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A NARRATIVE REVIEW OF RESEARCH ON LEARNING STYLES AND COGNITIVE STRATEGIES

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ABSTRACT

The aim of this article is to analyze the existing e-learning environment and to detect the different learning styles of an individual. In general, the e-learning system provides assistance to the learner's in terms of providing learning contents that spans from textual information to multimedia information. Though the existing system tries to maximize the aptitude of learning in users, it fails to act in a dynamic way. To bring the dynamic nature into the system, the learning behavior of an individual has to be modeled. In order to expedite the process, it is necessary to automate the process of detecting learning style based on the learning behavior. This paper attempts to uncover the specialties of the existing e-learning learning style models and cognitive strategies towards understanding and proposing the learning style for the learners based on the popular Felder Silverman Learning Style Model (FSLSM) learning input and dimensions.

Keywords: *E-Learning, Learning Style, cognitive, FSLSM, Learning dimension and Learning behavior*

1. INTRODUCTION

The popularization of the Internet has changed the face of the education system with the introduction of e-Learning. There has been an increase in the demands of e-learning systems that cater to all needs in various fields of educations. In general, the learners may be categorized based on their learning speed (fast/slow) and perceptive skills (exercises/analogy/hints/outlines/example) that contribute towards learning style of an individual. In order to explore the effectiveness of learner model usage personality factors (learning styles), behavioral factors (browsing history) and knowledge factors (prior knowledge) [20]. In fact to provide a better results, majority of the researchers have considered dynamic learning style for an individual determination of which is a cumbersome and challenging task. Thus this paper attempts to study the various approaches for learning style determination and to propose an integrated approach for learning style detection.

2. RELATED WORK

A lot of research work had been proposed for determining learning style of an individual either statically or dynamically. Recently, attempts are focused on automation of the entire process because of the dynamic change in the behaviour and the knowledge level of an individual to determine the learning style.

Various learning style models had been proposed in the past by researchers Myers-Briggs [3], Kolb [18], Honey & Mumford [17], Dunn & Dunn [9] and Felder-Silverman [10]. Mostly, all these techniques adopted either data driven methodology or literature based methodology. In addition to these approaches a questionnaire-based approach for detection learning styles also had been proposed by Richard M. Felder and Barbara A. Solomon [6][11][12]. Though the approaches appear to be appropriate it failed to address the self conceptions of students at specific time on a domain [8][15]. Also the approach didn't favour for tracking the changes in a learner's learning style.

To reduce these issues an alternate approach of automating the learning style was proposed. A lot of research work had been suggested in the field of automatic detection of learning styles and modelling of student behaviour for providing an adaptive personalized e-learning environment.

Initially, the concept of an adaptive system was emphasised by Bursilovsky and Peylo [4]. The system provided an improved system called Adaptive and Intelligent Web-Based Educational System (AIWBES) as an alternative to the traditional systems. The system considered the user's need, knowledge and behaviour like a real teacher with an integrated technology including adaptive hypermedia and intelligent tutoring methods. Adaptive hypermedia mainly consists of

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adaptive presentation and adaptive navigation support while intelligent tutoring mainly consists of curriculum sequencing, problem solving support and intelligent solution analysis.

In the mid of 2000's, Beragasa-Suso et al. [2] figured out the need of a new e-Learning system in fulfilling the drawbacks of the existing web server-based systems. It stated that lack of recommendations to websites, inconsideration of the students' activities and their learning styles, extra infrastructure requirements, limited set of functionalities as the major concern on the system. To provide a solution, an incremental attempt made by providing a web browser-based system embedded within Microsoft Internet Explorer to teachers (iLessons) for content authoring and course material reuse from WWW through simple drag drop, navigation options. In addition, the system provided a methodology to assess the student's learning styles for recommending relevant pages rather restricting the website usage. This resulted in a research oriented approach for learning style. Finally, an accurate rule to predict the active-reflective dimension of learning style was determined considering the ratio between the images and text in a page combined with other parameters such as the average time spent on a page, the scroll distance and direction changes and the mouse movements. An approximate 24% increase in the accuracy of active-reflective dimension of learning style was achieved over the naive prediction using this approach.

On the other hand, Garcia et al. [14] focussed on an adaptive and personalized system to spotlight the type of materials according to the learning style of individuals. The authors designed a Bayesian network based model to infer the learning styles of the engineering students according to their behaviour. The three dimensions of the Felder-Silverman Learning Styles Model namely perception, processing and understanding was considered for modelling student's behaviour. Though the model accommodated student's behaviour, it has omitted input and organization dimension because of the inductive learning style of the engineers. With the designed network in place, it was observed a precision of 77% in the perception dimension, 63% in the understanding dimension and 58% in the processing dimension.

In 2008, Garcia et al. [13] extended their previous work towards personalized assistance by providing suggestions based on the learning styles to the students. An intelligent agent – eTeacher is designed to assist the students through an e-learning system called SAVER. The e-learning system had a well-defined hierarchical structure for course materials. A well formulated suggestion like sequential reading for sequential learner and debate based learning in a forum for active learner was provided by the system. For analysis purpose, the option of accepting or rejecting a suggestion and even repeating a suggestion was provided to the student. During analysis, it was found 83% of the total feedback received was positive and demonstrated that the system to be very promising.

In the same way, Ozpolat and Akbar [20] proposed an automated learner modelling based on diagnosing and classifying the learning styles by NBTree classification and Binary Relevance Classifier. The benefit of this model is that it uses only the data objects selected by the user for its modelling and is independent of the underlying LMS and other time-dependent learner behaviour. For the testing part, a group of 30 graduate students were used for this model. The model yielded a success ratio of 70% in the processing dimension which is better than the previous attempt. The perception and understanding dimension yielded an accuracy of 73.3% which is close enough to the other works. But the model could yield only 53.3 % on input dimension.

Similarly, Chang et al. [5] made an attempt to a newer style of learning style detection by using an enhanced k-nearest neighbour (k-NN) combined with genetic algorithms (GA). The new algorithm was evaluated on a SCORM-compatible LMS by studying 117 elementary school students. It was observed that the use of GA reduces the needed number of learning behavioural features while increasing classification accuracy.

In 2010, Beragasa-Suso et al. [1] extended their work to change the prediction methodology to ensure the effectiveness of other dimensions. Accurate rules to predict the Active or Reflective, Visual or Verbal and Sequential or Global dimensions of the learning styles were designed. An unknown set also added so that user's mood, circumstances or need could be determined. The accuracy in determining between Active or Reflective increased from 71% to 81% and that of Visual/Verbal showed 71% to 82%. The Sequential or Global learners increased from 57% to 69% still leaving a gap for noticeable improvements.

Deborah et al. [7] outlined the methods of existing learning style models and the various metrics associated with them. The Felder-Silverman Learning Style Model was observed to be best suited for an e-learning system and suggested the use of fuzzy rules to handle certain

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uncertainty as proposed by Bergasa-Suso and Sanders [1]. For providing better classification, Deborah et al. extended the unknown category to be further classified as reflective, medium reflective, active and medium active, by using a bell-shaped membership function for the fuzzy rules. The Sanders et al. model is used as base and the classification was performed on the C-Programming of Computer Science and Engineering students of Anna University.

Apart from these data driven methodologies, several researchers had proposed ideas through literature based approach. Some of the noticeable methodologies are summarised in the subsequent sections.

Literature-based approach is a new methodology and is beneficial as it is LMS independent and also the data need not be present while modelling the students' behaviour. Some of the noticeable works are those done by Graf [15], Dung and Florea [8] and Simsek [21]. These works differ in terms of the behavioural patterns that are considered for calculating the matching hints.

According to Graf [13][14], student's learning style preferences are obtained from their behavioural patterns. A simple rule-based method is designed to determine the number of matching hints. The behavioural patterns for the individual learning style dimensions are obtained from literatures as well as from the study of the model itself. Their occurrences and thresholds are obtained after studying various research works that have already been carried out. The result showed a higher precision in detecting the learning styles than data driven approach.

In a similar way, Simsek et al. [21] proposed a literature-based approach for automatic student modelling taking into consideration the learner interface interactions. It was found that the approach utilized Moodle [19], to monitor a Mathematics course conducted for 27 learners. The learning styles were analysed with respect to active/reflective dimension of the Felder Silverman Learning Styles Model. The approach resulted in a precision of 79.6%. Using the literature based approach the behaviour patterns are extracted from handling of features such as videos, PDFs, forums, user profiles, quizzes and questionnaires. The active/reflective dimensions are predicted based on the study to assign thresholds. The prediction is compared with index of learning style developed by Garcia et al. [14].

Dung and Florea [8] used the same literature-based approach proposed by Graf et al. [15] for automatic detection of learning style preference but consider the number of visits and time that the learner spends on learning objects as parameters. This method evaluated the web-based LMS called POLCA by studying 44 under-graduate student over a course on Artificial Intelligence. Based on the characteristics of the FSLSM and the idea of Graf et al. [15][16], the learning objects were properly labelled into each dimension. Then, for each learning style, the average of the ratios of time spent on each learning object to the expected time spent and number of learning objects visited to the total number of learning objects, is determined to decide the final learning style preference.

With the study made on the collected literatures as in Table 1, a brief outline of detecting learning style is understood as shown in Figure 1.

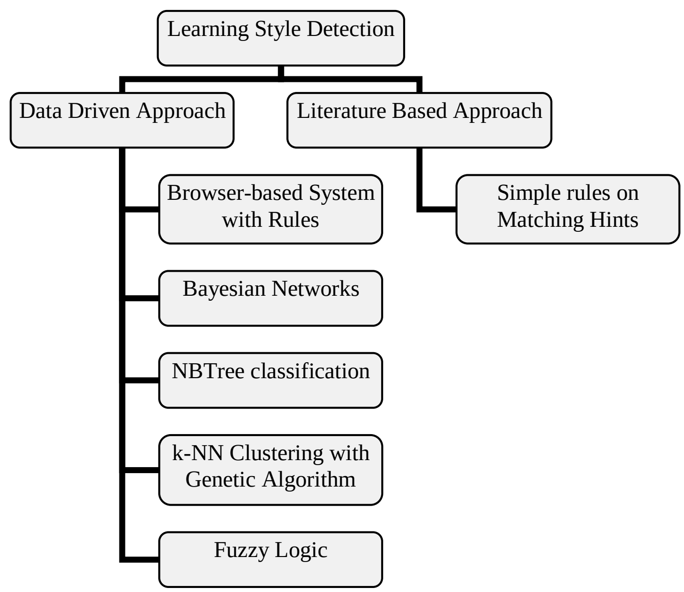

Figure 1: Approach for Learning Style Detection

3. PROPOSED METHODOLOGY (ADLS)

From the study performed, it is evident that the process of automatic detection of learning styles involves of mainly two phases: Identifying the relevant behaviour for each learning style and Inferring the learning style from the behaviour of an individual. Considering these two phases, a prototype is designed as shown in Figure 2.

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Table 1: Summary of the Literature Survey on Learning Styles

S. No	Paper	Approach	Technology	Key Points	Assessment Methods	Precision /Accuracy
1	**Bergasa-Suso et al. (2005) [2]**	Data-driven	Browser-based System with Rules	Processing dimension	67 students – ILS (Training) 7 students – **iLessons**	71% - Processing
2	**Garcia et al. (2007) [14]**	Data-driven	Bayesian Networks	Detection only	27 Systems Engineering students – AI – **SAVER**	58% - Processing 77% - Perception 63% - Understanding
3	**Garcia et al. (2008) [13]**	Data-driven	Bayesian Networks	Detection and suggestions	42 Systems Engineering students - AI - **SAVER** with **eTeacher**	83% feedback received was positive
4	**Graf et al. (2008)** *Based on* ***Graf's Ph.D. thesis work (2007)*** **[15]**	Literature-based	Simple rules on Matching Hints	• LMS Independent • Better results than data-driven approach	127 students – Info. Sys. & Comp. Sci. – Austria Univ. - Object Oriented Modeling - Moodle LMS	77.33% - Input 79.33% - Processing 76.67% - Perception 73.33% - Understanding
5	**Ozpolat and Akbar (2009) [20]**	Data-driven	NBTree classification with Binary Relevance Classifier	• Detection and suggestion • Uses only data objects selected by the user • LMS independent	10 graduate student (Training) 30 graduate students (Testing) – **PoSTech**	53.3% - Input 70% - Processing 73.3% - Perception and Understanding
6	**Chang et al. (2009) [5]**	Data-driven	Enhanced k-NN Clustering with GA	k-NN - Pre-Contrast and Post-Comparison Reduced no. of behavioral features	• IRIS dataset by UCI • 117 students - **SCORM-compatible Java-based LMS** - Windows XP	Increasing Accuracy
7	**Sanders and Bergasa-Suso (2010) [1]**	Data-driven	Browser-based System with Rules for Reasoning	• More dimensions • Improved rules • Unknown category	67 students – ILS (Training) 7 students – same research task – **iLessons**	82% - Input 81% - Processing 69% - Understanding
8	**Simsek et al. (2010) [21]**	Literature-based	Simple rules on Matching Hints	• Processing dimension • 6 features considered	27 students – Comp. Educ. –Derivatives – **Moodle LMS**	79.63% - Processing
9	**Deborah et al. (2012) [7]**	Data-driven	Fuzzy Logic	• Bell-shaped Membership function • Better classification for "Unknown"	Comp. Sci. & Engr. - Anna Univ. – C-language	-NA-
10	**Dung and Florea (2012) [8]**	Literature-based	Simple rules on Matching Hints	• LMS Independent • Parameters - No. of visits and Time spent	44 UG students – Comp. Sci. – Politechnica Univ., Bucharest – AI course – Web-based LMS **POLCA**	70.15% - Input 72.73% - Processing 70.15% - Perception 65.91% - Understanding

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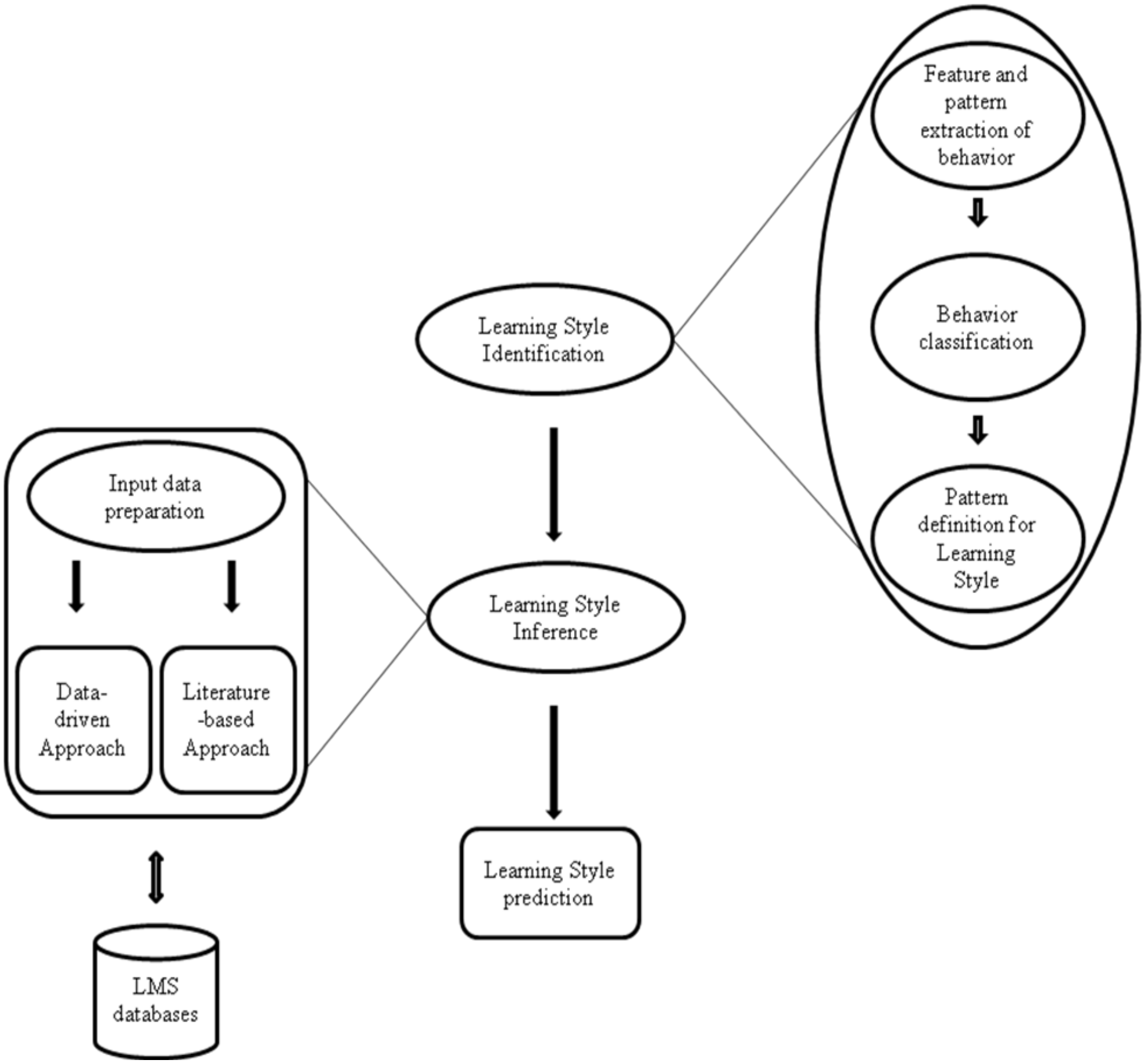

Figure 2: Automatic detection of Learning Style (ADLS)

In our proposal, Reinforcement approach of Machine Learning algorithm has been adapted.Pattern is defined with State-Action-Reward-State-Action (SARSA) algorithm. Possible states and actions define the dynamic nature of the learner, which is to be used for predicting Learning Style.

The relevant behaviour for each learning style is determined from selecting the relevant features and patterns of behaviour, classifying the occurrence of the behaviour and defining the patterns for each dimension of the learning style. As per the study, the following features had been identified as relevant features to determine the learning behaviour:

- Perception
- Understanding and
- Processing

In general, perception describes the auditory processing level and visual processing level of an individual. The understanding capability of an individual may be derived through reasoning capability, concentration and logical thinking. Finally, the processing skill of an individual is determined based on the memory and the ability to perform simple and complex tasks. Thus the study helped to identify the features and its associated factors for deciding the behaviour of an individual and thereby work on the possible learning style dimensions. The following Table 2 summarises the cognitive features, deciding factors and its related weakness. In addition, the impact of the related weakness with the possible learning style dimension as observed from the study performed is also tabulated.

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Table 2: Summary of Cognitive strategies, deciding factors and related weakness

Cognitive Features	Deciding Factors	Related Weakness	Impact	Possible input and Learning Style Dimension of FSLSM
Perception	Auditory processing Skill	Reading fluency, and comprehension.	Slow Textual processing	Verbal and Active
	Visual processing Skill	Difficulty in following instructions, reading maps, mapping word solving mathematical problems, and comprehending.	Slow Non Textual processing	Visual and Active
Understanding	Logical Thinking and reasoning skill	Unordered word mapping, difficulty in mathematical problems and abstract learning.	Vagueness , unstructured and non-systematic approach	Verbal / Non-verbal & Reflective
	Concentration skill	Difficulty in bringing perfectness.	Imperfect outcome	
Processing	Memory Skill	Poor remembrance. Difficulty in following multi-step instructions.	Poor Recall	Verbal / Non-verbal &Sensing
	Implementation skill	Delay and slow in completing even simple tasks.	Unproven Solutions and repeated implementation. Inefficient in performance	Verbal/Non-verbal & Intuitive

4. CONCLUSION

A Study of the different approaches for detecting learning style is attempted through this paper. Considering the existing system, features, deciding factors, their impact has been extracted from the study. Further the mapping between the features, impact and learning style input and dimension as observed from the literature is tabulated for an easy understanding. Thus the study provides an outline of existing methods for detecting learning styles which would help in improving the system to cater the needs of individuals of different capabilities.

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