HCI data-driven feedback in interactive learning environment

Chan, Matthias

2017

Chan, M. (2017). HCI data-driven feedback in interactive learning environment. Doctoral thesis, Nanyang Technological University, Singapore.

<http://hdl.handle.net/10356/72196>

<https://doi.org/10.32657/10356/72196>

NANYANG
TECHNOLOGICAL
UNIVERSITY

**HCI DATA-DRIVEN FEEDBACK IN
INTERACTIVE LEARNING
ENVIRONMENT**

MATTHIAS CHAN

**Interdisciplinary Graduate School
LILY**

2017

HCI DATA-DRIVEN FEEDBACK IN INTERACTIVE LEARNING ENVIRONMENT

MATTHIAS CHAN

**Interdisciplinary Graduate School
LILY**

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2017

Acknowledgments

I would like to thank my supervisors, Professor AN Bo for his contribution of time, strong support and inspiring ideas throughout the course of my Ph.D study. Their dedication to work has been a strong motivator for me and their insightful advice had helped me tremendously in this academic pursue.

I would like to extend my gratitude towards my associate supervisor, Professor CHANG Yun Ke for her constructive suggestions and kind support on research methodologies that supported me for deep learning and during the writing of this thesis.

I would like to express my sincere thanks to Interdisciplinary Graduate School (Nanyang Technological University, Singapore), for providing excellent research support, as well as the lecturers, teachers and students who were a part of my academic journey and research study.

Lastly, I would like to express my heartfelt thanks to my family members for their encouragement throughout this long journey.

Published Outputs from the Thesis

1. Lim, S.F., Chan, M., Ailiya, Miao, C.Y. & Shen, Zhiqi (2013). Persuasive Teachable Agent User Modeling. In Proceedings of 2013 IEEE 13th International Conference on Advanced Learning Technologies (ICALT), 307-308.
2. Chan, M., Miao, C.Y., An, Bo & Leung, C. (2015). Modeling Learner's Emotions with PAD. In Proceedings of 2015 IEEE 15th International Conference on Advanced Learning Technologies (ICALT), 49-51.
3. Chan, M., Miao, C.Y., Shen, Zhiqi & An, Bo (2015). Learning Personality Modeling for Regulating Learning Feedback. In Proceedings of 2015 IEEE 15th International Conference on Advanced Learning Technologies (ICALT), 355-357.

Table of Contents

ABSTRACT.....	9
<u>1 INTRODUCTION AND BACKGROUND</u>	<u>12</u>
1.1 INTRODUCTION	12
1.2 PROCESSES OF LEARNING.....	15
1.2.1 STIMULUS, ATTENTION AND PERCEPTION	16
1.2.2 ENCODING AND STORING.....	17
1.2.3 RETRIEVAL.....	17
1.3 THE TRADITIONAL LEARNING ENVIRONMENT.....	18
<u>2 RESEARCH AIMS AND QUESTIONS.....</u>	<u>21</u>
2.1 COMPUTING MODELS FOR ANALYSING ENGAGEMENT ASPECTS	22
2.1.1 COMPUTING MODEL FOR LEARNING AFFECTION AND ENGAGEMENT	23
2.1.2 COMPUTING MODEL FOR AUTOMATING LEARNING FEEDBACK BASED ON PERSONALITY	24
2.2 MAJOR CONTRIBUTIONS AND KEY RESEARCH QUESTIONS.....	25
<u>3 LITERATURE REVIEW.....</u>	<u>29</u>
3.1 LEARNING MOTIVATION AND ENGAGEMENT	29
3.1.1 UNDERSTANDING BEHAVIOUR THROUGH MOTIVATION AND ABILITY.....	30
3.1.2 SCALING THE CHANGE VIA MASS CUSTOMIZATION PRINCIPLES.....	36
3.2 ATTENTION	38
3.2.1 THE ROLE OF ATTENTION IN E-LEARNING	39
3.2.2 RELATION OF ATTENTION TO EMOTION.....	42
3.2.3 THE COGNITIVE BEHAVIOURAL THEORY.....	42
3.3 PSYCHOLOGICAL MODEL FOR COMPATIBLE LEARNING EXPERIENCE	47
3.4 UNDERSTANDING LEARNING THROUGH THE LEARNERS.....	48
3.4.1 DEFINING TYPES OF LEARNERS VIA PERSONALITY TRAITS	48
3.4.2 PERSONALITY	49
3.4.3 LEARNING STYLE.....	51
3.5 MODEL STRUCTURE FOR EMOTION-BASED EVALUATION.....	55
<u>4 EDUCATION-FOCUS RESEARCH METHOD.....</u>	<u>62</u>
4.1 REVIEWING THE METHODOLOGY	62
4.1.1 DATA COLLECTION METHODS.....	64
4.2 DEVELOPING A DESIGN-BASED RESEARCH	68
4.2.1 RATIONALE FOR DESIGN-BASED RESEARCH	68
4.2.2 PHASES OF A DESIGN-BASED RESEARCH.....	70
4.2.3 PHENOMENOGRAPHY AS THE ADOPTED METHOD FOR QUALITATIVE STUDY	71
4.2.4 STUDYING OF EXPERIENCES USING PHENOMENOGRAPHY	72
4.2.5 PHENOMENOGRAPHY FOR THE CATEGORIZATION OF EXPERIENCES.....	73
<u>5 THE STUDY PROCEDURE</u>	<u>75</u>
5.1 FURTHER STUDY PROCEDURE.....	77
5.1.1 RELIABILITY.....	78
5.1.2 VALIDITY	79

5.1.3	LIMITATIONS.....	80
5.2	APPLICATION INTO REAL-WORLD CLASSROOM	80
6	DESIGNING THE PAL MODEL	84
6.1	DESIGNING THE EXPERIENCE STRUCTURE	92
6.2	GOAL NET	95
6.3	COMPUTING MODEL FOR AUTOMATING FEEDBACK BASED ON LEARNING PROFILE.....	99
6.3.1	MEASURING THE PLEASURE “P” TRAIT VALUE.....	100
6.4	MEASURING THE AROUSAL “A” TRAIT VALUE	102
6.5	MEASURING THE DOMINANCE “D” TRAIT VALUE	106
6.6	DESIGNING THE EXPERIENCE MODEL	107
6.6.1	FROM TRADITIONAL TEACHING TO INTERVENTION MODEL DESIGN.....	110
6.6.2	GOAL SETTING PRINCIPLE	111
6.7	GOAL NET MODEL FOR PAL	113
7	CASE STUDY: USING THE SYSTEM IN REAL CLASSROOM TEACHING SCENARIO 117	
7.1	THE SYLLABUS.....	118
7.2	THE STUDY GROUP	118
7.3	THE PROCEDURE.....	119
7.3.1	LEARNING PERSONALITY EVALUATION.....	122
7.3.2	BLENDING LEARNING IN A TRADITIONAL CLASSROOM	122
7.3.3	INTERCEPTING RISK OF INTEREST LOSS VIA HCI DATA	123
7.4	ASSESSMENT RESULTS	124
7.4.1	ASSESSMENT OF LEARNER’S ENGAGEMENT (AFFECTION, BEHAVIOURAL AND COGNITIVE) 124	
7.5	FORMATIVE ANALYSIS AND EVALUATION	128
7.5.2	TEACHING & LEARNING SURVEY	130
7.5.3	SES INFLUENCES TO LEARNING MOTIVATION - COGNITIVE AND NON-COGNITIVE SKILLS . 134	
7.5.4	SES-INFLUENCED FACTORS THAT MAY CONTRIBUTE TO LAPSES IN SOFT SKILLS	136
7.6	SUMMATIVE ANALYSIS AND EVALUATION (QUANTITATIVE).....	139
7.7	RESULT ANALYSIS OF GCE N EXAMINATIONS AS QUANTITATIVE FEEDBACK.....	140
8	CONCLUSION AND FUTURE WORK	143
8.1	RESEARCH OUTCOME ANALYSIS	144
8.1.1	ACADEMIC ACHIEVEMENT	144
8.1.2	LEARNING EXPERIENCES	145
8.2	FUTURE WORK(s).....	149
8.2.1	SELF-DIRECTED LEARNING.....	151
9	WORKS CITED.....	154
10	ANNEX	171
10.1	ANNEX A	171
10.2	ANNEX B	175

List of Figures

Figure 1 Information Flow in Learning	16
Figure 2 Typical Learning Process	20
Figure 3 Co-dependencies in a Learning Process.....	23
Figure 4 Fogg's Behavioural Model.....	32
Figure 5 Evaluating PAD trait Values.....	56
Figure 6 Design-based Research Phases	71
Figure 7 Phenomenographic Relationality.....	72
Figure 8 Proposed Expansion to FBM for PAL.....	84
Figure 9 Overview of PAL (with integrated models)	85
Figure 10 From CBT to PAL (via FBM)	86
Figure 11 Integration of selected models for PAL	86
Figure 12 PAD combinations representation.....	89
Figure 13 System Overview.....	94
Figure 14 System Diagram of the proposal PAL.....	94
Figure 15 Goal NET Example	95
Figure 16 Goal NET.....	96
Figure 17 Overview of Lesson Experience Generation	99
Figure 18 "P" trait value evaluation using SAM	101
Figure 19 Activity Diagram.....	102
Figure 20 Logged Mouse Movement Data.....	104
Figure 21 Trajectories (Mouse Movement Data).....	104
Figure 22 Goal Net model for PAL.....	113
Figure 23 Syllabus, Contents and Receivers.....	121
Figure 24 Layout of Labs (Group A & B).....	123
Figure 25 Initiated Pause Prompt	124
Figure 26 Comparison of Summative Results	145

Figure 27 Comparison of TALIS data within study group.....	146
Figure 28 Comparison of TALIS data between study group and SA	147

List of Tables

Table 1 Understanding FBM using Real World Scenarios.....	32
Table 2 Personalities and Learning Characteristics.....	50
Table 3 Kolb's Learning Style and Characteristics.....	51
Table 4 Learner Type, Characteristics and Preferences.....	54
Table 5 Traits Combination for PAD Model	58
Table 6 Paradigm, method and Tools Examples	67
Table 7 Definition of PAD.....	88
Table 8 Mood Octants of the PAD space	88
Table 9 Definitions of OCC Emotions	90
Table 10 Mapping OCC into PAD with Focus Object.....	91
Table 11 "D" trait combinations and triggered actions	107
Table 12 PAD Triggered Adaptations	114
Table 13 Content Design Consideration	122
Table 14 TALIS.....	125
Table 15 T&L Survey 2013 - 2NT (1).....	131
Table 16 T&L Survey 2013 - 2NT (2).....	132
Table 17 T&L Survey 2014 - 3NT (1).....	133
Table 18 T&L Survey 2014 - 3NT (2).....	133
Table 19 Yearly Comparison of T&L Survey (5 Dimensions) of Study Group.....	134
Table 20 Yearly Comparison of T&L Survey (Engagement) of Study Group	134
Table 21 N-level's Grading Summaries (Class of 2013-2015)	141
Table 22 MSI comparison for 2013 to 2015 cohorts	142
Table 23 Self-directed Learning	152

ABSTRACT

Technological advancements have bridged the distance factor in learning communication (e.g. e-Learning platforms) by providing automated means for learners to access multimedia learning content and the integration of analytic methods to monitor a student's learning progress via attempted units and assessments. There still exist a gap in bridging the eLearning to be as effective and sustainable as traditional learning due to the absence of the human factor, the teacher. Traditional learning involves the provision of learning contents, necessary support (e.g. scaffold and hints) and assessments to monitor the learning progress. Where possible, a teacher would also provide assessment of emotional states of the learner for in-time adjustments to the learning pace based on non-verbal cues. A sustainable learning process is not one that will continue at a constant pace, but one that knows what and when feedback should be provided for optimal motivation.

As affection (or emotional state) constantly varies throughout a learning process, it is insufficient to evaluate effectiveness of learning only at sparse intervals. Furthermore, affection influences the cognitive ability as well as behaviours. Therefore, it is crucial that affection be monitored to allow appropriate feedback as frequent as possible. Human-Computer Interaction provides a valuable and minimally intrusive source of data that allows us to understand the learner in the absence of a human factor. As the mouse is a commonly used input device associated with e-Learning, I have proposed a method to focus on collecting HCI data through it. My proposed computing models will work collectively to gather HCI data of the learner, analyse it for changes in emotional states via a benchmark method and automating the

feedback that should be provided for the negotiation of positive emotional states during learning.

By observing emotional changes and evaluating the probable cause for the change and adjusting feedback to remedy the situation, i.e. when to provide a feedback and the likelihood of acceptance by a learner, my proposed research aims to provide a sustainable method of teaching and learning.

A design-based study was conducted to investigate issues in current teaching and learning methodologies and outcomes in the secondary school learning environment. Using that as a basis, a new and improved learning framework method was devised and applied to the group of learners. Their progress and learning experience using the devised framework was observed, recorded and analysed for comparison with the former via phenomenographical approach. The TALIS survey was used for the collection of qualitative data and the national assessment results provided the quantitative data. It was found that there was an increase in positive affection towards learning and there were improvements to the academic achievements.

This multidisciplinary research has been summarized to be significant: it enables a well-rounded learning process targeted for a more personalized experience; it makes the learning practical through enablement.

PART 1

INTRODUCTION

This part comprises 2 chapters that introduces the background of the research,
describes the research objectives and highlights the significance of this
research.

1 INTRODUCTION AND BACKGROUND

The school leaders are baffled. In bid to combat the declining exam results, they had implemented platforms that provided analytics to monitor the students' learning progress (i.e. pace and grades) with increased interactive learning. But the result was clearly not what was desired from these effort. It was assumed that the lack of motivation and ability was the main cause factors in the declining results.

A teacher had just been posted to the school and was tasked with the committee project to relook at the strategy for teaching and learning. After a couple of observations at how learning was conducted through the interactive platforms, he realised that the systems had some similarities in common:

1. The analytics were concerned with assessing the student's learning progress which was provided only at the end of each unit chapter.
2. It was assumed that the moderation of task difficulty would boost the motivation of the learner.
3. While learning was often user-based, feedback was only concerned with providing task-related scaffolds when the user had entered an incorrect answer to a task.

1.1 Introduction

Technological advancements have paved the way for learning process to break out of the boundary of Distant Learning (DE), evolving into that of e-Learning platforms pre-dominated by applying Internet Technologies. E-Learning is “the delivery of education (all activities relevant to instructing, teaching, and learning) through various electronic media” (Koohang & Harman, 2005) and

includes Intelligent Tutoring Systems (ITS), Smart Classrooms and Virtual Learning Environments (VLE). Many issues of the traditional classroom learning, such as the time-space constraint, have been resolved. While these developments have brought about vast improvements to learning, there still exists room for improvements to achieve a sustainable and effective end-to-end e-Learning process through a digital platform.

From an e-Learning technology adoption perspective, a good system should be capable of producing a good learning outcome while engaging its users in the learning process. From an educational perspective, the ultimate aim of all teaching and learning activities will be the leading of a learner towards the route of self-directed learning: being responsible for one's own learning through acquisition of the necessary tools and skills to do so. While the advent of computers has been recognized to facilitate lower levels of learning, such as rote memorization, there still exists vexing challenges in imparting other forms of higher level learning skills e.g. self-directed learning and critical thinking (Saade & Bahli, 2005). While some researchers have suggested that e-Learning factors, i.e. affordance of self-pacing and absence of time-constraint, could provide the opportunities for mastery of learning (Benson & Samarawickrema, 2009), there is still the critical need for the meaningful integration of creative instructional strategies with employed technological affordances to effectively and efficiently support higher-level learning skills while optimizing the engagement levels of the users.

When learning in a supervised environment, it may be easy for the teacher to “enforce” learning through imposing requirements for assignment submissions.

But what significant purpose will it truly serve for a disengaged user to merely follow through step by step instructions or page after page of text paragraphs?

Optimally, one should first look at the fundamental blocks of a learning process: stimulus, learner's perception, affection and the learning outcome.

When presented with a stimulus (i.e. the learning content), the learner would first receive and store this information in his "working" memory (the temporary memory storage for incoming information). Subsequently this information would then be evaluated subjectively for its relevancy to the user's current need. A positive perception of the information would aid the comprehension of the information. In addition, the learner's state-of-emotion (affection) can affect this process either way (positive or negative). For instance, a learner who is unable to understand or make sense of presented stimuli may end up feeling bored or even frustrated. This negative affection is detrimental to the overall learning outcome. This makes the factor of perception an important consideration (Song, Singleton, Hill, & Koh, 2004) when integrating technology with learning, e.g. e-Learning. Notably, a truly engaged learner is usually behaviourally, cognitively and emotionally involved in the learning tasks (Bangert-Drowns & Pyke, 2001). In order to achieve a positive perception to support an optimized learning engagement, developers must also cater to the target users' needs, habits and consider the anticipated emotional states experienced in the planning of learning processes to reduce the negative emotions that may arise from the interaction process and increase positive emotions to motivate increased frequencies of interaction.

Therefore, the emphasis of integrating technology with learning is not to drastically change the teacher-student interaction. Instead, the aim is to better

leverage on the affordances of technology to further enhance the facilitation of teaching and learning (T&L) by maximising learning personalization with limited human resources (i.e. manpower or T&L contents).

We will first discuss the processes of learning. Following which, the limitations of traditional T&L will be discussed in the subsequent section. Following which, the limitations of traditional T&L will be discussed in the subsequent section.

1.2 Processes of Learning

Learning is defined as the process of acquiring new knowledge in which a learner receives new information, retains it through assimilation of current knowledge and using it at a later time. To facilitate this, memory comes into play and the process of assimilation makes learning more effective as it involves the understanding and application of incoming information to the existing stored knowledge in the long-term memory. Learning involves the basic process of attention, encoding, storing and retrieving (Figure 1), which will be discussed in the following section.

Figure 1 Information Flow in Learning

1.2.1 Stimulus, Attention and Perception

When a learner is presented with a stimulus, the information enters the brains through the sensory receptors followed by the short term memory that facilitates the temporary retaining of information for mere seconds.

With potentially thousands of information bits entering through our sensory receptors i.e. eyes and ears, the brain works to filter and select relevant information that requires attention. When you pay conscious attention to something (i.e. a sign, text or sound information), this means your brain has filtered and received the required information and it is consciously perceived. This conscious perception is the first step of the memory process. That said, a human has limited attention span with the influx of information bits that can possibly be simultaneously presented, it may lead to an increase in cognitive load and decrease the efficiency of learning attention and processing of relevant

information. This situation is more likely to occur in e-Learning and is known as information overloading which will be discussed in another section.

Next, our brains will move these perceived information into either our (a) short-term/immediate memory which is capable of mere seconds of information retention or (b) "working" memory which is capable of holding more information for a slightly increased duration, but only if there is an active and current use of the information bits. In comparison to the mere seconds capacity of the short term memory, a working memory can retain information for 10-20 minutes (Sousa, 2001), and can concurrently hold 5-9 pieces of information each time.

1.2.2 Encoding and Storing

Moving information from the “working” to the long term memory requires one to assimilate the new information into existing knowledge. This allows the individual to make sense of the new information relevant to his current understanding or experience and organize information based on its meaning for later retrieval (Sousa, 2001). The moving of information from short-term to long-term memory can be done in a variety of ways, such as hands-on application or a demonstration, which leverages on the visual, auditory, and kinesthetic senses. Information stored using more than one "sensory mode" will enable ease of retrieval at a later time (Cuseo, Fecas, & Thompson, 2007).

1.2.3 Retrieval

The ability to freely retrieve information is based on various factors. The attention placed during the perception stage and the manner or encoding the

information and organizing it for storing are some of the major factors that affect this ability for information retrieval.

This section, however, discusses mainly the fundamentals of learning, from the receiving of stimulus, to perception and encoding for storing. These fundamental processes are what would occur in an ideal situation of effective learning, in which the learner and his learning motivation and engagement is optimized. But in reality, there are other underlying factors, i.e. reception towards the stimuli and affection resulting from the information-perception stages can affect the subsequent learning motivation and engagement (attention) which will ultimately affect the learning outcome. The use of any technology system and its ability to engage a learner is tied to his perception (Davis F. D., 1989), which makes perception an important consideration factor (Song, Singleton, Hill, & Koh, 2004) when integrating technology into learning, i.e. virtual learning.

Further details will be discussed based on the traditional learning environment (classroom).

1.3 The Traditional Learning Environment

In a traditional classroom setting, it is common for one teacher to be deployed (per subject basis) to a class with varied student number sizes (>5 students). In Singapore, the average class size for a secondary school setting is 40 students. Each increment to a class size of one corresponds to added complexities in the teaching and learning processes which stem from how students learn, how teachers teach and the interaction manner between student and teacher.

Interactions between student, teacher and contents are inter-dependent factors

for an effective and efficient learning process (Figure 2). For example, a teacher may provide stimuli (feedback in the form of instructions or learning content) that will be received and perceived by the student. The student's ability to accept or understand these stimuli will influence the developed affection towards the stimuli and correspondingly affect the learning outcome.

First, individuals possess varying personalities (hence learning style), background culture and knowledge. The larger the class size, the more diversified are the learners' profiles. Second, the teaching style of the one teacher may not be suitable for the varied learners. There are two factors that have been found to attribute to the varied teaching methods of teachers: (1) the preferred teaching style of a teacher is strongly related to his learning style (Gardner, 1999) (2) teachers tend to teach using the method that they were themselves taught (Jonassen, 1981).

These findings highlight the complicated problem of effectively applying teaching methods to develop the various learners in a class. Students are easily bored and frustrated in a learning environment which taps into only one learning style (Boydak, 2001), especially if the learning style mismatches with a learner with a strong preference for a specific and different learning style (Applications, 2005). Vice versa, learner's interest and success rate increase considerably when the learning process is aligned or targeted to his preference learning style (Kazu, 2009).

Figure 2 Typical Learning Process

While it may seem to be of low importance for a learner to be aware of his personality or learning style, possessing such knowledge will help an educator to better regular lessons and learning conditions (Entwistle, 1981) as well as helping learners learn efficiently and effectively. The speed and efficiency of learning corresponds to a learner's most and least preferred style of learning (Othman, Sumarni, & Foong, 2007).

As illustrated in Figure 2, affection drives the motivation and influences the cognitive ability to process incoming stimuli in a learning process. Therefore, the evaluation of learning effectiveness should not be assumed to be valid only at the end of a learning process. Instead, it should be monitored as frequent as possible at meaningful intervals while not disrupting learning flow.

2 RESEARCH AIMS AND QUESTIONS

As mentioned in the introduction, the classical learning support (i.e. personalization of learning feedback) has typically heavily depended on the human effort (teacher) in analysing the needs and adjusting to support these learning needs.

In a traditional classroom setting, the teacher often refers to the Cognitive Behavioural Theory (CBT) to guide the design of the learning experience. In this theory, considerations were made with the understanding that affection, behavioural and cognition (ABC) are inter-dependent and a change in one dimension would impact the others. Mostly, a teacher would base his method of teaching (content presentation, scaffold provision etc.) for optimal positive learning affection. This practice stems from the basis that a positive affection is critical for sustainable learning behaviour. Teachers often adapt their teaching methods (often on-the-fly) through the collection of verbal or visual cues the students may display.

With technological advancements, there have been a shift towards computer-assisted blended learning. How can we maintain such personalized support in the absence of a human tutor?

A possible solution to persuade an increase in student's learning engagement via an e-Learning platform is to develop and integrate computing models capable of automating the analysis of affective, behaviour and cognitive engagement aspects for a personalized learning process based on the learning-pattern analytics of the human learners.

This multidisciplinary research aims to design an integrated computing model to persuade optimal ABC engagements for a sustainable automated design of effective teaching and personalized learning process for human learners through the analysis of human-computer interactions (HCI) data.

2.1 Computing models for analysing engagement aspects

Motivation is the basis of all actions. People learn based on their needs or desire to gain knowledge; some learn in order to perform other livelihood related activities while others may learn for self-improvement. There are many factors that affect learning engagement such as learning content (information), assessment, feedback and affection. Affection engagement is a major contributor to significant changes in behaviour (Skinner, Furrer, Marchand, & Kindermann, 2008) and cognition (Ellis, Ottaway, Varner, Becker, & Moore, 1997) (Figure 3). It has also been shown that the teacher's support and students' self-perceptions are contributors to behavioural changes (Ellis, Ottaway, Varner, Becker, & Moore, 1997).

It is therefore evident that the affection engagement component should be prioritized for optimal student's learning engagement. However, an e-Learning process often indicates the absence of a human tutor, who plays the role of monitoring and evaluating cues that provide information of the behavioural, emotional, mental or physical states of the student in a traditional classroom set.

Figure 3 Co-dependencies in a Learning Process

Therefore, this thesis proposes the different computing models designed to automate the processes of analysing engagement factors for an optimal learning experience in a collective manner. In this research, two main computing models have been developed for this purpose. These models are as follows:

2.1.1 Computing model for learning affection and engagement

Affection influences learning behaviour and cognition. Negative emotional states arising from a learning process may directly put off a learner, reducing the level of motivation and engagement, resulting in an undesirable learning outcome. Designers of learning experiences and processes, strive to enable a positive emotional state in their users. In reality, it is impractical to expect a sustainable and positive emotional state of all learning experiences. There are numerous factors that can affect the development of emotional states through an experience, such as pace of learning, perception of stimulus and achievement of goal. Often, a teacher has to rely on visible cues (verbal and non-verbal) to assess the emotional state of a student and determine the next course of learning event (i.e. continue, stop or adjust). But this would be impossible if it is multiple students to a teacher, or if a student does not readily display his emotional states (i.e. frustration through sighing or slamming of the mouse on

the table top). This hindrance is even more prominent when learning takes place in a virtual environment. To ensure that the emotional states of the learner is duly considered in an e-Learning experience, a computer model based on the PAD have been proposed to analyse user's emotions throughout the process to appropriate the provision of learning contents and feedback.

2.1.2 Computing model for automating learning feedback based on personality

Learning personality can determine the effectiveness of any learning process and its learning outcome. An incompatible mode of information presentation can affect the learner in various aspects (behaviour, cognitive and affection). Traditionally, a teacher applies the same practice of modifying his teaching to cater to the learning needs of the student. However, effectiveness and efficiency decrease with an increase in number of students. Technology, on the other hand, provides the support for quick evaluation and data profiling of students learning progress and personality.

By researching on various learning feedback, this model seeks to address the allocation of appropriate feedback (types) at appropriate intervals to minimise interruptions that will devastate attention allocation (causing the inability to resume primary task). Ideally, this process should be automated and catered to varied learning personality for effective communication of the feedback to optimise the use of limited resources. Therefore, a computing model to evaluate timing interval and feedback type based on user's profile will be proposed and discussed to achieve this.

2.2 Major Contributions and Key Research Questions

The traditional method of teaching has allowed a teacher to observe for cues (verbal or non-verbal) for the adjustment of feedback (and contents) to boost motivation and match ability for learning persuasion. But with the shifting practice of traditional learning to one that is computer-assisted (blended e-Learning), it is hardly possible to devote sufficient attention to truly understand a student's learning behaviour and needs.

How then, can we translate this teaching practice into an e-Learning experience to persuade optimal learning behaviour?

Our study is guided by these questions:

1. How can we improve the collection and analysis of affection, behavioural and cognitive engagement via means of a standard HCI input device?
2. How can we integrate our knowledge of learning psychology with the understanding of a student's data (i.e. learning personality) to automate a personalized learning experience that can foster a stimulating and supportive learning environment?
3. Can the gathered data be used to enhance support of learning behaviour?

Using the Fogg's Behavioural Model (FBM) as a basis for persuasion, our proposed study expands this model (with technological affordances) by means of real-time data collection and analysis for improving a blended e-Learning via a proposed Personalized Adaptive Learning (PAL). This model leverages on a user's learning profile and real-time HCI data analysis to optimise this persuasion through the exploration of a combination of task knowledge and sensory input for selecting the most appropriate interruption breakpoints

(Molenaar & Roda, 2008) for learning intervention (task difficulty, content presentation and feedback). This is achieved through a combination of the task knowledge (Laukkanen, Roda, & Molenaar, 2007) and learning profile with simple sensory input that is minimally invasive.

While there have been extensive study of evaluating pleasure and arousal of users, the results have been vastly used in guiding the design of a learner's interactive experience. The novelty of our proposed study lies in the continual (real-time) assessment of incoming HCI data (user's selection, mouse movements and task performance) against the benchmarked data (practice and logged data) to adapt the learning intervention for the persuasion of optimal learning behavior.

Through the proposed PAL model, we were able to evaluate the affection, behavioural and cognitive state of the learner during the experience for a personalized learning strategy. Furthermore, it has been shown to improve quantitative learning via a non-intrusive personalization of learning pace, feedback and contents.

SUMMARY OF PART 1

Part I reviewed the problems of a traditional classroom learning environment and those of an e-Learning based environment. The typical learning process was also discussed and possible strategies to improve e-Learning were suggested.

While usability and integration of technological affordances (i.e. multimedia elements for learning) have been the focus in designing learning platforms, there still exists a gap in evaluating and understanding the learner to automate a unique learning experience that will motivate learning.

The research presented here aims to understand individual learners in the absence of a human tutor that can be integrated to empower new technologies with the ability to persuade self-directed learning. We also proposed and discussed about the various computing models developed to understand the varied needs of categorized learners, evaluating their learning processes and providing meaningful feedbacks.

In the following part of the thesis, we will review and discuss upon some methods that have been used in the evaluation of human user's affections and reactions towards external stimuli for mental and emotional state analysis.

PART 2

LITERATURE REVIEW

In order to persuade an effective and efficient e-learning behaviour, a collective model integrating aspects of education (such as learning psychology and personality), affections (simplified PAD Emotional Model) and persuasive model (such as Fogg's Behavioural Model) has been proposed. This collective model has to be able to perform the roles of analysing, capturing and documenting the user's data during a learning experience in the absence of human tutor. Data collected includes the understanding of learning preferences, average duration attention span and reception towards feedback types, attributes crucial to persuading an effective learning behaviour, engagement and motivation. This section of the thesis discusses the literature review for learning psychology (including personalities), the relation of emotional states for learning and current works that focus on understanding affection states by tapping on available technological affordances.

3 LITERATURE REVIEW

Our research is primarily focused on filling a gap in the eLearning field for an effective and sustainable learning experience. In order for us to begin discussion about the proposed computing models to achieve this, we will first need to understand the critical factors that affect the effectiveness of learning in a learning process (motivation and engagement) through the reviews of methodologies that allow us to understand cognitive abilities and behaviours from the perspective of our target users: the learners.

3.1 Learning Motivation and Engagement

Let us begin by discussing on the importance of motivation and engagement. As humans, we are understandably not motivated when a learning situation or information does not interest us; a high motivation corresponding increases the level of engagements when we are interested in or have a real purpose to be involved in a learning process. In short, providing mere instructions (top-down approach) without learning motivation is insufficient for an effective learning outcome (Kamil, 2003). Conditions that can facilitate motivation should involve the learner, including the understanding of learner's needs, autonomy, purpose, competence and encouragement.

Sustaining learning motivation is greatly dependent on the learner's confidence in his learning potential (Glaserfeld, 1989). This confidence is derived from the feeling of competency and belief in one's potential of overcoming challenges and stems from the personal experience of resolving issues (Prawat R. S., 1994). Similar ZPD, individuals need to be challenged beyond but within close proximity (slightly above) to their current level of development. The

experience from achieving such challenges can increase learning confidence and, spurring the learner to set a more challenging goal.

Through the leveraging of learning motivation, teachers are provided with a point of entry that will allow them to engage students in a learning process.

Learning engagement is important and critical, as the level of engagement in learning will influence the learning outcome. A sustainable level of engagement will ensure that the student continues with the learning process.

The introduction of Information and Communications Technology (ICT) in learning has provided the affordance for the use of multimedia in bid to engage learners. But the mere inclusion of varied media forms of learning contents does not equate to improving the effectiveness and efficiency of the learning process. We will look at how behaviours can be influenced by cognitive experience from emotional states that arise from situations (i.e. learning) can affects the level of motivation and ability of a learner in later sections.

3.1.1 Understanding Behaviour through Motivation and Ability

The Fogg's Behavioural Model (FBM) is an established model devised (2009) to understand human behaviour from the perspectives of motivation and ability for persuasion. It highlights the 3 principle elements of motivation, ability and triggers, that must be present for a behaviour change (i.e. participation in a learning process) to occur:

Motivation - refers to the self-perceived pros and cons of the end-result for a behavioural change (i.e. to be engaged or increase effort in a learning process). A higher level of motivation corresponds to a greater possibility of behavioural change.

Ability refers to the efficiency and effectiveness of t//he learning in achieving the learning goal and is attributed by 6 factors: brain cycles, money, physical effort, social deviance, time and “non-routine”. There are various ways to increase a learner’s ability, the easiest is to reduce the complexity of the task.

Triggers are reminder cues that inform the individual to perform a desired action. This element only comes into play when there is sufficient levels of motivation and ability.

Behaviour change will not happen if there is insufficient motivation or ability. However, it is possible to counter-balance both factors. For example, a highly motivated individual may still willingly perform an action that is self-perceived to be beyond his ability. In this instance, all that is required for the behaviour change is a trigger, such as a reminder or a random thought.

Figure 4 depicts a graphical model of the FBM.

Figure 4 Fogg's Behavioural Model

Table 1 Understanding FBM using Real World Scenarios

Scenarios	Motivation	Ability	Result
Uninterested student deciding whether to attend a lecture near his/her dormitory.	Low motivation – Feeling that it is not worth the time and effort.	High ability – Venue is easily accessible to all students.	If motivation is excessively low, the student will not attend regardless of how easy the task is.
Web users navigating a badly designed E-commerce site.	High motivation –Need to purchase the desired product.	Low ability – Confusing links increasing the complexity in site navigation.	May give up in frustration. Motivation has to be extremely high in order for user to willingly spend extra effort /time to learn its navigation (increase ability)
Young people joining Facebook (social networking)	High motivation. It is a “social	High ability. Account setup and maintenance is easy	Millions of Facebook users.

site).	norm” to have an account. It would lead to pain if one feels “left out” from the standard.	(commence use in minutes).	
--------	--	----------------------------	--

In order to engage a student in learning participation, merely increasing motivation does not always bring about the desired solution and focusing on reducing the learning task complexity to increase ability may not be the best method to use as it may jeopardise the desired learning outcome. There should be a balance between off-setting the two main elements of motivation and ability. With the increasing use of ICT in teaching and learning and the absence of a human teacher, there is a need to further extend this model with the technological affordances available to enhance the analysis and support of motivation and ability.

3.1.1.1 Information Overloading

As discussed, a learner’s behaviour can be directly affected by the factors of motivation and ability. Therefore, having too many variations of learning contents may have an adverse effect on learning due to information overloading if it leads to a decreased sense of motivation or ability.

A survey has found that 87% of nearly 2500 teachers believe new technologies are creating an “easily distracted generation with short attention spans” and 64% say that digital technologies of today “do more to distract students than to help them academically.” But is this really the case? As education researchers and learning designers, are we not able to leverage on the affordance of technology to improve learning attention and experience?

The answer would have to be a yes. In fact, Kristen Purcell (Associate Director for Research at Pew), has suggested an alternate point of view to the survey findings: the required adjustment to the education system to better accommodate the varied learning ways for optimising learning attention.

A Professor in the Information School at University of Washington, David Levy, has identified a common problem occurring in the many discussions of how and what technology use has re-shaped our brain. “So many of those debates fail to even acknowledge or realise that we can educate ourselves, even in the digital era, to be more attentive,” he says. “What’s crucial is education.”

Let us first begin by reviewing one of the most probable reasons for loss of learning attention during an e-Learning experience: Information Overloading. Indeed, in the absence of a teacher to guide or provide students with relevant learning contents, a student may be reviewing paragraph after paragraph of information that may not be relevant to his immediate learning needs. This may lead to cognitive overload and subsequently, the loss of learning attention. The following section will discuss about the issue of information overloading in further details.

“Information overload” (Toffler A. , 1970), refers to the difficulty in understanding an issue and making decisions due to excessive information (Yang, Chen, & Hong, 2003). Toffler had presented “information overload as the Information Age's version of sensory overload”, a term earlier introduced by Lindsley (1959) as the cause of disorientation and lack of responsiveness. Toffler had discussed that information overload had similar effects as that of sensory overload, but on the higher cognitive functions, writing: "When the

individual is plunged into a fast and irregularly changing situation, or a novelty-loaded context ... his predictive accuracy plummets. He can no longer make the reasonably correct assessments on which rational behaviour is dependent."

The integration of technology into learning (i.e. Internet and e-Learning platforms) has brought established a new era of globalization. Empowered by the ability to reproduce and consume large amounts of information (Bonfield, 2007) (Russo, 2005), the number of people conducting their own learning via the World-Wide Web (WWW) has correspondingly increased.

While this shift of consumption has opened the doors to more information, it has also exposed the users to the danger of excessive dependency on this mode of information access (Baxter, 2008) (Cheng, 2006). Flew (2008) and Graham (1999) had also warned of information overloading from the access to so much information without validation and the ability to comprehend the information.

Some cognitive researchers have discussed about the differences between receiving raw information and information that can be readily processed. The problem of information overload may also be seen as organization underload. The lack of a proper cognitive organizational structure, such as large amounts of information being presented in its raw form, can limit the processing of received information by learners.

Sheena Lyengar (2000), had similarly discussed upon how information overload result in the inability to make decisions. She noted that individuals struggled with the ability to more consciously and effectively decide and process information, when presented with large amounts of information.

One solution to address a problem of information overload is to design content databases with information sharing intentions with an organized system of information handling, such directories, to assist users to cope with quantities of information or recommending appropriate contents in bid to facilitate clear thinking. Such solution is akin to the principles of mass customization.

3.1.2 Scaling the Change via Mass Customization Principles

Mass customization principles (Pine, 1993), utilizes flexible computer-aided systems for customizable outputs with the extended flexibility of individual customization. Integration of such principles in the design allows for strategic advantages and economic value, usually without a corresponding increase in costs.

The concept of mass customization is attributed to Future Perfect (Davis S. , 1997) and as "producing goods and services to meet individual customer's needs with near mass production efficiency" (Tseng, 2001).

Mass customized technologies are pre-programmed as part of the system processes, varying it only when required as opposed to varying everything (Adsit, 2009). Implementing mass customization enables system designers to add and/or change functionalities of a core product. Aforementioned, every learner has his own learning capabilities, mind-set and attitude, which correspondingly influences his pace of learning absorption. Therefore, the integration of mass customization principles will enable e-Learning designers to broadly classify individuals with similar learning characteristics into groups and cater to their varied learning requirements. Furthermore, this integration will

also support the learning and teaching pedagogy of the Vygotsky's Zone of Proximal Development (ZPD) that will be discussed in the following section.

3.1.2.1 Customizing Sufficient Challenges to Address ZPD

Vygotsky believes that the process of learning and the construction of knowledge occur within a ZPD, which he defined as “the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers.” (Vygotsky, 1978).

The ZPD represents an area of competency which is slightly above the learner's current level. It is constantly evolving; learners must be assisted to develop beyond his current ability. The degree of success and timely progression across ZPDs is dependent on the interaction provided. For example, learners can be assisted by a more knowledgeable other, one capable of providing learning scaffolds that enables ZPD progression (e.g. completion of current tasks).

Stimuli such as feedback or dialogues (i.e. learning interactions) are essential to cognitive development. The scientific and spontaneous are two interrelated groups of concept. Spontaneous concepts arise from daily experiences, adhere to a common sense logic and are expressed informally. On the other hand, scientific concepts arise from organized activities (e.g. culturally coordinated school practices). Knowing the learner's ZPD facilitates the process by which a teacher can use learning dialogues and tasks to cognitively develop the learner's spontaneous concepts into scientific conceptions.

A ZPD-based learning is considerably simplified in a traditional learning environment, where physical teacher-learner interactions are possible. A teacher will be able to improvise learning feedback in response to the learner's verbal or non-verbal cues. The absence of such interactions poses more challenges for a ZPD-based learning via a technological platform. Due considerations have to be given in the design phases of both the system and the contents to support ZPD-based learning. First, the system designer should have sufficient understanding of the physiological and psychological conditions necessary for an effective and efficient e-Learning process. For example, what cues would indicate distress or boredom and how would the system capture or analyse it? Second, the teacher would have to consider varied levels of learning contents and feedback types to cater to the varied competencies of intended learners. For example, can a chapter or learning assignment be further broken down into sub-units and what forms of feedback would be necessary to facilitate learning that is appropriate for majority of the learners? Lastly, when will it be an appropriate pace of learning and when should feedback be provided to minimise interruptions and sustain engagement? To answer these questions, let us begin with the discussion on the factor of attention.

3.2 Attention

Over the years, the field of Attention has been extensively studied, with selection being the most common paradigm guiding such research (Driver, 2001). The premises of selection paradigm based research are based on the assumption of limited cognitive resources that has to be allocated based on selection of attention-focus.

3.2.1 The role of Attention in e-Learning

Attention is essential to task performance and interaction; it allows us to take action, communicate and reason, regardless of a physical or virtual environments. It is what makes it possible for us to execute goal-achieving and task-related actions (the interactions) without being distracted in an environment that is stimuli-exceeding (far more than what our self-perceived processing capability). Attention can be viewed from 2 board perspectives: exogenous and endogenous attention selection process and short or long time duration.

Interactions (between an individual and goal or task related elements i.e. activities or objects) are fundamentally guided by attentional processes, through which cognitive and physical resources are allocated to allow an individual to perceive a stimuli and act upon it (to achieve goal). Understanding attention allocation is useful in the guiding of interaction designs (Roda & Thomas, 2006) for systems i.e. attention-aware systems which recognizes problematic interaction situations in digital environments, importance of attentional processes to limit negative effects of interruptions, reducing information overload and increasing situation awareness. Such system is especially beneficial when integrated as part of a multi-tasking virtual learning environment as it facilitates as a user-support (Roda & Nabeth, 2007). Attention selectivity is guided by two primary mechanisms: ‘bottom-up’ (where attention is captured by external events i.e. sudden loud sound) or ‘top-down’ (voluntarily controlled by the individual i.e. following a line of text as it is being read). The attention allocation processes are referred to as being

exogenous (bottom-up) and endogenous (top-down) in reference to the external or internal basis (to the subject) of the events.

In an exogenous attention selection process, a stimulus is selected based on their saliency, which is determined by the degree in which the element stands out from its background based on basic features (e.g. colour, size).

In an endogenous attention selection process, a stimulus is selected based on their current task or goal relevancy (i.e. information). This degree of relevancy can be increased through breakdown and provision of small and immediate task-relevant features at any point of time. Allocation bias here can be manipulated using certain input characteristics that are dependent “on the difficulty of the task performed at the attended location” (Boudreau, Williford, & Maunsell, 2006). What this means is that the higher the difficulty in recognizing the stimulus (information), the stronger the support of the allocation bias (attention-focused).

Attentional breakdowns, defined as the situations in which there is a failure to allocate due or optimal attention on a goal or task, include prospective (memory for future events, plans and tasks) and retrospective memory (for past encounters and events) failures; disruption of primary tasks and task resumption failures. Forgetting to complete a task, task prioritization failure and inability to find and focus on relevant information, are all examples attributed to attentional breakdowns.

Attention is often lost due to unforeseen or undesired interruptions.

Interruptions negatively affect the effectiveness and agreeableness of task performance (Bailey, Konstan, & Carlis, 2001) (Grundgeiger & Sanderson,

2009). Interruptions, such the presentation of task-irrelevant information in a very conspicuous manner at the wrong timing (interval), trigger bottom-up processes that cause enough activation to override the existing attention selection (shift of current attention capture) and the primary task.

Thus far, what we have discussed about are the attention selection processes and how attention can be interrupted.

As time duration increase, attentional processes are increasingly seen as the coordinator of information flow (rather than the mere information selection in a short time span) to facilitate higher-level perception and action. Executive functions are a set of cognitive processes are necessary in the planning of activities and establishing of priority between simultaneous tasks. Deficits in the central executive are common causes of failing to initiate and monitor task performance, both in adults and children (Diamond, 2005). With respect to visual attention, attention can be viewed as the “establishment and maintenance of a coordinated information flow that spans through several processing levels” (Rensink, 2007)

With this understanding, we can see how attention affects the flow of information processing. Indeed, if the flow of information is direct and suited, attention allocated can be at one’s optimal cognitive capacity. This is aligned to the ideal that e-Learning or learning, in general, should never be about juggling multiple information bit but to gain knowledge.

While it has been argued that notifications containing task or goal relevant information are less disruptive than irrelevant ones (Czerwinski, Cutrell, & Horvitz, 2000), the automated process of evaluating relevancy is hardly a trivial

task as it requires semantic knowledge of the current activity (of the user) and the information content. The main question is, how can we automate the system to know when is the appropriate time (interruption interval) and content to present information?

The time cue for any form of ‘interruption’ is critical as it determines the make-or-break of the task resuming (Altmann & Trafton, 2002). More recent work has suggested finer-grained analysis for such interruption time using task-knowledge or sensory input. In task-knowledge based timing, the structure of the task being performed has to first be analyzed. In sensory-input based timing, input from sensors are used to detect user’s activity for analyzing the best appropriate intervals for interruption (Fogarty, et al., 2005) (Speier, Vessey, & Valacich, 2003).

3.2.2 Relation of Attention to Emotion

Emotional valence influences reaction to stimuli at all processing levels (Lim, Padmala, & Pessoa, 2008) (Pe[^]cher, Lemercier, & Cellier, 2009) (Pe[^]cher et al, 2009). Studies on this relation has analysed the effects of emotional stimuli depending on their valence (generally positive or negative stimuli i.e. happy/sad) and has shown that emotional valence is evaluated both at a perceptual and semantic level.

3.2.3 The Cognitive Behavioural Theory

The Cognitive Behavioural Theory (CBT) states that our thoughts will cause us to feel and act in certain ways, which are not always helpful or rational (Dobson & Dobson, 2009). The CBT has been widely used to address several emotional disorders such as anxiety and depression (Otte, 2011). The understanding of

this theory also provides information on how negative emotions can affect learning ability of learners, regardless of a physical or virtual environment. The example in Figure 3 **Error! Reference source not found.** illustrates how affection can influence cognition and behaviour. Therefore, it is essential to ensure minimal negative emotions arising from any experience.

While numerous emotional models have been proposed with the increase in affective-focused research, its related state of the art broken down into four components that reflect the different aspects of emotion (Ortony, Revelle, & Zinbarg, 2007). The four components are summarized as (1) the “input” of emotions which refers to the cognitive and perceptual aspects of emotions (Ortony, Clore, & Collins, 1988); (2) the “output” of emotion which refers to the action tendencies (Frijda, 1986); (3) the facial expressions of emotions (Ekman, 1982) (Izard, 1971); and (4) the affective neuroscience component which focuses on the brain structures and mechanisms (Lane, Nadel, & Ahern, 2000) (LeDoux, 1998) (Panskepp, Nelson, & Bekkedal, 1997). These four components are inter-dependent and are required for emotion generation.

3.2.3.1 Attention Span

A learner’s attention level vary widely and is based on factors such as motivation level, state of emotion, affection level (i.e. enjoyment) and even the time of the day.

Even in the instance where learners are motivated and excited about their learning (and e-Learning) experience, there is a limit to how long they will be able to concentrate through the process. Furthermore, attention span varies with different learners and the inability to focus or concentrate can affect

behavioural, cognition and affection engagements. For example, losing the ability to concentrate on a subject matter may result in cognitive overloading and disconnection with the learning process. Subsequently, such individual may not be able to resume learning momentum or catch up with the learning pace of the rest of the class (in a one teacher to many students scenario) and this may further lead to the behaviour of restlessness, or feeling boredom or negative emotions that the lesson is getting boring or negatively impacting their self-esteem. In addition, short attention span learners are considered to be one of the more challenging learner groups as they often lack the capacity to be able to concentrate on one task for prolonged duration and more likely to disengage from the learning experience when they are not fully engaged.

That said, one has to be realistic and understand that the traditional mode of teaching (one teacher to many) does not provide much opportunities to ensure that all students will be focused and lessons can be paced to suit the attention span of the individuals. Things changed with e-Learning, as students will be able to determine their learning paces, choosing to stop and resume whenever possible. But in many classrooms around the world, the traditional method of teaching is still practised, but is increasingly integrated with the use of Information Communication Technologies (ICT) to support teaching & learning, but not to replace the role of a teacher.

There are, however, ways that have been suggested to beat the issue of short attention spans that can be considered during the design of e-Learning courses to maximise knowledge retention and minimise cognitive overload. A couple of these methods and its disadvantages will be discussed:

1. Sectioning the courses into manageable modules – Rather than ostracizing short-attention span learners from the design consideration of an e-Learning pace, they can be taken as the standard benchmark during the creation of the e-Learning deliverables. Rather than designing the entire learning experience to last an entire hour, it could be divided into several modules that last minutes, giving the learner break intervals. This could possibly keep the learner fully focused on the screen. However, not all learners have similar attention spans (Wilson & Korn, 2007), and some learners may find it distracting to face ‘frequent’ intervals (cognition pause points) and this may negatively impact the learning experience (affection).
2. One of the main reasons for learning participation is to gain new knowledge or learn new skill(s). Often, a majority of learners are likely to anticipate immediate application of the new knowledge or skill with a minority being aware of the long term benefits of acquiring the information. To maintain learning engagement, it will be useful to include ‘practical’ activities of how these skills or knowledge can be applied, particularly those of daily activities. That said, the designer of such e-Learning courses should also be aware that the learning personality (i.e. visual learner) varies with the different users and there is no one-size fits all activity that can cater to the majority of its users.

3.2.3.2 Pedagogies and Learning Segments for Optimizing Attention Span

A research (Bunce, Flens, & Neiles, 2010) has had studied the frequency of learning attention lapses by adopting a simple method of tracking reported lapses using a “clicker.” This “clicker” method is the inspiration for adopting

the mouse as the device for capturing HCI data for evaluating emotional states. This will be further discussed in later parts.

The study group comprised of a course taught by a professor who has adopted three different pedagogies (lecturing, demonstrating, or asking a question) with no fixed sequence in each learning session and students who were asked to report attention lapse by pressing a button on provided clickers upon being aware they had experience a period of inattention. There were three buttons on the clicker, one for the indication of attention lapse of less than 1 minute (min), the second for the indication of lapse (between 2 to 3 mins) and the last one for the indication of a lapse of more than 5 mins. Clicker data were sent to a computer and mapped to a timeline categorized by the pedagogy used. The average length of the students' attention lapse, relation between these lapse and the adopted pedagogical method were measured and compared for analysis.

Regarding frequency of attention lapse, it was reported that attention lapses increased in frequency as the lecture progressed. By the end of the lecture, attention lapses frequented at intervals of two mins.

In addition, a relationship between attention and active learning, or “student-centered” pedagogies, was also reported. In the study, providing demonstrations or posing questions during learning are considered to be some of the active learning methods. It was found that there were fewer attention lapses during demonstrations and questions as compared to the lecturing segments (that preceded the active learning methods). However, an interesting observation was the decreased number of reported attention lapses during lectures that stems from either a demonstration or a question. This suggests the “dual benefits” of

adopting active learning methods in the design of learning experience: the engagement of attention during a learning segment and refreshing attention immediately after a segment.

3.3 Psychological Model for Compatible Learning Experience

Learning can be defined as the process in which new knowledge, skills, values or understanding can be acquired by synthesizing different information. These information can be presented in various ways, such as text, graphics, audio or tasks. Learning traits account for the characteristics and preferences in which individuals interact and perceive the environment, sort and process of information leading to a reaction to facilitate learning (Kazu, 2009).

There is no one model that can be used to address every learning process. They need to be designed and customised for specific types of evaluating learning progress or needs. This section introduces the various recognised learning personalities, traits and their influence on a learning process in bid to address to the varied learning needs of learners as it affects desired learning outcomes. In order to design an efficient and effective learning experience, due considerations should be placed on understanding the learners, catering to the varied learning needs (as far as possible) and learning experience through HCI-based emotion-evaluations. Firstly, defining learners using personality traits serves to guide the designing of learning contents and feedbacks that will appropriately support the learners and not put them off (i.e. by imposing additional cognitive load when presented with incompatible or inadequate content). Learners can be put off when presented with information that undermines or exceeds their ability and can affect motivation. Secondly, the contents designed should be presented in a manner that will facilitate learning

similar on a daily basis. When information is presented in a manner that is familiar or more likely to appeal to a learner's characteristic and style, it imposes fewer intimidations and therefore supports a supportive learning experience for a safe learning experience. Lastly, the assessment of designed learning experience is based on the analysis of reactions (emotional states) using HCI data. Due to the intertwining complexity of learning personalities and learning experiences, there is hardly a one-size-fits-all method that will assure that a similar learning personality will be adopted throughout a subject (macro-level) or unit (micro-level). Therefore, it is crucial that the learning experiences be frequently evaluated for its effectiveness (using emotional states) for in-time adjustments to reduce the likelihood of learner's rejection as it will reduce learning sustainability.

3.4 Understanding Learning through the Learners

As mentioned, the design of any good learning experience requires the understanding of its primary users: the learners. We shall therefore begin our literature review by focusing on defining the types of learners, variations in the learning personalities and styles. Furthermore, this portion of the literature review is critical as it offers the insight to the possible reactions to the learning contents and HCI data that should be captured and how it will affect the adjustments to the learning experience.

3.4.1 Defining Types of Learners via Personality Traits

In our everyday lives, we gather and make sense of information through various external stimuli from our surroundings. The process by which we capture the existence and the ability to extract meaningful information of these stimuli is

dependent on factors e.g. the learning motivation and the preferred stimuli presentations.

Learning behaviour and motivation of a learner are facilitated by his personality traits, and these traits are the decisive factors for the individuals in insisting or giving up during a learning process (Blickle, 1998). Mere effort may be insufficient for an effective learning progress. By using the compatible learning style suited for a personality, a learner can achieve higher motivation (e.g. cognitively) and better adaptation towards a learning process. Learning can be defined as the management of mental responses toward learning stimuli as well as the process of information based on perception, attention, memory and thinking elements. Personality traits define an individual's behaviour towards specific goal-accomplishment or situations (Caligiuri, 2000). And since learning styles emerge as habits, personality traits, acting as intermediary interferences, can therefore affect learning behaviour (De Raad & Schouwenburg, 1998) (Ibrahimoglu, Unaldi, Samancioglu, & Baglibel, 2013). Therefore, it is important to understand how personality traits affect a learner's response towards learning stimuli in order to optimise any form of learning. This is particularly essential in the absence of human tutoring, such as that of a VLE.

3.4.2 Personality

A personality can be evaluated using a brief and comprehensive measure of five personality dimensions based on the Five Factor Model (Table 2). The dimensions include Extraversion (E); Agreeableness (A); Conscientiousness (C); Neuroticism (N) and Openness to Experience (O). Each dimension of the Five Factor Inventory is assessed by 12 statements using the NEO-Five Factor

Inventory (NEO-FFI) (Costa & McCrae, 1992). The NEO-FFI is an abbreviated 60-items version of the original NEO Personality Inventory (Costa & McCrae, Personality Stability and Its Implications for Clinical Psychology, 1986) which contained 240-items and was deemed to be too lengthy for many research applications.

Individuals scoring high on the (E) scale tend to be sociable and assertive, with a preference to work with others. Agreeableness (A) is characterized by the tendency to be tolerant, trusting, accepting and easily moved. People high on the (C) scale are organized, purposeful, strong-willed and responsible. In addition, they are trustworthy, task-focused and achievement-oriented. Openness to Experience (O) is characterized by attributes such as open-mindedness, active imagination, less conservative with independence of judgment and preference for variety.

Table 2 Personalities and Learning Characteristics

Extraversion	+(E) individuals (Extraverts) are sociable, talkative and assertive. Require excitement, stimulation and activity (Wallach & Wing, 1969).
	-(E) individuals (Introverts) are independent, reserved, steady and enjoy being alone.
Agreeableness	Good-natured, cooperative, supportive and concerned for the well-being of others. -(A) individuals can be seen as indifferent and self-centered.
Conscientiousness	Dependable, responsible, rule abiding and achievement-oriented; possessing self-discipline (Costa, McCrae, & Holland, 1984). +(C) individuals focus on only a couple of tasks and works hard to accomplish goals. -(C) individuals are more impulsive, easier to persuade, less thorough and responsible.
Neuroticism	Anxious, insecure and self-conscious. Prone to psychological distress and cope poorly with stress (Costa

	& McCrae, 1986). Negatively linked to well-being.
Openness to Experience	Curious, imaginative, broad-minded and unconventional. Receptive towards experience (i.e. inner feelings and emotions). High openness corresponds to broader interests, degree of liberty and like novelty. This factor relates to intellect, openness to novel ideas and educational aptitude. (Wallach & Wing, 1969).

3.4.3 Learning Style

The Kolb's learning style (Kolb, 1999) model states that learners can be segregated based on how they gather information, through concrete experience (CE) or abstract conceptualization (AC), and how this information is processed, through reflective observation (RO) or active experimentation (AE). Four learning-style categories stem from the varying combinations of preferences in manner of gathering (CE and AC) and processing of information (RO and AE). The four learning styles are the: divergers (CE and RO); assimilators (RO and AC); convergers (AC and AE) and accommodators (CE and AE);. The learning behaviours of these learning styles are described in Table 3.

A significant relationship exists between learning styles and personality types (Highhouse & Doverspike, 1987). Determining the most effective learning form based on personality types is important (Fallan, 2006); the synchronization of learning styles and personality types can be used in the configuration of learning programs to enrich learning activities, curriculum and provide learners with a comprehensive experience.

Table 3 Kolb's Learning Style and Characteristics

Learning Style	Preference for Learning Process (Kolb, 1999)
Divergers	<ul style="list-style-type: none"> • Concrete learning experience with different perspectives • Organize relations between events in meaningful

	<p>ways</p> <ul style="list-style-type: none"> • Tend to make observations prior to taking actions in situations • Consider own feeling and thoughts during learning <p>Strength: Imagination, perception, identifying problems and evaluating them using various perspectives.</p> <p>Weakness: Difficulty in making decisions due to alternatives and likely to be inadequate in taking advantage of learning opportunities.</p>
Assimilators	<ul style="list-style-type: none"> • Interested in abstract learning concepts and ideas • Prefer to receive information from experts (i.e. teachers) and look upon these figures as important learning information source • Tend to learn through audio and visual, making them more suitable for traditional teaching methods <p>Strength: Skilled in plan-making and problem solving skills.</p> <p>Weakness: Inefficiency in practical studies (i.e. practical values and ideas).</p>
Convergers	<ul style="list-style-type: none"> • Uses abstract conceptualization and experiential learning • Often interested in technical issues • Not attracted to social and interpersonal activities (task oriented) <p>Strength: Skilled in problem solving, logical analysis and deductive reasoning skills.</p> <p>Weakness: Make hasty decisions and tendency to solve wrong problems. Often require teacher's feedback.</p>
Accommodators	<ul style="list-style-type: none"> • Uses abstract conceptualization and experiential learning • Social-beings; making use of interpersonal relationships and personal information rather than technical analysis during the course of learning • Open minded about learning with high curiosity and research motivation <p>Strength: High leadership skill and can easily communicate with others due to sociable personality. Highly adaptable to changes.</p> <p>Weakness: Tendency to reach correct information through trial and error and being involved in seemingly meaningless</p>

	activities.
--	-------------

3.4.3.1 *Visual, Auditory and Kinesthetic (VAK) Model*

This learning style model uses a human's main sensory receivers: Visual (V), Auditory (A), and Kinesthetic (movement) (K) to determine an individual's dominant learning style. It is based on the modalities — channels through which (human) expressions can occur and is made up of a amalgamation of perception and memory.

This learning style model is one of the more popular models due to its simplicity. Although modalities and learning styles are connected (Pennsylvania, 2009), there is no research evidence to prove that using one's own learning style will provide the best means for learning. This is due to the fact that the mode and method of learning could be more of a preference, rather than a style, and varies with the topic; one learning method does not fit all learning situation.

When learning, a learner taps on all three modalities to receive and assimilate new information. Nevertheless, according to the VAK learning style model, up to two of these styles are usually dominant which defines the optimal way for a person to filter and learn new information. It should be noted that this style may vary for different tasks. While there has been some evidence suggesting modality-specific strengths and weaknesses (Rourke, et al., 2002), we are unable to establish that a match between the instructional style and individual learning strength improves one's learning ability. Constantinidou and Baker (2002) had found that visual presentation was advantageous for all adults,

irrespective of a high or low preference for visual-based learning. In summary, a learner may have their own style preference for different tasks.

In a typical classroom setting, our learning style would have been forced upon us throughout our learning life: From Kindergarten and up to, at least, Primary school education, new information has generally been presented in a top-down manner (from teacher to student) via visual presentation; And in Secondary school, information is presented to us in lectures via auditory means. There has been a gradual change to learning experiences, with the introduction of Collaborative or Cooperative learning methods, in which students learn and share information with each other.

According to the VAK theorists, learning information has to be presented in all three styles to cater to the optimal range of learners as this provides the opportunity for all learners to become involved, regardless of their preferred learning style. However, this is practically impossible in a typical classroom teaching scenario due to the limitation of classroom time duration and manpower resources (especially in the preparation of learning contents).

The characteristics and preferences for the VAK learners have been summarized in Table 4.

Table 4 Learner Type, Characteristics and Preferences

Type of Learner	Characteristic(s)	Learning Preference(s)
Auditory	<ul style="list-style-type: none"> • Often talks to themselves or move their lips. • May face difficulty in reading and writing but often do better talking or listening. 	<ul style="list-style-type: none"> • Do best with an overview of learning objective(s) and summary (debrief) for new learning information. • Verbalization of questions. • Socratic discussion and questioning methods to

		draw as much information from learner will aid in the subsequent filling in of gaps with personal knowledge.
Visual	<ul style="list-style-type: none"> • Possesses two sub-channels—linguistic and spatial. • Visual (linguistic) learners tend to learn through reading and writing. • They remember through hand movements (e.g. writing down words). • Visual (spatial) learners tend to have difficulty with written languages and do better with visual materials (i.e. charts, demonstrations or videos). They easily visualize faces and places by using their imagination. 	<ul style="list-style-type: none"> • Do best with visual aids (e.g. charts and illustrations) and handouts with outlines, concept maps and agendas. • Handouts should have blank spaces for note-taking and include cues in lessons for learners to identify key areas for note-taking. • Supplement textual information with graphic aids where possible.
Kinesthetic	<ul style="list-style-type: none"> • Possesses two sub-channels: kinesthetic (movement) and tactile (touch). • Tend to lose focus when there is little or no external stimulation or movement. May take notes for the purpose of moving their hands while listening to a lecture. • When reading, they tend to scan through the material before focusing on the details. • Note-taking generally involves the use of color high lighters picture, diagram drawing or doodling. 	<ul style="list-style-type: none"> • Do best with activities that involvement movement (i.e. physical up and moving, mouse movements or experiments) • Require breaks during learning sessions (brain breaks) • Supplement text information with activities (i.e. visualization of complex tasks, transfer of text from screen to another medium such as the keyboard typing).

3.5 Model Structure for Emotion-based Evaluation

In a virtual environment where the user often pursues specific goals, an appraisal-based model, which computes the user's emotional state as a result of

the interaction between user goals and interactive choices, may be particularly relevant (Lazarus, 1991). Numerous studies have been conducted to predict emotions from user's interactions, e.g. keyboard strokes to mouse, but majority tend to evaluate emotion as a whole and not the specific areas influencing the negative emotion. The proposed agent model seeks to address this issue by evaluating emotion from various aspects and regulate the learning pace and feedback to address specific areas that contribute to a negative emotion (G., D., & A., 2011) (P. & M., 2010).

Figure 5 Evaluating PAD trait Values

The user's state of emotion is evaluated using Albert Mehrabian's Pleasure (P), Arousal (A) and Dominance (D) traits or otherwise known as the PAD emotion state model for evaluating mood (Mehrabian A. , 1980). Evaluating the PAD trait values within the virtual environment is a constant and ongoing process at designed interval points, e.g. task completion or accepting hints. The values of the traits lie between positive and negative.

The "Pleasure" trait refers to the degree which one feels good or satisfied in a situation. Pleasure is defined by the valence (negative or positive) of emotion that ranges from being unpleasant (e.g., unhappy) to pleasant (e.g., happy) (Clore, 1994). Detailed explorations of stimuli have been shown to be

encouraged by indicted pleasure in individuals. For example, Isen (1987) has discussed about the effect of positive emotions on an increased ability to process more complicated information as well as optimism towards accepting challenges. Positive emotions also increase one's sensibility to environmental stimuli. In an online context, pleasure is akin to "sense of likeability" (Poels & Dewitte, Getting a line on print ads, 2008).

"Arousal" comprises one's levels of mental alertness and physical activity. High-information (i.e. new or unexpected) events increase arousal. The activation state of emotion defines Arousal, which ranges from calm to excited (Clore, 1994). According to Berlyne's motivation theory (1971b), arousal can be identified as motivational conditions produced by external stimuli during a learning process. These conditions are related to the uncertainty, novelty, expectation, and complexity of the stimuli (Berlyne, 1974). Mehrabian & Russell's (1974) Information Rate-Arousal Theory has also discussed the direct co-relation of arousal to the amount of information in an environment. Reaction time is positively correlated to mental alertness and time-speed duration (Koga & Morant, On the degree of association between reaction times in the case of difference sense, 1923) of user accepting task events or mouse interactions, e.g. moving the mouse, and is evaluated as the A trait value.

"Dominance" trait deals with the feeling of control over situations and degree or freedom to act and is a relevant emotional response as users have more control over their environment (Richard, Modeling the impact of internet atmospherics on surfer behavior, 2005). Proshansky, Ittelson, and Rivlin (1970) had proposed choice-freedom as an emotional dimension to describe the sense of dominant feeling in an environment. For example, the provision of privacy

and territoriality allow for greater choice freedom; whereas formal social situations (including cyberspace interaction) tend to constrain behavior (Mehrabian A. , Nonverbal communication. , 1972). If one feels constricted by interactions (tasks or from another agent or player), he will likely feel a lower sense of dominance. An increase sense of physical stimuli corresponds to an individual's increased sense of suppression, hence are rated as more intense and more powerful, as they provide more constriction (Mehrabian & Russell, 1974). The learner's ability (accuracy and rate) to complete tasks is evaluated as the D trait value.

Mehrabian had defined eight mood types based on the combinations of each dimension in PAD (Table 5). For example, a +P-A-D could indicate an individual who is sleepy or being docile.

Table 5 Traits Combination for PAD Model

Trait Combination	Mood Type
+P+A+D	Exuberant, Bold, Creative
+P+A-D	Dependent, Amazed, Impressed
+P-A+D	Relaxed, Leisurely, Satisfied
+P-A-D	Docile, Sleepy, Tranquilized
-P+A+D	Hostile, Antagonistic, Belligerent
-P+A-D	Distressed, Humiliated, Upset
-P-A+D	Disdainful, Selfish-Uninterested, Unconcerned
-P-A-D	Bored, Depressed, Dull

One of the major contributions of my study is the translation of the PAD model from a physical work evaluation to one that is primarily data-driven by HCI via a screen. The proposed computing models that evaluates the Arousal / “A” and Dominance / “D” trait values by analyzing user’s mouse movement and decisions have been peer-reviewed in 2 separate publications under the ICALT. We aim to negotiate a positive emotional experience through the understanding of the learner’s current emotional states and reducing the assumptions for the various conditions that can contribute to a negative emotional experience. The abovementioned models will be further discussed in the following chapter.

SUMMARY OF PART 2

In Part 2, we reviewed the various types of learners, learning personalities and styles. Due to the nature of this research and goal, it is essential to understand the learners and their learning processes (who they are and how they learn).

Next, we discussed upon the factors (self-esteem and trust) that can influence the effectiveness of a learning process. The most important factor that can affect the sustainability of learning would be the state of emotion that arises during and after a learning experience.

We introduced the analysis of emotional states and reviewed some of the current methods that allow the capturing of data. These methods include the capturing of data based on the sense of smell, sight and touch to eyeballs, body movements and even speech. Next, we progressed into reviewing some of the models that allow for the analysis on captured data for emotional states. The PAD emotional state model was deemed to be of high compatibility as it allows for the translation into a HCI-based analysis of emotional states.

Based on the PAD model, the various aspects of data, methods of capture and varying emotional states that could be derived from analysed data were presented.

In the following part, we will discuss about the computing models (integrated with the knowledge reviewed in this current chapter) that have been proposed for our research.

PART 3

RESEARCH METHOD AND STUDY PROCEDURE

In this part of the thesis, we will first discuss about some education-focus research methods that are currently practised by researchers of the education field and their advantages, our proposed study method and the rationale behind the decision in chapter 4. Subsequently in chapter 5, we will provide the details of the study procedure to be implemented as part of our research.

Teaching and learning processes are complicated and can be influenced by various factors, understood from multiple perspectives and studied using various paradigms. The various methods that can be used to gathering information of effective teaching and learning can be broadly categorized as being qualitative and quantitative. Qualitative data collection methods include, but are not limited to, interviews, observations and surveys. Quantitative data collection methods include, but are not limited to, assessment results, data captured (i.e. use of system, HCI, attention duration and lapses). Once the data has been collected, the process for analysis and evaluation of the data follows.

4 EDUCATION-FOCUS RESEARCH METHOD

The premise of our thesis is primarily related to the field of education, it would only make sense if our research (data collection and analysis) method is similarly education-focused. This section presents the trials of the various model integrated in various learning processes. The educational study focuses on the effects and experience of learning while interacting with the discussed models.

The studies adopted the process guidelines of a design based research methodology and incorporated both qualitative and quantitative methods in the collection and analysis of the data.

4.1 Reviewing the Methodology

Research is one of the many ways to obtain new knowledge or understanding of a phenomenon. Educational research is defined as "the way in which people acquire dependable and useful information about the educative process" (Ary, Jacobs, & Sorensen, 2010), and uses scientific approaches to study educational problems. The ultimate aim of such research is an attempt "to discover general principles or interpretations of behaviour that people can use to explain, predict, and control events in educational situations..." (Ary, Jacobs, & Sorensen, 2010) through a designed and systematic process of collecting, analysing, interpreting and using data in similar contexts (Mackenzie & Knipe, 2006).

A paradigm refers to the "way of looking at the world. It is composed of certain philosophical assumptions that guide and direct thinking and action" (2005), with Mertens categorizing educational and psychological research approaches

into the post-positivism, constructivist, transformative and pragmatic paradigms.

The Post-positivism (developed from Positivism) Paradigm assumes that there is an apprehend-able reality driven by immutable natural laws and mechanism (Guba & Lincoln, 1994) and stems from the belief that the study of the social world is similar to that of the natural world (Mertens, 2005). It is primarily focused on controlled experiments through which researchers can discover reality and deem whether the findings are replicable and true. The positivism paradigm guided early research in the realm of education and psychology research, later developing into the post-positivism. Post-positivism paradigm emphasizes on the importance of adopting multiple methods of inquiry through validation (e.g. triangulation technique) to reduce bias due to the “...basically flawed human intellectual mechanisms and the fundamentally intractable nature of phenomena” (Guba & Lincoln, 1994). As it is impossible for humans to perceive reality in an accurate manner, it is deemed that “replicated findings are probably true (but always subject to falsification)” (Guba & Lincoln, 1994).

The Constructivist Paradigm believes that knowledge can be accumulated by active participation within a social-based research. Through this, researchers can therefore attempt to comprehend the complexity of the real world based on the viewpoints provided. This paradigm emphasizes that scientific knowledge are constructed by researchers and that “research is a product of the values of researchers and cannot be independent of them” (Mertens, 2005). Such researcher personnel adopt the mixed methods where the quantitative data is used to supplement the qualitative data.

The Transformative Paradigm emphasizes on the adoption of various study methods integrated with social justice. This paradigm is primarily focused on gender and social inequality or injustice related. Mertens (2005) has stated that “the transformative paradigm stresses the influence of social, political, cultural, economic, ethnic, gender, and disability values in the construction of reality” and “what is taken to be real needs to be critically examined via an ideological critique of its role in perpetuating oppressive social structures and policies”.

The Pragmatic Paradigm places emphasis on the research problem, stemming on the belief that the “truth is what works at the time” (Creswell, 2003).

Pragmatic researchers may adopt various methods of data collection and analysis to arrive at the optimal understanding relating to the research problem.

The pragmatic paradigm has influenced the method and type of data collected in this thesis research. The research questions which drive the data collection are focused on the aspects of learning outcomes, activities and experiences, which are deemed necessary to persuade a sustainable self-directed learning behaviour with minimal human supervision.

The methods used to collect, analyse and report the data in a research process are generally categorised as being of quantitative or qualitative in nature, or of mixed methods. The following section will describe and discuss on the mentioned methods and the appropriate method to be adopted in this thesis.

4.1.1 Data Collection Methods

Quantitative methods involve the collection of data (numerical) from participants which are then analysed with statistical, mathematical or computational techniques and subsequently used to investigate social

phenomena or the proving of theories. These methods are fundamentally used to develop theories relating to phenomena and usually rely on a hypothetical-deductive explanation model. The research process begins with an inquiry or a theory of the phenomenon which seeks investigation. Hypotheses are then formed and tested, from which theories are subsequently refined, extended or deserted (Ary, Jacobs, & Sorensen, 2010).

Qualitative methods are primarily used in constructivist based researches that are “designed to provide an in-depth description of a specific program, practice, or setting” (Mertens, 2005). The adoption of such methods is “to portray the complex pattern of what is being studied in sufficient depth and detail so that someone who has not experienced it can understand it” (Ary, Jacobs, & Sorensen, 2010). These methods collect data through field-work, which includes and is not limited to interviews, observations and document analysis. Data collected can be presented through Data collected include interview notes of discussions (individual or group), field notes of observation and reflection, photos and other materials. These data are then analysed in bid to interpret the phenomena in question. Such methods are fundamentally focused on the research context, meaning and setting; that “human behaviour is context bound - that human experience takes its meaning from and, therefore, is inseparable from social, historical, political, and cultural influences” (Ary, Jacobs, & Sorensen, 2010). In contrast to the quantitative methods, in the experimental context, “qualitative research studies behaviour as it occurs naturally” (Ary, Jacobs, & Sorensen, 2010) and, more often than not, consider a wide range of contextual factors and influences.

Mixed methods are often adopted as it is believed that a combination of multi-approaches will enable a better understanding of a particular phenomenon, by enabling researchers to utilize the various strengths of each method and hence provide more and better information. As stated, "by mixing methods in ways that minimize weaknesses or ensure that the weaknesses of one approach do not overlap significantly with the weaknesses of another, the study is strengthened" (Ary, Jacobs, & Sorensen, 2010). Mixed methods involve both qualitative and quantitative methods in a single study in bid to obtain a deeper understanding of a phenomenon. Both qualitative and quantitative data are collected and analysed. However, it must be noted that the process is not a mere combination of two different methods but "incorporates and embraces blends of paradigms, philosophical assumptions, and theoretical perspectives directly driven by the purpose of the study and the intended audience" (Ary, Jacobs, & Sorensen, 2010).

The choice of data collection method should be determined by the paradigm adopted and research question and it is noteworthy that it is feasible for all paradigms to adopt mixed methods, as opposed to a singular, to avoid the limitation of depth and richness in a study (Mackenzie & Knipe, 2006). In the table below Table 6, Mackenzie and Knipe has provided a summary of appropriate data collection method which corresponds to the research paradigms discussed in the previous chapter.

Table 6 Paradigm, method and Tools Examples

Paradigm	Data Collection Method	Tools Examples
Post-positivism	Predominantly quantitative but qualitative methods can be used.	Experiments, tests, scales.
Constructivist	Predominantly qualitative methods but quantitative methods can be used.	Interviews and observations
Transformative	Mixed methods (qualitative and quantitative).	Diverse range of tools.
Pragmatic	Mixed methods (qualitative and quantitative). Attention should be paid to research purpose and question.	Includes tools from both positivist and constructivist paradigms. E.g. interviews, observations and formative or summative assessment data.

My research will adopt the mixed methods for data collection and analysis.

While there are several advantages to conducting mixed methods research as opposed to conducting just a quantitative or qualitative research, I will discuss upon the primary reasons that are particularly of significance to my study:

- 1) Mixed methods allow the collection of various data that covers as many research aspects as possible. Particularly for research areas with limited existing knowledge (such as this study), it is of great importance to collect a wide range of data;
- 2) The mixed methods allow the collection and analysis of both types of data, qualitative and quantitative, providing opportunities for deeper insights as compared to deploying only either method. Hence, a more

comprehensive and in-depth understanding of the phenomena is achieved;

- 3) The mixed methods research allows for the compensation of one method's weakness with the strength of another.

4.2 Developing a Design-based Research

This thesis adopts a design-based research approach (Design-Based Research Collective, 2003). It integrates design and research to achieve a better understanding of educational phenomena and refers to the “systematic but flexible methodology aimed to improve educational practices through iterative analysis, design, development, and implementation, based on collaboration among researchers and practitioners in real-world settings, and leading to contextually-sensitive design principles and theories” (Wang & Hannafin, 2005).

Ultimately, this research aims to improve the benefits of e-Learning through the design and development of empowering new technologies with the ability to persuade self-directed learning.

4.2.1 Rationale for Design-based Research

The following section will elaborate on my rationale for adopting a design-based method:

- 1) It is deemed that in design-based research, “the central goals of designing learning environments and developing theories or 'prototheories' of learning are intertwined” (Design-Based Research Collective, 2003). In addition, it is a methodology that “seeks to increase the impact, transfer, and translation of education research into

improved practice... it stresses the need for theory building and the development of design principles that guide, inform, and improve both practice and research in educational contexts” (Anderson & Shattuck, 2012). Design-based research in education is fundamentally steered by two broad objectives – “to develop educational products... that work and to build a theoretical framework for future designs” (Bowler & Large, 2008). To sum it up, design-based research best-fits when the objective is to achieve both theoretical and practical goals. This affirms the needs of this research as the foremost priority purpose is to design and develop a collective methodology that can assist learners in discovering their self-directed learning method. Secondly, it is to study the learning experience from learning interactions to possibly generate future theories on e-Learning and discover guidelines for the betterment of learning system design and development. Therefore, the design-based method is fitting to the objective of this study.

- 2) Design-based research “typically involves mixed methods using a variety of research tools and techniques” (Anderson & Shattuck, 2012) and the “researchers assume the functions of both designers and researchers, drawing on procedures and methods from both fields, in the form of a hybrid methodology” (Wang & Hannafin, 2005). My research is aimed at studying the learning process from various perspectives, including learning outcomes (as the educator) and the experiences (as the learner). Therefore, a mixed methods research is a fit to my study as both in-depth analysis of qualitative and quantitative data is required, in order to provide and acquire a deeper understanding of e-Learning.

In summary, the design-based research approach can sufficiently support the practical and theoretical goals of my study.

4.2.2 Phases of a Design-based Research

There are four phases to a design-based research (Amiel & Reeves, 2008) in Figure 6. It begins with an analysis of practical problems whereby the researcher ascertains appropriate research questions and identifies potential problems as part of the study plan. Secondly, intervention is proposed to address the problem. Next, the proposed intervention is applied to the problem in a practical setting. Here, data will be collected for analysis and reflected upon to develop new or further designs. This is a cyclic process “of design-reflection-design” (Amiel & Reeves, 2008). Lastly, the researcher arrives at outcomes of “a set of design principles or guidelines derived empirically and richly described, which can be implemented by others interested in studying similar settings and concerns”.

This study follows the phases as proposed and described above and can be presented as:

- Review of existing e-Learning work developed to facilitate teaching and learning, document potential user and pedagogy-based issues and requirements of such learning systems.
- Design of the various computing models that support the fundamental requirements and solutions to issues.
- Implement a pilot study with real users. Using data evaluated from the pilot study, a subsequent follow up study should be conducted to resolve initial

problems (i.e. technical issues) and to obtain a more detailed understanding of the learning experience and outcome (if any).

- Collection and compilation of data for reflection and summarisation for the proposal of new or advancements to existing theories.

Figure 6 Design-based Research Phases

4.2.3 Phenomenography as the Adopted Method for Qualitative Study

Phenomenography extends from a set of investigations based upon learning effectiveness amongst students at the University of Goteborg from as early as the 1970s. It is a qualitative research method that is extensively adopted by researchers of the learning domain and deals with the content and act aspects of learning - different ways of understanding learning content, experience of learning and act of learning. In short, it can be described “a research method for mapping the qualitatively different ways in which people experience, conceptualize, perceive, and understand various aspects of, and phenomena in, the world around them” (Marton, 2001).

4.2.4 Studying of Experiences using Phenomenography

Phenomenological research "rooted in philosophy and psychology, the assumption is that there are many ways of interpreting the same experience and that the meaning of the experience to each person is what constitutes reality" (Ary, Jacobs, & Sorensen, 2010). Such research is directed towards the experiential description as perceived by the research subjects - to understand experiences through the analysis of descriptions. It is concerned with studying the human experience of and not merely a study of the given phenomenon and "the object of the research is the variation in ways of experiencing phenomena" (Marton & Booth, Learning and awareness, 1997).

Figure 7 Phenomenographic Relationality

In other words, a phenomenographic study studies the "internal relationship between the experiencers and the experienced." (Marton & Booth, Learning and awareness, 1997) (Figure 7). The study aims to analyse the collective experiences from individuals who are "seen as the bearers of different ways of experiencing a phenomenon, and as the bearers of fragments of differing ways of experiencing that phenomenon. The description we reach is a description of

variation, a description on the collective level, and in that sense individual voices are not heard. Moreover, it is a stripped description in which the structure and essential meaning of the differing ways of experiencing the phenomenon are retained, while the specific flavours, the scents, and the colours of the worlds of the individuals have been abandoned” (Marton & Booth, Learning and awareness, 1997).

4.2.5 Phenomenography for the Categorization of Experiences

Phenomenographers seek the totality of methods through which individuals are able to experience an object of interest (the given phenomenon) to distinguish, categorize and describe the essence of the variations of their experiences (Marton & Booth, Learning and awareness, 1997). It is noteworthy that the 'totality' here is viewed as a limited number of ways (qualitatively) in which the given phenomenon can be experienced differently and the researchers strive to find the limited experience categories of a subject group in their defined context.

As mentioned, the outcomes of a phenomenographic research are categories of descriptions and relations between these categories. They describe the internal relationship between the research subjects and the given phenomena – or their perceived experiences, and are in no part psychological or physical.

These various distinct categories of descriptions and relations together form the "outcome space", is usually displayed using a diagram format that indicates the categories and their respective relationships. The diagram information presents useful and meaningful information which describes the variations to the experiences to provide insight "into what would be required for individuals to

move from less powerful to more powerful ways of understanding a phenomenon” (Åkerlind, 2005).

Since the fundamental purpose of this research is to enrich the learning experience, the phenomenographical approach seems to be the fitting method for it provides varying insight from the individual learner’s multiple perspective (i.e. summative, formative, qualitative and quantitative). Furthermore, it provides the essential second order perspective necessary for the desired purposeful and meaningful learning experience, by having researchers report on the ideas of individuals with first-hand experience of the given phenomena.

5 THE STUDY PROCEDURE

Throughout the course of study procedure, various information (including student's learning profile, progress and quality of experience) were collected using varied means for a deeper and more extensive study scope. The methods include interviews, assessment results, time and HCI based data logs and questionnaires.

Training Sessions:

Training sessions are used to provide the benchmark data for the configuration of the users' profiles (mouse-movement, scales for pleasure, arousal and efficacy for dominance). The training sessions comprise of phases in which users are presented on-screen contents, feedback and tasks.

They were expected to report their level of "P" after reviewing on-screen contents which include learning contents and articles that reported happy and angry events. Mouse-movement data are recorded at intervals of 50ms and tagged with the reported "P" values.

For the configuration of the "A" setup, users had to undergo a training process, in which the benchmark of mouse cursor movement duration was captured via 2 activities: (1) user had to navigate the interface, sequentially identify the required icons that are equally spaced, and click on them; (2) repeat the same activity. Activity 1 serves to identify the average cursor movement and distance (interface navigation) for learners who are in the state of confusion, and the latter activity serves to provide the average mouse speed and distance of the learners in a normal setting (e.g. non-confusion).

Configuration of “D” data includes a self-efficacy assessment by means of a SAM Scale (similar to that of Pleasure pre-test) and knowledge of success and failure of solving from a fixed-set of problems.

Interview:

Students were individually interviewed, in attempt to capture the most truthful and authentic perceptions of their learning experiences. This data was analysed in attempt to understand problems (beyond usability aspects) in learning with current technologies. In the interviews, the study group was encouraged to discuss about the quality of learning experience, problems faced, suggestions and reasons for improvements.

Summative Assessment Results:

Summative assessments were conducted and the results were captured as valuable data to observe for negative consequences in academic learning due to the flexibility and personalized learning experience via the varied content presentation.

Time and HCI based Data Logs:

Time and HCI based data were captured and logged, from the time students logged onto the system until they are finished with the lesson session. This data was analysed for time increment (if any) in learning durations beyond standard learning duration to observe for learning behavioural changes. HCI based data was used to evaluate for attention lapses and identify possible difficulties for learning progression.

Questionnaire:

Questionnaires involved in the study includes a Teaching and Learning survey, for data related to learning engagement, Learning Personality survey, as well as a Self-Reported Interest Level survey that has been adapted from the Self-Assessment-Manikin (SAM) (Bradley & Lang, 1994) Point Scale, to gain awareness of student's self-reported interest level.

It has been shown that emotions are universal expressions; individuals from various cultures all over the world were able to accurately associate emotion descriptors (e.g., Sadness, Anger) to facial expressions. This supports the choice of SAM as the tool for self-reported emotional state in this thesis due to its use of graphic icons to illustrate emotions, reducing the likelihood for misinterpretation.

5.1 Further Study Procedure

The study group comprises of 40 secondary school students yes. in Singapore. The students generally possessed weaker learning abilities (Normal Technical), according to the national academic streaming, and common e-Learning problems the teachers faced were often related to attention span. The teacher was a friend of the researcher, easing the facilitation and organizing processes for the study. This arrangement also provided the convenience for conducting the study in a familiar learning environment (actual learning lab for the students on a daily basis). Students were explicitly instructed that they are allowed to leave without incurring any direct or immediate consequences.

The students were subsequently interviewed (one to one) to understand their learning experiences, in addition to the administered questionnaires and screen

recordings to ensure that data was collected from varied sources and could provide deeper insights to the understanding of the learning experience from various aspects.

5.1.1 Reliability

Reliability is commonly defined as the degree in which study findings can be replicated (Sin, 2010). It has, however, been argued that qualitative studies cannot be replicated due to the flexibility, dynamics and creativity in the examination of a phenomenon at one given point of time (Fidel, 1993). What this means is that data obtained from such a study can only be a reflection of the real world in the time it was collected, making absolute replication almost unachievable.

The research in this thesis involves the study of a student group's learning experience. The data collected will differ with varied participant groups, particularly those of different academic streams. In addition, the usage of unstructured interviews to gather experiential data as well as the integration of the researcher's ideas makes a qualitative research approach unavoidable. Therefore, a replicated study may not yield similar results.

To compensate this limitation, data collection method was focused on accuracy and comprehensiveness. A couple of steps were adopted to achieve this:

- 1) Interviewees were given the freedom and opportunity to openly discuss about their experience and share their thoughts without biased opinions and comments (safe environment) from the interviewer;

- 2) Interviews were recorded to reduce the need for interviewer to recall details from conversational dialogue or student's behaviours from memory.

5.1.2 Validity

Validity refers to “the extent to which any measuring instrument measures what it is intended to measure” (Carmines & Zeller, 1979), and is concerned with the accuracy of the means of measurement and if the data measured corresponds to the required and intended information (Winter, 2000).

The Triangulation techniques (Denzin, 1970) has been adopted as a strategy in this research to achieve optimal and strengthen validity of captured data by employing different methods to investigate the phenomenon from various angles (Golafshani, 2003). Triangulation, in this thesis, refers to the “combination of methodologies in the study of the same phenomena... involving varieties of data, investigators, and theories, as well as methodologies...” (Denzin, 1970)

Denzin (1970) has defined four basic triangulation types:

- 1) Data - Using various sources of data in one study;
- 2) Investigator - Using various researchers or evaluators in one study;
- 3) Theory - Using various theoretical schemes to interpret one phenomenon, and
- 4) Methodological - Using various methods for data collection.

The thesis primarily adopts the methodological triangulation for in-depth collection of various data (e.g. interviews, questionnaires and screen recordings) and stems from the belief that "engaging multiple methods, such as,

observation, interviews and recordings will lead to more valid, reliable and diverse construction of realities” (Golafshani, 2003).

5.1.3 Limitations

One of the main limitations that should be noted was the relatively small sample size ($n < 40$) of the study, making it a considerable factor before generalizing to a wider community. However, the results from analysing data collected from various sources makes it a rich and valuable information source that will provide deeper insights related to learning via new technologies.

5.2 Application into Real-World Classroom

In real classroom settings, an experienced teacher can quite easily detect (subjected to student teacher ratio) a student's emotional changes to render assistance or support. In contrast, online learning has decreased the possibilities for monitoring such learning reactions, and thus limits the ability for quick reactions to emotional changes in real time. In addition, learning systems are getting increasingly complex (Randall, Terwiesch, & Ulrich, 2007) and various emotional reactions (e.g., frustration) may arise from its usage. Particularly, negative emotions can result in premature termination of usage and negative impressions of the system will spread by word of mouth surpassing the positive aspects of it (Dellarocas, 2003) (Mulpuru & Hult, 2010).

The usual equipment or techniques that are used for emotion in a lab-based context involve electroencephalogram, skin conductance, blood volume and pressure (Chanel, Kronegg, Grandjean, & Pun, 2006) (Leon, G. Clarke, & Sepulveda, 2007) as well as gaze and facial data (Happy, 2013) (Jaques N. e., 2014). But in a real-world application, especially that of a classroom learning

environment, a significantly less or unobtrusive method has to be adopted.

First, the setup cost will be huge. Secondly, there is a need to minimize the disruption of the students' learning process for a safe learning environment, and in such scenarios, we can rely on the interactions between the user and the standard computer input devices e.g. keyboard or mouse.

SUMMARY OF PART 3

Part 4 reviewed various education-focus study methods and evaluated their compatibility for our study.

As the nature of our research is inclined towards the sustainability of learning engagement and motivation rather than mere quantitative results (i.e. assessment scores), there is a need for more focus to be placed on the emotional state and qualitative feedback of the learners. Therefore a phenomenographical approach seems to be the fitting method for it provides varying insight from the individual learner's multiple perspective (i.e. summative, formative, qualitative and quantitative).

In the second part, we discussed about the implementation considerations for an actual study for our research. This included the considerations that may influence the test results as well as the various learning experience and outcome evidence that we would like to collect to support the phenomenographical study.

In the following part, we will discuss the application procedure into a real-classroom learning scenario, procedure for data collection and the analysis to evaluate effectiveness of our proposed method.

PART 4

PROPOSED COMPUTATIONAL MODEL FOR PERSUASIVE ADAPTIVE LEARNING (PAL)

In this part, we propose a computational model for Persuasive Adaptive Learning (PAL). We will first discuss upon the extension to the FBM for the persuasion of targeted learning behaviour in a blended learning environment with the integration of the proposed computing models: (1) a computational model to analyse a learner's affection and cognition engagement levels based on the HCI-data to minimise intrusion; and (2) a computing model that automates feedback based on user's competency and acceptance of feedback. Subsequently, we will discuss our proposed method of evaluating HCI for the provision of feedback to reduce the assumptions of factors that hamper the negotiation of a positive emotional state (via the learning experience).

Feedback is critical in providing guidance and motivation for learners who may be facing difficulties or are low in motivation. An independent learner who refuses assistive feedback should not be compelled to accept assistance. That said, he should also not be left without guidance. The success of a learning process can be attributed to the learner's acceptance towards feedback type and content. In order to achieve this, the system would have to interpret the user's perceived state of experience (i.e. bored, frustrated or upset with inability to progress) in order to provide the necessary support that would reduce the negotiation of negative emotional states.

6 DESIGNING THE PAL MODEL

As mentioned, the FBM is an established persuasive model that can be used in the understanding and planning of a learning behaviour. However, the model would require expansion to enhance analysis and support of a learning behaviour with the increase in ICT-integration (blended learning).

Figure 8 Proposed Expansion to FBM for PAL

With blended learning comes the potential to support the monitoring of students' learning behaviours on a large scale, as compared to the traditional classroom ratio. Computational mechanisms have provided us the affordances in the real-time collection and manipulation of various data that can be leveraged on to enhance the FBM (Figure 8) for adaptive learning. In this chapter of the thesis, an overview of PAL (with its various computational models that have to be integrated) will be presented and discussed in detail (Figure 9).

Figure 9 Overview of PAL (with integrated models)

This includes the computing model for learning affection of the users and the automation of feedback generation to suit learners based on their learning profiles for maximising effectiveness. These models are critical to an optimal learning outcome as mood, engagement level and reception towards learning content and feedback can directly affect any learning process.

Figure 10 illustrates the how the data captured (user's self-assessment to HCI data) are used to establish the affection, behavioural and cognitive states of the learning experience to persuade the targeted learning behaviour..

Figure 10 From CBT to PAL (via FBM)

Figure 11 Integration of selected models for PAL

Fundamentally, the initial generated experience should cater to the learner based on his profiling but the assumption is verified through the analysis of captured HCI data (Figure 11). An observed digression in HCI data initiates the further analysis for possible motivation/ability issues that will result in an adjustment of feedback to reduce the assumed conditions that may result in the negotiation of a negative emotional state. Through this evaluation, or reduction of assumptions based on systematic analytic steps, the system serves as a more effective monitor of learning experience as compared to its human counterpart, the teacher.

Described in this subsequent work phase, identified learning goal(s) will be represented as nodes (round dots) using the Goal NET modelling structure. Each node can be indicated as a composite (sub-goals for differentiated learning processes) or atomic and represent the various learning sequences that is aligned to and will serve their higher level learning goals. Transitions (line with arrowhead) that connect these nodes depict the possible tasks the system is required to perform to transit from input to output (i.e. evaluation of content type, difficulty, need for scaffold and emotions). The systemic structure of learning goals allows for the allocation of suitable feedback – content or support, at the precise interval of the learning experience where a potential change in the emotional state of the learner (Trait A) triggers the need for further evaluation of cause (Trait P or D) (Table 7).

Evaluating P-A-D trait values within the virtual environment is a constant and ongoing process at designed interval points, e.g. task completion or accepting hints. The values of the traits lie between positive and negative. The “Pleasure” trait refers to the degree which one feels good or satisfied in a situation. In an

online context, pleasure is akin to “sense of likeability” (Poels & Dewitte, 2008). “Arousal” consists of a person's levels of mental alertness and physical activity. High-information (i.e., complex, new and/or unexpected) situations or events increase arousal (McNamara, Kintsch, Songer, & Kintsch, 1996). Reaction time is positively correlated to mental alertness and time-speed duration (Koga & Morant, On the degree of association between reaction times in the case of difference sense, 1923) of user accepting task events or mouse interactions, e.g. moving the mouse, is evaluated as the A trait value. “Dominance” trait deals with the feeling of control over situations and degree or freedom to act and is a relevant emotional response as users have more control over their environment (Richard, 2005). The learner’s ability (accuracy and rate) to complete tasks is evaluated as the D trait value.

Table 7 Definition of PAD

Pleasure (P)	Emotional State
Arousal (A)	Level of Physical Activity and mental alertness
Dominance (D)	Feeling of control

Table 8 Mood Octants of the PAD space

Trait Combination	Affect	Type	Trait Combination	Affect	Type
+P+A+D	Exuberant	Positive	-P-A-D	Bored	Negative
+P-A+D	Relaxed	Positive	-P+A-D	Anxious	Negative
+P+A-D	Dependent	Positive	-P-A+D	Disdainful	Negative
+P-A-D	Docile	Positive	-P+A+D	Hostile	Negative

The original PAD model had defined 8 combinations based on the combinations of the 3 trait values and Table 8 details these respective emotions that are arranged such that opposite moods (extreme opposing scales) are in the same row (Figure 12), e.g. Exuberant vs Bored. The first 2 rows correspond directly towards self-emotional states. The bottom 2 rows (i.e. hostile and disdain) relate towards reactions to an Other (e.g. in person-to-person interaction), and are less relevant in a blended learning experience (that often lacks a human tutor).

Figure 12 PAD combinations representation

In a blending learning environment, we are more concerned with row 1 and row 2, where both the complementary moods are taken into account. These are emotional states that can be resulted from interaction with a computer system.

The decision to select the 2 pairs of the PAD combinations was fundamentally based on their corresponding emotions and their focus objects. Since our proposed model seeks to personalize a blended learning experience for a user, the emphasis was to place the “self” as the focus object.

The OCC model (Ortony, Clore, & Collins, 1988) provides a clear and convincing structure of the eliciting conditions of emotions and the variables that affect their intensities. The intensities are primarily dependent on the events, other agents, or objects in the environment of the agent. This

psychological model is popular among computer scientists that are building systems that reason about emotions or incorporate emotions in artificial characters.

There are 22 emotion categories listed in the OCC model. These can be mapped into the dimensional space of the PAD emotional model (Bock, 2009) and further categorized into 2 main groups according to its focus object (self or other). The focus object categorization is derived from the definitions of the various emotion categories using a cognitive appraisal approach (Table 9). 20 of the OCC emotions clearly indicate the focus object as being self or other except for Love and Hate(Table 10). Due to this ambiguity, we will categorize them as being Self/Other.

Table 9 Definitions of OCC Emotions

OCC Emotion	Definition
Joy	(pleased about) a desirable event
Hope	(pleased about) the prospect of a desirable event
Relief	(pleased about) the disconfirmation of the prospect of an undesirable event
Pride	(approving of) one's own praiseworthy action
Gratitude	(approving of) <i>someone else's</i> praiseworthy action and (being pleased about) the related desirable event
Happy-for	(pleased about) an event presumed to be desirable for <i>someone else</i>
Gloating	(pleased about) an event presumed to be undesirable for <i>someone else</i>
Distress	(displeased about) an undesirable event
Fear	(displeased about) the prospect of an undesirable event

Disappointment	(displeased about) the disconfirmation of the prospect of a desirable event
Remorse	(disapproving of) one's own blameworthy action and (being displeased about) the related undesirable event
Anger	(disapproving of) <i>someone else's</i> blameworthy action and (being displeased about) the related undesirable event
Admiration	(approving of) <i>someone else's</i> praiseworthy action
Resentment	(displeased about) an event presumed to be desirable for <i>someone else</i>
Fears-confirmed	(displeased about) the confirmation of the prospect of an undesirable event
Pity	(displeased about) an event presumed to be undesirable for <i>someone else</i>
Gratification	(approving of) one's own praiseworthy action and (being pleased about) the related desirable event
Reproach	(disapproving of) <i>someone else's</i> blameworthy action
Shame	(disapproving of) one's own blameworthy action
Satisfaction	(pleased about) the confirmation of the prospect of a desirable event
Love	(liking) an appealing object
Hate	(disliking) an unappealing object

Table 10 Mapping OCC into PAD with Focus Object

Emotion	Mood Type	Focus Object
Joy	+P+A+D (Exuberant)	Self
Hope	+P+A-D (Dependent)	Self
Relief	+P-A+D (Relaxed)	Self
Pride	+P+A+D (Exuberant)	Self

Gratitude	+P+A-D (Dependent)	Other
Happy-for	+P+A+D (Exuberant)	Self
Gloating	+P-A-D (Docile)	Other
Distress	-P-A-D (Bored)	Self
Fear	-P+A-D (Anxious)	Self
Disappointment	-P+A-D (Anxious)	Self
Remorse	-P+A-D (Anxious)	Self
Anger	-P+A+D (Hostile)	Other
Admiration	+P+A-D (Dependent)	Other
Resentment	-P-A-D (Bored)	Other
Fears-confirmed	-P+A-D (Anxious)	Self
Pity	-P-A+D (Disdainful)	Other
Gratification	+P-A+D (Relaxed)	Self
Reproach	-P+A+D (Hostile)	Other
Shame	-P+A-D (Anxious)	Self
Satisfaction	+P-A+D (Relaxed)	Self
Love	+P+A+D (Exuberant)	Self/Other
Hate	-P+A+D (Hostile)	Self/Other

6.1 Designing the Experience Structure

The Goal NET model is a fitting model to use in our design as it supports the translatability of learning objective and sub-goals into transitions and nodes.

Through this, it value-adds to the design process as it supports the designers

and educators in thinking on both the macro and micro levels to minimise commonly overlooked areas by acting as a check-list.

Human-Computer Interaction (HCI) data is derived via a system based on a mouse tracker system which made available as a purchased module. We do not seek to reinvent the wheel as the focus of this thesis is not focused on building a tracker, but rather to take advantage of ready technology to support and enhance learning by leveraging on HCI information.

The mentioned mouse tracker is known as the “userTrack - Mouse Monitoring System” which is available on the envatoMarket. The system is a HTML5 based platform that uses jQuery and PHP to communicate in addition to a MySQL based server for data logging and retrieval of learner’s profile information. It is used to record user’s mouse interactions on a site and generates data that includes click, mouse movement and scroll heat-maps with the ability to do full recordings of all user interaction activities and idle times between events. The installation requirement (file size) is compact and its system requirements are affordable and common. One disadvantage, however, is that while it is minimally taxing on data communication with the servers (small data packet), there is still a need to cap simultaneous users (<50 simultaneous connections) for optimal results.

Figure 13 System Overview

Figure 14 System Diagram of the proposal PAL

Figure 13 and Figure 14 shows an overview of the system (processes and components) involved in the study. Interactions refer to the learner's human-computer interactions with learning contents (i.e. feedback, information and assignments). These HCI data is captured by the userTrack system which has been modified to the drive a server-side script that tracks and monitors data for changes and triggers the automation of feedback. Learning contents used in the experience are designed by their teachers and store in the server along with

documented HCI and learning personality data of the students. Details of our proposed computing models will be discussed in the sections after this.

In the integrated system comprising of the computing models (learning affection & engagement and automated feedback), HCI data is monitored, captured and analysed at 2 levels: understanding the current emotional state of learning to decide the next course of action (i.e. proceed with learning content or rest-break) and the feedback type (i.e. type of learning content) with the former superseding the latter in a pre-defined Goal NET sequence. For example, a learner displaying boredom will trigger a rest-break prompt and a pause in learning content presentations even when he is assessed to be proceeding above average on the current task-performance (Figure 15). More details of the Goal NET graphical representation and computing models will be discussed in the following sections.

Figure 15 Goal NET Example

6.2 Goal NET

An example of a Goal NET graphical representation is shown in Figure 16.

Figure 16 Goal NET

S	defines a set of goal states that needs or can be achieved. Start and Terminal states are special states represented as S and E respectively. Goal states are represented as nodes ($S_0...S_n$) in a GOAL NET graphical representation.
Arc	defines a set of arcs that connects goal states from one to another to a unified goal structure. They are represented as arrows .
T	defines a set of transitions and states the specific task requirements before progressing from one goal state to the next. Each Arc is coupled with a transition (stating the task to be fulfilled) and indicates the possible selectable path between goal states. Transitions are represented as a vertical bar ($t_1...t_n$).

The Goal NET modelling has the following properties:

- **Hierarchy** – Goals (**S**) can be categorized as atomic or composite. A composite type of goal represents a higher level of behaviours comprising of a hierarchy of sub goals that states other lower level behavioural implementations.
- **Temporal** – Transitions(**T**) occur in a temporal manner of relationship which includes sequence, concurrency, choice and synchronization.
- **Polymorphism** – Associated with each transition are specific action strategies that can be realized. These action strategies include direct, conditional and probabilistic.

A Goal NET allows for automated reasoning and decision-making on selections of next goals (**goal selection**) and which possible actions (**action selection**) that should be performed so that the goals can be achieved.

Goal selection defines the process of identifying a sequence of goals, including sub goals, and highlighting the arc sequence for goal-achievement.

Action selection defines the process of transition selections on an arc. It is responsible for the sequence of tasks that has to be executed for an arc to be completed to enable goal-accomplishment.

There are three types of action selection strategies, which includes:

1. Sequential execution – actions are selected based on a fixed sequence, regardless of external factors.
2. Rule-based inference – a set of rule can be applied to influence the selection of action. When the information required for action selection is clearly-defined and complete, it allows for the establishment of the premise of an action-selection rule that can be triggered when the requirements are fulfilled.
3. Probabilistic inference – Adopts the Bayesian networks model of inferring the relationship between states and optimal actions based probabilities in the event of incomplete and uncertain information.

The Goal NET modelling approach has been adopted for various practical reasons which include:

- While the ultimate goal is to facilitate learning, this higher-level goal can be decomposed into various sequences of lower-level learning sub

goals, e.g. learning pre-knowledge engagement, learning feedback and scaffolds or even the various sub-units within a learning chapter. The nature of sub goals composition allows for this flexibility.

- Learning experience varies with individuals, learning contents and even learning feedback. A static and linear setup of goals would hardly suffice for varied learning experiences. The Goal NET modelling approach allows for an establishment of a root goal, and the flexibility for sequential connecting all the sub goals (and states) that allows for the various evaluation of learning experience (i.e. emotion and performance) and selection of appropriate actions that will allow the root goal to be achieve.

Following the introduction of the Goal NET model, the next section will discuss on attributes that make good fittings for automation of a personalized learning experience. These attributes include considerations for personality, goal setting and feedback generating. There are multiple advantages in understanding these attributes, the learning experience designer will have a better knowledge of the various psychological issues (i.e. UI and information presentation) that can affect learning outcomes, the pedagogies in designing age and context appropriate feedback and contents as well the need to decompose higher level learning goals into ‘bite-size’ proportions to suit varied learning abilities. For a start, we will propose the need for a computing model that is based on the understanding of some general learning personalities and their learning needs (i.e. requirements to support their cognitive and emotional processes), both of which are crucial to attain a desirable learning outcome.

6.3 Computing Model for Automating Feedback based on Learning Profile

Figure 17 Overview of Lesson Experience Generation

In the figure above, an overview of the lesson experience generation is illustrated. In the planning phase, the authors (teachers) will decide on the lesson objectives (i.e. lesson chapters), learning content (i.e. information presentation style) and feedback (i.e. break intervals). The engineers will assign the relevant type of learning content and feedback in accordance to learning personality requirements in attempt to generate the best experience for first-time users to reduce the assumption of a potential negative emotional state

experienced as a result of mismatched learning content. Once the lesson experience has been generated, HCI (i.e. mouse movement speed and idle durations) and quantitative (i.e. task errors) data are captured and logged for user profiling (benchmarking). Computational models are integrated in this collective process to automate the generation of lesson experience based on the analysis of these data. The data include information of the learner's affection, behaviour changes and cognitive ability and progress. The models may seemingly work independently but the outputs from the analysis are used in decision making for the assignment of appropriate learning contents, feedback and intervals to sustain engagement and motivate the learner. In the following sections, the models will be further discussed upon.

However, learning styles may vary with topics and it should not be assumed that the generated experience would be consistently compatible. Hence, the generation process will be executed when triggered by a change in incoming HCI data (increase or decrease "A" trait value). The computing model for analysing HCI data will be presented in the following section.

6.3.1 Measuring the Pleasure "P" trait value

Emotions have been shown to influence users' actions in a situations; it has been demonstrated that hand movements (e.g. control of the mouse input device) can be influenced by different emotions (Maehr, 2005) (Zimmermann, Guttormsen, Danuser, & Gomez, 2003). Negative emotions (with over 81.7% accuracy) have been known to increase the distance and reduces the speed of mouse cursor movements during the task (Martin, Jeffrey, Christoph, & Markus, 2017).

The first component of measuring affection (“P”) elicits the learner’s self-evaluated affection towards screen elements that provide information, e.g. hints, or interactions using a Self-Assessment Manikin (SAM) shown in Figure 18 and evaluating it against logged mouse-movement data to reduce noise data and validating the “A” data that will be discussed in the following section.

This value is constantly evaluated to derive changes in “likeability” of the screen elements before and after interactions, e.g. task completion.

Figure 18 "P" trait value evaluation using SAM

The SAM is fundamentally based on a scale of 1-10 with the value of 5 representing the benchmark. Values of 1-4 represent a “-P” while 6-10 denotes a “+P”. The attribute can be calculated according to the formula below:

Let x = average mouse-movement capture in 50ms.

If

$$(value \geq 5 \rightarrow "P" = +P) \wedge (value < 5 \rightarrow "P" = -P)$$

The logs of mouse-movement data and self-assessed pleasure states set the threshold for defining the Arousal states (-A or +A). Excessive mouse-movement (spike in movement and beyond the significance of 10% data change from previous recorded interval) indicates that there is a possibility that the user is in a state of high arousal or negative emotion. The mentioned threshold provides the model a means to differentiate between a “-P” or “+A”.

While the “P” value can be obtained via the simple method of using a SAM, there still exists the need to further analyse HCI data to derive the “A” and “D”

trait values for a clearer evaluation of the learner’s emotional state. In the following section, we will discuss upon the computing model that allows us to derive arousal (“A”) and how mouse-movement data is used to validate this data.

6.4 Measuring the Arousal “A” trait value

Figure 19 Activity Diagram

In a restricted learning environment, students tend to keep their feelings to themselves, but will readily vent out their frustrations or boredom in the

comfort of their home. What we are concerned here is the affection state that can influence the goal of negotiating a positive emotional state.

In our computing model, we are concerned with detection changes to HCI data (mouse movements). This concept stems from the theory of “grounded cognition” and have been used in various studies (Scheirer, Fernandez, Klein, & Picard, 2002) (Zimmermann, Guttormsen, Danuser, & Gomez, 2003) (Maehr, 2008).

As an experiment to assess effectiveness of our proposed computing model (emotional change detection), a standalone application (prototype system) was made to run concurrently with the learning session involving WizLearn. The infrastructure was implemented to record each learner’s mouse cursor parameters and corresponding timestamps. In addition, a calculation script (MT Calculation) was developed to establish a benchmark and analyzing current mouse cursor movement parameters (Figure 20), for deviations which stored in an external database.

Normalized time	X (Cond 1)	X (Cond 2)	Y (Cond 1)	Y (Cond 2)
1	0	0	0	0
2	0.0002	0.0001	0.002	0.002
3	0.0002	0.0001	0.002	0.002
4	0.0002	0.0001	0.002	0.002
5	0.0002	0.0004	0.002	0.002
6	0.0002	0.0004	0.002	0.002
7	0.0002	0.0004	0.002	0.002
8	0.0002	0.0004	0.002	0.002
9	0.0002	0.0004	0.002	0.002
10	0.0002	0.0004	0.002	0.002
11	0.0002	0.0004	0.002	0.002
12	0.0002	0.0004	0.002	0.002
13	0.0002	0.0004	0.002	0.002
14	0.0002	0.0004	0.002	0.002
15	0.0002	0.0004	0.002	0.002
16	0.0004	0.0004	0.002	0.002
17	0.0005	0.0004	0.0022	0.002
18	0.0007	0.0004	0.0025	0.002
19	0.0011	0.0004	0.0025	0.002
20	0.0014	0.0004	0.0028	0.002
21	0.0015	0.0004	0.0032	0.002
22	0.0017	0.0004	0.0035	0.002
23	0.002	0.0004	0.0038	0.002
24	0.0024	0.0004	0.0039	0.002
25	0.0027	0.0004	0.0041	0.002
26	0.0027	0.0004	0.0043	0.002
27	0.003	0.0004	0.0045	0.002
28	0.0032	0.0004	0.0046	0.002
29	0.0035	0.0004	0.0049	0.002
30	0.0037	0.0004	0.0051	0.002
31	0.0039	0.0004	0.0053	0.002
32	0.0044	0.0002	0.0057	0.0021
33	0.0049	0.0001	0.0065	0.0023
34	0.0051	0.0001	0.0072	0.0025
35	0.0056	-0.0001	0.0079	0.0026
36	0.0061	-0.0002	0.0082	0.0026

Figure 20 Logged Mouse Movement Data

Figure 21 Trajectories (Mouse Movement Data)

In this system, data captured includes the cursor's x and y coordinates and timestamp. The cursor speed was adopted as an exemplary movement parameter to indicate emotional changes (Maehr, 2005), due to its importance as defined in Fitts' law (1954). The benchmark value was established via calculation of average session speed (V) using the formula, $V=D/T$, where D (cursor distance) is the sum of the Euclidean distances between captured x and y cursor positions during movement time (T). The calculation script then

compares new cursor parameter with benchmark value for existing deviations in the form of trajectories (Figure 21). As illustrated in the figure, the horizontal line indicates the benchmark, a data line moving northward of this line denotes a “+A”. Vice versa, a southward moving data line denotes a “-A”. The attribute can be calculated according to the formula below:

Let x = average mouse-movement capture in 50ms.

1. If

$$\max_{0 < i < n} x_i \times 0.9 > \frac{\sum_{i=1}^{20} x_i}{20} > \left(\frac{\sum_{i=0}^n x_i}{n} \right) \times 1.1$$

Then,

$$"A" = +A$$

2. If

$$\frac{\sum_{i=1}^{20} x_i}{20} > \left(\frac{\sum_{i=0}^n x_i}{n} \right) \times 0.9$$

$$"A" = -A$$

3. However, if a spike in mouse-data is detected, then the following would superceed the self-assessed “P” attribute value as such

$$\frac{\sum_{i=1}^{20} x_i}{20} > \max_{0 < i < n} x_i \times 0.9$$

Then,

$$"A" = -P$$

As the interaction via the mouse is almost continuous throughout the learning session, using HCI data to drive emotional state observation would be best-fitting. In our model, it evaluates differences from threshold values and trigger events that would further evaluate the probable conditions that would

potentially result in negative emotional states for the timely intervention of experience adjustments.

6.5 Measuring the Dominance “D” trait value

The measurement of the Dominance “D” trait is based on the profile self-efficacy of the user and the summative data from attempted tasks.

Self-efficacy is an individual’s belief about his ability to perform (well) in a task scenario (Bandura A. , 1995). It has been used in the prediction of the type of problems or sub-problems a student will select to solve, the duration of student’s persistence in attempting the selection and the overall effort they will expend (Schunk & Pajares, 2002). A highly efficacious student would view challenges as a motivator (Malone & Lepper, 1987) and exhibit more control over their future through their actions, thinking, and feelings than inefficacious students (Bandura A. , 1986). A student with low self-efficacy would perceive tasks to be more challenging, which often leads to feelings of anxiety, frustration and stress.

There are two important requirements for an accurate diagnosis of self-efficacy in learner via an ITS:

1. Realization through a computational mechanism at runtime as self-efficacy varies throughout a learning experience and pre-test data may be an inaccurate prediction.
2. Ability to satisfy the real-time demands of interactive learning.

Our system includes static and dynamic self-efficacy models that learn from pre-test data (using Self-Efficacy Assessment Scale) as well as runtime data from intentional summative data (performance) for formative analysis and an increased refined data of self-efficacy information (Table 11).

Intentional summative info (rate of task performance) here refers to the learning progression, for the measurement of how a student's abilities can match the demands of learning tasks.

Table 11 "D" trait combinations and triggered actions

Self-Efficacy and Intentional Combinations	Triggered actions	"D" trait
Low Self-Efficacy + Low Performance	Low-tier task	$(-D)+(-D) = -D$
Low Self-Efficacy + High Performance	High-tier task	$(-D)+(D) = D$
High Self-Efficacy + Low Performance	Low-tier task	$(-D)+(D) = D$
High Self-Efficacy + High Performance	High-tier task	$(D)+(D) = +D$

As illustrated in the table above, the perceived self-efficacy levels of a user is validated using intentional summative data for evaluation of "D" trait. While a learning behaviour needs to be motivated based on the learner's self-efficacy, it is also important to note that a student would have to be challenged to sustain motivation and to progress academically.

6.6 Designing the Experience Model

This section primarily introduces the proposed Affective Teaching Model that is based on a goal-oriented modelling approach. This model is designed to refine the analysis of assumed conditions that is detrimental to the negotiation of a positive emotional state. For example, a decrease of A value (decrease in mouse movement data) triggers the experience model to analyse and determine the conditions (learning goal achievement or compatibility of feedback) that require adjustments.

This model is focused on two outcomes: First being the ability to facilitate teaching while the second being the ability to monitor and evaluate the learning affection (experienced emotion) to regulate the learning process for optimal effectiveness and efficiency.

These abilities are integrated and executed as a system using a goal-oriented modelling approach. The goal-oriented system will monitor, evaluate and propose the best course of action, by selecting the next goal, of a learning process. This is achieved through a hierarchy of goals, the proposed model will be able to actively monitor the affective progression of the student during the learning process, and provide them with appropriated learning feedback for better communication and a motivated learning experience.

Integrating learning objects (contents, feedback and goals) with the Goal NET model requires two major aspects of work that primarily involve the teachers and programmers.

In order to achieve this, there are some pre-requisites required in the authoring phase. There are three parties involved in the authoring process: (1) the teachers as instruction designers who abstract domain knowledge into learning goals and detailing contents (e.g. feedback and scaffolds), programmers who will implement learning goals, contents and feedback according to input and output and the students as the users of the implemented system (input providers and output receivers).

The first is to identify and design the learning goals (or otherwise known as learning objectives by educators), contents (learning materials) that are extracted from the domain knowledge and feedback required (i.e. scaffold).

The important considerations to be captured during this identification and design of learning goals are: the extraction of learning contents and design of the feedback (i.e. scaffolding) that is to be experienced by users of varied learning abilities. While the ideal scenario is to customize learning for each individual learner, this is hardly possible even with technological affordances provided by today's technology. Hence, teachers often design learning goals using the Visual, Audio and Kinesthetic (VAK) learning model and feedback types based on possible scenarios that may arise when designing a learning process or experience.

Learning goals have to be realistic and scalable; learners need to be constantly challenged at the appropriate levels. A learning goal may be decomposed into varied sub-goals that will provide this condition of varied challenges according to the learner. Even in a physical classroom teaching scenario, educators constantly design learning goals that divides the curriculum (i.e. concepts) into varied sequences which may leverage on related different examples or transferred situations to cater to the varied learning progress and abilities of the learners. Once the teachers have abstracted the critical information from the domain knowledge and designed the appropriate learning contents, feedback and goals, the next phase will be handed over to the programmer.

The following sections will discuss about features that would be required to attain these goals and the proposal of a formalized representation of the model. Following which, the goal-oriented modelling approach will be discussed and utilized as a representation of the model in a practical implementation.

6.6.1 From Traditional Teaching to Intervention Model Design

The ultimate goal of all educational system designs is to facilitate, motivate and sustain learning. In order to design an effective intervention model to achieve this goal, it is crucial for the designers to have an understanding of learning process and its participants. Some questions that should be pondered upon and answers prior to the design process include:

- What are some critical factors that influence the desirable learning outcome?
- What affects the ability to learn?
- What does a learning process entail?
- How can technology facilitate the above?

Agents are goal oriented; goal and further concrete behaviour selections are the foundation of an agent's initiative. One of the approaches to achieve this autonomous mechanism is through goal-orientation. A goal-oriented design provides more flexibility for highly active interactions due to its ability to selection and act out its own goals.

The ultimate goal of a learning-experience related system designs is to facilitate learning with the sub-goals of stimulating and sustaining learning interest. Nested within each of these sub-goals, are multiple conditions that have to be observed and requirements that have to be fulfilled. The sub-goals are often inter-dependent, therefore making the Goal Net modelling methodology a fitting tool for this hierarchical nature.

6.6.2 Goal Setting Principle

Goal setting is a major component of personal development which has been studied extensively by sociologists and psychologists, particularly due to its effects on human motivation and behaviour. Goal setting involves the establishment of individual objectives that are specific, measurable, achievable and realistic within a defined time frame. The Locke and Latham's goal-setting theory (GST) (2002) is one prominent theory that has been researched for over 35 years. A goal-setting related study has shown that goal sources (i.e. who should set the goal) and goal timeframes (i.e. time period to achieve the goal) have varying impacts on the participants' participation (motivation and commitment) level (P. K. S. Consolvo, 2009).

Due to its effectiveness in behaviour change, the deployment of goal-setting strategies may prove to be equally effective in persuading self-directed learning.

This theory provides understanding into factors which affect the level of goal-related performance, such as the level of participation in the goal setting process, the level of commitment of the individual and self-efficacy. It also states that continuous feedback of progress towards a goal is required for goal-setting to be effective.

Setting a goal can affect performance in 4 ways, by providing:

- i. Direction – Directing attention, focus and effort towards goal-relevant activities.
- ii. Motivation – Realistic (perceived as achievable) goals create greater willingness to put in effort.

- iii. Persistence – Increased resistance to setbacks when faced with a difficult task.
- iv. Cognition – Goals indirectly lead an individual to develop cognitive strategies, through arousal and discovery.

The importance of setting a realistic goal and why systems should provide independent goal setting as learns may be unrealistic. Now that we have an insight on how goal setting can be supported, the next step is to integrate it as part of a learning experience. In a typical classroom setting, a teacher would be monitoring the student and providing relevant and appropriate feedback that can guide the direction, motivate or cognitively challenge the learner. Similarly, in an e-Learning process, feedback is also a crucial and integral part of the experience. Without feedback, a user would have no knowledge if he is correctly using the system features or if the system is responding appropriately. Therefore, the feedback approach is best-fitting to integrate our goal-setting supports. Feedback exist in varied forms and used for various purposes. Since our study is education-focused, we will adopt and review feedback system that is commonly or primarily used in educational platforms

6.7 Goal Net model for PAL

Figure 22 Goal Net model for PAL

Figure 22 illustrates the Goal Net design of our proposed model and the table below describes the learning adaptations triggered by the analysis of the PAD combinations.

Table 12 PAD Triggered Adaptations

(Input) Trait Combination	Affect	(Output) Triggered Adaptation
+P+A+D	Exuberant	Can increase the difficulty tier of assignments (novice, intermediate and expert)
-P-A-D	Bored	Initiate pause, change of content presentation and difficulty tier of assignments
+P-A+D	Relaxed	Change of content presentation (text reading, video, hands-on practical)
-P+A-D	Anxious	Change of content presentation and difficulty tier of assignments

SUMMARY OF PART 4

In this part, we presented an overview of the system with the integration of the proposed computing models. The Goal NET modelling method was introduced and adapted for use in the learning experience design planning and computational model for automating feedback generation.

A computing model to analyse a learner's affection and engagement level based on the HCI-data to minimise intrusion was proposed. We also discussed upon the need to avoid frustration by evaluating abnormal HCI data against the learner's normal interaction data. Based on the CBT, a frustrated learner is more likely to be easily distracted, bored, disengaged and avoid further learning.

In the later sections, we presented a proposed computing model for automation of feedback based on user's competency and acceptance. Through the discussion, we reviewed and discussed upon the existing feedback methods of an ITS and how it would be adapted as part of our computing model for feedback generation. An independent learner who refuses assistive feedback should not be compelled to accept assistance. That said, he should also not be left without guidance. Feedback is critical in providing guidance and motivation for learners who may be facing difficulties or are low in motivation. The success of a learning process, be it a traditional classroom or e-Learning, can be attributed to the learner's acceptance towards feedback type and content. Therefore, our proposed system seeks to provide guidance through the understanding of the learner (i.e. learning personality) rather than using an authoritative stand.

PART 5

Application into Real-Learning Scenario

In this part, the procedure for our applied study in a real-learning scenario will be described and discussed in detail.

An introduction to the background of student profiles of our study group will be provided following which the qualitative (i.e. survey and observation) and quantitative data (i.e. formal assessment results) will also be analysed and discussed following which, a conclusion and future works will be presented to end off our study and thesis.

7 CASE STUDY: USING THE SYSTEM IN REAL CLASSROOM TEACHING SCENARIO

We will introduce the real world application of the project in classroom teaching. This study spans over a duration of 3 years and comprising of a year of learning materials planning. The teachers-in-charge of the class was assigned to the same study group class for the whole duration of 4 years (secondary 1 to 4) and taught the same subject, Computer Applications (CPA). The subject was an examinable curriculum that was assessed at a national level, the GCE 'N' Levels. The GCE examination system is intended to standardise the academic grading. The class profile of the students comprised of 18 girls and 22 boys, a total of 40 students ($n = 40$), and this class size remained constant throughout the study period and the students studied CPA from the age of 13 to 16. Academically, students of this study group were streamed as the Normal Technical (NT) academic group and generally deemed to be weaker in terms of learning abilities.

In Singapore, the secondary school education is based on three main streams: Express, Normal Academic (NA) and the Normal Technical (NT). Students are streamed based on their national Primary School Leaving Examination (PSLE) results; seats in the next phase of their academic pursue is allocated according to their performance in this exam. The PSLE results are based on the combined scores of the English, Mother-tongue language, and the average score of Maths and Science combined. The Normal stream is split into two sub-streams: Academic (NA) and Technical (NT), with the NT students taking subjects that are more technical or hands-on i.e. Computer Applications (CPA) or Design and Technology (D&T).

7.1 The Syllabus

The CPA syllabus is intended to prepare the students to be technologically adept, and be able to function and contribute effectively in our increasingly technologically-driven society. The contents of the syllabus emphasize on fundamental theoretical knowledge, practical and technical skills, including the use of software applications such as Microsoft Word, Game Design and Programming.

The examination for the syllabus will primarily assess the student's ability to:

- Demonstrate the use of applications and/or associated computer hardware to complete a series of designated tasks and sub-tasks
- Demonstrate problem-solving skills for varied scenarios

In general, the curriculum contents and an overview of fundamental learning objectives have been provided in the syllabus package. However, teachers are given the liberty to design additional learning contents and decide on their teaching pace in accordance to their students group.

7.2 The Study Group

In the initial control group setup, the students were split into two groups, comprising of 9 girls and 11 boys, each under the charge of a teacher sharing the same syllabus package. Typically, the class is split up into two groups that are based on the odd-even index numbers of the students: odd-numbered students in a class and the even-number students in the other. For this study, we extended the study group control by ensuring an equal number of boys and girls in group A and B respectively.

As mentioned, students in the NT stream have been grouped based on their PSLE results. Typically, the deviation of students' results in a NT class would be around 2 aggregate points (e.g. 188-190), and learning abilities are deemed to be similar. It should be noted that varying schools would have varying entry point requirements for their streams. However, a school would generally maintain its entry requirement scores over a period of 4 years as requirements are subjected to reviews based on overall cohort of graduated students from both primary and secondary levels.

While it is commonly discussed that students have varied learning needs, it remains typically unaddressed when students are assigned to schools and allocated to classes due to the limitations of teachers or classrooms. In general, students are merely grouped according to their academic results.

There are various components to be considered in the planning phase for the study which includes: the decomposition of learning curriculum and task into sub-tasks, the inclusion of necessary learning feedback and types of learning materials. Data captured through user interactions, task-adoptions and goal-accomplishments are tapped on for the evaluation of the learner's motivation and ability and current state of emotion. This is to facilitate the provision of the necessary support for learning by applying appropriate persuasive strategies catered for individual learners. Further details of the process will be discussed in the following sections.

7.3 The Procedure

As the students that are grouped into their secondary 1 class are likely to be from different primary schools, it is almost impossible to assure that all of them

would have similar technical knowledge. To minimise the impact of this varied background knowledge on the study results, the study procedure was deliberately designed to begin only at the start of their secondary 2 academic year. The first year focused primarily on providing the basic technical knowledge which would be deemed necessary for learning in the following years until graduation.

As mentioned, the syllabus comprised of theoretical and practical-based technical knowledge. The students had 3 sessions of 1-hour lesson per week, with 2 sessions focusing on theoretical knowledge and the other lesson conducted as a practical session using guided assignments.

While the overview of the syllabus and learning contents (i.e. learning objectives and assignment files) are provided, the teachers-in-charge typically re-design the curriculum, using the provided syllabus as a basis, along with its learning objectives, to cater to their students' varied learning needs Figure 23. This preparation is usually done towards the end of each academic semesters after an assessment review of their students overall performance.

Figure 23 Syllabus, Contents and Receivers

There are 2 semesters in each academic year: January to May and July to November which is further divided into 2 terms (January to March, March to May, July to September and September to November) each. For purpose of this study, we shall refer to the year of this study as Sxx, followed by the student's school academic year as Yxx and, lastly, term as Txx, where xx is the year/term number. For example, the first year of this study was formally conducted during the student's second year in the school during their first academic term. This would be denoted as S01Y02T01.

In our study, this preparation is further advanced using the VAK model; learners can be broadly categorized as Visual (V), Auditory (A) or Kinaesthetic (K) learners. In addition to prepare additional materials deemed necessary to boost the academic result of students, the teachers are required to adapt the learning instructions to cater to the varied learning needs of the VAK learners.

The numbers of sub-tasks and interactions are considered and prepared based on three categories of learner-types: efficient, normal and needy (Table 13).

Table 13 Content Design Consideration

Strong	Normal	Needy
<ul style="list-style-type: none">• Goal oriented• Few interactions• Demand feedback• Point hint-feedback	<ul style="list-style-type: none">• Sub-tasks available with reminder system• Few interactions• Demand and Delayed feedback• Point and Teach hint-feedback	<ul style="list-style-type: none">• Sub-tasks available with reminder system• Increased interactions• Demand, Delayed and Immediate feedback• Point, Teach and Bottom-out hint-feedback

7.3.1 Learning Personality Evaluation

The VAK survey was performed by the students during Secondary 1 (S00Y01T02), a year before the implemented study of this thesis, in preparation of the required materials. The survey results showed that the students of the class were mainly V and K learners, with A learners taking up a small minority of the group. It should be noted that this survey was conducted based on general learning behaviour and not targeted to any learning content in particular. Due to time considerations and based on the VAK theorists' belief that learners are capable of VAK learning, materials were prepared in consideration of the V and K learners.

7.3.2 Blending Learning in a Traditional Classroom

Both groups, A and B, had lessons conducted in the computer labs 3 and 4. The labs were air-conditioned and had the similar workstations loaded with the same operating system (and upgrades when necessary) and required applications (i.e. MS Office, web browsers) provided for each of the students.

Workstation layouts differ in the labs due to pre-existing local area network (LAN) and power supply points (Figure 24).

Figure 24 Layout of Labs (Group A & B)

Since the lessons are intended to be more individual as opposed to being Collaborative or Cooperative, the layout of the labs were deemed to be of insignificant influence to the study.

7.3.3 Intercepting Risk of Interest Loss via HCI Data

The feature of “Intelligence Assistance” is integrated as a background component during learner’s interaction with the platform. It is responsible for providing appropriate assistance to the learner when he is assumed to be stuck or simply bored (based on a pre-defined idle duration using average of user’s cursor activity).

By monitoring the user actions and provides context-relevant information when required, it functions as a persuasion mechanism through the lowering of task

complexity, reducing time and mental effort (ability moderators) via providing learning feedback (i.e. pause initiation). For example, when a learner becomes idle for the pre-defined duration, the probable deduction is that the learner is stuck or bored and invokes a message to user Figure 25.

Figure 25 Initiated Pause Prompt

The process flow of learning is described in the diagram:

7.4 Assessment Results

7.4.1 Assessment of Learner's Engagement (Affection, Behavioural and Cognitive)

Where learning effectiveness is concerned, the Teaching and Learning International Survey (TALIS) is a globally adopted method of evaluating the conditions of teaching and learning. It provides an extensive evaluation of learning effectiveness from various perspectives and analysed data are used in

providing insights to suggesting improvements to existing educational policies and outcomes. The survey measures 12 dimensions rated on a 6-point scale, 1 being strongly disagree and 6 strongly agree (Table 14).

Table 14 TALIS

5 Dimensions of Engaged Learning	3 Dimensions of Student's Learning Engagement	4 Dimensions of Measuring Student's Attainment of Desired Attitudes
1. Pedagogy 2. Experience of Learning 3. Tone of Environment 4. Assessment 5. Learning Content	1. Affective Engagement 2. Behavioural Engagement 3. Cognitive Engagement	1. Balanced Perspectives 2. Flexibility & Adaptability 3. Passion 4. Positivity

There are 5 dimensions of engaged learning:

- a) Pedagogy –strategies that can be used to manage teaching instruction for learners to understand concepts and content, and develop skills (Banilower, Boyd, Pasley, & Weiss, 2005).
- b) Experience of Learning –the interactions between a learner and the external conditions present that evokes reactions. Learning occurs through a learner's active participation (Tyler, 1949). A meaningful Experience of Learning takes place when teachers stretch students' thinking so that they can acquire a deep understanding of what they learn; assimilation of new information to learner's existing knowledge; and foster learning ownership.

- c) Tone of Environment –the degree to which learning is supported. An environment with good tone is one that is emotionally safe for learning and is “the overall climate and structures of the classroom that influence how students respond to and remain engaged in learning tasks; the context in which teaching acts are carried out” (Arends, 2001).
- d) Assessment - activities, carried out by teachers and their students to assess themselves, that “provide information to be used as feedback to modify teaching and learning activities” (Black & Wiliam, 1998a).
- e) Learning Content - what a learner should and can learn. It comprises knowledge, skills and values (or attitudes) and presented as a curriculum.

The next 3 dimensions are used in the measurement of a learner’s degree of engagement, or his overall motivation to learn. When successfully engaged, a student will demonstrate positive attitudes as well as a desire to enhance and increase his mastery and understanding of a subject (Fredricks, Blumenfeld, & Pasir, 2004).

- a) Affective Engagement - refers to a student’s positive emotional reaction to the people, content and the environment. Affectively engaged students view learning as fun, interesting and rewarding, and these students experience feelings of happiness in the learning environment.
- b) Behavioural Engagement - refers to active involvement by students in learning activities or tasks. Students are behaviourally engaged when they view learning and schooling as relevant to their lives, and hence demonstrate high levels of participation. It also refers to observable

students' actions or performances that entail positive conduct, such as following the rules, adhering to classroom norms and avoidance of disruptive behaviours.

- c) Cognitive Engagement - refers to the degree of self-regulation (Corno & Mandinach, 1983) where students display commitment, willingness and effort to mastering complex concepts. It can be observed in the way students plan and manage their own learning and demonstrate personal control and autonomy in these processes (Stoney & Oliver, 1999).

The last 4 dimensions measure the learner's attainment of desired attitudes namely Balanced Perspectives, Flexibility and Adaptability, Passion and Positivity.

- a) Balanced Perspectives – refers to the ability to look at issues from various viewpoints, and to take in ideas and opinions from various sources to make informed decisions.
- b) Flexibility and Adaptability – refers to the ability to thrive in diverse situations and environments, and flexible enough to work with people of varying profiles.
- c) Passion – refers to the level of enthusiasm with a love for learning.
- d) Positivity – refers to the level of resilience, with a positive outlook, and ability to persist in challenging situations.

In our research, we are more concerned with the engagement dimensions as they provide for a more immediate feedback in a short duration of study (3 years). On the other hand, attitude change may occur in a short duration of time but may also span across a longer duration. In addition, the dimensions for

engagement, which includes cognitive, behavioural and affection, are similar to the attributes our proposed method is based on.

7.5 Formative Analysis and Evaluation

Formative assessment is a commonly used practice in a typical classroom teaching scenario. Information deprived from such assessments is crucial for the teacher's evaluation of teaching and learning (T&L) effectiveness and inform the individual of the need for further modification to the structure of the T&L experience (e.g. pace of teaching). In short, formative assessment provides information on the acceptance of the designed T&L experience by the students.

Formative assessment can be presented in the forms of subjective and descriptive evaluations via questionnaires or observations. It should be ongoing throughout the life cycle of a T&L design to provide timely information on improper design and limitations. They are usually considered to be of low-stake and can also provide information used in guiding students to identify their own strengths or weaknesses (target areas for improvement).

In our study, questionnaires using both SAM and Likert scales coupled with open-ended questions were used in conjunction with observations and interviews to gather feedbacks from these aspects:

- Enjoyment of learning experience
- Satisfaction with learning experience
- Self-Perceived effectiveness of learning
- Self-Perceived improvement to learning behaviour
- Self-efficacy (learning attitude) at the end of experience

7.5.1.1 Attendance Rate Improvement (Formative Information)

One interesting observation is the increase in attendance rate over the course of study. Towards their graduation (S03Y04T04), the class was attended by 35 students as compared to the initial 20 students (75% increment), with 5 of the students being requested to attend a focused micro-study group due to their specialised learning needs.

At the start of the second year of study test S02Y03T01, approximately 5 students whom were in group B had requested to join group A citing reasons that they have heard good reviews of the teaching method. This request was initially rejected as the Head-of-Department (HoD) was not comfortable to allow change of class as it may affect the morale of group B and the teacher in charge and out of fear that students wanted a change to be in the same grouping as their close peers.

Despite the first request being rejected, an increase number of students sent in their request to be transferred in group A before the start of S02Y03T02 due to the increase in qualitative feedback of learning effectiveness in that particular group. The HoD relented and a special arrangement was made for the requestors to join group A for a trial period and subjected to good learning behaviour (based on the feedback of the teacher in charge). By the end of S02Y03T04, there were 35 students in group A.

The students had to sit for their GCE examinations at the end of S03Y04T03 and the results were made available at the end of S03Y04T04. There was an increased in the overall number of students who had obtained a passing grade in the subject, along with almost a 100% increase in the number of students with

distinctions (>75%) despite a larger class size. The results were compared to the national levels and the graduates from the previous batch. As the syllabus for both batches were similar, there was negligible influence to the test results comparison. The results are shown in the following tables.

While the quantitative results were evident of the overall learning effectiveness, and the increase in number of attendees for group A could be evidence of qualitative effectiveness, a survey was conducted and a number of students were interviewed on their learning experience.

7.5.1.2 Self-reported Qualitative Data from Questionnaire and Interviews

Learning experiences were documented via questionnaires and interviews:

students described their learning using a pool of adjectives provided in the questionnaire. These data collected were analysed to reveal the qualitatively varied learning experiences using a phenomenographic approach. Some of the common adjectives used includes fun and enjoyable with the most frequent being effective.

7.5.2 Teaching & Learning Survey

This section reports the results of the T&L Survey for the whole school and stream or class segment for the study group. Three indicators are used to describe the results. They are as follows:

- MRI: Mean rating index
- PR1: Percentage of students who rated 1
- PR6: Percentage of students who rated 6

The following guidelines can be used to evaluate the results

- MRI: < 2 = Low; 2 – 4 = Moderate; > 4 = High
- PR1: < 5 = Low; 5 – 10 = Moderate; > 15 = High
- PR6: < 5 = Low; 5 – 10 = Moderate; > 15 = High

The result evaluated from this survey can be used to:

1. Review the effectiveness of the curriculum for each student segment.
2. Measure the progression of each student segment.

To review the effectiveness of the T&L for each student segment, the 2014 results of a student segment will also be compared with the 2013 results of the same student segment e.g. 3NT '14 with 3NT '13. In the tables, SA denotes the School Average and this includes all students in the same academic level.

Table 15 T&L Survey 2013 - 2NT (1)

Dimension	PR1		PR6		MRI	
	SA '13	2NT '13	SA '13	2NT '13	SA '13	2NT '13
Pedagogy	2.38	3.16	14.11	16.84	4.31	4.20
Experience of Learning	2.38	5.26	16.62	14.21	4.35	4.05
Tone of Environment	3.42	4.21	16.99	16.84	4.29	4.19
Assessment	2.99	5.26	15.04	16.84	4.28	4.19
Learning Content	2.91	4.21	15.04	15.79	4.25	4.21

Table 16 T&L Survey 2013 - 2NT (2)

Engagement Dimension	PR1		PR6		MRI	
	SA '13	2NT '13	SA '13	2NT '13	SA '13	2NT '13
Affective	3.09	4.21	14.86	15.26	4.26	4.07
Behavioural	2.51	6.31	18.84	21.05	4.39	4.26
Cognitive	3.55	5.26	14.09	14.21	4.18	3.97

The first T&L survey was conducted in 2013 (S01Y02T04) and our study group represented the NT stream (2NT). In general, they had rated all the dimensions lower than the school's average. Of note is a low rating of 4.05 on the 'Experience of Learning', which received a PR1 of 5.26%, although this may not be very significant given the small size of the cohort (n = 40). Evident from the survey, NT students generally have lower self-efficacy and learning morale and are often deemed to be low in self and learning motivation. The low survey ratings of our study group can be attributed to the background and profile of the students. Due to the SES profiles of the majority of the students that make up our study group, 20% of the students came from a single-parent family and 40% of the students were on financial assistant scheme (FAS), the findings did not come as a surprise. The FAS is a government assessed and assisted funding that provides daily meals and learning subsidies (for learning materials and enrichment programmes) for students from lower-income families. The benchmark for the income is evaluated as $\frac{\Sigma(\text{household income})}{\Sigma(\text{family members})}$ and is currently capped at \$700 per household member. The possible reasons for the lower ratings of learning engagement (and motivation) will be further discussed in the following section.

7.5.2.1.1 Secondary 3 Normal Technical (2014)

Table 17 T&L Survey 2014 - 3NT (1)

Dimension	PR1		PR6		MRI	
	SA '14	3NT '14	SA '14	3NT '14	SA '14	3NT '14
Pedagogy	1.68	2.50	17.15	21.00	4.47	4.46
Experience of Learning	1.61	1.50	17.98	23.50	4.47	4.53
Tone of Environment	3.29	3.50	20.05	23.00	4.40	4.50
Assessment	2.29	3.00	15.25	22.00	4.36	4.44
Learning Content	3.04	3.00	16.28	26.00	4.34	4.49

Table 18 T&L Survey 2014 - 3NT (2)

Engagement Dimension	PR1		PR6		MRI	
	SA '14	3NT '14	SA '14	3NT '14	SA '14	3NT '14
Affective	2.71	4.50	16.91	23.50	4.39	4.49
Behavioural	1.74	2.50	22.49	27.50	4.56	4.58
Cognitive	2.62	2.00	13.98	23.50	4.27	4.40

In the following year (S02Y03T04), the general ratings returned by our study group (3NT) are now comparable with the school, with the MRI in the high range. The cohort also returned higher ratings than when they were in 2NT '13, as evident by the lower PR1 and higher PR6 and MRI. The ratings indicate a satisfied cohort. Details can be seen in the tables below Table 19.

Table 19 Yearly Comparison of T&L Survey (5 Dimensions) of Study Group

Dimension	PR1		PR6		MRI	
	2NT '13	3NT '14	2NT '13	3NT '14	2NT '13	3NT '14
Pedagogy	3.16	2.50	16.84	21.00	4.20	4.46
Experience of Learning	5.26	1.50	14.21	23.50	4.05	4.53
Tone of Environment	4.21	3.50	16.84	23.00	4.19	4.50
Assessment	5.26	3.00	16.84	22.00	4.19	4.44
Learning Content	4.21	3.00	15.79	26.00	4.21	4.49

However, based on the results analysed by comparing the data between 2013 and 2014, there is an increased in the MRI of all 5 dimensions and 3 engagement dimensions Table 20. This is indicative of an increase in cognitive engagement, learning engagement and motivation.

Table 20 Yearly Comparison of T&L Survey (Engagement) of Study Group

Engagement Dimension	PR1		PR6		MRI	
	2NT '13	3NT '14	2NT '13	3NT '14	2NT '13	3NT '14
Affective	4.21	4.50	15.26	23.50	4.07	4.49
Behavioural	6.31	2.50	21.05	27.50	4.26	4.58
Cognitive	5.26	2.00	14.21	23.50	3.97	4.40

7.5.3 SES Influences to Learning Motivation - Cognitive and Non-Cognitive Skills

What has the socio-economic status (SES) has to do with the learning motivation, engagement and esteem? Thinking back, teachers and learning in a

formal classroom environment (structured to be at least 6 hours in our study context) does not occur in a child's growing up until the age of 6-7 when they enter Primary school. Prior to this and even up till the early levels of Primary school education, the child will be observing, being influenced and learning of the people around them. In most cases, these 'people' would likely be referring to their immediate family members. Studies have shown a correlation between the involvement of parent(s) and their child's academic development and motivation (Gottfried, Fleming, & Gottfried, 1994).

While it may not be possible for all parents to receive adequate education or be equipped with the appropriate skill knowledge to guide their children, they can continue to play the vital role of providing encouragement to boost their children's self-confidence in terms of competence, control and positive attitudes towards academics (Grolnick, Friendly, & Bellas, 2009). "When parents believe in children's competence and have high expectations for them, provide the resources that children need to feel connected to others, and facilitate a sense of autonomy by supporting children's initiations and problem-solving, children's motivation is most likely to thrive". Research has suggested that parents can promote reading at home or discussing read materials to encourage enjoyment in learning. In summary, the development of feelings of competence, curiosity or even a positive attitude towards academic can be fostered with the active involvement of parents in the educational pursue of their children.

In reality, many factors hamper active participation from parents. For example, some parents are overwhelmed by various stressors e.g. constraints with finance or other resources, or just simply with the unfamiliarity of the role they have to

play. Therefore, the degree of involvement differs with each family's unique context (Grolnick, Friendly, & Bellas, 2009). While parent involvement can be limited by external resources, it does not correspond to the level of desire (can also be referenced as motivation) to be involved as parents with far less resources may participate less actively in school activities but are still entirely in the know and supportive of their children's academic progress (Grolnick, Friendly, & Bellas, 2009).

On top of resources, parents' beliefs and expectations are strongly linked to the influence on their children's motivation. For example, high expectations, competence, cultivating a curious mind and resilience can aid in the fostering of an intrinsic motivation for learning. Vice versa, controlling parents who use negative reinforcements e.g. display anger towards academic results can discourage this development (Gottfried, Fleming, & Gottfried, 1994).

That said, student learning motivation can also be influenced by their teachers and peers who provide similar social support as they begin to learn in a formal education setting (i.e. classroom learning) (Wang & Eccles, 2012).

7.5.4 SES-influenced factors that may contribute to lapses in soft skills

According to James Heckman (2011), non-cognitive skills, or "soft skills" as he has put it, refer to the attributes that include learning disposition, ability to work in a team, focus on learning tasks, deferring of gratification, self-regulation (control) of learning progress and self-esteem. Heckman (2008) has written extensively on how non-cognitive skills contribute to the success in school life and adulthood. He also noted that by the time these children begin formal education, children with lower SES backgrounds are more prone to lag in terms

of cognitive and non-cognitive skills. To make it worse, such gaps have been shown to persist into their later lives (Heckman 2008; 2011). Another study has also shown that students from higher SES backgrounds will approach challenges with better internal control than their counterparts (Young, Johnson, Hawthorne, & Pugh, 2011).

Although it is not fully appreciated, studies have deduced that the differences in parenting skills and social context will attribute to deficiencies in non-cognitive skills. Lower SES-profiled children, particularly those from single-parent homes, are less likely to gain from activities that stimulate non-cognitive skills (i.e. parental attention or learning activities) (McLanahan, 2004). It has been found that disadvantaged mothers “talk to their children less and are less likely to read to them daily . . . [they] tend to encourage their children less, adopt harsher parenting styles, and be less engaged with their children’s school work” (Heckman, 2011). To put it simply, children from below average SES backgrounds tend to possess fewer opportunities for the fostering of competencies, and to receive encouragement to discover interest and value in learning processes or to develop social relationships that provide support and value achievements.

Do these findings infer that those from below average SES backgrounds are sentenced to a life-time of skill gaps and low academic motivation? The answer is no. While it may seem that a family’s SES is a major predictor of the children’s cognitive and non-cognitive skill developments and accomplishment, these outcomes are more predetermined. As mentioned, SES disadvantages does not relate to the level of desire (motivation) to provide a stimulating home environment that can foster cognitive and non-cognitive skills. In fact, it has

been shown that a child's academic motivation is more likely to be influenced by the home environment (e.g. parental guidance) than by SES. In other words, there exists motivational differences within home environments even within the same SES group and it is this motivational factor (of parents) to provide the requirements for fostering cognitive and non-cognitive skills.

However, based on the information of our study subjects, it is likely that the low levels of engagement and low learning motivation are likely the results of multiple factors such as coming from disadvantaged-SES background and low self-esteem due to the perceived social image of being streamed as a NT student (the weaker learners).

'Self-perceived image' can be detrimental to one's self esteem and efficacy, with several studies that have explored the effects of social and cultural factors on the bearing on a student's motivation and aspiration. I will attempt to further elaborate on these factors and its possible relation to the observed low rating of learning motivation and engagement (refer to Table 15 &

Table 16).

Some researchers have asserted that perceptions of discrimination experienced by a student can damage his confidence which is a contributing factor to academic or learning disengagement. In addition, this experience of prejudice may also lead to the mindset that failures are attributed to external factors and beyond one's control. This is of great significance as such externally attributed mindsets can weaken the sense of autonomy and control, which are imperative

for the fostering of a strong learning motivation.

‘Group’ or ‘self’ identify that is based off a social context (i.e. the NT group of students are the weakest learners) can lead to the self-perception of behaviour types, i.e. doing or spending time on assignments are pointless or “is not intended for people like me” (Oyserman & Destin, 2010). The context of grouping students who are not able to perform well in one academic stream, can lead the students in the group to accept such negative stereotyping (the inability to obtain academic excellence) as a realistic nature of their ‘group’ identity (Murdock, 2009) (Graham & Hudley, 2005). This is especially detrimental to fostering learning motivation as such self-acceptance (of stereotype) can dampen one’s competence through the deletion of one’s self-regulation skills or may spur the student to avoid challenges to protect himself from further disapprovals (Steele & Aronson, 1995) (Aronson & Steele, 2005).

By considering the psychological factors through the analysis of T&L survey data, it allows the teachers to better understand the students.

7.6 Summative Analysis and Evaluation (Quantitative)

Summative assessment is to evaluate the effectiveness of learning at the end of an instructional unit(s) by comparing data (i.e. grades) against some standardised benchmark (i.e. moderated examination). They are often considered to be high-stakes and some examples of summative assessments include a final project, mid or end term exams.

Summative assessment is used to evaluate the ultimate T&L effectiveness of our study and will be derived from quantitative results analysis via the comparison of results using data of the previous cohort of NT students (school

and nation-wide). As mentioned, the students accepted by the school are generally deemed to be of the same learning ability (based on their PSLE scores), learning the same topics within the same learning time, and should therefore not much of an influence to the study test results.

7.7 Result Analysis of GCE N Examinations as Quantitative Feedback

The study group participated in the GCE N Examinations in the year 2015 and their results were released in November of the same year. For analysing the overall results and evaluating the effectiveness of implemented study, the results for the study group and the batch of 2013 and 2014 graduated seniors have been provided in the tables below. This will provide a refined analysis on the overall effectiveness of learning through the discussed system as all three batches have undergone the same syllabus.

The grading system for the GCE examination is as follows:

Marks	75-100	70-74	60-69	50-59	0-49
Grading	A	B	C	D	U
Grade Point	1	2	3	4	U

M.S.I is calculated as such:

$$MSI = \frac{\Sigma(GP_1 + GP_2 .. GP_n)}{n}$$

, where GP represents the grade point obtained by each student in a class or grouping and n represents the total number of students. This calculation method works like an average and is able to provide an overview of students' progress.

The tables below provide the results overview and breakdown of the 2013-2015 cohorts (Table 21). The results have been broken down into the number of students who scored the grading A, B, C, D and U, along with the total number of passes, fails, M.S.I, and percentage (%) of overall passes, fails and distinctions.

Due to the increasing difference in student count over the years, we will base our analysis using the percentile (%). Evident in the result analysis, there was an improvement in the overall assessment of the study group, including % of passes and distinction rates.

The lower the M.S.I indicates an greater level of overall performance and the higher the M.S.I indicates a poorer overall performance. By observation of the M.S.I Table 22, it is shown that the 2015 study group did better in the national exams. That is to say, their overall learning effectiveness had increased. To examine whether this is statistically significant, t-tests were conducted.

Table 21 N-level's Grading Summaries (Class of 2013-2015)

2013		
Grading (by Student Count)	A	7
	B	9
	C	12
	D	3
	U	4
Passes and Failures (by Student Count)	Total Students	35
	Pass	31
	Fail	4
%	M.S.I	2.7
	%Pass	88.6
	%Fail	11.4
	%Distinction	20.0

2014		
Grading (by Student Count)	A	8
	B	9
	C	6
	D	8
	U	3
Passes and Failures (by Student Count)	Total Students	34
	Pass	31
	Fail	3
%	M.S.I	2.7
	%Pass	91.2
	%Fail	8.8
	%Distinction	23.5
2015		
Grading (by Student Count)	A	15
	B	12
	C	9
	D	2
	U	2
Passes and Failures (by Student Count)	Total Students	40
	Pass	38
	Fail	2
%	M.S.I	2.1
	%Pass	95.0
	%Fail	5.0
	%Distinction	37.5

Table 22 MSI comparison for 2013 to 2015 cohorts

Group	No. of Students	M.S.I
2013	35	2.7
2014	34	2.7
2015	40	2.1

8 CONCLUSION AND FUTURE WORK

In this thesis, we proposed a model that integrates Human-Computer Interaction (HCI) data with learning pedagogies (Learning Personalities, Goal Setting and Learning Feedback) in a goal-oriented approach to facilitate Teaching & Learning. The design personalizes a learning experience by pacing the learning progress based on individual's attention needs, providing learning contents that support the learning preferences and provides timely reports of required assistance based on the learner's HCI data and profile.

In part 1 of this thesis, we discussed about the differences between traditional classroom learning to that of eLearning. Some of the critical factors to a sustainable and effective learning experience and progress were highlighted. Computing models that would allow a system to fill "otherwise human factor" gaps were proposed.

In part 2, we discussed about the importance of understanding learners and the processes involved in learning. Information regarding the typical learner personalities and styles were also presented along with the reviews of the various methods to capture interaction data and methodologies that allowed for the analysis of emotional states.

In part 3, the overview of our proposed system was presented and the integrated computing models were discussed. The structures for the models were fundamentally based on the Goal NET hierarchical model. The methods for capturing, analysing and automating feedback based on HCI data were presented.

In part 4, we reviewed the various existing education-focused research methods and discussed upon the compatible methods that would be adopted in our study procedure and how we had implemented the study. As the nature of our research is inclined towards the sustainability of learning more than mere quantitative results, we decided on a phenomenographical approach as it provides insights from multiple perspectives.

In the last part, we presented the application procedure of our study in a real-learning scenario and the background profile of our study group. Documented qualitative and quantitative observations were also presented and discussed in the same chapter. With the proposed PAL model, we were able to tap on the basic HCI affordance of a standard mouse device to boost the effectiveness of persuading an adaptive learning experience. This has also allowed us to better understand the learning profiles of the students that would not have been possible in a traditional learning setting.

8.1 Research Outcome Analysis

8.1.1 Academic achievement

The analysis of the national exam results has shown that the application of the system has little adverse effect and can significantly improve quantitative learning. The effectiveness of our proposed method comes from the personalization of learning pace, intervals, feedback and contents that is constantly updated during learning.

While it seems that there is only a 3.8% increase in the number of passes (Figure 26), the data that we are more concerned with is the 14% increase in the distinction rate and 3.3% decrease in failures.

Figure 26 Comparison of Summative Results

8.1.2 Learning experiences

In our study, the qualitative data from the T&L survey and improved attendance rates have shown significant learning gains at the end of the trial process. In particular, it was surprising as the study group comprised mainly of students who were more likely to have low motivation and learning ability. This demonstrated that the methodology was effective in increasing motivation, engagement as well as self-efficacy.

Figure 27 Comparison of TALIS data within study group

These research findings are significant as they clearly demonstrate the advantages of applying HCI-driven data into translated learning pedagogies for teaching & learning. There is an increase of 8.24%, 6% and 9.29% in the students who rated their corresponding dimensions of affective, behavioural and cognitive engagement as 6 (strongly agreed) (Figure 27).

When compared to the school's average (Express, Normal Academic and Technical student population combined), the P6 % figure was also higher across the three dimensions (Figure 28).

Figure 28 Comparison of TALIS data between study group and SA

The analyzed results have showed that our proposed system has improved students' results, while fostering a more positive attitude towards the learning activity with increased engagement.

As shown from the gathered qualitative and quantitative data, the study has shown that the overall learning effectiveness has increased. Before we conclude, let us review our proposed system and how the computing models have contributed to this improvement.

As in our study group, the usual teacher-to-students' ratio is often 1:40. There is hardly sufficient time for the teacher(s) to complete the syllabus, let alone understand each and every one of his students. Furthermore, this is more likely to be a cyclic process, as teachers may not be assigned to the same class in the following year. While the prepared lesson materials may be used in the following years, there is still the need for adjustments to learning pace to suit different learning needs.

8.1.2.1 Computing model for learning affection and engagement

While various factors can affect cognitive resources (attention and memory) and behaviours, emotions have been accredited to be one of the major influencing factors. During a lesson, students may experience various attention or emotional states, some of which may be detrimental to the learning experience (i.e. inability to focus, perform task and negative emotions) and prolonged experience may adversely affect learning sustainability. Realistically, it would be impossible for the teacher to constantly monitor individual students for their emotional or attention states.

Our computing model integrated in the study system seeks to fill this gap by evaluating HCI data for lapse in attention or emotional states. This data is further processed by the second computing model to generate the appropriate feedback to support continual learning that determines the cause of the change in HCI data.

It is not uncommon, even for the best student, to experience weariness during the course of learning. And the last thing any individual would want, when tired, is a long list of information to process or tasks to perform. When our computing model detects a significant change in tracked mouse data, it triggers the computing model for automating feedback to reduce or even cease the presentation of learning feedback and prompt for rest-breaks. Student engagement can be optimal when their cognitive resources are at its optimal and this would not be possible if the learning momentum is not synced to their learning paces.

8.1.2.2 Computing model for automating feedback based on learner's profile

Every once in a while, we may initially find it hard to interpret or comprehend

information that has been presented to us until we re-process it in a manner we are familiar or comfortable with. Similarly, with any learning process, compatibility of feedback (i.e. learning content) is vital to the sustainability and effectiveness of learning.

Processed HCI data is made accessible to the computing model for automating feedback based on the learner's personality and competency (his learning profile). When the initial generated learning experience is deemed to be compatible with the learner, it verifies this compatibility using HCI data and degree of goal completion (success or failure). When the computing model for affection triggers the computing model for feedback with a decreased HCI data, it evaluates if the cause is due to the inability to complete a task (frustration) or other emotional state changes (e.g. boredom). With this, timely adjustments to learning feedback can be made to prevent further increase of negative emotions being experienced. The ability to automate evaluation and adjustment (personalization of learning experience) on a large scale is a luxury which can now be easily achieved compared to the traditional 1:40 teacher-student ratio.

8.2 Future Work(s)

As we have mentioned, one of the major setbacks of a traditional classroom teaching approach is the inability for one teacher to reach out to all his students. The traditional method of teaching also relies heavily on resources, such as manpower and time. Therefore, our proposed method leverages on the technological affordances to store and profile student's learning needs and preferences as well as to monitor their progress for adjustments to the learning pace to motivate engaged learning and sustain attention.

The work done here presents a stepping stone towards future works that involve the understanding of students and providing the relevant support required in T&L processes through educational data mining (EDM).

EDM is an emerging discipline concerning the development of analysing methods of various data from educational settings to foster a better understanding of the relationship between students and the learning environment (Baker & Yacef, 2009). Romero & Ventura (2007) had proposed the division of educational data mining into two main schools: web mining and statistics with visualization. Baker (2010) had further specified this field into five perspectives: prediction, clustering, relationship mining, model discovery, and distillation of information for human justification.

Conducting the discussed data mining in a virtual learning environment (i.e. e-Learning) has various benefits for education-related research. First, it allows for the documentation of time and HCI (i.e. mouse keyboard and clicks) based data. Virtual learning allows for the scalability to support a wider number of users and learning personalities. The mined student data will also allow for the assessment and facilitation for collaborative and cooperative based learning processes (i.e. grouping of learning personalities for optimal learning outcomes) and ultimately Self-Directed Learning (SDL). The profiling based on historical behaviours (such as number of learning tasks undertaken) can indicate a student's learning desire, self-monitoring and self-management abilities. For example, students who have attempted more teaching tasks are more likely to possess a higher degree of learning desire than students who only attempted few tasks.

“Self-management” has been used to describe such behavioural task control relating to learning management (Candy, 1991) (Garrison, 1997). Self-monitoring, on the other hand, has been used to describe the internal cognitive dimension that relates learner’s thinking and monitoring of learning (Garrison, 1997). In contrast, self-management is identified by the management of external learning tasks and resources, whereas self-monitoring necessitates the internal cognitive processes of thinking, reflection and making improvements on a learning process.

Self-monitoring focuses on the internal processing aspects, both cognitive and metacognitive, of learning. Cognitive processes include thinking, making sense or meaning of new information and integrating new knowledge into an existing knowledge structure (current knowledge). Metacognitive processes refer to the learner’s ability to self-reflect on their learning (thinking about thinking or learning to learn). While self-monitoring can be viewed upon as an internalized process, external factors (i.e. teacher’s feedback) can influence the learner’s reflections.

8.2.1 Self-Directed Learning

SDL is a form of teaching-learning transaction, almost akin to individualised instruction, that involves the negotiation of learning needs assessment, identification and implementation of resources as well as evaluation of learning outcomes between learner and teacher.

As many process components of SDL are internalized, the theoretical ideas of learning ownership, self-management and monitoring have to be translated into possible observable behavioural indicators for actual classroom use.

Behavioural indicators provide useful information, by allowing teachers to monitor the engagement and readiness level of SDL in their students, for appropriate planning of instructional strategies.

Some possible behavioural indicators for SDL are shown in Table 23.

Table 23 Self-directed Learning

Aspect of SDL	Possible Behavioural Indicator(s):
Learning ownership	<ul style="list-style-type: none"> • Identifying, determining and setting own learning goals • Identifying learning tasks required for goal-accomplishment • Charting of own learning processes • Setting learning challenges and standards for the achievement of own learning goal
Self-management and monitoring of Learning	<ul style="list-style-type: none"> • Formulating and generating relevant questions • Exploring range of possibilities and making sound decisions • Self-planning and management of learning duration • Performing critical reflection of own learning and initiate feedbacks from appropriate authorities to achieve learning goal
Extension of own learning	<ul style="list-style-type: none"> • Applying learnt knowledge to new contexts and utilising acquired knowledge to learn beyond curriculum contents

In a recent report, “We are Social” (Simon, 2016), there is a recorded 8.30 million mobile connections and 4.45 million active Internet users out of the total population of 5.47 million people. Furthermore, a majority of these active users would likely be digital natives and the numbers will only increase over time. With the improvement of technology and increasingly tech-savvy users, it is not surprising that mobile learning will be gradually become a norm. Therefore, it is good time for us, education researchers, to work in the same direction to support the learning of future generations. With the help of affection, behavioral and cognition assessment integrated, we will be able to

explore better and proper ways of enhance e-Learning experiences based on learning progress and its diversified needs.

9 WORKS CITED

- Adolphs, R., & Damasio, A. R. (2001). The interaction of affect and cognition: A neurobiological perspective. *Handbook of affect and social cognition*, 279.
- Adsit, D. (2009). *Mass Customization and the Transformation of the Call Center Industry*. Retrieved 11 March, 2015, from Kombea Press Releases: <http://www.kombea.com/RecentPress.htm>
- Åkerlind, G. (2005). Learning about phenomenography: Interviewing, data analysis and the qualitative research paradigm. In J. A. Bowden, & P. Green, *Doing Developmental Phenomenography* (pp. 63-73). Melbourne: RMIT University Press.
- Alschuler, A., Tabor, D., & McIntyre, J. (1971). *Teaching achievement motivation*. Middletown, CT: Educational Venture Inc.
- Altmann, E. M., & Trafton, J. G. (2002). Memory for goals: An activation-based model. *Cognitive Science*, 26(1), 39–83.
- Amarakeerthi, S., Ranaweera, R., & Cohen, M. (2010). Speech-based emotion characterization using postures and gestures in CVEs. *International conference on cyberworlds*, 72-76.
- Amiel, T., & Reeves, T. C. (2008). Design-based research and educational technology: Rethinking technology and the research agenda. *Educational Technology & Society*, 11(4), 29-40.
- Arnold, M. B. (1960). *Emotion and Personality*. New York: Columbia University Press.
- Anderson, T., & Shattuck, J. (2012). Design-based research: a decade of progress in education research? *Educational Researcher*, 41(1), 16-25.
- Andrews, P. Y. (2012). System personality and persuasion in human-computer dialogue. *Interactive Intelligent Systems*, 2(2).
- Applications, R. a. (2005). Applications, Reliability and Validity of the Index of Learning Styles. *International Journal on Engineering Education*, 21 (1), 103-112.
- Arends, R. I. (2001). *Learning to Teach*. Boston: McGraw-Hill.
- Aronson, J., & Steele, C. M. (2005). Stereotypes and the fragility of academic competence, motivation, and self-concept. In A. J. Elliott, & C. S. Dweck, *Handbook of competence and motivation* (pp. Aronson, J., & Steele, C. M.). New York & London: Guilford Press.
- Ary, D., Jacobs, L. C., & Sorensen, C. (2010). *Introduction to research in education (8th ed)*. Belmont, CA: Wadsworth.

- Bailey, B. P., Konstan, J. A., & Carlis, J. V. (2001). The effects of interruptions on task performance, annoyance, and anxiety in the user interface. *INTERACT '01*, (pp. 593–601).
- BAKER, R. S. (2010). Data Mining For Education. In *International Encyclopedia of Education*. Oxford, UK.
- Baker, R., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, vol 1, 3-17.
- Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*, vol 84 (2), 191-215.
- Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.
- Bandura, A. (1995). Exercise of Personal and Collective Efficacy in Changing Societies. In A. Bandura, *Self-efficacy in Changing Societies* (pp. 1-45). Cambridge, MA: Cambridge University Press.
- Bangert-Drowns, R., & Pyke, R. (2001). A taxonomy of student engagement with educational. *Educational Computing Research*, 24(3), 213–234.
- Banilower, E. R., Boyd, S. E., Pasley, J. D., & Weiss, I. R. (2005). *Lessons from a decade of mathematics and science reform: A capstone report for the local systemic change through teacher enhancement initiative*. Chapel Hill, NC: Horizon Research, Inc.
- Barab, S., & Squire, K. (2004). Design-based research: Putting a stake in the ground. *Journal of the Learning Sciences*, 13(1), 1-14.
- Barsalou, L. W. (2008). Ground Cognition. *Annual Review of Psychology*, vol 59, 617-645.
- Baxter, A. (17 March, 2008). *Better interactivity benefits student faculty*. Retrieved 16 April, 2015, from Financial Times: <http://www.ft.com/cms/s/2/4bdbaa60-f1a3-11dc-9b45-0000779fd2ac.html#axzz23WiVo3yq>
- Beaudrya, O., Roy-Charlanda, A., Perrona, M., Cormierb, I., & Tappa, R. (2014). Featural processing in recognition of emotional facial expressions. *Cogn Emot*, vol 28(3), 416-432.
- Belschak, F. D., & Den Hartog, D. N. (2008). Consequences of positive and negative feedback: the impact on emotions and extra-role behaviors. *Applied Psychology*, vol. 58, 274-303.
- Benson, R., & Samarawickrema, G. (2009). Addressing the context of e-Learning: Using transactional distance theory to inform design. *Distance Education*, 30, 5-21.

- Berlyne, D. E. (1971b). *Arousal-moderating devices, aesthetics and psychobiology*. New York: Appleton-Century-Crofts.
- Berlyne, D. E. (1974). *The new experimental aesthetics, in studies in the new experimental aesthetics*. New York: John Wiley & Sons.
- Biswas, G., Leelawong, K., Schwartz, D., Vye, N., & Vanderbilt, T. (2005). Learning by teaching: A new agent paradigm for educational software. *Applied Artificial Intelligence, vol 19*, 363-392.
- Black, P., & Wiliam, D. (1998a). Assessment and Classroom Learning. *Assessment in Education, vol. 5*, 7-71.
- Blickle, G. (1998). Personality traits, learning strategies, and performance. *European Journal of Personality, 10 (5)*, 337-352.
- Blumenfeld, P. C. (1992). Classroom learning and motivation: Clarifying and expanding goal theory. *Journal of Educational Psychology, 84*, 272-281.
- Bock, T. (2009). *Artificial Emotions 2 : An Implementation of OCC, Including Middle-term Dynamics*.
- Boggiano, A. K., & Barrett, M. (1985). Performance and motivational deficits of helplessness: The role of motivational orientations. *Journal of Personality and Social Psychology, 49*, 1753-1761.
- Bonfield, B. (2007). Information Overload. *Consuming Information Library Journal, Vol 137(17)*, 26.
- Booth, M. (2009). The AI systems of Left4Dead. In *Keynote, Fifth Artificial Intelligence and Intelligence and Interactive Digital Entertainment Conference (AIIDE09)*.
- Boudreau, C. E., Williford, T. H., & Maunsell, J. H. (2006). Effects of task difficulty and target likelihood in area V4 of macaque monkeys. *Journal of Neurophysiology, 96*, 2377–2387.
- Bower, G. H. (1981). Mood and Memory. *American psychologist, vol. 36*, 129-148.
- Bower, G. H., & Forgas, J. P. (2001). Mood and Social Memory. *Handbook of affect and social cognition*, 95-120.
- Bowler, L., & Large, A. (2008). Design-based research for LIS. *Library and Information Science Research, 30*, 39/46.
- Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry, vol 25(1)*, 49-59.

- Bunce, D. M., Flens, E. A., & Neiles, K. Y. (2010). How Long Can Students Pay Attention in Class? A Study of Student Attention Decline Using Clickers. *Journal of Chemical Education*, 87(12), 1438-1443.
- Caligiuri, P. (2000). The big five personality characteristics as predictors of expatriate's desire to terminate the assignment and supervisor-rated performance. *Personnel Psychology*, 53 (1), 67-88.
- Candy, P. C. (1991). *Self-direction for lifelong learning*. San Francisco: Jossey-Bass.
- Carmines, E. G., & Zeller, R. A. (1979). *Reliability and validity assessment*, Sage University Paper series on quantitative applications in the social sciences. Thousand Oaks, CA: Sage Publications Inc.
- Chan, T. W. (1996). Learning Companion Systems, Social Learning Systems, and the Global Social Learning Club. *Journal of Artificial intelligence in Education*, vol 7, 125-159.
- Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006). Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals. *Int. Workshop on Multimedia Content Representation, Classification and Security*, (pp. 530-537).
- Chen, M., Anderson, J., & Sohn, M. (2001). What can a Mouse Cursor Tell Us More? Correlation of Eye/Mouse Movements on Web Browsing. *Extended Abstracts CHI 2001* (pp. 281-282). ACM Press.
- Cheng, R. (2006). Design and Evaluation of an adoptive incentive mechanism for sustained educational online communities, User modeling and user-adapted interaction. *User Modeling and User-Adapted Interaction*, Vol 16(3/4), 321-348.
- Clarke, J., & Dede, C. (2009). Robust designs for scalability. *Learning and instructional technologies for the 21st century*, 1-22.
- Cleary, T., & Zimmerman, B. (2004). Self-regulation empowerment program: a school-based program to enhance self-regulated and self-motivated cycles of student learning. *Psychology in the Schools*, 41 (5), 537-550.
- Clore, G. L. (1994). Why emotions vary in intensity. In P. E. (Eds.), *The nature of emotion, fundamental questions* (pp. 386-393). Oxford: Oxford University Press.
- Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). *Learning styles and pedagogy in post-16 learning: a systematic and critical review*. . London: LSRC reference, Learning & Skills Research Centre.
- Collins, A., Brown, J., & Newman, S. E. (1989). Cognitive apprenticeship: Teaching the craft of reading, writing and mathematics. In L. B. (Ed.), *Knowing, learning and*

instruction: Essays in honor of Robert Glaser (pp. 543-594). Hillsdale, NJ: Lawrence Erlbaum Associates.

- Constantinidou, F., & Baker, S. (2002). Stimulus modality and verbal learning performance in normal aging. *Brain and Language*, 82(3), 296-311.
- Corno, L., & Mandinach, E. (1983). The role of cognitive engagement in classroom learning and motivation. *Educational Psychologist*, 18, 88-100.
- Costa, P. T., & McCrae, R. R. (1986). Personality Stability and Its Implications for Clinical Psychology. *Clinical Psychology Review*, 6, 407-423.
- Costa, P. T., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO PI) and NEO Five Factor Inventory (NEO FFI): Professional Manual*. Odessa, FL: Psychological Assessment Resources.
- Costa, P., McCrae, R., & Holland, J. (1984). Personality and Vocational Interests in an Adult Sample. *Journal of Applied Psychology*, 69, 390-400.
- Covington, M. V. (1984). The motive of self-worth. In R. E. Ames, & C. Ames, *Motivation in education: student motivation, vol 1* (pp. 77-113). San Diego: Academic Press.
- Creswell, J. W. (2003). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (2nd ed.)*. Thousand Oaks, CA: Sage Publications.
- Cuseo, J., Fecas, V. S., & Thompson, A. (2007). *Thriving in College & Beyond: Research-Based Strategies for Academic Success and Personal Development*. Dubuque, IA: Kendall/Hint.
- Czerwinski, M., Cutrell, E., & Horvitz, E. (2000). Instant messaging: Effects of relevance and time. *HCI 2000 – 14th British HCI Group Annual Conference*, (pp. 71–76).
- Darling-Hammond, L., Orcutt, S., Strobel, K., Kirsch, E., Lit, I., & Martin, D. (2003). Feelings Count: Emotions and Learning. In *The Learning Classroom* (pp. 89-104). Stanford University School of Education.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance in information technology. *MIS Quarterly*, 13 (3), 319-340.
- Davis, S. (1997). *Future Perfect*. Boston: Addison-Wesley Publishing.
- De Raad, B., & Schouwenburg, H. C. (1998). Personality in Learning and Education: A Review. *European Journal of Personality*, 10 (5), 303-336.
- Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, vol 49 (10), 1407-1424.
- Delon, W., & Mclean, E. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, vol 3 (1), 60-95.

- Denzin, N. K. (1970). *The research act: A theoretical introduction to sociological methods*. London: AldineTransaction, A Division of Transaction Publishers.
- Design-Based Research Collective. (2003). Design-based research: an emerging paradigm for educational inquiry. *Educational Researcher*, 32(1), 5-8.
- Diamond, A. (2005). Attention-deficit disorder (attention-deficit/hyperactivity disorder without hyperactivity), A neurobiologically and behaviorally distinct disorder from attention-deficit/hyperactivity disorder (with hyperactivity). *Development and Psychopathology*, 17, 807–25.
- Dobson, D., & Dobson, K. S. (2009). *Evidenced-based practice of cognitive-behavioral therapy*. New York: Guilford.
- Ekman, P. (1982). Methods for measuring facial action. *Language*, 45-90.
- Ekman, P. (1982). Methods for measuring facial action. *Language*, 45-90.
- Ellis, H. C., Ottaway, S. A., Varner, L. J., Becker, A. S., & Moore, B. A. (1997). Emotion, motivation, and text comprehension: The detection of contradictions in passages. *Experimental Psychology* 126(2), 131-146.
- Ellis, H. C., Ottaway, S. A., Varner, L. J., Becker, A. S., & Moore, B. A. (1997). Emotion, motivation, and text comprehension: The detection of contradictions in passages. *Experimental Psychology* 126(2), 131-146.
- Entwistle, N. J. (1981). An Integrated Outline of Educational Psychology for Students, Teachers and Lecturers. In *Styles of Learning and Teaching* (p. 306). Chichester: Wiley.
- Epp, C., Lippold, M., & Mandryk, R. (2011). Identifying emotional states using keystroke dynamics. *Proceedings of the 2011 annual conference on human factors in computing systems*, (pp. 715-724).
- Eysenck, H. (1978). The Development of Personality and its Relation to Learning. In S. (. Murray Smith, *Melbourne studies in education* (pp. 134-181). Melbourne: Melbourne University Press.
- Fallan, K. (2006). Quality reform: Personality type, preferred learning style and majors in a business school. *Quality in Higher Education*, 12 (2), 193-206.
- Fantuzzo, J. W., King, J. A., & Heller, L. R. (1992). Effects of reciprocal peer tutoring on mathematics and school adjustment: A component analysis. *Journal of Educational Psychology*, vol 84, 331.
- Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology*, vol 47(6), 381-391.
- Flew, T. (2008). *New Media: An Introduction*. Australia: Oxford University Press.

- Fogarty, J., Hudson, S. E., Atkeson, C. G., Avrahami, D., Forlizzi, J., & Kiesler, S. (2005). Predicting human interruptibility with sensors. *ACM Transactions on Computer-Human Interaction*, 12(1), 119–146.
- Fogg, B. (2009). *A Behavioral Model For Persuasive Design*. Retrieved 1 March, 2011, from BJ Fogg's Behavior Model: <http://www.bjfogg.com/fbm.html>
- Fogg, B. J. (2003). *Persuasive Technology: Using Computers to Change What We Think And Do*. San Francisco, CA: Morgan Kaufmann.
- Fredricks, J. A., Blumenfeld, P. C., & Pasir, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74, 59-109.
- Frijda, N. H. (1986). *The emotions*. Ed. de la Maison des Sciences de l'Homme.
- G., T., D., G., & A., K. (2011). Detection of Learner's Affective State Based on Mouse Movements. *Computing* 3(11), 9-18.
- Gardner, H. (1999). *Intelligence Reframed: Multiple Intelligences for the 21st Century*. New York: Basic Books.
- Garrison, D. R. (1997). SDL: Toward a comprehensive model. *Adult Education Quarterly*, 48(1), 18-33.
- Gazzaniga, M. (1989). *Mind Matters: How Mind and Brain Interact to Create Our Conscious Lives* Boston. Boston: Houghton Mifflin.
- Gilbert, L., & Moore, D. R. (1998). (1998). Building interactivity into web courses: tools for social and instructional interaction. *Educational Technology*, 38 (3), 29-35.
- Glaserfeld, E. (1989). Cognition, construction of knowledge, and teaching. *Synthese*, Vol 80(1), 121-140.
- Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The Qualitative Report*, 8(4), 597-606.
- Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (1994). Role of parental motivational practices in children's academic intrinsic motivation and achievement. *Journal of Educational Psychology*, 86(1), 104-113.
- Graham, G. (1999). *The Internet: A Philosophical Inquiry*. London: Taylor & Francis.
- Graham, S., & Hudley, C. (2005). Race and ethnicity in the study of motivation and competence. In A. J. Elliott, & C. S. Dweck, *Handbook of competence and motivation* (pp. 392-413). New York & London: Guilford Press.
- Grolnick, W. S., Friendly, R. W., & Bellas, V. M. (2009). Parenting and children's motivation at school. In K. R. (Eds.), *Handbook of motivation at school* (pp. 279-300). New York & London: Routledge.

- Grundgeiger, T., & Sanderson, P. (2009). Interruptions in healthcare: Theoretical views. *International Journal of Medical Informatics*, 78(5), 293–307.
- Gu, W., Xiang, C., Venkatesh, Y., Huang, D., & Lin, H. (2012). Facial expression recognition using radial encoding of local Gabor features and classifier synthesis. *Pattern Recogn*, vol 45(1), 80-91.
- Guangying, Y., & Shanxiao, Y. (2010). Emotion recognition of electromyography based on support vector machine. *Third international symposium on intelligent information technology and security informatics*, 298-301.
- Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. In N. K. Denzin, & Y. S. Lincoln, *Handbook of qualitative research* (pp. 105-117). Thousand Oaks, CA: Sage Publications.
- Happy, S. e. (2013). Automated Alertness and Emotion Detection for Empathic Feedback During E-Learning. *IEEE Digital Library*.
- Heckman, J. J. (2008). Schools, skills, and synapses. *Economic Inquiry*, 46, 289-324.
- Heckman, J. J. (2011). The American family in black & white: A post-racial strategy for improving skills to promote equality. *Daedalus, the Journal of the American Academy of Arts & Sciences*, 140, 70-80.
- Hertel, P. T., & Rude, S. S. (1991). Depressive deficits in memory: Focusing attention improves subsequent recall. *Experimental Psychology* 120(3), 301-309.
- Highhouse, S., & Doverspike, D. (1987). The validity of the learning style inventory 1985 as a predictor of cognitive style and occupational preference. *Educational and Psychological Measurement*, 47 (3), 749-753.
- Hume, G., Michael, J., Rovick, A., & Evens, M. (1996). Hinting as a tactic in one-on-one tutoring. *Journal of the Learning Sciences*, 5 (1), 23-49.
- Hume, G., Michael, J., Rovick, A., & Evens, M. (1996). Hinting as a tactic in one-on-one tutoring. *Journal of the Learning Sciences*, vol 5 (1), 23-49.
- Ibrahimoglu, N., Unaldi, I., Samancioglu, M., & Baglibel, M. (2013). The Relationship Between Personality Traits and Learning Styles: A Cluster Analysis. *Asian Journal of Management Sciences & Education (AJMSE)*, 2 (3).
- Ilbeygi, M., & Shah-Hosseini, H. (2012). A novel fuzzy facial expression recognition system based on facial feature extraction from color face images. *Eng Appl Artif Intell*, vol 25(1), 130-146.
- Isen, A. M. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology*, 52, 1122-1131.
- Isen, A. M. (2000). Positive affect and decision makin. In M. L. (Eds.), *Handbook of emotions* (p. 720). Guilford, New York: The Guilford Press.

- Izard, C. E. (1971). *The face of emotion*. New York: Appleton-Century-Crofts.
- Jaques, N. e. (2014). Predicting Affect from Gaze Data during Interaction with an Intelligent Tutoring System. *Lecture Notes in Computer Science*, vol 8474, 29-38.
- Jaques, P. A., & Vicari, R. M. (2007). A BDI approach to infer student's emotions in an intelligent learning environment. *Computers & Education*, vol. 49, 360-384.
- Jonassen, D. H. (1981). Personality and Cognitive Style, Predictors of Teaching Style, Preferences: An exploratory study. In *Association for the Educational Communications and Technology Convention, Symposium conducted at The Annual Convention of the Association for Educational Communications and Technology*. Philadelphia, PA.
- Kamil, M. (2003). *Adolescents and Literacy: Reading For The 21st Century*. Washington, DC: Alliance for Excellent Education.
- Kazu, Y. E. (2009). The Effect of Learning Styles on Education and the Teaching Process. *Journal of Social Sciences*, 5 (2), 85-94.
- Kleckova', J. (2009). Important nonverbal attributes for spontaneous speech recognition. *Fourth international conference on systems*, 13-16.
- Koga, Y., & Morant, G. M. (1923). On the degree of association between reaction times in the case of difference sense. *Biometrika*, 15, 346-372.
- Koga, Y., & Morant, G. M. (1923). On the degree of association between reaction times in the case of difference sense. *Biometrika*, 15, 346-372.
- Kolb, D. A. (1999). *The Kolb Learning Style Inventory*. Hay Resources Direct.
- Konar, A., Chakraborty, A., Halder, A., Mandal, R., & Janarthanan, R. (2012). Interval type-2 fuzzy model for emotion recognition from facial expression. In M. S. Kundu MK, *Perception and machine intelligence* (pp. 114-121). Heidelberg: Springer.
- Koohang, A., & Harman, K. (2005). Open source: A metaphor for e-learning. *Informing Science Journal*, 8, 75-86.
- Kort, B., Reilly, R., & Picard, R. W. (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion. *IEEE International Conference on Advanced Learning Technologies*, 43-46.
- Kort, B., Reilly, R., & Picard, R. W. (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion. *Proceedings of the IEEE International Conference on*

Advanced Learning Technologies (pp. 43-46). Los Alamitos: CA: IEEE Computer Society Press.

- Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in human behavior*, 335-353.
- Lane, R. D., Nadel, L., & Ahern, G. L. (2000). *Cognitive neuroscience of emotion*. USA: Oxford University Press.
- Lasarus, R. (1966). *Cognitive Views of Human Motivation*. New York: Academic.
- Laukkanen, J., Roda, C., & Molenaar, I. (2007). Modelling tasks: A requirements analysis based on attention support services. *workshop on contextualized attention metadata: personalized access to digital resources, CAMA 2007 at the ACM IEEE Joint Conference on Digital Libraries* (pp. 1-7). Vancouver: ACM.
- Lazarus, R. (1991). *Emotion and adaptation*. New York: Oxford University Press.
- LeDoux, J. (1998). Fear and the brain: where have we been, and where are we going? *Biological Psychiatry*, vol. 44, 1229-1238.
- Leon, E., G. Clarke, V. C., & Sepulveda, F. (2007). A user-independent real-time emotion recognition system for software agents in domestic environments. *Engineering Applications of Artificial Intelligence*, vol 20 (3), 337-345.
- Levinthal, C. (1988). *Messengers of Paradise: Opiates and the Brain*. New York: Doubleday.
- Lewis, M., Haviland-Jones, J., & Barrett, L. (2010). The cultural psychology of the emotions—ancient and renewed. In A. Richard, J. Shweder, R. Horton, & C. Joseph, *Handbook of emotions (3rd ed)* (p. 19). New York: The Guilford Press.
- Li, H., Pang, N., Guo, S., & Wang, H. (2008). Research on textual emotion recognition incorporating personality factor. *International conference on robotics and biomimetics* (pp. 2222-2227). IEEE.
- Lim, S. L., Padmala, S., & Pessoa, L. (2008). Affective learning modulates spatial competition during low-load conditions. *Neuropsychologia*, 46(5), 1267–1278.
- Lindsley, D. B. (1959). Are there common factors in sensory deprivation, sensory distortion and sensory overload? . *Sensory Science*, Vol 129(3343), 221-225.
- Locke, G. E. (2002). Building A Practically Useful Theory of Goal Setting and Task Motivation. *American Psychology*, Vol 57(9), 705-717.
- Loyall, B., Bryan, A., & Bates, L. J. (1991). Hap A Reactive, Adaptive Architecture for Agents. *CMU-CS-91-147* (pp. 91-147). Carnegie Mellon University.

- Lyengar, S. S. (2000). When Choice is Demotivating: Can One Desire Too Much of a Good Thing? . *Journal of Personality and Social Psychology*, Vol 79(6), 995-1006.
- M., B., & Skaalvik, E. M. (2003). Academic Self-Concept and Self-Efficacy: How Different Are They Really? *Educational Psychology Review*, 15(1), 1-40.
- Mackenzie, N., & Knipe, S. (2006). Research dilemmas: Paradigms, methods and methodology. *Issues in Educational Research*, 16(2), 193-205.
- Maehr, W. (2005). *Estimation of the user's emotional state by mouse motions*. Dornbirn: FH Vorarlberg (Austria).
- Maehr, W. (2008). *eMotion: Estimation of User's Emotional State by Mouse Motions*. VDM Verlag.
- Malone, T., & Lepper, M. (1987). Making Learning Fun: a Taxonomy of Intrinsic Motivations for Learning. In R. Snow, & M. Farr, *Aptitude, Learning, and Instruction: Conative and Affective Process Analyses*, vol 3 (pp. 223-253). Hillsdale, NJ: Erlbaum.
- Mandler, G. (1984). *Mind and Body: Psychology of Emotion and Stress*. WW Norton & Co Inc.
- Martin, H., Jeffrey, L., Christoph, S., & Markus, W. (Jan, 2017). How Is Your User Feeling? Inferring Emotion Through Human-Computer Interaction Devices. *MIS Quarterly*.
- Marton, F. (2001). Phenomenography: A research approach to investigating different understandings of reality. In R. R. Sherman, & R. B. Webb, *Qualitative research in education: Focus & methods* (pp. 141-161). London: RoutledgeFalmer.
- Marton, F., & Booth, S. (1997). *Learning and awareness*. Mahwah, New Jersey: Lawrence Erlbaum Associates, Inc. Publishers.
- Maslow, A. H. (1970a). *Motivation and Personality*. New York: Harper & Row.
- McArthur, D., Lewis, M., & Bishay, M. (1994). *The Role of Artificial Intelligence in Education: Current Progress and Future Prospects*. Santa Monica, CA: RAND Corporation.
- McLanahan, S. (2004). Diverging destinies: How children are faring under the second demographic transition. *Demography*, 41(4), 607-627.
- McNamara, D. S., Kintsch, E., Songer, N. B., & Kintsch, W. (1996). Effects of prior knowledge and text coherence. *Discourse Processes*, 22(3), 247-288.
- Mehrabian, A. (1972). *Nonverbal communication*. . Chicago: Aldine-Atherton.

- Mehrabian, A. (1980). *Basic dimensions for a general psychological theory*. Oelgeschlager: Gunn & Hain.
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. Cambridge, MA: The MIT Press.
- Merrett, T. (2008). *Query by humming*. Montreal: McGill University.
- Mertens, D. M. (2005). *Research and evaluation in education and psychology: Integrating diversity with quantitative, qualitative, and mixed methods (2nd ed.)*. Thousand Oaks, CA: Sage Publications.
- Molenaar, I., & Roda, C. (2008). Attention management for dynamic and adaptive scaffolding. *Pragmatics and Cognition*, 16(2) , 225–271.
- Monrose, F., & Rubin, A. (2000). Keystroke dynamics as a biometric for authentication. *Future Gener Comput Syst*, vol 16(4), 351-359.
- Mulpuru, S., & Hult, P. e. (2010). *US online retail forecast, 2009 to 2014*. Retrieved from Forrester Research:
http://www.forrester.com/rb/Research/us_online_retail_forecast,_2009_to_2014/q/id/56551/t/2
- Murdock, T. B. (2009). Achievement motivation in racial and ethnic context. In K. R. Wentzel, & A. Wigfield, *Handbook of motivation at school* (pp. 433-461). New York & London: Routledge.
- Neal, G. (2013). Accommodating new learning in different school cultures. In M. T., C. M., & V. M., *Engaging the disengaged: Inclusive approaches to teaching the least advantaged* (pp. 17-36). New York: Cambridge University Press.
- Northrup, P. (2001). A framework for designing interactivity in web-based instruction. *Educational Technology*, 41 (2), 31–39.
- Oatley, K. &. (1996). Rethinking the role of emotions in education. In D. R. Torrance, *The handbook of education and human development: New models of learning, teaching and schooling* (pp. 257-274). Cambridge, MA: Blackwell.
- O'Regan, K. (2003). Emotion and e-learning. *Journal of Asynchronous learning networks*, 7, 78-92.
- Ortony, A., Clore, G., & Collins, A. (1988). *The cognitive structure of emotions*. Cambridge University Press.
- Ortony, A., Revell, W., & Zinbarg, R. (2007). Why Emotional Intelligence needs a fluid component. *The science of emotional intelligence. Knowns and unknowns series in affective science*, 288-304.
- Othman, W., Sumarni, R., & Foong, L. M. (2007). The Relation between Personality Types, Learning Styles and Problem Solving Approach of Technical and

- Vocational and Vocational Education Student. *Pertanika J. Soc. Sci. Hum.*, 15 (1), 1-8.
- Otte, C. (2011). Cognitive behavioral therapy in anxiety disorders: Current state of the evidence. . *Dialogues in clinical neuroscience*, 13(4), 413-421.
- Oyserman, D., & Destin, M. (2010). Identity-based motivation: Implications for intervention. *The Counseling Psychologist*, 38, 1001-1043.
- P. K. S. Consolvo, D. M. (2009). Goal-Setting Considerations for Persuasive Technologies that Encourage Physical Activity. *The International Conference on Persuasive Technology: Persuasive '09* (pp. 1-8). New York: ACM.
- P., K., & M., S. (2010). Recognising Emotions from Keyboard Stroke Pattern. *Computer Applications*, 11(9).
- Panskepp, J., Nelson, E., & Bekkedal, M. (1997). Brain systems for the mediation of social separation-distress and social-reward. *Annals of New York Academy of Sciences*, vol. 807, 78-100.
- Pe[^]cher, C., Lemerrier, C., & Cellier, J. M. (2009). Emotions drive attention: Effects on driver's behaviour. *Safety Science*, 47(9), 1254–1259.
- Pennsylvania, U. o. (2009). *Visual Learners Convert Words To Pictures In The Brain And Vice Versa, Says Psychology Study*. Retrieved 13 June, 2015, from ScienceDaily: <http://www.sciencedaily.com/releases/2009/03/090325091834.htm>
- Picard, R. W. (1997). *Affective computing*. MIT press.
- Pine, J. (1993). *Mass Customization*. Boston: Harvard Business School Press.
- Pittermann, J., Schmitt, A., & El Sayed, N. (2008). Integrating linguistic cues into speech-based emotion recognition. *4th international conference on intelligent environments*, 1-4.
- Poels, K., & Dewitte, S. (2008). Getting a line on print ads. *Journal of Advertising*, 37(4), 63-74.
- Poels, K., & Dewitte, S. (2008). Getting a line on print ads. *Journal of Advertising*, 37(4), 63–74.
- Prawat, R. S. (1994). Philosophical Perspectives on Constructivist Views of Learning. *Educational Psychologist*, Vol 29(1), 37-48.
- Prawat, R. S. (1994). Philosophical Perspectives on Constructivist Views of Learning. *Educational Psychologist*, Vol 29(1), 37-48.
- Proshansky, H. M., Ittelson, W. H., & Rivlin, L. G. (1970). Freedom of choice and behavior in a physical setting. In W. H. H. M. Proshansky, *Environmental*

- psychology: Man and his physical setting* (pp. 173-183). New York: Holt, Rinehart & Winston.
- Rahulamathavan, Y., RC-W, P., Chambers, J., & Parish, D. (2013). Facial expression recognition in the encrypted domain based on local fisher discriminant analysis. *IEEE Trans Affect Comput*, vol 4(1), 83-92.
- Randall, T., Terwiesch, C., & Ulrich, K. T. (2007). User design of customize products. *Marketing Science*, vol 26(2), 268–280.
- Rensink, R. A. (2007). The modeling and control of visual perception. In W. Gray, *Integrated Models of Cognitive Systems* (pp. 132–148). New York: Oxford University Press.
- Richard, M. O. (2005). Modeling the impact of internet atmospherics on surfer behavior. *Journal of Business Research*, 58(12), 1632-1642.
- Richard, M. O. (2005). Modeling the impact of internet atmospherics on surfer behavior. *Journal of Business Research*, 58(12), 1632–1642.
- Roda, C., & Nabeth, T. (2007). Supporting attention in learning environments: Attention support services and information management. *Creating New Experiences on a Global Scale. Second European Conference on Technology Enhanced Learning, EC-TEL 2007* (pp. 277-291). Crete.
- Roda, C., & Thomas, J. (2006). Attention aware systems: Theories, applications, and research agenda. *Computers in Human Behavior* 22(4), 557–587.
- Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005 . *Expert Systems with Applications*, vol 33, 135-146.
- Roseman, I. J. (1984). Cognitive determinants of emotion. *Review of personality and social psychology*, vol. 5, 11-36.
- Rourke, B., S., A., Collins, D., Hayman-Abello, B., Hayman-Abello, S., & Warriner, E. (2002). Child clinical/pediatric neuropsychology: some recent advances. *Annual Review of Psychology*, 53, 309-339.
- Rourke, L. (2000). Operationalizing social interaction in computer conferencing. *Proceedings of the 16th Annual conference of the Canadian Association for Distance Education*. Quebec City. Retrieved from . In Proceedings of the.
- Rovai, A. P. (2001). Classroom community at a distance: a comparative analysis of two ALN-based university programs. *Internet and Higher Education*, 4, 105-118.
- Russo, A. (2005). Digital Cultural Communication: Enabling new media and co-creation in Asia. *International Journal of Education and Development using Information and Communication Technology*, Vol 1(4).

- Saade, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model. *Information and Management*, 42, 317-327.
- Schaaff, K., & Schultz, T. (2009). Towards emotion recognition from electroencephalographic signals. *Affective computing and intelligent interaction and workshops*, 1-6.
- Scheirer, J., Fernandez, R., Klein, J., & Picard, R. W. (2002). Frustrating the user on purpose: a step toward building an affective computer. *Interacting with computers*, vol 14, 93-118.
- Scherer, K. R. (1984). On the nature and function of emotion: A component process approach. *Approaches to emotion*, 293-317.
- Schmidt, K., & Cohn, J. (2002). Human facial expressions as adaptations: evolutionary questions in facial expression. *Am J Phys Anthropol*, vol 33, 3-24.
- Schuller, B., Rigoll, G., & Lang, M. (2004). Emotion recognition in the manual interaction with graphical user interfaces. *International conference on multimedia and expo 2* (pp. 1215-1218). IEEE.
- Schunk, D., & Pajares, F. (2002). The Development of Academic Self-Efficacy. In A. Wigfield, & J. Eccles, *Development of Achievement Motivation* (pp. 15-31). San Diego, CA: Academic Press.
- Simon, K. (30 01, 2016). *2016 Digital Yearbook*. Retrieved from We Are Social: <http://wearesocial.com/sg/special-reports/digital-2016>
- Skinner, E., Furrer, C., Marchand, G., & Kindermann, T. (2008). Engagement and Disaffection in the Classroom: Part of a Larger Motivational Dynamic? *Journal of Educational Psychology*, Vol 100(4), 765-781.
- Song, L., Singleton, E. S., Hill, J. R., & Koh, M. H. (2004). Improving online learning: Student perceptions of useful and challenging characteristics. *Internet & Higher Education*, 7 (1), 59-70.
- Sousa, D. A. (2001). *How the Brain Learns (A Classroom Teacher's Guide)*. (2nd Ed.). USA: Corwin Pres.
- Speier, C., Vessey, I., & Valacich, J. S. (2003). The effects of interruptions, task complexity, and information presentation on computer-supported decision-making performance. *Decision Sciences*, 34(4), 771-797.
- SRamaraj, V., Ravindran, A., & Thirumurugan, A. (2013). Emotion recognition from human eye expression. *IJRCCCT*, vol 2(4), 158-164.

- Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, 69(5), 797-811.
- Steunebrink, B., Dastani, M., & Meyer, J. (2009). *The OCC model revisited*. The Netherlands: Utrecht University.
- Stipek, D. (The development of achievement motivation, 1984a). The development of achievement motivation. In R. A. (Eds.), *Research on motivation in education (Vol. 1)*. Orlando, FL: Academic Press.
- Stipek, D. (1984b). Young children's performance expectations: Logical analysis of wishful thinking? In J. N. (Ed.), *The development of achievement motivation*. Greenwich, CT: JAI Press.
- Stoney, S., & Oliver, R. (1999). Can higher order thinking and cognitive engagement be enhanced with multimedia? *Interactive Multimedia Electronic Journal of ComputerEnhanced Learning*, 1 (2).
- Sylwester, R. (1994). How Emotions Affect Learning. *Reporting What Students Are Learning*, 52(2), pp. 60-65.
- Toffler, A. (1970). *Future Shock*. New York: Random House.
- Toffler, A. (1970). *Future Shock*. New York: Random House.
- Tseng, M. A. (2001). Mass Customization. In *Handbook of Industrial Engineering, Technology and Operation Management (3rd ed.)*. New York: Wiley.
- Tu, C. H., & McIsaac, M. S. (2002). 'An examination of social presence to increase interaction in online classes. *The American Journal of Distance Education*, vol 16(2).
- Tyler, R. W. (1949). *Basic Principles of Curriculum and Instruction*. Chicago: University of Chicago Press.
- Vanlehn, K. (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education*, 227-265.
- Vincent, J.-D. (1990). *The Biology of Emotions*. Cambridge, MA: Basil Blackwell.
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.
- Wallach, M. A., & Wing, C. W. (1969). *The Talented Student*. Retrieved from <http://home.ku.education.tr/~earik/personality/wallach.html>
- Wang, F., & Hannafin, M. J. (2005). Design-based research and technology-enhanced learning environments. *Educational Technology Research and Development*, 53(4), 5-23.

- Wang, M., & Eccles, J. (2012). Social support matters: Longitudinal effects of social support on three dimensions of school engagement from middle to high school. *Child Development*, 83(3), 877-895.
- Wang, Y., & Guan, L. (2008). Recognizing human emotional state from audiovisual signals. *Multimed IEEE Trans*, vol 10(5), 936-946.
- Watkins, R., & Corry, M. (2007). *E-learning companion: a student's guide to online success*. Boston, MA, USA: Houghton Mifflin Co.
- Watkins, R., & Corry, M. (2010). *E-Learning companion: A student's guide to online success*. Wadsworth Publishing Company.
- Wegerif, R. (1998). The social dimension of asynchronous learning networks. *Journal of Asynchronous Learning Networks*, 2 (1), 34-49.
- Weisz, J. (1979). Perceived control and learned helplessness among mentally retarded and non-retarded children: A developmental analysis. . *Developmental Psychology*, 15, 311-319.
- Wilson, K., & Korn, J. H. (2007). Attention during Lectures - Beyond Ten Minutes. *Teaching of Psychology*, v34 n2, 85-89.
- Winter, G. (2000). *A comparative discussion of the notion of 'validity' in qualitative and quantitative research*. Retrieved from The Qualitative Report, 4(3&4): <http://www.nova.edu/ssss/QR/QR4-3/winter.html>
- Woolf, B. P. (2010). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann.
- Yang, C., Chen, H., & Honga, K. (2003). Visualization of large category map for Internet browsing. *Decision Support Systems - Web retrieval and mining*, Vol 35(1), 89-102.
- Young, A., Johnson, G., Hawthorne, M., & Pugh, J. (2011). Cultural predictors of academic motivation and achievement: A self-deterministic approach. *College Student Journal*, 45(1), 151-163.
- Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of educational psychology*, vol 81, 329-339.
- Zimmermann, Guttormsen, P. S., Danuser, B., & Gomez, P. (2003). Affective computing - a rationale for measuring mood with mouse and keyboard. *International journal of occupational safety and ergonomics*, vol 9, 539-551.

10 ANNEX

10.1 Annex A

VAK Learning Styles Self-Assessment Questionnaire

Circle or tick the answer that most represents how you generally behave.

1. When I operate new equipment I generally:
 - a) read the instructions first
 - b) listen to an explanation from someone who has used it before
 - c) go ahead and have a go, I can figure it out as I use it

2. When I need directions for travelling I usually:
 - a) look at a map
 - b) ask for spoken directions
 - c) follow my nose and maybe use a compass

3. When I cook a new dish, I like to:
 - a) follow a written recipe
 - b) call a friend for an explanation
 - c) follow my instincts, testing as I cook

4. If I am teaching someone something new, I tend to:
 - a) write instructions down for them
 - b) give them a verbal explanation
 - c) demonstrate first and then let them have a go

5. I tend to say:
 - a) watch how I do it
 - b) listen to me explain
 - c) you have a go

6. During my free time I most enjoy:
 - a) going to museums and galleries
 - b) listening to music and talking to my friends
 - c) playing sport or doing DIY

7. When I go shopping for clothes, I tend to:
 - a) imagine what they would look like on
 - b) discuss them with the shop staff
 - c) try them on and test them out

8. When I am choosing a holiday I usually:
 - a) read lots of brochures
 - b) listen to recommendations from friends
 - c) imagine what it would be like to be there

9. If I was buying a new car, I would:
- a) read reviews in newspapers and magazines
 - b) discuss what I need with my friends
 - c) test-drive lots of different types
10. When I am learning a new skill, I am most comfortable:
- a) watching what the teacher is doing
 - b) talking through with the teacher exactly what I'm supposed to do
 - c) giving it a try myself and work it out as I go
11. If I am choosing food off a menu, I tend to:
- a) imagine what the food will look like
 - b) talk through the options in my head or with my partner
 - c) imagine what the food will taste like
12. When I listen to a band, I can't help:
- a) watching the band members and other people in the audience
 - b) listening to the lyrics and the beats
 - c) moving in time with the music
13. When I concentrate, I most often:
- a) focus on the words or the pictures in front of me
 - b) discuss the problem and the possible solutions in my head
 - c) move around a lot, fiddle with pens and pencils and touch things
14. I choose household furnishings because I like:
- a) their colours and how they look
 - b) the descriptions the sales-people give me
 - c) their textures and what it feels like to touch them
15. My first memory is of:
- a) looking at something
 - b) being spoken to
 - c) doing something
16. When I am anxious, I:
- a) visualise the worst-case scenarios
 - b) talk over in my head what worries me most
 - c) can't sit still, fiddle and move around constantly

17. I feel especially connected to other people because of:
- a) how they look
 - b) what they say to me
 - c) how they make me feel
18. When I have to revise for an exam, I generally:
- a) write lots of revision notes and diagrams
 - b) talk over my notes, alone or with other people
 - c) imagine making the movement or creating the formula
19. If I am explaining to someone I tend to:
- a) show them what I mean
 - b) explain to them in different ways until they understand
 - c) encourage them to try and talk them through my idea as they do it
20. I really love:
- a) watching films, photography, looking at art or people watching
 - b) listening to music, the radio or talking to friends
 - c) taking part in sporting activities, eating fine foods and wines or dancing
21. Most of my free time is spent:
- a) watching television
 - b) talking to friends
 - c) doing physical activity or making things
22. When I first contact a new person, I usually:
- a) arrange a face to face meeting
 - b) talk to them on the telephone
 - c) try to get together whilst doing something else, such as an activity or a meal
23. I first notice how people:
- a) look and dress
 - b) sound and speak
 - c) stand and move
24. If I am angry, I tend to:
- a) keep replaying in my mind what it is that has upset me
 - b) raise my voice and tell people how I feel
 - c) stamp about, slam doors and physically demonstrate my anger
25. I find it easiest to remember:
- a) faces
 - b) names
 - c) things I have done

26. I think that you can tell if someone is lying if:

- a) they avoid looking at you
- b) their voices changes
- c) they give me funny vibes

27. When I meet an old friend:

- a) I say "it's great to see you!"
- b) I say "it's great to hear from you!"
- c) I give them a hug or a handshake

28. I remember things best by:

- a) writing notes or keeping printed details
- b) saying them aloud or repeating words and key points in my head
- c) doing and practising the activity or imagining it being done

29. If I have to complain about faulty goods, I am most comfortable:

- a) writing a letter
- b) complaining over the phone
- c) taking the item back to the store or posting it to head office

30. I tend to say:

- a) I see what you mean
- b) I hear what you are saying
- c) I know how you feel

Now add up how many A's, B's and C's you selected.

A=

B=

C=

10.2 Annex B

General Self-Efficacy Scale

Rating Scale:

1 = Not at all true	2 = Hardly true	3 = Moderately true	4 = Exactly true
---------------------	-----------------	---------------------	------------------

1. I can always manage to solve difficult problems if I try hard enough.
2. If someone opposes me, I can find the means and ways to get what I want.
3. It is easy for me to stick to my aims and accomplish my goals.
4. I am confident that I could deal efficiently with unexpected events.
5. Thanks to my resourcefulness, I know how to handle unforeseen situations.
6. I can solve most problems if I invest the necessary effort.
7. I can remain calm when facing difficulties because I can rely on my coping abilities.
8. When I am confronted with a problem, I can usually find several solutions.
9. If I am in trouble, I can usually think of a solution.
10. I can usually handle whatever comes my way.