

IMPLICIT DETECTION OF LEARNING STYLES – THE SMALT WAY

Wei Meng SON, Siew Wee KWEK, Dr. Fan LIU

School of Engineering, Nanyang Polytechnic, Singapore

ABSTRACT

Research in teaching and learning space has shown that students tend to learn with their individual learning styles while teachers deliver lessons in class using appropriate teaching strategies that are best suited to the instructional goals and subject domains or teachers usually present material in a manner that suits their own individual teaching style or preference. Such teaching strategies may not match students' diverse learning styles. Learning will be more effective if teachers can provide different teaching strategies that cater to students with different learning styles. The development of SMALT (SMart Advisor for Learning & Teaching) aims to systematically bridge the gap between learning styles and teaching strategies through dynamic alignment of the two in order to achieve optimal learning performance. Detecting students' individual learning styles is the essential step in the research towards attaining the goal of dynamic alignment. In order to avoid the psychometric flaws of the traditional explicit measuring instruments such as surveys or questionnaires, and also to enable continuous tracking and more accurate determination of learning styles, an implicit learning styles detection method based on Felder-Silverman Learning Style Model is proposed. Students' learning preferences are established implicitly by analyzing their behavioural patterns when they interact with an online tutoring system. This paper will highlight the method of collecting and analyzing students' behavioural patterns while interacting with the online tutoring system as well as the method of determining students' learning styles using these behavioural pattern values.

KEYWORDS

Learning style, behavioural patterns, Felder-Silverman learning style model, online tutoring system, implicit detection method

INTRODUCTION

Research in teaching and learning space has shown that students have different ways of learning. For example, some students prefer visual representations and remember best what they see while others prefer verbal materials and remember best what they hear. According to research on the learning process [1], the reason is students tend to learn in different ways and use different resources to aid in their learning [2], which is known as learning styles. The definition of learning style is the characteristic preference for alternative ways of taking in and processing information of learners. The concept arose with the research work by Kolb [3], Dunn and Price [4], as well as Felder and Silverman [5]. Generally, education systems provide a unique and standardized teaching material to all students that tend to benefit those whose learning styles fit well with such teaching material [6]. In other words, learning will be more effective if teachers can provide different teaching strategies and material that cater to students with different learning styles [7].

The development of SMALT (SMart Advisor for Learning & Teaching) aims to systematically bridge the gap between learning styles of students and teaching strategies of teachers through alignment of the two in order to achieve optimal learning performance. SMALT consists of two major components: Online Tutoring System (OTS) and Teaching Strategies System (TSS). In this paper, an implicit learning styles detection method based on Felder-Silverman Learning Style Model (FSLSM) is proposed to detect students' learning styles implicitly and automatically through the way they navigate and interact with the OTS.

The rest of the paper is organized as follows: the next section gives a critical literature review of existing methods used for detecting students' learning styles, including the explicit and implicit detection methods. The section that follows addresses the proposed implicit learning styles detection method. This section describes succinctly FSLSM and the relevant behavioural patterns associated with each learning dimension of FSLSM from which students' learning styles are determined. The interface description of the OTS is presented and the evaluation method including reliability and validity analyses is proposed in the subsequent sections. Finally, the last section outlines the conclusion as well as future work directions.

LITERATURE REVIEW

There has been a great interest in the investigations of learning style detection and analysis over the past decades. In literature, these methods are classified in two categories: (1) explicit detection methods based on questionnaires, surveys [8] [9] or evaluation test [10] and (2) implicit detection methods. In general, implicit detection methods are based on the students' feedback on the learning process or students' observable behaviour. An example of implicit detection methods is the iWeaver system [11], which was based on the Dunn and Dunn learning style model [12]. Recently, most of implicit detection methods are based on students' behaviour such as the method developed by Graf and Kinshuk [13], where a Learning Management System (LMS) was used to detect learning style based on the students' behaviour during an online course. In [14], individual's learning style was diagnosed from learner's behaviour patterns on the user interface by using Decision Tree and Hidden Markov Model approaches. Garcia and colleagues [15] detected the learning style of a student by using a web-based tutoring system. Popescu [16] developed a notable implicit detection method based on Unified Learning Style Model (ULSM).

The main disadvantage of explicit detection methods using questionnaires, surveys or evaluation test is that students may not be patient to answer survey questions and often leads to biasness in the results. In order to overcome these psychometric flaws of the traditional measuring instruments, an implicit learning styles detection method based on FSLSM is proposed for SMALT in this paper. The review on the implicit detection methods shows that it is important to choose appropriate students' behaviour patterns that are used to determine the learning styles of students

IMPLICIT DETECTION METHOD

We seek to develop an implicit learning style detection system to detect students learning styles based on FSLSM by analyzing the collected behavioural patterns of students as they interact with the OTS. We begin with an introduction to FSLSM.

Felder-Silverman Learning Style Model (FSLSM)

There are many learning style models in the literature such as FSLSM model [5], Kolb model [3], Honey and Mumford model [17], Dunn and Dunn learning style model [18], and VARK model [19]. In the SMALT system, FSLSM model is selected as the learning style model of students for the following reasons:

- The reliability and validity of FSLSM have been proven by experimental method [20].
- FSLSM describes the learning style of a student in more detail, distinguishing between preferences on four dimensions [21].
- The four dimensions of FSLSM are easy to interpret and can actually be implemented [22].
- FSLSM has been successfully implemented in previous work when adapting the electronic learning materials [7] [22] [23].

The four learning dimensions of FSLSM [5] are briefly described as follows:

- *Sensing/Intuitive* – Sensing learners like to learn facts and concrete learning material. They like to solve problems with standard approaches and are more patient with details. In contrast, intuitive learners prefer learning abstract learning materials. They are better at discovering possibilities and relationships and more innovative and creative than sensing learners.
- *Visual/Verbal* – Visual learners remember best and prefer to learn from visual representations, such as pictures, diagrams and flow charts while verbal learners get more out of textual representations, such as written and spoken explanations.
- *Active/Reflective* – Active learners learn best by working actively with the learning material, by applying the material or by trying things out. They tend to be more interested in communication with others and prefer to learn by working in groups while reflective learners prefer to think about the material and work alone or in a small group.
- *Sequential/Global* – Sequential learners learn in small incremental steps. They tend to follow the logical stepwise paths in finding solutions, while for the global learner, they prefer to use a holistic thinking process and learn in large leaps. Global learners are able to solve complex problem, find connections between different areas and put things together in novel ways.

Behavioural Patterns

For each dimension of FSLSM, relevant behavioural patterns are used for detecting students' learning styles. Table 1 lists these relevant patterns and their relative weights.

Table 1. Relevant Patterns for FLSM Dimensions

FLSM Dimensions	Patterns (Weights)			
Sensing/ Intuitive	seq_Definition_before_Example	hW	seq_Pointer_before_Guideline	hW
	t_Definition	hW	t_Pointer	hW
	t_Example	hW	t_Guideline	hW
	n_Revision_test	hW	t_Test	hW
	grade_Detail	mW		
Visual/ Verbal	t_Image	hW	h_Image	mW
	t_Video	hW	h_Video	mW
	t_Text	hW	h_Text	mW
	t_Sound	hW	h_Sound	mW
	grade_Image	mW		
Active/ Reflective	t_Exploration	hW	t_Exercise	mW
Sequential/ Global	n_nextButton	hW	n_preButton	hW
	n_Outline	hW	t_Outline	mW
	n_skippedLO_temp	hW	n_skippedLO_perm	mW

Notes: (1) Each pattern is associated with a weight denoted by hW (high weight), mW (medium weight), lW (low weight) which indicates the relevance it has on identifying a learning dimension. Since the patterns with low weights (lW) have less influence on identifying a learning dimension, we only choose patterns with high and medium weights (hW, mW). (2) The meaning of prefixes in the pattern names are: “t” stands for “time”, “h” stands for “hits” and “n” stands for “number”.

The OTS is structured as topics and sub-topics with teaching materials developed as Learning Objects (LOs). The LOs include outlines, content materials, exercises and a quiz.

The outline provides an overview of the sub-topics and the patterns to be collected are number of visits, denoted by *n_Outline*, and the time a student spends on it, denoted by *t_Outline*.

The LOs for content materials of a sub-topic are categorized into Definitions, Examples, Pointers and Guidelines. We are interested in the time a student spends on these LOs, which are denoted by *t_Definition/Example/Pointer/Guideline*. These content materials are presented in various forms, such as image, video, text or sound. In relation to the presentation of such contents, we consider the behavioural patterns to be the number of visits, denoted by *h_Image/Video/Text/Sound*, as well as the time a student spends on the contents, denoted by *t_Image/Video/Text/Sound*. In addition, we consider the student’s navigation between LOs such as how often the LOs are skipped, how often he/she jumps back to the skipped LOs, as well as the number of times he/she clicks the Next and Previous buttons of the content pages. These navigational patterns are denoted by *n_nextButton*, *n_preButton*, *n_skippedLO_temp* and *n_skippedLO_perm*.

Exercises are included for the student to practice new concepts or solve problems using new methods. The times a student spends on these are denoted by *t_Exercise*. At the end of the course, a quiz is included to check a student’s level of understanding for the newly acquired knowledge. Patterns to be collected relate to how often a student revises his/her answers before submitting, denoted by *n_Revision_test*, the time he/she spends on the quiz, denoted by *t_Test*, and the grades he/she obtains, denoted by *grade_Image* and *grade_Detail*.

Finally, we consider the patterns of the sequence in which a student visits specific LOs, such as the number of times he/she accesses Definitions content before Examples, or the number of times he/she accesses Pointers content before Guidelines. These patterns are denoted by *seq_Definition_before_Example* and *seq_Pointer_before_Guideline*.

Online Tutoring System

Here, we show an example of collection of some pattern values from a student's interactions when he/she interacts with the OTS. Our OTS showcases a course in the domain of Communication Skills, focusing on the topic Netiquette. Figure 1 shows a screenshot of the Definitions LO of sub-topic "Online Discussion Group".

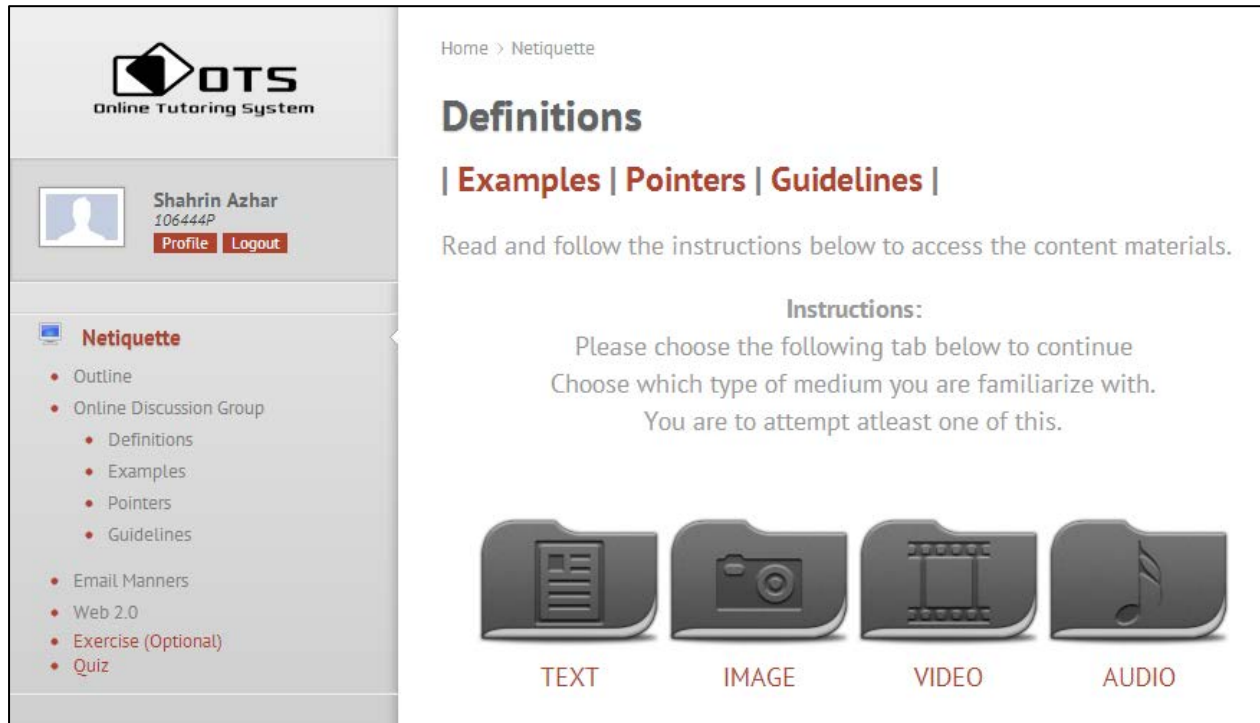


Figure 1. Screenshot of sub-topic "Online Discussion Group"

The sidebar shows the navigation menu which consists of the Outline, 3 sub-topics ("Online Discussion Group", "Email Manners" and "Web 2.0"), an Exercise and a Quiz. The expanded menu for "Online Discussion Group" also shows 4 LOs, namely "Definitions", "Examples", "Pointers" and "Guidelines". Each LO is presented in the format of Text, Image, Video and Audio as shown by the buttons at the bottom of the screenshot. A student who wants to study the detail contents in these formats can choose one of the 4 buttons, or he/she can go through all the formats.

As a student interacts with the OTS, the number of times he/she visits the Outline page is collected as $n_{Outline}$ and the time he/she spends on this page is collected as $t_{Outline}$. The number of times he/she visits the different formats of contents, denoted by $h_{Image/Video/Text/Sound}$, as well as the time he/she spends on each content, denoted by $t_{Image/Video/Text/Sound}$ are similarly collected.

Detection Algorithm

The learning styles are detected and identified by utilizing the values of the patterns relevant to each dimension of FLSM. Specifically, learning styles of FLSM is denoted by $FSLM = \{Visual/Verbal, Sensing/Intuitive, Sequential/Global, and Active/Reflective\}$. Hence, FLSM has

8 learning styles and 4 learning dimensions. For any learning dimension $D_i \in FSLSM, i = 1, \dots, 4$, the set of relevant patterns is given in Table 1. For example, the learning dimension *Visual/Verbal* has 9 relevant behavioural patterns, which are denoted by $t_Image/Video/Text/Sound, h_Image/Video/Text/Sound$ and $grade_Image$.

After the quantitative data of the relevant patterns of a learning dimension are collected through the interaction of the student with the OTS, we need to transform them into an equivalent mathematical scale to be used in the detection algorithm. This is accomplished through applying threshold rules based on the recommendations in the literature [15] [21], to give each pattern a value of High (*H*), Medium (*M*) or Low (*L*). A value of “*H*” would point towards strong evidence that the student has a preference for a particular learning style in the corresponding learning dimension. For example, an “*H*” value for the t_Image pattern would suggest that the student prefers a *Visual* learning style in the *Visual/Verbal* learning dimension.

It is noted from learning style measurements of FSLSM using the Index of Learning Styles (ILS) [8] that FSLSM learning styles come in opposite pairs within the corresponding learning dimensions. Therefore, by definition, if an “*H*” value for a pattern P is associated with a learning style denoted by $C \in FSLSM$, then an “*L*” value for the same pattern indicates the association with the opposite learning style of C , denoted by \bar{C} . For example, if an “*H*” value for the t_Image pattern is associated with the *Visual* learning style in the *Visual/Verbal* learning dimension, then an “*L*” value for t_Image would be associated with the *Verbal* learning style. Table 2 shows the associations of “*H*” pattern values with learning styles.

Table 2. Association of “*H*” Pattern Values with Learning Styles

Sensing	Intuitive
<ul style="list-style-type: none"> • seq_Pointer_before_Guideline • t_Guideline • t_Test • n_Revision_test • grade_Detail 	<ul style="list-style-type: none"> • seq_Definition_before_Example • t_Definition • t_Example • t_Pointer
Visual	Verbal
<ul style="list-style-type: none"> • t_Image • t_Video • grade_Image • h_Image • h_Video 	<ul style="list-style-type: none"> • t_Text • t_Sound • h_Text • h_Sound •
Active	Reflective
<ul style="list-style-type: none"> • t_Exploration • t_Exercise 	
Sequential	Global
<ul style="list-style-type: none"> • n_nextButton 	<ul style="list-style-type: none"> • n_preButton • n_Outline • t_Outline • n_skippedLO_temp • n_skippedLO_perm

Considering Table 1 and Table 2, for each learning style C within a learning dimension D , there are a set of relevant patterns P_1, P_2, \dots, P_n with values $\{H, M, L\}$ and associated weights w_1, w_2, \dots, w_n with values $\{HW, mW, hW\}$ in which each value $\in [0,1]$. We compute the values of the j^{th} student's preference for learning style C by using the following formula adapted from [16]

$$V^j(C) = \frac{\sum_{i=1}^n P_i^j * w_i}{n} \quad (1)$$

where

$$P_i^j = \begin{cases} 1 & \text{if } p_i^j = P_i \\ 0 & \text{if } p_i^j = M \\ -1 & \text{otherwise} \end{cases} \quad (2)$$

For example, if the values of relevant patterns p_1^j and p_2^j of the j^{th} student for learning style C are "H" (which is associated with learning style C as according to Table 2), we have $p_i^j = P_i, i = 1, 2$. Hence, according to Eqn (2) we have $P_i^j = 1, i = 1, 2$. Values of the other relevant patterns can be calculated using the same method.

If $V^j(C) > 0$ it indicates that the student has a preference towards learning style C while if $V^j(C) < 0$ the student has a preference towards learning style \bar{C} . From Eqn (1) it can be seen that

$$V^j(C) \in \left[-\frac{\sum_{i=1}^n w_i}{n}, \frac{\sum_{i=1}^n w_i}{n} \right] \subseteq [-1, 1] \quad (3)$$

The maximum value of $V^j(C)$ is obtained when all the relevant patterns have values indicating towards the learning style C while the minimum value of $V^j(C)$ is obtained when all the patterns have values indicating towards the opposite learning style \bar{C} . Let $W = \frac{\sum_{i=1}^n w_i}{n}$ then $V^j(C) \in [-W, W]$. Therefore $V^j(C)$ can be mapped to three scales:

- $V^j(C)$ has a value greater than $\frac{W}{3}$, indicating a strong preference towards learning style C .
- $V^j(C)$ has a value smaller than $-\frac{W}{3}$, indicating a strong preference towards learning style \bar{C} .
- $V^j(C)$ has a value in $[-\frac{W}{3}, \frac{W}{3}]$, which indicates a balanced preference.

By means of these three scales, each learning dimension of FLSM can be classified into three bands.

Students' behavioural patterns are collected through interacting with the OTS and relevant values of patterns are stored in a database. The values of each student's preference for learning styles are calculated according to Eqn (1). Therefore students' learning styles can be determined by using implicit detection method.

Evaluation Method

To evaluate the reliability and validity of our proposed approach, we will deploy two analyses.

The first analysis is related to the reliability of our proposed approach, which can be estimated through test-retest analysis. Students' learning styles will be detected implicitly at the beginning and at the end of the semester to ensure a reasonable spacing of the two tests. The collected data will then be analyzed using statistical software for reliability.

The second analysis relating to validity of our proposed approach is adapted from other approaches [14] [15] [21], which are also based on FLSM. The learning styles detected implicitly through interactions with the OTS will be compared with the learning styles obtained from the ILS questionnaires [8], which will be conducted in a controlled examination-like environment. The precision is then calculated as follows

$$Precision = \frac{\sum_{j=1}^n Sim(LS_{OTS}^j, LS_{ILS}^j)}{n} \quad (4)$$

where n is the number of students. In Eqn (4), Sim is 1 if the values obtained by the OTS and ILS are equal, 0 if they are opposite, and 0.5 if one is balanced and the other is an extreme value along the FLSM learning dimensions. The value of $Precision$ can then inform the validity of our proposed approach.

CONCLUSION AND FUTURE WORK

This paper described an implicit detection method of individual students' learning styles. The method proposed in this paper diagnoses students' learning styles based on the behaviour of students while interacting with the OTS. Evaluations will be conducted progressively in education environments through our collaboration with secondary school students as well as polytechnic students in the future work.

ACKNOWLEDGEMENT

This research work is supported by the Singapore Ministry of Education Innovation Fund (IF) 2010 Award MOE2010-IF-1-008 to W. M. Son for a period of 3 years.

REFERENCES

- [1] Jonassen, D.H & Grabowski B. L., *Handbook of individual differences, learning, and instruction*. Lawrence Erlbaum Associates. Hillsdale, NJ, 1993.
- [2] Franzoni, A. L. & Assar, S., Student learning styles adaptation method based on teaching strategies and electronic media. *Educational Technology & Society*, 12 (4), 2009, 15-29.

- [3] Kolb, D. A., *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, New Jersey: Prentice Hall, 1984.
- [4] Dunn, R., Dunn, K., & Price, G. E., *Learning Style Inventory*. Lawrence, KS, USA: Price Systems., 1984.
- [5] Felder, R. M., & Silverman, L. K., Learning and Teaching Styles in Engineering Education. *Engr. Education*, 78(7), 1988, 674-681.
- [6] Ford, N., & Chen, S., Matching/mismatching revised: an empirical study of learning and teaching styles. *British Journal of Educational Technology*, 32(1), 2001, 5-22.
- [7] Carver, C. A., Howard, R. A., & Lane, W. D., Enhancing student learning through hypermedia courseware and incorporation of student learning styles. *IEEE Transactions on Education*, 42(1), 1999, 33-38.
- [8] Soloman, b., & Felder, R. M., Index of learning styles questionnaires, 1998. Retrieved May 23, 2008, from <http://www.engr.ncsu.edu/learning-styles/ilsweb.html>.
- [9] Myers, I. B., & McMauley, M. H., *Manual: a guide to the development and use of the Myers-Briggs Type Indicator*. Palo Alto, CA: Consulting Psychologists Press, 1985.
- [10] Triantafillou, E., Pomportsis, A., & Demetriadis, S., The design and the formative evaluation of an adaptive educational system based on cognitive styles. *Computers & Education*, 41, 2003, 87-103.
- [11] Wolf, C., iWeaver: Towards an interactive web-based adaptive learning environment to address individual learning styles. *European Journal of Open, Distance and E-learning*, 2002. Retrieved May 23, 2008, from <http://www.eurodl.org/materials/contrib/2002/2HTML/iWeaver.htm>.
- [12] Dunn, R., & Dunn, K., *Teaching secondary students through their individual learning styles*. Needham Height, MA: Allyn and Bacon, 1992.
- [13] Graf, S., & Kinshuk., An approach for detecting learning styles in learning management systems. *Proceeding of the International Conference on Advances Learning Technologies*. 161-163. Kerkrade, Netherlands: ICALT 06, 2006.
- [14] Cha, H. J., Kim, Y. S., Park, S. H, Yoon, T. B., & Jung, Y. M., Learning Styles Diagnosis Based on User Interface Behaviors for the Customization of Learning Interfaces in an Intelligent Tutoring System. *Computer and Information Science*, 4053(3), 2006, 513-524.
- [15] Garcia, P., Amandi, A., Schiaffino, S., & Campo, M., Evaluating Bayesian network's precision for detecting students' learning styles. *Computers & Education*, 49, 2007, 794-808.
- [16] Popescu, E., "Diagnosing Students' Learning Style in an Educational Hypermedia System," in *Cognitive and Emotional Processes in Web-based Education: Integrating Human Factors and Personalization, Advances in Web-Based Learning Book Series*, Mourlas, C., Tsianos, N. and Germanakos, P. Eds., IGI Global, 2009, 187-208.
- [17] Honey, P., & Mumford, A., *The manual of learning styles*, Peter Honey, Maidenhead, 1992.
- [18] Dunn, R., & Dunn, K., *Teaching students through their individual learning styles: A practical approach*. Reston, VA: Reston Publishing, 1998.

- [19] Flemming, N. D., I am different; not dumb. Modes of presentation (V. A. R. K.) in the tertiary classroom. In A. Zelmer (Ed.): *Research and development in higher education. Proceeding of the 1995 annual conference of the higher education and research development society of Australia (HERDSA)* 18, 1995, 308–313.
- [20] Felder R. M., & Spurlin, J., Application, reliability and validity of the index of learning styles, *International Journal of Education*, 21(1), 2005, 103-112.
- [21] Graf, S., & Kinshuk., Analysing the behaviour of students in learning management systems with respect to learning styles. *Studies in Computational Intelligence (SCI)* 93, 2008, 53-73.
- [22] Paredes, P. & Rodriguez, P., Considering sensing-intuitive dimension to exposition-exemplification in adaptive sequencing, *Lecture Notes in Computer Science*, 2347, 2002, 556-559.
- [23] Hong, H., & Kinshuk., Adaptation to student learning styles in web based educational system, *Proceeding of ED-MEDIA 2004*, Chesapeake, VA: AACE, 2004, 21-26.
- [24] Son, W. M., Kwek, S. W., & Ng, G. S., Towards Dynamic Alignment Of Learning Styles & Teaching Strategies – The SMALT Approach. *5th International Symposium on Advances in Technology Education*, Singapore, 2011.

BIOGRAPHICAL INFORMATION

Wei Meng SON, is a Deputy Manager in the School of Engineering at Nanyang Polytechnic, Singapore. He is the Principal Investigator of the research project “SMALT – SMart Advisor for Learning & Teaching” which is funded under Singapore Ministry of Education Innovation Fund (IF) 2010 Award MOE2010-IF-1-008. He is also leading the strategic directions and implementations of various e-Learning and education technologies initiatives at the School.

Siew Wee KWEK, is a Manager in the School of Engineering at Nanyang Polytechnic, Singapore. Her current research focuses on CDIO methodology and studying student motivations towards engineering.

Fan LIU, Ph. D. is a Development Engineer in the School of Engineering at Nanyang Polytechnic, Singapore. Her current research focuses on education technologies, applied intelligent algorithms and machine learning.

Corresponding author

Mr. Wei Meng SON
School of Engineering
Nanyang Polytechnic
180 Ang Mo Kio Avenue 8
Singapore 569830
65-6550-0867
SON_Wei_Meng@NYP.gov.sg



This work is licensed under a [Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License](https://creativecommons.org/licenses/by-nc-nd/3.0/).