Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities.

Highlights

- Review on how learning styles were integrated into adaptive e-learning systems.
- Felder-Silverman's is found to be the most popular theory that was applied.
- Explore online learning styles predictors and automatic classification methods
- Examine different applications of learning styles in adaptive learning system.
- Recommendation and future research opportunities are proposed

Abstract

Learning styles which refer to students' preferred ways to learn can play an important role in adaptive e-learning systems. With the knowledge of different styles, the system can offer valuable advice and instructions to students and teachers to optimise students' learning process. Moreover, e-leaning system which allows computerised and statistical algorithms opens the opportunity to overcome drawbacks of the traditional detection method that uses mainly questionnaire. These appealing reasons have led to a growing number of researches looking into the integration of learning styles and adaptive learning system. This paper, by reviewing 51 studies, delves deeply into different parts of the integration process. It captures a variety of aspects from learning styles theories selection in e-learning environment, online learning styles predictors, automatic learning styles classification to numerous learning styles applications. The results offer insights into different developments, achievements and open problems in the field. Based on these findings, the paper also provides discussion, recommendations and guidelines for future researches.

Keywords

Learning Styles; Adaptive Learning System; Literature Review; E-learning; IT in education.

1 Introduction

Different students have different preferred ways to learn. Some may understand quickly through images, others may prefer texts and readings. Some may deal well with theories, others may learn through experiments and examples. By gaining insights into different learning styles, it offers means to design and provide interventions that tailored to individual needs. Moreover, several valuable advice can be provided to a wide range stakeholders. For example, for learners, insights into their own styles will enable them to be more confident in learning and optimize their learning paths (Herod, 2004). For teachers, it will be able to offer valuable feedback on how to match suitable instructions and learning materials to different groups of students at the appropriate stage of the learning process (Stash, 2007). For instance, under Felder-Silverman's theory (Felder & Silverman, 1988), learning styles can be differentiated between the way students process information: active experimentation or reflective observations. For

“active” students, they do not perform very well in a standard classroom situation. Conversely, they learn effectively through interaction with other students. Thus, it is advisable for teachers to provide such group the opportunity to cooperate and discuss the topic. Furthermore, there is evidence in previous researches (such as in David A. Kolb, Boyatzis, & Mainemelis, 2001 and Plovnick, 1975) which shows the connection between learning styles and career choices. Based on this, recommendations and guidance to support the career path planning can be developed. With this strong appeal, learning styles have been gaining significant interest from researchers and educators. Coffield, Moseley, Hall, & Ecclestone, (2004), in their review, reported over 70 theories that were developed over the past 30 years.

In a more comprehensive way, learning styles, which according to Keefe (1979) can be defined as: “The composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment”. The crowed theories area can be divided into five groups depending on their assumptions on how flexible the learning styles can change over the lifetime (Coffield et al., 2004). On one extreme, there are theories such as Dunn and Dunn’s models and instruments of learning styles (cited in Dunn & Griggs, 2003), which suggests that learning styles are constitutionally based, that is fixed. On the other extreme, researchers consider tactics rather than learning styles. Learning tactics assume that learning behaviours can change depending on the situation. This branch includes theories such as Entwistle's approaches and study skills inventory for students (Entwistle, 1997), and Vermunt's inventory of learning styles (Vermunt, 1998). Other prominent theories include Kolb’s (D. A. Kolb, Osland, & Rubin, 1995) and Felder-Silverman’s (Felder & Silverman, 1988) which consider learning styles as rather stable indicators but may change over the lifetime.

Traditionally, learning styles are mainly measured using surveys and questionnaires, asking students to self-evaluate their own behaviours. This development is suitable with the traditional classroom where it is difficult to observe and analyse students’ preferences over the whole learning process. However, as for every qualitative survey, this type of measurement suffers many drawbacks. Firstly, it can be biased as it depends on students’ judgment. Secondly, it is done only at a point in time while the learning styles, according to several theories, can change over time. Some of these surveys can reach over 40-question long (such as Vermunt’s (Vermunt, 1998) and Felder-Silverman’s (Felder & Silverman, 1988)) and hence, they are not easy to update.

These drawbacks have encouraged a growing number of researchers to integrate the framework of learning styles into e-learning system. On one hand, e-learning system, which allows researchers to observe students’ behaviours throughout the learning process and with the use of data mining and computerised algorithms, to quickly identify and analyse trends in big dataset, opens opportunities to develop new framework to observe and measure learning styles through online behaviours. On the other hand, learning styles are also useful sources to develop an adaptive e-learning system that effectively personalises learning resources to individuals’ learning needs. With strong appeal, the integration of the IT-related and psychology and pedagogy-related area have gained significant interest over the past years. A recent paper surveying e-learning system developers by Thalmann, (2014) even suggested that learning styles models were the most useful frameworks for adaptive system development among other sources such as previous knowledge and student background.

The constructs and applications of learning styles into adaptive e-learning system have observed several positive results in both learning styles detection (such as in García, Amandi, Schiaffino, & Campo, 2007; Scott, Rodríguez, Soria, & Campo, 2014' Graf, Kinshuk, & Liu, 2009; Özpolat & Akar, 2009) and applications (such as personalising learning materials and learning contents as in Kurilovas, Kubilinskiene, & Dagiene, 2014 and developing educational games as in Lin, Yeh, Hung, & Chang, 2013). This paper provides an update and a systematic review on this integration of learning styles into adaptive e-learning system. Through the literature review, it offers insights into different methodologies, constructs, developments and applications that have been studied in the research field. Moreover, broadening from previous reviews such as papers by Vandewaetere, Desmet, & Clarebout, (2011) and Akbulut & Cardak, (2012) which either only briefly looked at learning styles as part of many other personalisation characteristics or only presented parts of the whole applications, this paper, focusing on learning styles, delves deeply into the integration process. It captures several aspects from learning styles measurement in e-learning system, to the usage of learning styles in e-learning application. Based on the findings, it also provides new insights into current developments, issues and challenges and as the result, valuable recommendations can be offered for future studies.

2 Search Methods

Different studies on the integration of learning styles and adaptive learning system reviewed in this paper were collected through three search systems: Google Scholar, Scopus and Science Direct. Articles for the last 10 years (from to 2004 to 2014) were considered. The search process terminated in November 2014. Comprehensive searches were carried out using a variety of search terms and their combinations including: "learning styles | (or) style", "measurement | classification | prediction | evaluation | modelling | detection | recognition", "adaptive | personalised | individualised | personalisation", "integration | application | using", "automatic", "learning system | learning management system", "intelligent tutoring system", "student | user modelling", "online |e- learning", "computer-assisted learning", "adaptive instructions", "adaptive hypermedia", "artificial intelligent", "education data mining".

The scope of this research surrounds the current application and integration of learning styles theories in adaptive learning system. Hence, the following inclusion criteria was applied: learning styles theory/theories had to be included as part of the design/ structure/ development/ modelling of the e-learning system; there were evidences of implementation (e.g. there was description or demonstration of the actual implementation, or there were evidences of models evaluation/ testing). Considering such inclusion criteria, the searches resulted in 51 papers among which 39 were journal papers and 12 were conferences papers. These articles were then analysed, synthesized, and grouped using similar themes. The results are shown in the next section.

3 Results: The Current Developments

3.1 Classification of results: Learning styles integration process

By reviewing previous literature, it was identified that all the articles followed a very similar integration and development process and thus, the results of the analysis are also presented according to this course which is shown in Figure 1. Through this result classification approach, it can be helpful for future researchers and e-learning system analyst to quickly gain insights into different required parts of the development process.

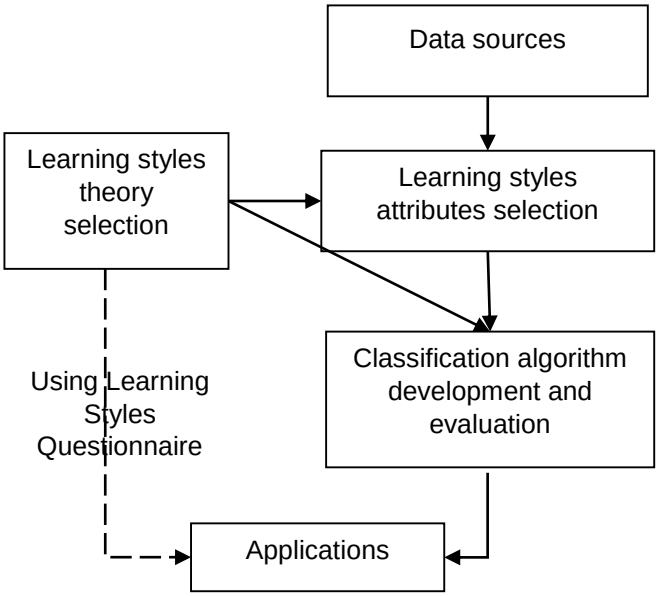

Figure 1 Learning Styles Integration Process

The process of integrating learning styles into adaptive learning system can be divided into two main areas: learning styles prediction using online data (or the online learning styles classification model) and the application of this model into adaptive learning system. The development starts with choosing the learning styles framework. This is followed by the determinant of data sources and learning styles attributes and classification algorithm selections. After evaluating, the suitable classification models and their results are applied for different aspects of the adaptive e-learning system.

Not all of the papers manage to present the whole process. In this literature survey, while some articles focus on the online learning styles classification model development using different computerised and statistical algorithms, others focus on the application of learning styles and hence, traditional measurement method which is questionnaire was used. This second group of papers is portrayed by the dashed line showed in figure 1.

Table 1 presents the results distribution of the articles reviewed in this work.

Topic	Number of articles	%
Online learning styles classification models development	12	23.5%
Application of learning styles in adaptive learning system development	25	49.0%
Both	14	27.5%

Table 1 Overview of results classifications

Among 51 papers, majority of the articles, 49%, emphasize the application of learning styles themselves in the development of adaptive learning system. 23.5% of the papers provide insights into detailed online learning styles classification models and 27.5% manage to present both aspects and how the two parts of the development process were interconnected.

In the next sections, each stage of the integration process: Learning styles theories selection, learning style attributes selections, learning styles classification algorithms, applications in adaptive learning system will be explored and discussed which will provide insights into the current practice as well as different open problems and challenges that require further studies.

3.2 Learning styles theories

The first step of the integration process is to select the right learning styles framework which can be a challenge for researchers and developers. This is the case because firstly, the learning styles theories landscape is crowded. In the last 30 years, over 70 theories were developed (Coffield et al., 2004). Some of them can overlap. For example, Felder-Silverman's shares some very similar dimensions with Kolb's and Riding's models. Secondly, according to Coffield et al., (2004), most of learning styles theories suffer some issues in terms of validity and reliability. Consequently, there is no theory that outperforms others.

In adaptive learning system application, a variety of theories have been used. Results of the content analysis according to which learning styles have been applied are presented in Table 2. References of articles are also included.

Theories used	Number of articles	%	References
Felder-Silverman	36	70.6%	(Akbulut & Cardak, 2012; Alkhuraiji, Cheetham, & Bamasak, 2011; Baldiris et al., 2008; R. Cabada et al., 2009; R. Z. Cabada, Barrón Estrada, & Reyes García, 2011; Carmona, Castillo, & Millán, 2008; Cha et al., 2006; Dorça, Lima, Fernandes, & Lopes, 2013a, 2013b; Dwivedi & Bharadwaj, 2013; Essalmi, Ayed, Jemni, Kinshuk, & Graf, 2010; Feldman, Monteserin, & Amandi, 2014; Franzoni, Assar, Defude, & Rojas, 2008; García et al., 2007; García, Schiaffino, & Amandi, 2008; Germanakos, Tsianos, Lekkas, Mourlas, & Samaras, 2008; Graf, Kinshuk, & Liu, 2008; Graf et al., 2009; Graf, KinshuN, Maguire, & Shtern, 2010; Hong & Kinshuk, 2004; Jovanovic, Gašević, & Devedžić, 2009; Kelly & Tangney, 2005; Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011; Latham, Crockett, & McLean, 2014; Latham, Crockett, McLean, & Edmonds, 2012; Limongelli, Sciarrone, Temperini, & Vaste, 2011; Lin et al., 2013; Özpolat & Akar, 2009; Sancho, Martínez, & Fernández-Manjón, 2005; Sanders & Bergasa-Suso, 2010; Sangineto, Capuano, Gaeta, & Micarelli, 2008; Schiaffino, Garcia, & Amandi, 2008; Scott et al., 2014; Sevarac, Devedzic, & Jovanovic, 2012; Villaverde, Godoy, & Amandi, 2006; Wen, Graf, Lan, Anderson, & Kinshuk, 2007; Yang, Hwang, & Yang, 2013)
Honey & Mumford	2	3.9%	(Del Corso, Ovcin, & Morrone, 2005; Kurilovas et al., 2014)

Kolb	2	3.9%	(Botsios, Georgiou, & Safouris, 2008; Moura, Franco, Melo, & Fernandes, 2013)
VARK	5	9.8%	(Özyurt, Özyurt, & Baki, 2013; Özyurt, Özyurt, Baki, & Güven, 2013; Peter, Bacon, & Dastbaz, 2010; T.-I. Wang, Wang, & Huang, 2008; Yasir & Sami, 2011)
Others	6	11.8%	(Essaid El Bachari & El Adnani, 2011; Popescu, 2010; Siadaty & Taghiyareh, 2007; Sun, Joy, & Griffiths, 2007; Tseng, Chu, Hwang, & Tsai, 2008; Zakrzewska, 2012)

Table 2 Learning Styles theories applied in adaptive learning system

Felder-Silverman's model (Felder & Silverman, 1988), which differentiates learning styles through four dimensions: perception (Sensory/Intuitive), information input (Image/Verbal), information process (Active/Reflective) and understanding (Sequential/Global), is by far the most widely used theory in adaptive learning system (accounted for 70.6% of all the papers in the survey). Other notable theories include VARK which stands for Visual, Auditory, Read, Kinesthetic and Kolb's Learning styles inventory (Kolb et al., 1995) and Honey and Mumford's Learning styles (Honey & Mumford, 1986) which both divide styles based on their proposed learning cycles.

It is interesting to note that all of the above learnings styles belong to the same group of theories which proposes that learning styles are rather stable indicators but may change over time (according to Coffield et al., 2004). Or in other words, this group which assumes that learning styles is neither fixed nor changing very rapidly for every situation is appeared to be favoured over others in online environment. The explanation of a certain theory choice is not always clear. Only a small number of reviewed papers includes some motivation and intuition behind their applications. For examples, Germanakos et al., (2008) suggested that theory such as Kolb's was complex and strongly correlated with personality theories and thus it was not adequate nor easily quantified. Consequently, they proposed to apply Felder-Silverman's as the theory comprised of distinctive scale corresponding to different aspects of the learning process. Feldman et al., (2014) justified their choice of focusing on particularly perception style as it showed strong connection with other important factors such as career preferences, aptitudes, management styles etc. Dorça et al., (2013b), in addition, argued that Felder-Silverman's stood out because it combined different main learning styles models.

3.3 Learning styles predictors

While literature is one of the places that researchers turn to first for hints and guidelines for potential measurements and variables, for the case of online learning styles, several sources of useful data have been identified which can create a challenge in terms of attributes selection. The potential sources of data and the corresponding attributes can be summarized as below:

- Log files: this source tracks users' actions and interaction with the system's interface. Whilst all articles use some forms of log file, the useful attributes used for classification vary widely. The focuses are mainly on number of visits, time spent, performances, characteristics and types of objects chosen, sequences of actions and selected search terms. There are also several activities have been tracked including searching,

taking online exam, quiz, puzzles or self-assessment test, playing games, using forum, mail and discussion board and reading and downloading materials.

- Users' history and background data: this includes static information such as gender, education majors and ethnicity and culture. They are rarely incorporated in automatic classification, although previous researches have shown that these factors can play an essential role in determining learning styles (David A. Kolb, 1981; Reid, 1987; Vita, 2001).
- Besides those directly associated with Learning styles as above, it is also important to note that there are other personalization sources which include background knowledge, intelligent capability, cognitive traits (working memory capacity, processing speed, learning stills, reasoning ability), study goals, language and motivation level which in some case, were considered alongside with learning styles (such as Germanakos et al., 2008)

The identification of these sources show a dynamic picture of potential attributes and behaviours that can be taken into account. With similar learning styles framework, variables used in previous studies can be varied. For instance, with both studies used Felder-Silverman's, García et al., (2007) employed variables related to forums, chats, exam revision etc., while Wen et al., (2007) detected styles using attributes relate to assessment such as time spent for certain type of questions, performance on the test, time taken to check the question etc.

Nevertheless, even though there are several predictors that have been taken into account, none of the papers found in this review manages to compare the power of different attributes in predicting learning styles. The finding of such comparisons can play an important role in improving the performance and efficiency of different prediction and classification models.

3.4 Learning Styles classification algorithms

Table 3 provides an overview of different classification algorithms that have been applied in adaptive learning system. In a number of articles, more than 1 method was used.

Classification method used	Number of articles	References
Bayesian Network	7	(Alkhuraiji et al., 2011; Botsios et al., 2008; Carmona et al., 2008; Essaid El Bachari & El Adnani, 2011; García et al., 2007, 2008; Schiaffino et al., 2008)
Naïve Bayes	3	(Feldman et al., 2014; Kelly & Tangney, 2005; Zakrzewska, 2012)
Rules	8	(Dorça et al., 2013b; Graf et al., 2008, 2009, 2010; Latham et al., 2012; Sangineto et al., 2008; Scott et al., 2014; Wen et al., 2007)
Neural Network	3	(R. Cabada et al., 2009; R. Z. Cabada et al., 2011; Villaverde et al., 2006)
Decision Tree	2	(Cha et al., 2006; Özpolat & Akar, 2009)

Others	5	(Cha et al., 2006; Dorça et al., 2013a; Hong & Kinshuk, 2004; Özpolat & Akar, 2009; Sanders & Bergasa-Suso, 2010; T.-I. Wang et al., 2008)

Table 3 Learning Styles classification algorithms

One of the most popular methods is rules-based (applied by 8 papers) in which researchers "translated" different styles according to the theories into different statistical rules. For example, Graf et al., (2009) used the description of learning styles from Felder and Silverman's to get "hints" such as if a student visited exercise more often, he/she is more likely to prefer active learning style. Then, they set threshold for each attributes to divide behaviours into "strong indication", "average" or "in disagreement" with a certain learning style. The information from every attribute of the user then was averaged and normalized to the scale from 0 to 1, which in turn, was used to identify learning styles using pre-set threshold. By testing on 127 students, the proposed methods did show reasonable precision compared to results from the questionnaire.

The second popular method is Bayesian network which is based on Bayes theorem:

$$P(A/B) = \frac{P\,(B/A)\,P(A)}{P(B)}$$

The theorem can be interpreted as the probability of A given B is equal to the probability to B given A times the probability of A, divided by the probability of B. When apply to learning styles classification, the researchers use the equation to estimate the probability a user belongs to a certain style given their actions. Over the review, 7 studies applied this method, while 3 other studies used Naïve Bayes which is also a special case of Bayesian Network. This algorithm has also showed promising results from many studies. One example can be study by García et al., (2007) which showed the accuracy levels compared to questionnaire ranging from 58% to 77% for three dimensions of Felder-Silverman's learning styles theory.

Among 51 studies, almost all of the reviewed papers used single algorithms. While advanced algorithms combining different single algorithms (or hybrid or ensemble classification) have showed good results in a variety of applications such as medical and finance (Bhattacharyya, Jha, Tharakunnel, & Westland, 2011; G. Wang, Hao, Ma, & Jiang, 2011) , only 2 studies in the review explore this option. Cha et al., (2006) and Özpolat & Akar,(2009) both combined the application of Naïve Bayes and Decision Tree (or so-called NBTree) to automatically predict learning styles. In addition, among the papers reviewed, only 2 papers provide comparison between the performances of different methods. Besides applying NBTree, Cha et al., (2006) also employed Hidden Markov Chain on the sequences of students' actions. The study showed that while NBTree was better in classifying Visual and Auditory, Hidden Markov Chain provided better performance in distinguishing between Sequential student who studies in a very steady progression and Global student who prefers to jump from sections to sections based on their interests. Dorça et al., (2013a) compared Genetic algorithm and Markov chain using simulation data in which Genetic algorithm was shown to have a better performance. Table 4 below shows an overview and related references of methods combination and comparison.

	Number of articles	References

Single methods	23	(Alkhuraiji et al., 2011; Botsios et al., 2008; Carmona et al., 2008; Essaid El Bachari & El Adnani, 2011; García et al., 2007, 2008; Schiaffino et al., 2008) (Feldman et al., 2014; Kelly & Tangney, 2005; Zakrzewska, 2012) (Graf et al., 2008, 2009, 2010; Latham et al., 2012; Sangineto et al., 2008; Scott et al., 2014; Wen et al., 2007) (R. Cabada et al., 2009; R. Z. Cabada et al., 2011; Villaverde et al., 2006) (Hong & Kinshuk, 2004; Sanders & Bergasa-Suso, 2010; Wang et al., 2008)
Combination of methods	2	(Cha et al., 2006; Özpolat & Akar, 2009)
Compared methods	2	(Cha et al., 2006; Dorça et al., 2013a)

Table 4 Overview of classification methods combination and comparisons

3.5 Adaptive learning system using learning styles applications.

The target for adaptation of learning styles is shown in Table 5. It is also worth to note that one paper may also have more than one target.

Adaptive Target	Number of articles	References
Learning contents, learning resources	25	(Alkhuraiji et al., 2011; Baldiris et al., 2008; R. Cabada et al., 2009; R. Z. Cabada et al., 2011; Del Corso et al., 2005; Dwivedi & Bharadwaj, 2013; Germanakos et al., 2008; Jovanovic et al., 2009; Kelly & Tangney, 2005; Klašnja-Milićević et al., 2011; Kurilovas et al., 2014; Limongelli et al., 2011; Moura et al., 2013; Özyurt, Özyurt, & Baki, 2013; Özyurt, Özyurt, Baki, et al., 2013; Popescu, 2010; Sancho et al., 2005; Sangineto et al., 2008; Sevarac et al., 2012; Siadaty & Taghiyareh, 2007; Sterbini & Temperini, 2009; Sun et al., 2007; Tseng et al., 2008; Yang et al., 2013; Yasir & Sami, 2011)
Learning resources format and media	4	(Baldiris et al., 2008; Franzoni et al., 2008; Kelly & Tangney, 2005; Yasir & Sami, 2011)
Teaching strategies and intelligent/ recommendation system	8	(R. Cabada et al., 2009; Essaid El Bachari & El Adnani, 2011; Franzoni et al., 2008; Latham et al., 2014, 2012; Limongelli et al., 2011; Schiaffino et al., 2008; T.-I. Wang et al., 2008)
Educational Games	1	(Lin et al., 2013)

Assessment and Practice	3	(Baldiris et al., 2008; R. Z. Cabada et al., 2011; Wen et al., 2007)
Others	2	(Sanders & Bergasa-Suso, 2010; Zakrzewska, 2010)

Table 5 Learning Styles application in developing adaptive learning system

Adaptive learning contents and learning resources are still the targets that receive the most interest with 25 papers that have touched the topic. Besides choosing which resources would fit which individual, learning styles have also been applied to a wide variety of applications such as developing adaptive teaching strategies, intelligent tutoring and recommendation systems where classes are organised and teaching language, hints and guidelines are provided in a way that fit to different individuals. Latham et al., (2014), for example, used learning styles to develop a personalised conversational tutorial. Limongelli et al., (2011), on the other hand, under lecomp5 framework, provided a planner in which not only resources, learning sequence but also courses of action recommendation were matched to students' styles.

Other applications found through the review contain: format of learning materials, media, assessment and practice, grouping of students and adaptive web-learning environment. Notable examples include papers by Wen et al., (2007) which employed learning styles to reduce the bias in peer assessment, Baldiris et al.,(2008) in which different media, format and semantic density of learning resources were matched to different learning styles and Sanders & Bergasa-Suso, (2010) in which under the course to investigate and collaborate on the internet, suitable webpages were recommended.

One of the new applications in recent years is the adaptive educational games or gamification. While Feldman et al., (2014) provided experiment evidences that learning styles can be measured through students' behaviours when they were playing games, Lin et al., (2013) used decision tree to predict learning path of students' with different learning styles which in turn, were used for setting educational games. The result of such adaptation system was showed to improve the chance that the student had above-average creativity score.

While not all studies provide evaluation and testing on the system, those who did show very promising initial results. The overview of their evaluation results are shown in Table 6.

Reference	Result
Cabada et al., 2011	Satisfaction survey showed that most of the group "agree" or "strongly agree" with respect to the usability of the system and easiness and time to create an intelligent tutoring system
Jovanovic et al., 2009	The interview with students in the course indicated that students founded the tool useful and handy.
Klašnja-Milićević et al., 2011	Leaners in experiment group were revealed to complete the lesson in less time than the control group. They also completed more lessons than those in control group. >70% of the learners found the system

	convenient and >60% of them found the system adaptive, accurate and delivery at satisfied speed.
Limongelli et al., 2011	The survey evaluated teachers' opinions showed that >70% of them found it useful or very useful. Less time for teachers to analyse learning objects in the tool were recorded
Özyurt, Özyurt, Baki, et al., 2013	The evaluation survey presented that most of the students "agree" or "strongly agree" with different statements relate the usefulness and helpfulness of the system such as helped to understand subject better, facilitate learning etc. The interview with 26 students supported further the result from the surveys.
Sangineto et al., 2008	Through the analysis of students' performance before and after using the system, it showed that students who have accessed the system have made a much sharper progress.
Sevarac et al., 2012	The evaluation pointed out that the system could be useful for students and teachers. 80% of the students found it easy to use after some help introduction in the beginning and 79% of the teachers had positive opinion about the recommendation system
Siadaty & Taghiyareh, 2007	Students who experienced a match between their styles and pedagogy strategy produced higher results than those who did not have this matched pedagogy strategy.
Tseng et al., 2008;	Statistical tests on pre and post-tests as well as time spent on searching for materials showed that students who used adaptive system performed better than those who did not and it could also increase the learning efficiency by reducing searching time.
Yang et al., 2013;	The system was showed to require lower mental effort (cognitive loads) for experiment group than control group. In addition, the finding also revealed that the system was able to engage students in the learning process.
Yasir & Sami, 2011	Experiment results showed that students who had matched materials perform statistically better than those in the control group. The survey also presented positive feedback from the students.
Essaid El Bachari & El Adnani, 2011	Students who used the adaptive system achieved higher significant post-test compared to those who did not.
Latham et al., 2012	Students who used the Oscar system were shown to have an increase in average post-test score. The qualitative survey added that >80% of

	the students rated the system highly. Some even suggested that they would use it as their main method of studying.
Schiaffino et al., 2008	70% of the student found the recommendation provided by eTeacher was useful.
Wang et al., 2008	Both learners and teachers had positive feedback on the system efficiency. They suggested that the system could be apply in the learning process, although there were still a number of concerns existed.
Latham et al., 2014	Students who used adaptive system had higher average post score as well as higher test score improvement.

Table 6 Evaluation results of adaptive learning system using learning styles

The most popular evaluation method is satisfaction survey which have been carried out by almost all of the papers as the main or complementary evaluation methods. Although not as popular as survey, a variety of statistical evaluation tests have been found including evaluations based on control and experiment groups' pre and post-test performance, time spent on the task, level of completeness, engagement and cognitive loads level.

4 Discussion: Open Problems and Opportunities

The integration of learning styles and adaptive learning system still requires further researches and experiments. The results found through the literature review point out not only several interesting developments but also opportunities and challenges.

The findings of section 3.2 reveal that theories considering learning styles as stable indicators but may change over the lifetime are preferred over other groups of theories. In addition, Felder-Silverman's is by far the most popular theory applied in adaptive learning system. Thus, as a significant proportion of researches has applied this theory, it will allow opportunity to compare and evaluate the findings. This direction of classifiers comparison is highly encouraged as through this review, there is not many papers of such type that can be found. Moreover, another existing problem is that adaptive systems using other learning theories are still underexplored, hence it is recommended for future research to provide models for quantifying and integrating other theories into adaptive learning systems. The performances of such systems compared to ones using Felder-Silverman's can be further analysed based on their impact on students' learning outcomes. Nevertheless, whichever theories chosen by scholars, full recognition of strengths and limitation should be provided. Finally, there is an opportunity for combining learning styles theories as they may support and add values to each other, which may promise higher adaptability and recommendation ability. This is also the view shared by authors such as Ocepek, Bosnić, Nančovska Šerbec, & Rugelj (2013).

The identification of different potential learning styles predictors as shown in section 3.3 displays a very complex picture of the interconnection between a certain styles and their actual behaviours. While the theory might be the same, the measurements may vary between studies. There are three main sources of variables that have been identified: log files, static information and other personalisation sources. As none of the papers reviewed so far have

been able to evaluate all these features, it points out an open question regarding different online attributes' power and performances in predicting learning styles and as the result there is demand for future studies to tackle the issue. The findings of such research can not only serve as guideline for adaptive learning system developers but also contribute to improve the performance and efficiency of classification and prediction models.

Another important part of learning styles classification modelling is the selection and evaluation of classification algorithms. Previous researches have managed to examine a wide range of algorithms for automatic online learning styles classification ranging from questionnaire, rules based, Bayesian Network, decision trees to neural networks. Each of these methods has its own strengths and weaknesses. For instance, a number of systems identify users' styles by asking them to carry out a learning styles survey. Although such method stays close with the theories and their proposed measurements, the problem with this classification is that there is very little or no update throughout the course. Furthermore, as several theories suggest that learning styles may change over time, the fixation in the method makes the classification inaccurate and as a result, reduce its adaptability ability. Moreover, as shown in section 3.4, several studies follow Bayesian network or rules-based method. Both approaches have achieved very promising results. In addition, they are both interpretable. While the rules-based method allows learning styles to be quickly updated over time, Bayesian Network is able to estimate certainties for unobservable attributes (Jensen, 1996). However, both methods rely heavily on several assumptions and/or authors' "translation" of the theories into the online world. For the case of Bayesian network, the method is based on Bayes' theorem. For such equation to work, it requires not only the values of different probabilities components but also the structure of the network which are both not always easy to obtain. Previous papers overcome this issue through authors' interpretation, assumptions and in some cases, for example, see García et al.,(2007) estimation has been done on a relatively small sample of 50 users. As for rules-based method, assumption and interpretation on the theories have to be made to generate thresholds or to associate certain actions to certain styles. Such assumptions make current methods difficult to be transferred to others context and user groups.

For the remaining studies, single learning algorithm where one individual algorithm is built on the dataset is the method mostly observed. This leaves opportunity for more advanced methods which are still less explored such as hybrid and ensemble learning, where different algorithms are combined in different ways to produce a higher accuracy. In more detail, under hybrid learning, the first technique will be used to produce initial output which in turn, will be processed by the second technique to get the final output (Tsai, Hsu, Lin, & Lin, 2009). On the other hand, ensemble learning uses the idea of developing and combining results of a diverse set of single models to obtain the final output (Seni & Elder, 2010). In the simplest case, each individual model has the same equal vote. Then the output, which in this case, is the probability that the student belongs to a certain style A will be the total proportion of models that classifies/votes for the student to be belong to A. Both methods have several benefits. For example, ensemble learning helps the model become more flexible in comparison to single learning algorithm, reduces variance and overcomes the bias of individual models (Paleologo, Elisseeff, & Antonini, 2010) and improve the accuracy compared to single algorithm (Oza & Russell, 2000), while hybrid learning can improve accuracy by using initial algorithms to tune and filter the data (Tsai et al., 2009).

Finally, the finding from section 3.5 provides a very promising picture of how learning styles can be used in adaptive learning system. Several applications have been found such as adaptive learning contents, teaching strategies, intelligent tutor system, adaptive media, assessment and educational games. Many among these applications for

example assessment and educational games are still at their early stages which require further exploration and development. Another issue identified is that not all of the reviewed articles include an evaluation of the systems. Those who did assert very promising initial results. There are two types of evaluation tests that have been identified that offer insights into the performance of the system under different aspects. Firstly, the most popular evaluation method is satisfaction survey. Although the result of such type of test relies heavily on how questions in the surveys have been constructed and implemented, all of the surveys reviewed in this paper produce very encouraging findings, which may suggest the positive impact of adaptive systems using learning styles on students and teachers' satisfaction. Though not as popular as satisfaction survey, a variety of statistical experiments have been identified, emphasising the positive effect of adaptive learning systems using learning styles on different factors such as performance, efficiency (time spent on different activities), cognitive loads and engagement. As many papers in the review did not include these two tests, further evaluation and especially statistical evaluation, which is still behind compared satisfaction survey, for existing system and in future studies are high recommended.

5 Conclusions

By reviewing 51 studies and carefully examining different parts of the learning styles integration process, this paper offers insights into current practices, opportunities and different issues existing in the area. A variety of aspects from choosing learning styles theories, selecting learning styles predictors, and developing classification algorithms to applying learning styles in adaptive learning systems development are explored and discussed.

5.1 Summary of current developments and open problems

The findings reveal a complex picture of the research field with promising results and widening applications, yet many open problems. It is found that Felder-Silverman is by far, the most popular theory that has been applied in e-learning system. While the theory can be similar, there are several variables used for measurement that have been identified. Nevertheless, the results also point out an issue which is that none of the previous studies provide information on the power of different attributes in classifying learning styles. In addition, although many classification algorithms have been explored among which Bayesian Network and Rules-based are the most widely uses, only a small proportion of papers considers classification methods comparison or methods combination. The review also reveals that whilst adaptive learning content and learning strategies dominates the application targets, in recent years, the applications of learning styles are also expanded to other areas such as assessment, educational games and media choices. Some systems using learning styles have shown initial positive results, however areas such as assessment or educational games are still in the early stage of development which require further research and exploration.

5.2 Recommendations and future research opportunities

Through the findings and discussion, different recommendations for future studies opportunities have also been proposed. Firstly, there is opportunity to explore the integration of different learning styles other than Felder-Silverman's or the combination of different learning styles into adaptive e-learning system. Nevertheless, regardless of which theory is applied, it is recommended that future studies should fully recognise the strengths and limitations of the learning styles theories selected. Secondly, one of the future research directions can focus on evaluating the power of different online attributes in predicting learning styles. The solution for such problem can contribute in improving the efficiency and performance of classification models. Furthermore, there is opportunity to apply other

advanced classification methods which combine different algorithms together such as ensemble and hybrid learning. In addition, papers that compare performances of different classification methods are also highly encouraged. Finally, many adaptive applications using learning styles are still at the early stage, thus further development and studies are required. Evaluation for such future studies and existing systems, especially statistical evaluation is highly recommended.

5.3 Limitations

While the review offers insights into trends, open problems and recommendations for future research opportunities, it is still important to point out its limitations. As faced by many literature review researches, there is the possibility of missing out published papers in the field which may due to a number of sources.

First, there is a huge amount of search strings as well as their synonyms that can be related to the topic. For example, while there are authors associate the task of “detecting” online learning styles as learning styles “classification”, others denote it as “prediction” or “modelling” or “evaluation” or “diagnosis” etc. Or in another sample, the application of learning styles can be found in “intelligent tutoring systems”, “adaptive instruction system”, “ personalised learning system” or “adaptive system” etc. To minimize the chance of missing out important research papers, in this review, a comprehensive list of key terms and synonyms was, first, brainstormed. This list and research papers were, then, to increase the coverage, kept being updated during research process through “snow ball” method that uses hints from other research papers. The final list of individual keywords is shown in section 2. This big number of individual keywords generated an even bigger number of potential keywords combinations. Under a limited time frame, maximum of 3-keyword combination was considered at a particular search. Thus, there is possibility of missing out research papers due to missing individual keywords and missing keywords combinations.

In addition, with hundreds of thousands of results generated by search engine such as Google Scholar, only top articles could be considered and as the result, the quality of the research is search engine’s efficiency dependent. There are 3 search systems were taken into account: Google Scholar, Scopus and Science Direct. Consequently, there might also be published papers available in other databases which have not been taken into account.

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