

STATE OF THE ART OF LEARNING STYLES-BASED ADAPTIVE EDUCATIONAL HYPERMEDIA SYSTEMS (LS-BAEHSS)

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ABSTRACT

The notion that learning can be enhanced when a teaching approach matches a learner's learning style has been widely accepted in classroom settings since the latter represents a predictor of student's attitude and preferences. As such, the traditional approach of 'one-size-fits-all' as may be applied to teaching delivery in Educational Hypermedia Systems (EHSs) has to be changed with an approach that responds to users' needs by exploiting their individual differences. However, establishing and implementing reliable approaches for matching the teaching delivery and modalities to learning styles still represents an innovation challenge which has to be tackled. In this paper, seventy six studies are objectively analysed for several goals. In order to reveal the value of integrating learning styles in EHSs, different perspectives in this context are discussed. Identifying the most effective learning style models as incorporated within AEHSs. Investigating the effectiveness of different approaches for modelling students' individual learning traits is another goal of this study. Thus, the paper highlights a number of theoretical and technical issues of LS-BAEHSS to serve as a comprehensive guidance for researchers who interest in this area.

KEYWORDS

Learning Styles, Deducing Approaches, Adaptive Educational Hypermedia Systems.

1. INTRODUCTION

Filtering and sorting pedagogical resources for learners in a huge hyperspace is a vital aspect in order to improve learning experience and learners' motivation towards learning process in EHSs. To achieve this goal, adaptive hypermedia represents a "crossroad of hypermedia and user modeling" [1]. Hence, Adaptation Model (AM) comprises many methods and approaches for adaptive systems' presentation, navigation support [2][3], collaboration [4] and assessment mode [5][6]. *Adaptive* and *adaptable* are considerably used terminologies in this area. However, the main distinction between them is what plays the role of adaptation and how learners' features are modelled. Adaptive system can be defined as implicitly inferring users' preferences by observing their interaction with a system in order to tailor its output. Adaptable systems, on the other hand, means providing explicit input in order to personalize output [7]. Brusilovsky [2] identified the main criteria of adaptive hypermedia systems (AHSs) as follows: "it should be a hypertext or hypermedia system; it should have a user model; it should be able to adapt the hypermedia using this model".

Generally speaking, *adaptive* and *adaptable* can serve many goals: enhancing assimilation of learning content, reducing forgetting, motivating students, providing learners with flexible choices to develop their autonomous learning strategies, guiding learners to the optimal pathway, tackling the issue of cognitive overload, reducing learning cost and enhancing systems' usability.

This means that adaptivity can play the role of promoting and improving learning. However, the mainstay of this process is to which learners' features and traits this information can be presented and how learners can be precisely modelled.

Different individual features have been considered in the literature to be accounted for the User Model (UM), for example, prior knowledge, background, interests, goals, learning styles, cognitive traits and learning approaches. Recently, researchers have largely focused on learning styles due to several reasons. From a perspective of psychologists and evidence of empirical research, the learning process can be enhanced if teaching approaches and learning styles are well-matched [8][9][10][11][12][13][14][15][16][17]. Another reason is the stability or eventually stability of these traits comparing with others [18][19][20][3][21][22].

Although learning styles represent a predictor for individual differences, optimal modelling and integration of learning styles in AEHSs still requires further research. This claim can be supported by the confirmation of Brusilovsky and Millán [18] "There are no proven recipes for the application of learning styles in adaptation". In general, all approaches for student modelling can be classified into two categories: explicit and implicit approaches. However, the shortage in each category represents an obstacle to accurately model such traits. It is noteworthy that user modelling does not represent a core objective of AEHSs. On the other hand, suiting pedagogical resources with regard to individual user cannot be achieved without modelling learners accurately.

This paper reviews seventy six studies from 2000 to 2013 in the area of learning style-based adaptation in order to answer the following questions:

1. What are the benefits of LS-BAEHSs?
2. What are the most effective learning style models in this area?
3. How previous studies have modelled learning styles?
4. What are the main issues which have to be addressed?

The literature is objectively analysed by providing some statistical results and considering their content. Although there are other studies that have reviewed the area of AEHSs in general [23][24] or focused especially on LS-BAEHSs [25], the core contribution of our work is the intensive review to different technical and theoretical issues in order to provide a comprehensive guidance for researchers in this area.

The rest of this paper is organised as follows. Section 2 highlights our crucial criteria for including related work. Subsequently, the main concepts of learning styles and the contradictory theories which surround it are covered in Section 3. Approaches to deduce learning styles are classified in Section 4. Section 5 discusses the findings of this work. Finally, Section 6 concludes the main ideas of the paper and future work.

2. INCLUSION CRITERIA FOR RELATED STUDIES

In order to organise the literature, a systematic search considering many criteria was applied. Google Scholar search engine was used with library of University of Reading, IEEE, Science Direct, ACM, and EThoS library. The significance of each paper was noted by taking into account the number of citations. Papers which were published two or more years ago with no citations should be included because perhaps they have not been reviewed yet. An extensive search were applied which relates to learning styles and their usage in e-learning systems, learning recommender systems (LRSs), and blended learning by using variety of keywords such as "Adaptive/ Adaptable e-learning", "Technology Enhanced Learning", "Adaptive/Adaptable

educational system”, “Personalise educational system”, “Personalise learning system”, “Recommender learning system”, “Learning styles”, “Cognitive styles”, “Individual differences in educational systems”, and “Adaptive in blended learning” in order to retrieve the most relevant literature. Other works which used adaptation in general such as commercial recommender systems and Adaptive Hypermedia Systems (AHSs) for non-educational purposes were discarded. Papers which relate to the psychological basis of learning styles also were considered.

3. LEARNING STYLES (LS)

The concept that individual user learns and processes information in different ways has led to consideration of these differences in learning settings by accommodating teaching styles in accordance with such differences. However, many contradictory theories have surrounded the notion of learning styles and their pedagogical influences on learning process. This include: an obvious definition for learning styles is unavailable, an absence of valid and reliable measurement to deduce learning styles, no DNA research that shows which genes are associated with learning style [26], shortage of empirical studies, convincing evidence and statistical significance to prove the value of learning styles [26][27], the influences of these on learning gain is very modest [25][28] and the variance between psychologists to differentiate between LS and Cognitive Styles (CS).

This leads to identifying four directions in this context. Firstly, these terminologies can be used interchangeably [29]. Another direction has suggested that learning styles represent an umbrella to cover other traits [26][30][31]. Hayes and Allinson [32] and Brusilovsky and Millán [18], in contrast, stated that learning style is a sub-set of cognitive style or narrower in scope. Learning and cognitive styles are two independent constructs [33][34]. However, we agree with the conclusion of Kozhevnikov [20] that the interrelation between these traits is still an open question. This can be accounted by the obvious overlap between their definitions and the interlocking between dimensions of different learning and cognitive style models.

3.1 Definitions of LS

A clear definition for learning styles is unavailable since researchers have separately worked to tackle many issues in the field of style [35]. Dunn and Dunn [36] defined learning style as "the manner in which at least 18 different elements from four basic stimuli affect a person's ability to absorb and retain". Felder and Silverman [16] defined it as “characteristic strengths and preferences in the ways they ‘learners’ take in and process information”. It is also defined as “a description of the attitudes and behaviours which determine an individual’s preferred way of learning” by Honey and Mumford [37]. As such, Brusilovsky and Millán [18] tried to differentiate between learning and cognitive styles by defining the former as an individual’s preferred ways to learn. The latter, on the other hand, was defined as “an individually preferred and habitual approach to organizing and representing information” [18][38]. Cognitive style was also defined by Hayes and Allinson [32] as “individual differences in information processing”. Furthermore, Clarke [39] defined it as “essentially means the unique and preferred way in which individuals process information”. Investigating these definitions clearly indicates that both of them have been defined as a preferred way of learning, processing and organising information.

3.2 Overlap between LS and CS Models

In order to illustrate the interlocking between dimensions of different models, Felder and Silverman Learning Style Model [16] will be taken as an example. Myers-Briggs model was classified as a stable personality type [26]. *Sensitive/ Intuitive* dimension of this model was

borrowed by Felder and Silverman to represent the perception dimension in their model. Building on Kolb's model as a flexibly stable learning style [26], the *Active/ Reflective* dimension was used in Felder and Silverman model to indicate the processing dimension. Moreover, Pask [16] stated that *Holist/ Serialist* dimension in his model is relevant to learning approaches rather than learning or cognitive style models. This dimension is correspondent to the learning approaches (surface, deep) in Biggs's [22] classification. The sequential/ global dimension in Felder and Silverman model is identical to the Pask's model (*Holist/ Serialist*) and *Wholist/ Analytics* dimension in Riding and Cheema model. According to Sadler-Smith [33] and Rezaei and Katz [40], the *Wholist/ Analytics* dimension is congruous to the *Field Dependence/ Field Independence* in Witkin's cognitive style model. The input dimension of Felder and Silverman model (*Visual/ Verbal*) is corresponding to *Verbalise/ Imagery* dimension in Riding and Cheema cognitive style model. According to Cassidy [41] and Zhang [42], Riding and Cheema reviewed and investigated thirty cognitive style models to conclude that different models can be grouped into two bipolar dimensions which so-called *Wholist/ Analytical* and *Verbalise/ Imagery*.

To recap, the most popular cognitive style models (Witkin's model and Riding and Cheema model) and learning approaches theory have been included in FSLSM. This confirms the conclusion of Clarke [39] that these styles "differ in name than nature". Building on the above discussion, we use LS in this paper as a general concept to include CS as well.

3.3 The Significance of LS

Irrespective of the above mentioned critique, studies have shown, on the other hand, the importance of incorporating learning styles in learning settings. The outcome of learning process positively influenced by teaching styles and learning styles if these are well-matched [22][8][43][9][11][12][14][15][16][17]. Other studies have confirmed their positive impacts on learners' satisfaction [44][9][45][46], learners' navigational behaviour [38][47], learners' learning patterns [48], learning performance [15][49][50][46], learning efficiency and effectiveness [51] and learning time [52][53]. Furthermore, Learners' awareness of their own LS can save learning cost by helping them select and adopt learning strategies most suited to their LS. However, forcing students to acquire a variety of learning materials that do not match their styles also can promote an individual's learning experience [54].

Although the core strength of these traits is their stability even over years [20][21], "they may also change and develop in response to specific environmental circumstances" [20]. This clearly indicates the importance of assessing them in certain time intervals in order to tackle the issue of *concept-drift* and dynamically update user models. However, the approaches that are used to model users' LS in AEHSs need further research.

4. APPROACHES FOR DEDUCING LS INTEGRATED WITHIN AEHSS

The importance of incorporating students' individual traits in AEHSs has led to implementing many approaches in order to get more accurate results and mimic the actual users' preferences. Gleaning users' data represents the first step of building user models. If systems can precisely represent LS, a robust user model will undoubtedly be built. Then, the symmetry between Learning Objects (LO) and each style can be identified in order to present the most relevant resources for each learner. In general, these approaches can be classified into two categories.

4.1 Explicit Approach

Explicit Approach is also known as user guided modelling [55], explicit user feedback [56] or collaborative approach [57]. The information can directly be gathered by using one or more of

users' query methods. However, the issues of using such instruments cannot be overlooked as summarised in table 4. Regardless of this shortage, our review shows that approximately half of the reported literature has explicitly collected learners' individual traits to personalize systems or assess other aspects that relate to personalization process. This is due to the ease of collecting and interpreting such data. However, a majority of them are from 2000 to 2005 since the usage of automatic approaches has dominated in recent years.

Due to the wide variety of LS models in psychological research, many psychometric instruments and tests have been invented. For instance, Index of Learning Styles (ILS) of Felder and Soloman [58], the Learning Style Questionnaire (LSQ) of Honey and Mumford [37], the Learning Style Inventory (LSI) of Kolb [59], the group embedded figure test (GEFT) of Witkin [60], Cognitive Style Index (CSI) of Allinson and Hayes [32] and Cognitive Style Analysis (CSA) of Riding [61]. According to our review, the most dominant psychometric instruments and tests are:

- *Index of Learning Style (ILS)* [58]: is a free available instrument with 44-item self-report to identify LS according to Felder and Silverman Learning Style Model (FSLSM) [16]. Using scales between (+11, -11) and only the odd numbers was suggested in order to characterise each learning style by assigning four numbers. Such scales allow determining mild, moderate and strong learning styles as well as facilitating the description of learners' preferences in more details. Although Hawk and Shah [62] doubted in the reliability and validity of this instrument, other studies have proven both [63][64][65][66]. As such, pioneer research has used this questionnaire to represent learning style in a user model [67]. Subsequently, other studies have used it to explicitly gathering learners' preferences in order to accommodate EHSs according to their styles [15][68] [9][69][48][70][71].
- *Kolb's Learning Style Inventory (LSI)* [59]: it is commercially available with 12-item self-assessment inventory and 'scores are between 13- 48'. It was "designed to measure the degree to which individuals display different learning styles" in accordance with Kolb's learning style model [72]. With regard to its validity and reliability, a host of studies have supported both [62]. Therefore, it was used in [73] to adapt a web-based learning system.
- *Group Embedded Figure Test (GEFT)* [60]: this test was devised to diagnose learners' field dependency of Witkin's CS model [74]. Learners perceive a sequence of simple figures from a complex figure independently where the simple figures are embedded. Users who are depending on external cues and have difficulty to distinguish an embedded figures will be classified as field dependent (FD), whereas, users who depend on internal cause and are able to distinguish an embedded figure from an organising field will be classified as field independent (FI). Panek, Funk and Nelson [75] and Kepner and Neimark [76] confirmed the validity and reliability of this test. In adaptation process, it has been used by Triantafillou et al [77] in order to deliver adaptive resources as well as adapting navigation support in AES-CS system.
- *Learning Style Questionnaire (LSQ)* [37]: an 80-item self-report instrument based on Kolb's model [72] to be as an alternative to LSI. It was developed to be used specifically in industry and management [41]. Although it has applied in learning settings, Duff and Duffy [78] concluded that the level of consistency of this questionnaire is modest and is not appropriate to be an alternative to Kolb's LSI as well as using it in the education level of universities is 'premature'. However, a highly cited study of Grigoriadou et al. [13] used this questionnaire to personalise INSPIRE system. Furthermore, in [79], this questionnaire was applied to assess the synergy between CS and learning process (LP). The results confirmed that personalising EHSs in accordance with CS can improve the efficacy of LP.
- *Cognitive Style Index (CSI)* [32]: it is a 38-item self-assessment instrument. The answer for each item could be true or false. The scores between 0- 76 since the nearer number to 0 means intuitive user, whereas, the nearer number to 76 means analytical user. It was developed to be

used in organisational settings. However, Allinson and Hayes [32] stated that this questionnaire has been successfully applied in learning settings. Hence, Song et al [80] used it to adapt a Bioinformatics course according to students' cognitive styles at high schools.

- *Cognitive Style Analysis (CSA) Test* [61]: this is a computer-based test. It was designed to assess the two dimensions (*Wholist/ Analytical* (WA) and *Verbal/ Imagery* (VI)) of Riding and Cheema Cognitive Style Model [30] by using three sub-tests. Presenting 48 statements one at a time in 12 minutes, in the first sub-test, the *Verbal/ Imagery* dimension is assessed by choosing true or false for each statement. To measure the *Wholist/ Analytical* dimension, the second and third sub-tests (three minutes for each) are used. In the second sub-test, twenty items containing pairs of complex geometric figures are presented in order to be judged by an individual as either the same or different, whereas, in the last sub-test, twenty items are presented. Each comprises simple and complex geometrical shapes in order to be determined by the individual if the simple shape is contained in complex one or not. Although Sadler-Smith and Riding [81] supported the construct validity of CSA test and the independency of the two dimensions from intelligence, Peterson et al. [82] and Rezaei [40] concluded that the measuring of this test shows low reliability. John [83] used this test to personalise Telecare system.

4.2 Implicit Approach

Other synonyms to this name are dynamic user modelling [55][57], automatic user modelling [2] or implicit user feedback [84]. It can provide more accurate results than psychometric instruments or tests [25] since users cannot express their psychological traits accurately. This approach reflects natural learners' attitudes which can more precisely represent their actual preferences. However, an implicit student modelling is one of the classification issues. Subsequently, the difficulty of measuring and interpreting users' behaviour represents the main drawback of this approach [85].

The core characteristics of implicit approach are an automatic and dynamic student modelling. Automatic student modelling implies that the behaviour and actions of students are observed in order to deduce their LS. The latter means that student models are updated by using information which is collected automatically. Implicit approach is classified into two categories: data-driven and literature-based approaches. An obvious difference between them is the reliance on the availability of data.

4.2.1 Data-Driven Approach

In this approach, sample data are used as an input for training purposes. The main advantage of such approaches is the accurate classification from real data. However, this is understandably restricted by the availability of data.

The use of data-driven approach is not a new direction in student modelling. Conati et al. [86] used Bayesian network and Xu Wang and Su [87] used fuzzy approach to implicitly model students' knowledge. However, the popularity of such direction in order to construct LS in EHSs has approximately started from the middle of the last decade. The following literature presents application different approaches in order to implicitly deduce LS.

4.2.1.1 Bayesian Networks (BN)

In case of a non-deterministic relationship between class variable and the attribute set, probabilistic models are needed. This represents the concept of Bayesian Networks. It is a directed acyclic graphical model in which a set of variables represent nodes and arcs represent "probabilistic dependence or causal relationship among variables" [23][88]. The relationship

between patterns of behaviour and LS represent the arrows of the networks, whereas, the LS dimensions represent network's nodes.

This method has attracted a significant attention in student modelling due to its robust mathematical foundation and the natural ability to represent uncertainty applying probabilities [88]. Hence, Piombo et al. [89] and Alkhuraiji et al. [90] suggested a framework to model FSLSM by using Bayesian network. The goal was to personalise e-learning system automatically. However, the work of García et al [12] represents the basis of particularly applying this method in learning styles-based adaptation. Bayesian networks were used to implicitly detect learners' LS by observing their behaviour in SAVER system. Eleven patterns of behaviour were used to detect three dimensions of FSLSM (active/ reflective, sensing/intuitive and sequential/ global). In order to evaluate the accuracy of their approach, two experiments were carried out with two samples in 2005 [12] and 2007 [91]. The results were compared with the results which were directly gleaned from the samples by filling ILS. The accuracy of these two experiments is illustrated in table 1.

Table 1: Evaluating Bayesian Network (BN).

Year	Sample	Understanding	Perception	Processing
2005	10	100%	80%	80%
2007	27	63%	77%	58%

The low accuracy of processing dimension in the second experiment was explained by the shortage encouragement for the students to use communication tools in the system. Furthermore, the accuracy cannot be generalised with such small samples. Graf [57], on the other hand, used this approach with FSLSM as well. The experiment was conducted with 75 students and iterated five run for each BN of each dimension. The average results were: 62.50%, 65.00%, 68.75% and 66.25% for the four dimensions (Perception, Input, Processing and Understanding) respectively. Even though García et al [12][91] concluded that the results are promising, Graf [57] concluded that the accuracy is moderate. It is noteworthy that these two experiments have carried out in different environments and conditions. However, the experiment of Graf [57] might be more accurate since it was conducted with larger sample (75 students) and run five times.

In order to fine-tune learning styles-based student models and provide immediate adaptivity, Carmona et al. [92] applied Dynamic Bayesian Networks (DBN) by monitoring students' interaction with learning objects. This can be a good solution to address the issue of *concept-drift* and provide immediate adaptation. However, as we discussed before that learning styles are not changeable trait during short time. Hence, defining certain time intervals to assess the changing in learners' behaviour can be a good solution in order to update user models.

4.2.1.2 Decision Tree (DT) and Hidden Markov Model (HMM)

Using a number of input variables (learners' pattern of behaviour), the value of a class (learning styles) can be predicted. The advantages of DT have been exploited in order to classify students into their identical LS.

Cha et al. [10] used 58 patterns of behaviour to automatically deduce the four dimensions of FSLSM by observing the behaviour of 70 students in web-based learning course. Decision tree (DT) and Hidden Markov Model (HMM) approaches were used. The results showed that one approach could be better than another in respect to specific dimension as illustrated in table 2.

Table 2: Applying DT and HMM for Deducing LS.

FSLS Dimensions	Processing	Perception	Input	Understanding
Error Rate (DT)	33.33%	22.22%	0%	28.57%
Error Rate (HMM)	33.33%	22.22%	14.28%	14.28%

It shows that DT achieved better in input dimension, whereas, HMM achieved better in understanding dimension since HMM is better in analysing sequential data. However, the balanced data of ILS have been excluded from the experiment to just include moderate and strong preferences in evaluation process. This led to predicting LS of students who just have moderate or strong tendencies. This can be a clear shortcoming of such models.

Özpolat and Akar [93] applied DT to diagnose learners' LS from selection of learning objects rather than learners' interaction behaviour. The experiment with 30 graduate students showed that the accuracy of obtaining results comparing with ILS data as follows: 73.3%, 73.3%, 70% and 53.3% for the perception, understanding, processing and input dimensions respectively.

Chen and Liu [48] used DT (C4.5) and K-means approaches as well as traditional statistics to discover the synergy between learners' learning patterns and cognitive styles by analysing the explicit data which were collected by using Cognitive Style Analysis (CSA). The findings depicts that cognitive styles have significant impact on learners' learning patterns in a web-based learning environment.

4.2.1.3 Artificial Neural Network (ANN)

Neural Network (NN) is a computational model which was inspired from the biological neural structure of the brain for solving the classification issues. The accuracy of such models has been proven to be one of the most accurate classifiers [94]. The neuron represents a basic unit in the network. The main layers in each network are:

- *Input layer*: receives the signal from environment.
- *Hidden layer*: receives the signal from other neurons and sends the output to others.
- *Output layer*: transmits its output to the environment.

This means that the main distinction between layers is from where it receives an input and to where it transmits an output.

Villaverde et al. [94] used Feed Forward Neural Network to model LS from learners' actions by identifying ten patterns of behaviour to be as a network input. The output of this model represents the corresponding dimensions of FSLSM except the input one. However, the model has been evaluated with simulation data which did not represent natural attitudes of learners. In [95], Feed Forward Neural Network also proposed to classify learners to their corresponding LS of FSLSM by monitoring their actions with an e-learning system. This model was chosen due to two reasons. It can deduce LS automatically without needing learners intervention. Such models rely on history profile which can be used to distinguish changes in users' behaviour.

Latham et al. [96] proposed personalising learning resources, feedback mode and problem solutions in Oscar system. In this system, LS was elicited by using a tutoring conversational agent. A Multi-layer Perceptron Artificial Neural Network (MLPANN) was applied for the purpose of deducing two dimensions of FSLSM (Processing and Understanding) since the suitability of such approaches for modelling nonlinearities and dealing with outliers and noise have been proven. Comparing the results of 75 undergraduate students with the results which

were explicitly gleaned by ILS showed that the accuracy of such results were 89% and 84% for the two dimensions respectively.

In [97], students behaviour was monitored and analysed by applying Multi-Layer Feed Forward Neural Network (MLFF-NN) to infer learners' cognitive style and accommodating learning content building on the relationship between identified CS in user model.

Applying such approaches can precisely classify students' styles. However, they have high computational requirements, cost and complexity. Furthermore, there is a separation between providing adaptivity and deducing learner' behaviour since analysis process has to be done offline.

4.2.2 Literature-Based Approach

This approach to some extent similar to data-driven approach since the relationship between patterns of behaviour and LS has to be identified first. Then, the behaviour and actions of users are monitored to be used as hints about their preferences by applying simple rule method. It was innovated by Graf [98] in order to overcome the shortcoming of data-driven approach. However, the problem of estimating the importance of different hints which are used to calculate LS has to be considered [51].

According to Graf [57], the core strength of literature-based approach is the ability of deducing LS without needing training data. This means that data-driven approach solely rely on available data set, whereas, literature-based approach depends directly on learning style model. Although Graf [57] presented the synergy between Felder and Silverman model, Index Learning Style (ILS) and automatic approaches, figure 1 depicts the relationship between collaborative and automatic approaches and learning style models in general.

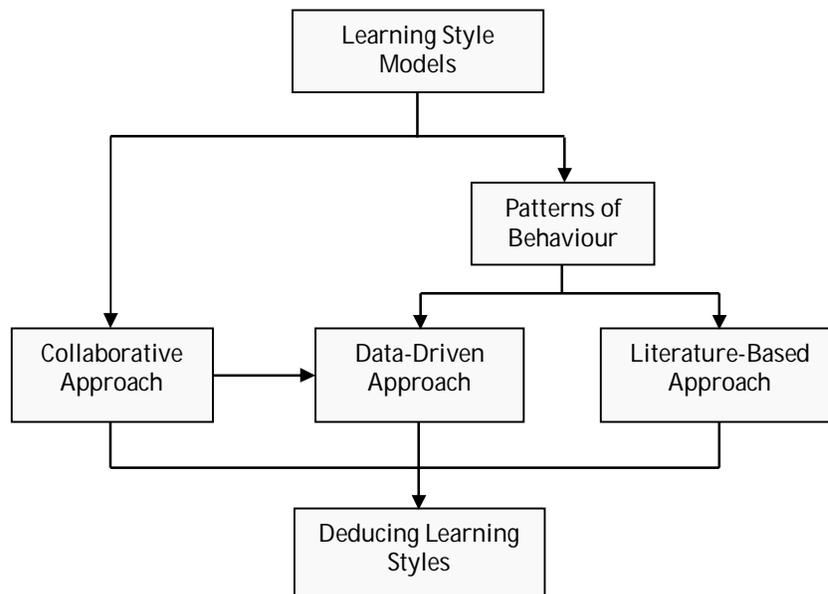


Figure 1: Relationship between the Three Approaches and LS Models

Even though this approach has the advantage of independently deducing styles, the process of inferring LS has to be executed offline. Thus, there is no immediate adaptation that can be

provided to meet individual user’s needs. Table 3 compares three studies that deployed literature-based approach to deduce learning styles implicitly.

Table 3: Comparing the Results of Literature-Based Approach in Three Studies

Study	LSM	System	Sample	Patterns	Ac/ Rf	Se/ In	Vi/ Vr	Sq/ Gl
[57]	FSLSM	Moodle	75	39	72.73%	70.15%	79.54%	65.91%
[4]	ULSM	WELSA	71	100	84.51%	-	73.94%	78.17%
[51]	FSLSM	POLCA	44	-	79.33%	77.33%	76.67%	73.33%

It is noteworthy that Popescu [4] used other dimensions in his learning style model. However, the corresponding results to FSLSM were compared in this table. The high accurate results in processing and understanding dimensions in [4] perhaps can be accounted due to the using of more informative patterns of behaviour. Other studies have also applied this approach to model learning styles [99][100][101][44]. The main pros and cons of all above discussed three approaches are summarised in table 4.

Table 4: Pros and Cons of Collaborative, Data-Driven and Literature-Based Approaches

	Collaborative Approach	Data-Driven Approach	Literature-Based Approach
Pros	This provides data collected as authentic self-expressions.	This reflects the natural attitudes of learners.	This reflects the natural attitudes of learners.
	Reduced noise and spurious data.	More precisely represents their actual preferences.	More precisely represents their actual preferences.
	Data can be extracted in a structured and standardised format.	This is a dynamic process which means it can be used to build student models from scratch as well as update it.	Dynamic process which means it can be used to build student model from scratch as well as updating it.
			Depends solely on student behaviour and actions in EHSs.
Cons	Users may be unable to express their preferences directly.	“High complexity and computational cost”.	“High complexity and computational cost”.
	Arbitrary answers are likely to be chosen in case of unclear questions or long questionnaire or test and it might be prone to bias.	Difficulty of measuring and interpreting users’ behaviours.	Difficulty of measuring and interpreting users’ behaviour.
	Data are static whilst learners’ preferences can change.	The process of classifying learning and cognitive style patterns is offline.	The process of classifying learning and cognitive style patterns is offline.
	This approach can be perceived by users as disruptive, cumbersome and time consuming process.	The accuracy of the results is reliant solely on available data and identifying patterns of behaviour.	

5. RESULTS AND DISCUSSION

Suiting pedagogical resources in accordance with learners' features and preferences represents the main goal of tailoring educational systems. The majority of reviewed studies have developed their own systems to provide adaptivity such as MAS-PLANG [68], AES-CS [77], INSPIRE [13], POLCA [51][102], ADOPTA [46], iWeaver [103][31], WELSA [4], ALS-LSCS [104], SAVER [12], LS- AEHS [73] and Oscar [105] due to the ease of building a system which consider such traits from scratch than incorporating them in a system which has been built for offering a classic e-learning. However, the most popular open source Learning Management System (LMS) Moodle has been also extended in some studies in order to generalise the benefits of LS-BAEHSs [57][101][99][5].

Our review comprises four PhD dissertations (5.26%), thirty three proceeding papers (43.42%) and thirty nine articles (51.31%). Thirty five studies (46.05%) have applied collaborative or automatic approach for adaptation. Eleven studies have suggested framework (14.47%), five studies (6.57%) have built on LS to reveal cross-cultural differences between learners [106][107][108][109][110], whereas, the rest have investigated the impacts of LS on other systems' aspects which relate to adaptation process such as assessing the synergy between LS and students' achievement or exploring the relationship between students' behaviour and LS in web-based learning systems. These studies have adopted different LS models and confirmed that there is a statistical significance of delivering learning materials which match students' LS on their achievement [111][112][113][45][48][114][54]. However, Campbell and Johnstone [115] have found no difference. The findings of [115] have to be interpreted with caution if they are compared with the opposite results of a host of studies that used similar evaluation approaches and sample. Exploring students' behaviour in web-based learning systems has shown that students with different styles behave differently in a system's browsing [116][48][117]. In [118], findings showed that no statistical significance between students' behaviour and their styles. However, because of the small sample of participants (24 students), this finding cannot be generalised. Integrating LS with other features and traits has been considered to build more robust user models. This integration is chronologically summarised in table 5.

Table 5: Integrating Learning Styles with Other Features and Traits in AEHSs

Study	LS	WMC	Knowledge	Interest	Background	Demographic	Goals
[13]	√		√				
[77]	√		√				
[119]	√		√		√		
[57]	√	√					
[9]	√		√				
[69]	√		√		√	√	
[120]	√		√			√	
[52]	√		√	√			
[102]	√		√				
[99]	√		√		√		
[121]	√		√				√
[96]	√		√				

Our review shows that the most dominant learning style models are: Felder and Silverman, Kolb's, Witkin's, Riding and Cheema, Pask's, Dunn and Dunn and VARK models. Some studies have proposed their own model [4][122][123]. These results to some extent support the finding of [25].

From the viewpoint of literature, the popularity of FSLSM is due to many reasons. This model is comprehensively and inclusively classifying students into 16 styles [10][100], the validity and reliability of ILS [59][60][61][66][64], more consistent with learners' preferences [94] and the suitability and feasibility of this model for technology enhanced learning [57][10][124][6][71][64]. However, the most important reason is the suitability of this model for engineering students since the majority of experiments have been carried out with such population.

Table 6 illustrates the top 10 cited studies which accommodated EHSs. Such studies have opened the area of learning styles-based adaptation for further research or proposed new direction for deducing such traits.

Table 6: Top-10 Cited Studies

Study	Approach	Citation	Citation Per Year	LSM
[91]	Bayesian Network	191	31.83	FSLS
[38]	Proposing Framework	285	25.9	Witkin's M
[50]	Collaborative	44	22	Pask's M
[15]	Collaborative	188	18.8	Pask's M
[57]	Literature-Based	112	18.66	FSLSM
[101]	Literature-Based	75	15	FSLSM
[93]	NBTree	60	15	FSLSM
[70]	Collaborative	74	14.8	FSLSM
[9]	Ontology	71	14.2	FSLSM
[10]	DT and HMM	94	13.42	FSLSM

Although the direction of incorporating LS in AEHSs started from the beginning of the last decade, the field is still premature. This claim can be supported by noting that most studies which provided adaptation according to this trait have been undertaken with particular sample and in specific circumstances of learning settings. This is due to the difficulty of deducing and updating such traits by psychometric instruments or observation. As such, there are many issues that have to be taken into account in LS-BAEHSs.

- *Choosing a suitable learning style model to enrich systems' adaptivity:* the main criteria which have to be considered in such models are i) theoretical basis: a model that will be chosen has to have a strong theoretical basis in psychological research. Hence, there is no need to propose a learning style model by researchers who are working in the field of computer science as some studies have done. However, researchers can integrate two models in order to consider different styles, ii) applicability: some models have a strong and acceptable basis between psychologists. On the other hand, it is too complex to be integrated in AEHSs, iii) reliability and validity of psychometric instrument: it is crucial to choose model which has a valid and reliable instrument since researchers will need it in one of their research stages such as initialising user models, evaluation process and so on.

- *Identifying an appropriate approach for deducing learning styles:* using collaborative approach as dominated in this area has been changed with automatic approaches due to their ability for deducing and updating users' preferences automatically and dynamically. However establishing and implementing reliable approaches for matching the teaching delivery and modalities to LS still represents an innovation challenge which has to be tackled. Although psychologists have emphasised that LS is one of the most stable features over time. Learning styles have to be assessed in a certain time interval since some users might change their behaviour to be adapted to special environmental circumstances. This issue has been identified as *concept-drift*. Collaborative approach cannot deal with such issues because data are collected and represented statically in user model. Some studies have provided users flexibility to change their models. However, automatic and dynamic approaches can be used to address this issue. Hence, automatic user modelling has changed the direction of LS-BAEHSs to be more promising.
- *Dealing with the issue of Cold-Start:* The *cold-start* issue means that users do not have any previous profile in a system. Subsequently, the adaptation process cannot meet their needs until gathering and analysing their data. Studies have suggested two solutions: i) asking learners to self-report their preferences in order to initialise user models and then updating it by observing their behaviour with a system [100][125] ii) another solution is initialising user models by default [92]. However, studies that investigated the relationship between cross-cultural differences and learning styles and learning styles and other background and demographic features have concluded that "cultures do have distinctive learning style patterns and learning styles are a function of both nature and nurture" [126]. Yamazaki [109] and Joy and Kolb [107] studied the relationship between a particular culture and a certain LS by using Kolb's LSI. The results illustrated that each particular culture adopts a certain learning style. As a consequence, the collaborative approaches which are applied in the field of recommendation systems can be used to initialise a model of a new user in accordance with the features of other similar users by considering different variables.
- *Using a variety of evaluation approaches:* Evaluating adaptivity in e-learning systems has to be given more attention. A multilayer evaluation approach and the consideration of all users' perspectives (designer, instructor and learner) are very significance to enhance this process. Although all studies that applied automatic approach have criticised using psychometric instruments, they evaluate the accuracy of their results by comparing them with results of self-assessment approach. Our review shows that empirical evaluation approach has dominated in such assessments. Pre-test and post-test, before and after or match and mismatch approaches are widely accepted in order to evaluate the efficiency of adaptation process. However, Brown et al. [27] stated that there is a limitation in quantitative evaluation approaches which indicate a limited usefulness of LS accommodating e-learning systems since studies have inadequately applied experimental design. From this criticism, it can be recommended that evaluating the adaptation in such systems has to apply more statistical methods in order to prove the statistical significance of the obtained findings. We can agree that some experiments were carried out with small or bias samples. However, as confirmed in our review and [25] that the majority of experiments have supported the value of LS. Other evaluation methods such as using expert-based evaluation approach can precisely reflect the limitation in such systems and enhance their feasibility rather than relying solely on participants' viewpoint.

6. CONCLUSION

In order to meet individual user's needs instead of adopting a 'one-size-fits-all' to teaching delivery, effective LS models have to be established and integrated within EHSs by dynamically characterising the learning-specific traits of each learner. The review as conducted in this study has confirmed the significant role that reliable learning style models can play in enhancing the

learning efficacy and learning experience. The results have shown that the Felder and Silverman Learning Style Model (FSLSM) which represents one of the most comprehensive Learning Styles is a dominant model for LS adaptation in EHSs. However, identifying a reliable approach for deducing and evolving LSs to support AEHSs represents an outstanding research issue for further study.

Although the implicit approach can be used to build or update student models automatically and dynamically, the deducing of learners' styles in current implementations is still an offline process whereas real-time dynamic updates of the LS are required for truly responsive adaptation to a user's learning needs.

In this paper a comprehensive review for the area of learning styles-based adaptation are presented. It shows that integrating LS in web-based learning systems still in a premature stage which needs further research. Although the value of incorporating learning styles in learning settings has been questioned, our review confirms that tremendous psychological and empirical research have proven the impacts of such traits on students' satisfaction and systems' usability in general. More specifically, the synergy between this trait and users' behaviour or their performance in e-learning settings has been emphasised. As a consequence, this represents evidence to confirm the positive value of incorporating learning styles in educational systems. However, this does not mean that this direction has become mature since there are many issues that have to be tackled in such adaptation.

Our future work will concentrate on proposing a general framework which can be applied in Learning Management Systems (LMSs) as well as dealing with the main issues of LS-BAEHSs as highlighted in this study.

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