Claxton and Murrell 1987) and Felder and Silverman’s learning style model (Felder and Silverman 1988).

The Felder and Silverman Learning Style Model (FSLSM) was selected by the authors as the most appropriate to be applied to personalise open learning environments. A number of reasons led to this selection. First, a study that was conducted to compare the suitability of different learning style models to be applied to online learning concluded that the FSLSM was the most appropriate model as it is comprised of important categories of cognitive learning behaviours which are frequently discussed in various learning style theories (Kuljis and Liu 2005). Secondly, the mechanism of the FSLSM Index of Learning Style (ILS) questionnaire (Soloman and Felder n.d.) that identifies learning styles can be easily applied to adaptive systems. This view was supported by a number of studies that were conducted to build adaptive courseware (Carver et al. 1999; García et al. 2008). In addition, and more importantly, different studies have shown the validity and reliability of the ILS (Felder and Spurlin 2005; Zywno 2003). A correlation between learners’ online behaviours and their learning styles identified using ILS was also shown in Graf (2007). Furthermore, it has been shown that the FSLSM is the most appropriate and feasible model for adaptive courseware (Carver et al. 1999; García et al. 2008).

The FSLSM was originally developed to assist teaching in engineering education (Felder and Silverman 1988). However, the use of this model has gone beyond that as it has been adopted by educators in different disciplines. FSLSM classifies learning styles into four dimensions and identifies two types of learners for each dimension. The dimensions are perception, input, processing and understanding. Table 1 lists these styles and their associated types. The first dimension of the FSLSM is the perception dimension which 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 learners prefer to learn with: visual learners prefer pictures, diagrams and flowcharts while verbal learners prefer written or spoken explanations. The processing

Table 1 Felder and Silverman learning styles

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

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.

The Index of Learning Styles (ILS) questionnaire is the instrument to identify learning styles based on the FSLSM (Soloman and Felder n.d.). The questionnaire consists of forty-four questions – eleven questions per each dimension. It asks about learners' preferences in different scenarios such as problem solving, entertainment, group working, writing, thinking and memorising. The calculation of the ILS is based on a bipolar scale with mutually exclusive answers to items, i.e. either (a) or (b). Because there is an odd number of items on each scale, if items are scored as +1 and −1, respectively, the total score on a scale from −11 to +11 shows an emerging preference for the given dimension (Zywno 2003). If the score on a scale is within ±1 to ±3, that indicates a balanced learning style for that dimension. If the score is within ±5 to ±7, this indicates a moderate preference for a style in that dimension. If the score is within ±9 to ±11, this indicates a strong preference for a particular style in that dimension.

Building adaptive systems that adapt to learning styles has been an interest for researchers and developers. In general, two different approaches –collaborative and automatic– have been used in literature for user modelling in adaptive systems (Brusilovsky 1996). A number of studies were conducted to build an adaptive system that used the collaborative approach in which learners had to answer the ILS questionnaire to allow the system to identify and adapt to their learning styles. Examples of these studies include: an adaptive PHP programming course (Hong and Kinshuk 2004), CS383 (Carver et al. 1999), MASPLANG (Peña et al. 2002), Learning Style Adaptive System (LSAS) (Bajraktarevic et al. 2003) and the Task-based Adaptive learNer Guidance On the WWW (TANGOW) (Carro et al. 2001).

In addition to the previous studies, other studies were conducted to build adaptive systems that used the automatic approach to identify learners' learning styles. In the literature, a variety of methods and techniques have been used to achieve this goal. These methods differ based on the attributes that are used for detecting learning styles (personality factors, behavioural factors), the underlying technique (literature-based, data-driven) and the underlying infrastructure (learning management systems, special user interface). Two main approaches are found in the literature for automatic learning style identification – the data-driven approach and the literature-based approach. In the data-driven approach, data mining and machine learning algorithms have been used to automatically identify the learners' learning styles. Examples include: Bayesian networks (Carmona et al. 2008; García et al. 2007), neural networks (Cabada et al. 2009;

Latham et al. 2013), decision trees, 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). In the literature-based approach, patterns of learners' behaviour with learning objects are determined and monitored in relation to predefined threshold values. Graf was the first to use the literature-based approach to automatically identify learning styles (Graf 2007; Graf et al. 2008). Graf (2007) determined different patterns of learner behaviours and actions based on common learning objects in LMSs. Other studies have also used this approach to identify some dimensions of the FSLSM (Ahmad et al. 2013; Atman et al. 2009; Şimşek, Ö et al. 2010). Graf (2007) found that the literature-based approach gives better results and precision in detecting learning styles in comparison to the data-driven approach. For these reasons, the authors decided to use a literature-based approach in this study to identify learner's learning styles in open learning environments.

3 Research design

This study aims to evaluate the precision of the automatic identification of learning styles in order to build an adaptive framework that can personalise open learning environments. In order to achieve this aim, research into learning styles literature was essential to select a suitable model from the several available models. As discussed in section 2, the FSLSM was found the most suitable model to be applied to online learning environments for building adaptive systems. After selecting the FSLSM as the preferred learning style model to identify learning styles of online learners in open learning environments, selecting an approach for automatic identification of learning styles was the next step. As discussed, two main approaches (date-driven and literature-based) exist for determining learning styles. It has been shown in Graf (2007) that the literature-based approach is more accurate than the data-driven approach and thus the literature-based approach was selected to identify learning styles in this study. In this approach pre-determined patterns of learner interactions are monitored in relation to pre-determined threshold values in order to identify the learning styles.

In order to build an adaptive framework for open learning environments using the literature-based approach, patterns of behaviours and thresholds need to be determined in a way that corresponds to the nature and learning conditions of open learning environments. This study aims to identify patterns and thresholds that lead to optimal precision in detecting learning styles by tracking learners' behaviours in open environments. Hence, the following research questions and sub-questions were proposed for this study:

- Can a satisfactory level of precision in identifying learning styles be achieved using the literature-based method in open learning environments?

– What patterns of behaviour need to be tracked?
– What threshold values for the patterns of behaviour give the highest precision?

Precision is computed as the similarity of the identified learning style to the learning style determined by the ILS survey. In order to evaluate the precision of identifying learning styles with pre-determined patterns and thresholds, a prototype of an open learning environment which tracks and monitors learners' behaviour against pre-determined patterns was developed and piloted on an undergraduate course. The pilot study gave the authors the opportunity to collect data about learners' behaviour, interacting with learning objects by tracking them with respect to pre-determined patterns. This also gave the opportunity to evaluate different threshold values and consequently to assess the resulting precisions. Figure 1 presents an illustration of the research design. Steps 1 and 2 in Fig. 1 have been discussed previously. In step 1, the FSLSM was selected for the study and in step 2 the literature-based approach was selected to identify the learning style based on learner behaviour. Details of other steps are discussed in the sections below.

4 Determining patterns of behaviours and learning styles calculation

As this study is looking at open learning environments, determining patterns to identify learning styles should be based on the learning objects in these environments. For that, the authors observed learning objects provided in well-known MOOCs, such as edX, Coursera, Udemy and Udacity. The identified learning objects include course overviews, outlines, video lectures, a variety of textual-based and visual-based learning objects, 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; Atman et al. 2009; Cha et al. 2006; Graf et al. 2008; Graf and Viola 2009). These patterns consider the previously listed learning objects. In addition, knowledge maps have been added as a learning object for organising learning concepts to support learners in open learning environments (Fasihuddin et al. 2013; Fasihuddin et al. 2015b).

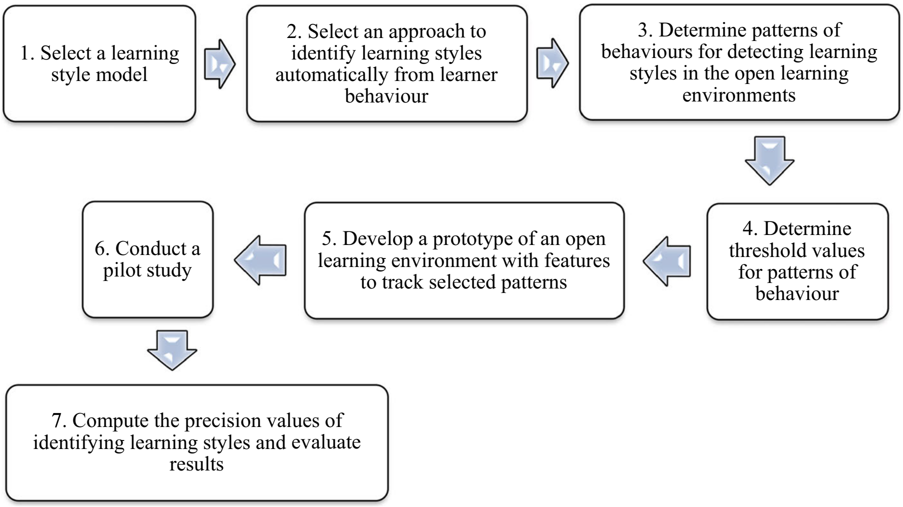


Fig. 1 Research study design

The table in Fig. 2 provides a list of the determined patterns of behaviour for each dimension of the FSLSM. In the table the (+) sign indicates a high occurrence of the pattern for the associated learning style, while the (−) indicates less occurrence of the pattern for the associated learning style. More detailed descriptions of the determined patterns can be found in Fasihuddin et al. (2014).

To identify the preferred learning style for each dimension using the literature-based method, 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 min, the time that a learner spends is recorded and then a ratio is calculated and compared to the pre-determined threshold value 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 given as 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. Values between 1 and 3 are classified into three equal numerical periods and from the resulting value the learning style and its strength (i.e. strong/moderate) are specified. This calculation is computed for each of the four dimensions of the FSLSM. The calculation method to determine learning styles is summarised in Fig. 2.

5 Determining threshold values

Assigning threshold values for a literature-based approach needs to consider the nature and conditions of the targeted environment. Most of the previous studies have assigned

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:
  - calculate the hint values of the performed action $(h_{dim,i})$, where $(h_{dim,i}) = \{1,2,3\}$
  - End 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

Fig. 2 Pattern calculation method for identifying learning styles in open learning environments their threshold values based on the literature with some modifications to make them more suitable to the provided courses and learning environment conditions (Ahmad et al. 2013; Atman et al. 2009; Graf et al. 2008; Şimşek et al. 2010). These studies were conducted in different contexts (i.e. LMS, web-based) with similarities and differences in subjects, learning material forms and learners' computer knowledge. The authors believe that thresholds from previous studies can be used in open learning environments, though some modification might be required to achieve optimal results.

A combination of various patterns and threshold values were found in the literature for detecting learning styles (see Table 2). Garcia et.al (2007) defined a set of pattern for identifying the perception, processing and understanding dimensions. They set thresholds for accessing examples and exercises to 25 and 75 % of the number of available examples or exercises. For time spent on examples and exercises as well as quizzes, the threshold was set to 50 and 75 % in relation to the expected time for mastering them. For the content learning objects they set threshold values of 75 and 100 % for accessing them in relation to all available learning objects, and 50 and 75 % for the time spent in relation to the expected time. Graf (2007) has also proposed threshold values for learning styles identification. These thresholds were based on the values introduced by Garcia et.al (2007), but with some modifications. In Graf's study, the threshold values for accessing the content learning objects were set to 10 and 20 %. This modification was based on the assumption that learners will have the content in print and will not be fully dependent on accessing them online only. Another modification that Graf (2007) made was on the examples access which was set to be 50 and 100 %. In addition, Graf (2007) assigned 75 and 150 % for outline access and 50 and 75 % for outline time. A combination of the previous thresholds was selected and used in another study that also evaluated the precision of identifying learning styles (Şimşek et al. 2010). Atman et al. (2009) also presented a study to evaluate the precision of identifying learning styles, but their learning objects were limited in comparison to other studies. Similar to Graf (2007) and Garcia et.al (2007), Atman et al. (2009) set the threshold for exercise, example and quiz time to 50 and 75 %. The example and exercise access was set to 25 and 50 %. Atman et al. (2009) only tracked patterns on the introduction access and spent time and set these thresholds to 75 and 100 %, 75 and 125 % respectively. Another study was conducted to find threshold values by analysing learners' behaviour while they are learning (Ahmad and Tasir 2013). This study found that threshold values were dramatically different to the ones proposed by Garcia et.al (2007) and Graf (2007). Based on that study, the difference was that the data in one was collected for a face-to-face provided course and learners used the online contents only for seeking information, solving exercises or participating in forums.

In this study, the authors determined thresholds by selecting values from previous studies and applying modifications to make them suitable to open learning environments. Thresholds for example accessing are determined based on Graf's (2007) suggestion and therefore were set to 50 and 100 %. For exercise access the authors decided to raise the ratio to 50 and 100 %, as it is expected that learners in open environments will be willing to practice more exercises to enrich their understanding and evaluate their progress. In terms of example and exercise time, as in previous literature, the values were set to 50 and 75 %. For accessing the learning content, the values proposed by Garcia et.al (2007) were followed and thresholds set to 75–100 %. This was determined based on the assumption that learners will only be able to access

Table 2 Threshold values based on the literature

Pattern of behaviour	Description	Threshold Values			
		García et al. (2007)	Graf (2007)	Ahmad and Tasir (2013)	This study
Example access	The ratio of the accessed examples in relation to all available examples	25–75 %	50–100 %	–	50–100 %
Example time	The ratio of the time spent on examples in relation to the expected time	50–75 %	50–75 %	–	50–75 %
Exercise access	The ratio of the accessed exercises in relation to all available exercises	25–75 %	25–75 %	60–80 %	50–100 %
Exercise time	The ratio of the time spent on exercises in relation to the expected time	50–75 %	50–75 %	30–50 %	50–75 %
Additional reading access	The ratio of the accessed additional reading materials in relation to all available learning objects	75–100 %	10–20 %	60–80 %	60–80 %
Additional reading time	The ratio of the time spent on additional reading materials in relation to the expected time	50–75 %	50–75 %	20–45 %	10–20 %
Detailed learning object time	The ratio of the time spent on detailed learning objects in relation to the expected time	50–75 %	50–75 %	20–45 %	50–75 %
Abstract learning object time	The ratio of the time spent on abstract learning objects in relation to the expected time	50–75 %	50–75 %	20–45 %	50–75 %
Visual learning object access	The ratio of the accessed visual learning objects in relation to all available learning objects	75–100 %	10–20 %	60–80 %	75–100 %
Visual learning object time	The ratio of the time spent on visual learning objects in relation to the expected time	50–75 %	50–75 %	20–45 %	50–75 %
Verbal learning object access	The ratio of the accessed verbal learning objects in relation to all available learning objects	75–100 %	10–20 %	60–80 %	75–100 %
Verbal learning object time	The ratio of the time spent on verbal learning objects in relation to the expected time	50–75 %	50–75 %	20–45 %	50–75 %
Quiz time	The ratio of the time spent on quizzes in relation to the expected time	50–75 %	50–75 %	20–45 %	50–75 %
Outline time	The ratio of the time spent on the outline in relation to the expected time	–	50–75 %	20–45 %	50–75 %
Outline access	The ratio of the accessed outline in relation to all available learning objects	–	75–150 %	60–80 %	75–100 %

the learning contents online. For the learning content time, the values are determined based on literature and were set to 50 and 75 %. In terms of the additional reading materials, the authors distinguished them from other learning contents as they were considered as extra additional learning contents and learners may just access them occasionally for a quick scan. Hence, the thresholds for accessing additional reading were set to 60 and 80 %, and for time spent they were set to 10 and 20 %. In terms of the outline materials, following Graf (2007), the thresholds for time spent were set to 50 and 75 % while the thresholds for accessing them were modified to 75 and 100 %. Finally, the threshold for time spent on quizzes was set to 50 and 75 %. Table 2 presents the different threshold values that were found in the literature to calculate learning styles as well as the threshold values used in this study.

Each set of the threshold values gives different precision values in different contexts. In this study, in order to evaluate the determined threshold values for open learning environments, the authors decided to evaluate the precision of identifying learning styles using the determined set of thresholds as well as other sets used in literature, such as Graf (2007) and Ahmed and Tasir (2013).

6 Prototype development and piloting

In order to evaluate the accuracy of identifying learning styles in open learning environments, a prototype was developed and a pilot study was conducted. The prototype was developed as a website called Cloud Adaptive Learning Courses (CALC) using ASP.net. The website simulates the conditions of open learning in order to meet the context 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 store 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. Every form of learning object is annotated in CALC so that it can be recognised and consequently patterns can be tracked and learning styles identified. Table 3 provides descriptions of the available forms of learning objects in CALC and their annotations.

In CALC, every single learner has an account in order to allow the tracking of his/her interactions with the learning objects and to store the resulting hints in his/her profile to calculate his/her learning style. Interactions that are tracked in CALC are based on the patterns listed in Fig. 2. The 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 number of these learning objects accessed in each module and consequently to calculate hints that lead to identification of learning styles. Also, the order of accessing the learning objects is tracked and the ratio of skipping and jumping learning objects are calculated.

CALC was piloted at the University of Newcastle on an undergraduate course. Two modules of that course - Systems and Network Administration - were designed to be provided online through CALC and learnt independently by students. To fulfil the requirements of the study, various learning objects were developed for each module.

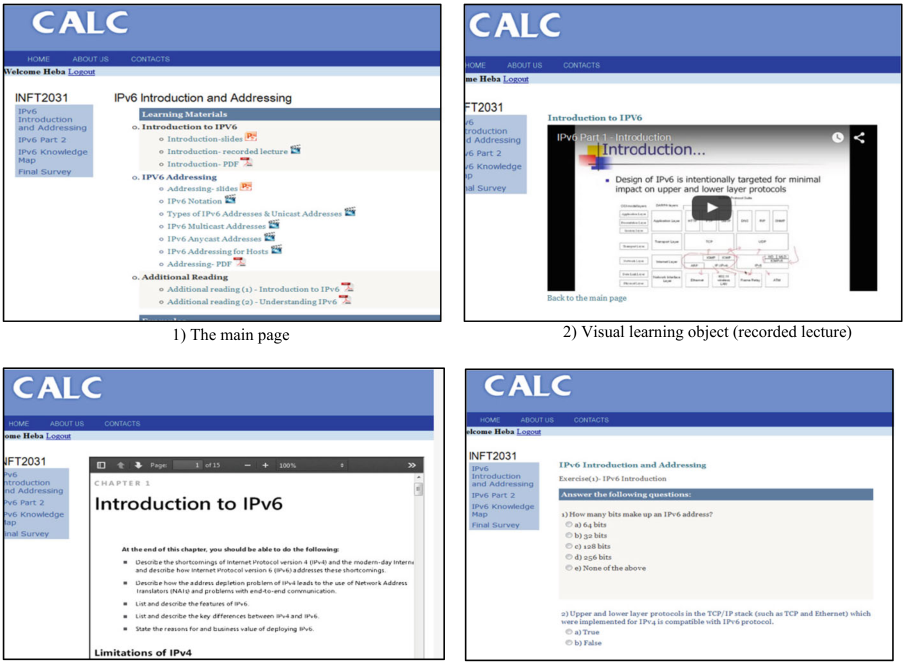
Table 3 Learning objects provided in CALC

Learning Object	Description	Category	Annotation
Module overview	Provides an indication of the module contents and the main learning objective	Outline	OUT
Lecture slides	Presentation slides that provide learning content in an abstract form	Abstract	ABS
Recorded videos	Recorded videos of the lecturer's explanation about 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 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 indicate whether a module has been successfully completed.	Quiz	QUIZ

These learning objects included the module overview, lecture slides, recorded videos, textual explanation documents, additional reading materials, examples, exercises, concept maps and quizzes. Some screenshots of CALC are presented in Fig. 3.

All enrolled students in the selected course were invited to participate in the study and learn from the provided modules at their own pace. They had the opportunity to access and learn these modules for around 7 weeks. Participation in the study was optional. Out of the enrolled students, eighty-three students participated and used CALC. These students also had to take the ILS questionnaire (Soloman and Felder n.d.) to identify their learning styles before they started using CALC. This was necessary to evaluate the precision of the proposed identification technique as the computed learning styles were compared with the results of the ILS questionnaire for each student.

The prototype was developed in a way that allows the use of different threshold values for pattern tracking. This was necessary in order to evaluate the precision of identifying learning styles with these different values and consequently to find the values that gave the best results. After the students used CALC, their behaviours and tracking data were stored in the database. This provided an opportunity to analyse these data using the different threshold values and consequently to compare the precision values. Details about the evaluation method and results are given below.



1) The main page

2) Visual learning object (recorded lecture)

3) Verbal learning object (textual document)

4) Exercise

Fig. 3 Screenshots from CALC

6.1 Evaluation method

In order to evaluate the precision of the proposed method in identifying learning styles in open learning environments, the same evaluation method that was used in Ahmad et al. (2013), Atman et al. (2009), García et al. (2007), Graf (2007) and Şimşek et al. (2010) was also used in this study. This method was proposed by Garcia et al. (2007) and it is based on measuring how close the identified style is to the style identified by the ILS questionnaire using the following formula:

$$Precision = \frac{\sum_{i-1}^{n} Sim\ (LS_{Predicted},\ LS_{ILS})}{n}.\ 100$$

In the formula, $LS_{Predicted}$ refers to the identified learning style by the proposed approach, LS_{ILS} refers to the learning style identified by the ILS questionnaire and n is the number of students who have available data (i.e. patterns) to infer their style for a particular dimension. The function *Sim* compares the two parameters and returns 1 if both are a similar style, 0.5 if one is balanced and the other represents a preference to a style or 0 if they represent opposite styles.

7 Results and discussion

To evaluate the precision of the proposed framework in identifying learning styles the precision formula that was presented in the previous section was used. The precision of identifying learning styles for the four dimensions of the FSLSM were calculated. In addition, the authors calculated the precision using different threshold values, so that precision results could be compared and those thresholds that gave the best result could be identified. Table 4 shows the calculated precision for each dimension using the determined thresholds in this study along with other studies (Ahmad and Tasir 2013; Graf 2007). As Ahmad and Tasir (2013) did not provide thresholds for the example access and spent time, the same thresholds as exercises were used in the calculation. The thresholds values of Atman et al. (2009) were not used as they did not include most of the required learning objects or patterns of behaviour used in this study.

It can be seen in Table 4 that the resulting precision of the perception dimension are similar using the different sets of threshold values. This is due to the fact that some of tracked patterns of behaviour for this dimension are based on tracking the interaction with examples, exercises and quizzes and the threshold values for these patterns are quite close which led to very close results. In regard to the input dimension, it can be noticed that the highest precision value was obtained using the determined threshold values used in this study. This result may due to the fact that identifying the input style is based on tracking the behaviour with visual/verbal learning objects as well as the additional reading materials, and in this study the determined thresholds for tracking the content objects are the highest compared to the one proposed by Graf (2007) and Ahmad and Tasir (2013). Graf assigned very low thresholds for accessing the content objects based on the assumption that learners have the learning contents in print and do not need to access them online for learning. Using Graf's thresholds gave a precision of 67.12 %, which indicates that rising the thresholds for accessing content objects is good as learners in open learning environments are expected to access these content mostly online. In terms of the processing dimension, it can be noticed that the precision values using the determined thresholds and Graf's thresholds are higher than the one resulting using Ahmad and Tasir's thresholds. In the proposed method identifying the processing styles is mainly based on tracking the behaviour with examples and exercises. The determined thresholds for example and exercise accessing were set to 50 and 100 % which seems to give better results in comparison to the values set by Ahmad and Tasir which were 60 and 80 %. Finally, in regard to the understanding dimension, it can be noticed that the resulting precision of using the thresholds of this study, which are close to those proposed by Graf (2007), is dramatically higher than the precision using Ahmad and Tasir's values. This indicates that this study's determined threshold values are more suitable for open learning environments.

Table 4 The resulting precision values with different thresholds

FSLSM dimensions	Precisions		
	Thresholds determined in this study	Thresholds based on Graf (2007)	Thresholds based on Ahmad and Tasir (2013)
Perception	71.23 %	71.23 %	71.91 %
Input	80.13 %	67.12 %	77.39 %
Processing	78.08 %	78.08 %	58.21 %
Understanding	81.50 %	81.50 %	17.12 %

From the previous results it can be stated that determining threshold values needs to be with consideration to the nature and condition of the learning environments. As shown above, threshold values that gave high precision results for variable learning contexts did not give the same results in open learning environments. This view is also supported by Ahmad and Tasir (2013) as they stated that threshold values differ depending on course structure, subjects and the experience of different students.

In order to evaluate the proposed framework and the determined patterns of behaviour and how effective they are in identifying the learning styles in open learning environments, the resulting precision in this study was compared with the resulting precision of other studies that also used the literature-based method. Table 5 shows the resulting precision values. As shown in the table, some of the studies were conducted with consideration only to the processing dimension of the FSLSM. Also, it can be noted that the resulting precision values of this study are quite satisfactory and can be considered as an indication that the literature-based method may be a suitable approach to identify learning styles in open learning environments as in blended learning environments.

As shown in Table 5 the precision of identifying the style of the perception dimension in this study is 71.23 % which is quite close but lower than the result achieved by Graf et al. (2008) which is 77.33 %. This may be due to the fact that Graf considered more patterns of behaviour than were considered in this study. Graf's study considered patterns that are related to learners' performance in quiz questions. The percentage of correctly answered questions and what these questions asked about (i.e. details, facts, graphics, etc.) were monitored and used as patterns to identify style in the perception dimension. Based on that, it can be concluded that monitoring learners' behaviour with quiz questions has the possibility to improve the precision of detecting the learning style for the perception dimension in open learning environments.

In regards to the input dimension, 80.13 % is the precision result of this study while it was 76.67 % in Graf et al. (2008). Monitoring the spent time and the access to learning contents represents the patterns that were used to identify the style of the input dimension. In addition, Graf's study considered other patterns that monitored learners' participation and activities in discussion forums as well as their performance in quizzes with questions that asked about verbal and visual contents. The authors believe that in environments such as open learning environments in which learning is completely self-regulated and accessing the learning contents is the main source for learning, monitoring behaviour with the learning contents is probably a good approach to achieve a high

Table 5 Resulting precision values from different studies using the literature-based approach

	This study	Graf et al. (2008)	Atman et al. (2009)	Ahmad et al. (2013)	Şimşek et al. (2010)
Perception precision	71.23 %	77.33 %			
Input precision	80.13 %	76.67 %			
Processing precision	78.08 %	79.33 %	83.15 %	75.00 %	79.60 %
Understanding precision	81.50 %	73.33 %			

precision value. Nevertheless, other patterns that are based on monitoring forum participation and quiz performance can also be included and may lead to better results and a higher precision in identifying the learning style for the input dimension in open learning environments.

In regards to the processing dimension, a number of studies have been conducted to identify learning styles in different learning contexts (e.g. LMS, web-based). The resulting identification precision ranges from 75 to 83.15 %. In these studies, there were some similarities in the considered patterns of behaviour to identify the learning styles, as these patterns were based on monitoring the spent time on and access to examples, exercises and other contents. In the studies that were conducted by Graf et.al (2008) and Ahmad et al. (2013) monitoring forum participation was also used as a pattern in both, however the resulting precision value for Graf et al. (2008) was slightly higher. This might be due to the difference in sample size or the subject. Also, it can be seen in Table 5 that the resulting precision of the study by Atman et al., (2009) has the highest precision value; however the sample size of this study was only 17 students which is small compared to the sample sizes of the other studies. Although the resulting precision of this study is quite close to the other studies, the authors believe that the addition of patterns of behaviour with forums will support the learning style identification for the processing dimension and may lead to a better precision value.

Finally, in regards to the understanding dimension, it can be noticed in Table 5 that a high precision value (81.5 %) was obtained by this study. In this study, the pattern of behaviour with concept maps, which was assumed to be more interesting for global learners, was considered. In addition, monitoring the navigation path and the accessing order of learning objects was another main behaviour that was used to detect learning styles. Monitoring the access order is believed to boost the identification precision of the understanding dimension in open learning environments as learning is completely reliant on accessing the provided learning materials online.

It should be noted that the reported findings rely on the collected data from the participants in this study, which involves their responses to the ILS questionnaire and their behaviour with the learning objects in CALC prototype. Also, this study was conducted on an IT based course, so different courses and different students can lead to different results.

The automatic identification of learning styles using the proposed technique is mainly based on students' behaviours and interactions with the learning environment. This implies possible errors and inaccuracies that might affect the reliability of the identified learning style. Tracking the time spent or even the number of times a learning object is accessed does not guarantee that the learner attentively reads or learns it. Thus innovative techniques and technology advancements can be applied in the future to enhance the accuracy of the tracking approach.

8 Conclusion

This paper introduces an evaluation of an automatic technique to identify learners' learning styles in open learning environments. This technique can be used in developing an adaptive framework to personalise the open learning environments and address the learners' various needs. It is believed that this study is the first of its kind in focusing on personalising the open learning environments. The proposed technique is based on the theory of learning styles and particularly the Felder and Silverman Learning Style Model (FSLSM). It is an automatic adaptive technique that identifies learning style using the literature-based method. This is mainly based on monitoring learners' behaviour against pre-determined patterns based on the FSLSM and in relation to predefined threshold values. The patterns were selected based on descriptions by Felder and Silverman as well as previous studies. Determining the threshold values for open learning was another significant outcome. Thresholds were determined based on the literature with modifications to make them more suitable for open learning environments.

A software prototype that simulates an open learning environment in terms of offering open online courses was developed. This prototype was piloted on two modules of an IT undergraduate course. Learning materials for these modules have been developed in such a way that they fulfil the requirements of testing and evaluating the precision of identifying learning styles. Eighty-three students participated in using the prototype and answering the ILS questionnaire. Finally, the precision of the proposed method was analysed by comparing how close the identified learning style was to the ILS style of each student. In addition, precision values were calculated using different thresholds so that the thresholds that gave the higher precision could be identified. Data analysis and precision calculation showed that the use of literature-based method to identify learning styles in open learning environments is efficient and useful for developing an adaptive framework.

Future work of this study will consider finding techniques to personalise learning environments by adapting to identified learning styles. Navigational support based on the learning styles of learners is one of the adaptation techniques that can be considered and evaluated in open learning environments. In addition, more patterns of behaviour can be considered in the framework design and evaluated in order to discover whether they improve identification precision. Another research focus could be evaluating a dynamic calculation of learning style by finding the mean value of the previously stored learning styles in the learner's profile. Furthermore, conducting the study on longer periods might be needed in order to specify the optimal period of time or number of previous values that need to be considered in the calculation process.

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