

# Students' Satisfaction in Learning Style-Based Adaptation

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**Abstract**— Initiatives based on learning style adaptation are often marked by a lack of experimental evaluation of their efficacy in general and satisfaction in particular. Satisfaction of students can increase their motivation, engagement and experience; it is therefore expected to improve learning. This paper is concerned with the investigation of the effect of adaptation based on learning style on students' satisfaction. An adaptivity approach which involves the construction of personalised learning paths based on learning style was implemented in an adaptive e-learning system. A controlled experiment in a learning environment was conducted with sixty undergraduate students to evaluate their level of satisfaction with the system. The experiment produced positive results; the students were generally satisfied with their learning experience. It can be concluded that adaptive e-learning systems based on learning style can play an important role in enhancing their experience and motivation.

**Keywords**- *adaptive e-learning; learning style; information perception; student satisfaction; experimental evaluation*

## I. INTRODUCTION

Although traditional e-learning systems may provide useful learning environments, they suffer from several limitations. They usually do not take into account the characteristics of the students such as their knowledge, skills, abilities and learning style. They provide static sequences and presentation of learning material and ignore the different needs of students. This may lead to the dissatisfaction and frustration of the students with their learning process. This may reflect on the quality and the effectiveness of learning.

Enhancing traditional e-learning systems through adaptation can address their limitations. Adaptive e-learning systems (AESs) personalise the presentation of learning material and adapt the course content and sequence based upon the students' characteristics [5, 6]. Among student characteristics, learning style is recognised as an important factor in learning [1, 10]. Students process, manipulate and acquire information in different ways according to their learning styles [9].

Several AESs based on learning style that apply different adaptive methods and techniques have been deployed [11, 12]. For example, an intelligent human-like agent is built in the eTeacher system to suggest personalised content according to an inferred learning style profile of each student [12]. The INSPIRE system provides some adaptivity features according to the learning style of students - such as link annotation and direct-guidance [11].

Although there are numerous attempts to incorporate learning style in AESs, learning style-based adaptation is still a debatable issue [1, 5]. The way in which to provide adaptation based on learning style is not always apparent. Furthermore, the learning efficacy and satisfaction of students when adapting learning material according to learning style is still unclear despite intensive research [1]. There is also a lack of studies that are based on well-designed and robust experimental evaluations [1, 4, 5].

Students' satisfaction plays an important role in learning as it increases their engagement, motivation and experience [1, 2]. This paper presents the results of an investigation into the impact of learning style-based adaptation on students' satisfaction. An AES that constructs personalised learning paths based on learning style is implemented. It mainly takes into account the information perception dimension of learning style as a basis to provide adaptation. This dimension has received the least attention in published research [1, 6]. Additionally, a controlled experimental evaluation is conducted to measure the student satisfaction.

This paper is structured as follows. Section II covers the learning style background. Section III presents the learning style-based adaptation. Section IV details the experimental evaluation, and Section V offers the results. Section VI concludes the paper with pointers for future work.

## II. LEARNING STYLE

### A. Introduction

Learning style is defined as a composite of affective and cognitive factors that specify the student perception and interaction behaviour in the learning environment [10]. A large number of learning style models and frameworks have been proposed [7]; however, the Felder-Silverman model is the most widely used and accepted model for online learning, especially in science and engineering education [1]. It provides a complete description of each of its dimension, and each dimension is associated with a teaching style. The Felder-Silverman learning style model is comprised of four dimensions as follows [9]: (1) information processing (active-reflective), (2) input modality (visual-verbal), (3) information understanding (sequential-global) and (4) Information perception (sensory-intuitive).

The information processing dimension can be implicitly supported by interactive and hypermedia systems and by collaborative learning features [14]. The input modality dimension has been a subject of intensive research, and no significant effect has been detected [4]. The information

understanding dimension seems to be more related to the design of system interfaces; its learning effectiveness may be limited [4]. The information perception dimension of learning style is discussed in details in the next section because of its importance and relevancy to this work.

### B. Information Perception Style

The information perception style (sensory/intuitive) is one of the most important factors that should be taken into account in instruction [8]. Importantly, this style is also correlated with various behavioural tendencies, learning styles, management styles and even with career aptitudes and preferences [9]. However, it has rarely been incorporated and evaluated as a single dimension in AESs [1, 6]. This situation warrants a study of its use as a basis to provide adaptation and of its influence on students’ satisfaction.

The information perception dimension of learning style concerns the appropriate type, presentation and order of information to be perceived by individual students. It classifies students into two categories: sensory and intuitive. Felder and Silverman define sensing and intuition as follows: “Sensing involves observing, gathering data through the senses; intuition involves indirect perception by way of the unconscious—speculation, imagination, hunches. Everyone uses both faculties, but most people tend to favour one over the other.” [9]. Sensory students favour data, facts, real-world examples and experimentations; intuitive students prefer principles, theories and mathematical models. Sensory students may perform better with concrete information; intuitive students may benefit more from abstract concepts.

## III. LEARNING STYLE-BASED ADAPTATION

A specific adaptivity approach based on the information perception style is proposed. Personalised learning paths are constructed through LOs in an implemented AES [3]. The system represents the course structure at two levels. Level one consists of a number of learning units. A learning unit focuses on a single sub-subject of the course. Each learning unit is comprised of interrelated LOs. Each LO is simply annotated based on its type as an “abstract” or “concrete” object according to the teaching style that corresponds to the information perception style following the Felder-Silverman model [9].

The system generates personalised learning paths for sensory and intuitive students. They are mainly constructed within each learning unit. The sensory students study “concrete” LOs first related to each learning unit, and then they interact with “abstract” LOs (i.e., concrete-to-abstract). Conversely, the intuitive students interact with “abstract” LOs first, and then they study “concrete” LOs (i.e., abstract-to-concrete). Concrete LOs include real-world examples, exercises and practical tools. Abstract LOs involve concepts, theories, mathematical models and principles. Fig. 1 presents an abstract LO example as provided by the system.

This approach is, to some extent, generic and can be adapted to any learning domain because of its simple, yet effective annotation of LOs and generation of learning paths.

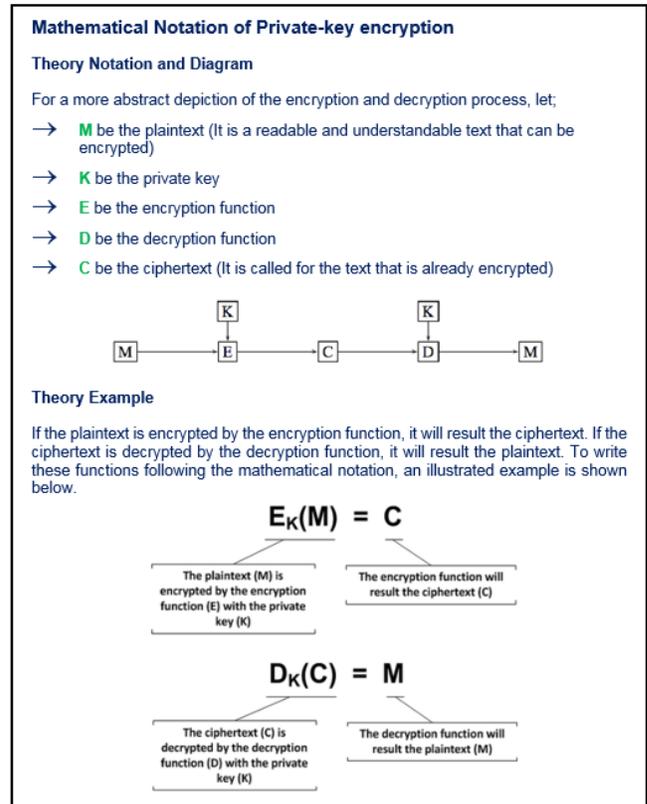


Figure 1. Abstract LO.

## IV. EVALUATION

### A. Introduction

A controlled experiment was conducted at university level in a computer laboratory in order to evaluate the proposed approach in terms of students’ satisfaction. Each experimental session lasted for about 60-75 minutes.

Two experimental conditions in the experiment were put forward. In the first condition, the system matches the sequence of LOs according to the information perception style (i.e., the matched condition). In the second condition, it provides a mismatched sequence of LOs (i.e., the mismatched condition).

### B. Data Collection

Two data collection tools were used in the experiment. The learning style was identified by the Index of Learning Style<sup>1</sup> (ILS) questionnaire [9]. A subset of the questionnaire containing 11 questions related to the information perception style was used; this style is used as a basis to provide adaptation in the AES. The student satisfaction was measured by the conceptualisation of e-learner satisfaction (ELS) tool [13]. Three components of the tool were taken into account: the system interface, the learning content and the system personalisation. These components are comprised of 13 questions with 7-points Likert scale with anchors ranging from “strongly disagree” to “strongly agree”.

<sup>1</sup> <http://www.engr.ncsu.edu/learningstyles/ilsweb.html>

### C. Procedure

Participants were first introduced to the main objectives and the procedure of the experiment. They accessed the system via an Internet browser, completed personal information data and the 11 questions (i.e., related to the information perception style) of the ILS questionnaire. The system then randomly assigned participants in either the matched or the mismatched condition. Using the system, participants studied two learning units in a course related to information security: private-key encryption and key-management protocols. Each learning unit contains a combination of concrete and abstract LOs. The system generated customised sequence of those objects according to the assigned condition of each participant. At the end of the learning process, participants completed the satisfaction questionnaire.

### V. RESULTS

The experimental evaluation was conducted with undergraduate students (N=60) studying for a computer science degree. The matched condition consisted of 29 participants whereas the mismatched condition involved 31 participants. The mean age of participants was 25 (SD=5.49). All of students completed the experiment successfully. In the experiment, 72% of the participants were sensory students and 28% were intuitive students.

Based on the analysis of the student satisfaction questionnaire, the group in the matched condition (M=6.17) which was provided with personalised learning paths based on their information perception style achieved higher general satisfaction scores than those in the mismatched case (M=5.35).

TABLE I. SATISFACTION SCORES OF PARTICIPANTS

Component	Matched condition (N=29)		Mismatched condition (N=31)	
	Mean	SD	Mean	SD
System interface	5.93	1.03	5.12	1.54
Learning content	6.14	1.03	5.41	1.57
System personalisation	6.16	1.05	5.45	1.48
General satisfaction	6.17	0.84	5.35	1.49

Table I summarises the results of the students' satisfaction. In an investigation of the satisfaction in terms of the system interface, the learning content and the system personalisation, it was found that participants in the matched condition achieved higher satisfaction mean scores than those in the mismatched condition for the interface, content and personalisation.

Although the system provides the same interface layout and learning content for both experimental groups where the difference is the customised sequence of LOs, satisfaction scores related to these components in the matched condition were better than the mismatched condition.

The results indicate that students are more satisfied if AESs provide adaptation according to their learning style. The results suggest that the information perception style should be incorporated in e-learning systems in order to enhance the motivation and experience of students.

### VI. CONCLUSION AND FUTURE WORK

An investigation into student satisfaction with learning provision in an adaptive e-learning system was presented in this paper. The adaptivity approach involved the construction of personalised learning paths according to learning style. The approach was validated by a controlled experimental evaluation which was conducted with sixty students. The results indicate an adequate level of satisfaction with the system and the learning material.

This work is part of an investigation into learning style-based adaptation and students' satisfaction. The proposed system will be extended to incorporate the knowledge level of students besides their learning style. A long-term experimental evaluation that measures the satisfaction and perception of students, with more learning objects and with a large number of participants is currently being carried out.

### REFERENCES

- [1] Akbulut, Y. and Cardak, C.S. 2012. Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011. *Computers & Education*. 58, 2 (2012), 835–842.
- [2] Alshammari, M. et al. 2014. Adaptivity in E-Learning Systems. *The 8th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS 2014)* (Birmingham, United Kingdom, 2014), 79–86.
- [3] Alshammari, M. et al. 2015. An E-Learning Investigation into Learning Style Adaptivity. *The 48th Hawaii International Conference on System Sciences (HICSS-48)* (2015), pp11–20.
- [4] Brown, E.J. et al. 2009. Evaluating learning style personalization in adaptive systems: Quantitative methods and approaches. *Learning Technologies, IEEE Transactions on*. 2, 1 (2009), 10–22.
- [5] Brusilovsky, P. and Millán, E. 2007. User models for adaptive hypermedia and adaptive educational systems. *The adaptive web*. (2007), 3–53.
- [6] Chrysafiadi, K. and Virvou, M. 2013. Student modeling approaches: A literature review for the last decade. *Expert Systems with Applications*. 40, 11 (Sep. 2013), 4715–4729.
- [7] Coffield, F. et al. 2004. *Learning styles and pedagogy in post-16 learning: A systematic and critical review*. Learning and Skills Research Centre London.
- [8] Felder, R.M. et al. 2002. The effects of personality type on engineering student performance and attitudes. *Journal of Engineering Education*. 91, 1 (2002), 3–17.
- [9] Felder, R.M. and Silverman, L.K. 1988. Learning and teaching styles in engineering education. *Engineering education*. 78, 7 (1988), 674–681.
- [10] Keefe, J.W. 1979. Learning style: An overview. *Student learning styles: Diagnosing and prescribing programs*. (1979), 1–17.
- [11] Papanikolaou, K.A. et al. 2003. Personalizing the Interaction in a Web-based Educational Hypermedia System: the case of INSPIRE. *User Modeling and User-Adapted Interaction*. 13, 3 (2003), 213–267.
- [12] Schiaffino, S. et al. 2008. eTeacher: Providing personalized assistance to e-learning students. *Computers & Education*. 51, 4 (2008), 1744–1754.
- [13] Wang, Y.-S. 2003. Assessment of learner satisfaction with asynchronous electronic learning systems. *Information & Management*. 41, 1 (2003), 75–86.
- [14] Zhan, Z. et al. 2011. Effects of an online learning community on active and reflective learners' learning performance and attitudes in a face-to-face undergraduate course. *Computers & Education*. 56, 4 (2011), 961–968.