Enhancing student engagement and interaction in e-learning environments through learning analytics and wearable sensing

Jingjing Chen

Follow this and additional works at: https://repository.hkbu.edu.hk/etd_oa

Recommended Citation
Chen, Jingjing, "Enhancing student engagement and interaction in e-learning environments through learning analytics and wearable sensing" (2016). Open Access Theses and Dissertations. 287. https://repository.hkbu.edu.hk/etd_oa/287

This Thesis is brought to you for free and open access by the Electronic Theses and Dissertations at HKBU Institutional Repository. It has been accepted for inclusion in Open Access Theses and Dissertations by an authorized administrator of HKBU Institutional Repository. For more information, please contact repository@hkbu.edu.hk.
DATE: August 26, 2016

STUDENT'S NAME: CHEN Jingjing

THESIS TITLE: Enhancing Student Engagement and Interaction in E-learning Environments through Learning Analytics and Wearable Sensing

This is to certify that the above student's thesis has been examined by the following panel members and has received full approval for acceptance in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Chairman: Dr. Tong Tiejun
Associate Professor, Department of Mathematics, HKBU
(Designated by Dean of Faculty of Science)

Internal Members:
Prof. Cheung Yiu Ming
Professor, Department of Computer Science, HKBU
(Designated by Head of Department of Computer Science)

Dr. Chu Xiaowen
Associate Professor, Department of Computer Science, HKBU

External Members:
Dr. Bälter Olle
Associate Professor
School of Computer Science and Communication
KTH Royal Institute of Technology
Sweden

Dr. Cheng Shiwei
Associate Professor
College of Computer Science & Technology
Zhejiang University of Technology
China

Proxy: Dr. Cheung Kwok Wai
Associate Professor, Department of Computer Science, HKBU
(as proxy for Dr. Bälter Olle)

In-attendance: Prof. Xu Jianliang
Professor, Department of Computer Science, HKBU

Issued by Graduate School, HKBU
Enhancing Student Engagement and Interaction in E-learning Environments through Learning Analytics and Wearable Sensing

CHEN Jingjing

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Principal Supervisor: Prof. XU Jianliang
Hong Kong Baptist University
August 2016
DECLARATION

I hereby declare that this thesis represents my own work which has been done after registration for the degree of PhD at Hong Kong Baptist University, and has not been previously included in a thesis or dissertation submitted to this or any other institution for a degree, diploma or other qualifications.

Signature: [Signature]

Date: August 2016
Abstract

E-learning refers to computer-based learning experiences, self-paced or instructor-led, supported and enabled by information technology. Virtual Learning Environments (VLEs), as a major form of e-learning systems, are increasingly adopted in universities and educational institutions for supporting various types of learning. Student engagement is critical for successful teaching and learning in VLEs. In existing VLEs, feeling isolated without adequate supervision from teachers may cause negative emotions such as anxiety. Such emotions may in turn significantly weaken students’ motivation to engage in learning activities. In addition, the lack of effective interaction in learning activities also results in poor performance and engagement, even dropouts from online courses. In this thesis, we explore a set of approaches and tools to enhance student engagement and interaction in e-learning environments: (1) extract valuable information from the user posts in online course forums to advise the content organization of web pages; (2) instantly monitor and visualize students’ interaction statuses in instructor-led learning; (3) identify and highlight the hotspot time slots and contents of the lecture recordings; (4) dynamically provide biofeedback-based visualization via wearable devices to reduce students’ anxiety in self-paced learning.

We present a page-segmentation-based wrapper (eCF-wrapper) designed for extracting learner-posted data in online course forums. It consists of a novel page segmentation algorithm and a decision tree classifier. We also develop a web-based interaction-aware VLE (WebIntera-classroom), which employs a ubiquitous interactive interface to enhance the learner-to-content interactions, and a learning analytics tool to instantly visualize learners’ interactions in learning activities. Additionally, we propose a high-granularity Learning Analytics Engine (hgLAE) to play a lecture recording, identify hotspots in a lecture recording and raise students’ awareness of these hotspots. A questionnaire survey, interview and case study were conducted to investigate the instruction effect of WebIntera-classroom. Besides, we develop a physiologically-state-aware self-paced learning environment (FishBuddy) to alleviate anxiety and promote student engagement in self-paced
learning by using wearable technology. The between-groups evaluation result shows that FishBuddy is useful in promoting student engagement (i.e., the consistency of engagement), and the students’ self-reports indicate that FishBuddy is helpful for reducing anxiety and experience of isolation during the self-paced learning exercises. Finally, the thesis is concluded with a discussion on the future work.

Keywords: Virtual Learning Environment; Learning Analytics; Interaction; Engagement; Wearable Technology
Acknowledgements

I would like to present great praise and thanks to my supervisor, Prof. Jianliang Xu, for encouraging me surviving from the Ph. D. study and finally completing the thesis, and also providing me with constructive suggestions and professional guidance to my study.

I would like to thank Dr. Byron Choi, who is my co-supervisor, and the other members (including the previous and current members) of the Database group with the Department of Computer Science of HKBU: Dr. Zhiwei Zhang, Dr. Haibo Hu, Dr. Rui Chen, Dr. Yun Peng, Dr. Xin Lin, Dr. Qilong Han, Dr. Zhe Fan, Dr. Yafei Li, Mr. Shen Gao, Mr. Lei Chen, Mr. Zhuo Chen, Mr. Peipei Yi, Mr. Cheng Xu, Mr. Xiaojing Xie, Mr. Jiaxing Jiang and Ms. Xiaoyi Fu. The thesis could not have been completed without the supervision and encouragements from many people. It’s not possible to mention all of them in this thesis, but I extremely appreciate what they did for me.

I acknowledge the members of the Adaptive Learning Centre with the Institute of Computing and Theory Studies at HKBU: Prof. Tao Tang, Dr. Xiaowen Chu, Dr. You Li, Dr. Weiwen Zou, Mr. Qingchang Yang, Mr. Shaohuai Shi, Mrs. Qi Sun, Miss Xiwen Sun, and Mr. Biao Li. I present special thanks to Prof. Tao Tang and Dr. You Li for they providing me the opportunity to work and study with excellent researchers at HKBU, and also provided lots of constructive suggestions and supports to my research.

I also acknowledge the members of the Department of Media Technology and Interaction Design at KTH the Royal Institute of Technology, and present special thanks to Dr. Olle Bälter, Mrs. Bin Zhu, Mr. Erik Isaksson, Prof. Ann Lantz and Prof. Haibo Li, with whom I enjoyed a wonderful time and achieved an interesting research work during the oversea attachment in Sweden.

My final debt is to my family: my dear parents and my beloved wife. I extremely appreciate the sacrifice they made in order to make me complete the Ph. D. study. In the coming days, what I need to do is to make sure that all my family members will be happy all the time.
Table of Contents

DECLARATION ii

Abstract iv

Acknowledgements v

List of Figures ix

List of Tables xi

Chapter 1 Introduction ..................................................................................1
  1.1 Background & Motivations ...............................................................1
  1.2 Thesis Outline ..................................................................................8

Chapter 2 Literature Review .......................................................................11
  2.1 Introduction to E-learning ...............................................................11
    2.1.1 Instructor-led e-learning ...........................................................12
    2.1.2 Self-paced e-learning ...............................................................12
    2.1.3 Blended Learning .....................................................................13
  2.2 E-learning Environments ..................................................................14
    2.2.1 Learning Management Systems (LMSs) .................................14
    2.2.2 Virtual Learning Environments (VLEs) ....................................15
    2.2.3 Wearable-based Enhanced Learning Environments (WELEs) ...16
  2.3 Learning Interactions ......................................................................16
  2.4 Student Engagement ......................................................................18
  2.5 Data Extraction ..............................................................................19
  2.6 Learning Analytics ........................................................................21
  2.7 Wearable Technology ......................................................................22
  2.8 Summary .........................................................................................24

Chapter 3 ......................................................................................................27
  3.1 Preliminaries and Concepts ............................................................27
    3.1.1 Concept Definition ..................................................................30
  3.2 Design Rationale & Implementation ................................................31
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.3.1 Experimental Settings</td>
<td>90</td>
</tr>
<tr>
<td>5.3.2 Experimental Hypotheses</td>
<td>91</td>
</tr>
<tr>
<td>5.3.3 Experimental Procedures</td>
<td>92</td>
</tr>
<tr>
<td>5.3.4 Results and Findings</td>
<td>93</td>
</tr>
<tr>
<td>5.4 Summary</td>
<td>97</td>
</tr>
<tr>
<td>Chapter 6 Conclusion</td>
<td>99</td>
</tr>
<tr>
<td>6.1 Research Conclusion</td>
<td>99</td>
</tr>
<tr>
<td>6.2 Summary of Research Contributions</td>
<td>101</td>
</tr>
<tr>
<td>6.3 Future Work</td>
<td>102</td>
</tr>
<tr>
<td>References</td>
<td>105</td>
</tr>
</tbody>
</table>
List of Figures

1.1 An example of online course forum.............................................. 3
3.1 A web page of an online course forum with noises....................... 27
3.2 The correspondent relationship between the page module and DOM 
Tree Structure .............................................................................. 28
3.3 Abstract layout of a web page in a course forum............................. 30
3.4 The system architecture of eCF-wrapper...................................... 30
3.5 The comparison of the optimized post list page (based on the 
information provided by eCF-wrapper) and the original one............. 41
3.6 The comparison of the optimized topic list page (based on the 
information provided by eCF-wrapper) and the original one............. 42
4.1 Overview of the combination of instructor-led learning and self-paced 
learning........................................................................................... 48
4.2 Workflow of the pen-and-paper Interface...................................... 50
4.3 A teacher/ student uses the Anoto pen to write on the paper in 
WebIntera-classroom..................................................................... 51
4.4 Interface for learners: (a) Webpage running on a plain browser; (b) 
Webpage running on a mobile browser; (c) iPad App; (d) iPhone 
App .................................................................................................. 52
4.5 A student communicated with the teacher by text chat tool.......... 53
4.6 An example of the discussion between a learner and the 
instructor ......................................................................................... 54
4.7 The overview of the high-granularity Learning Analytics 
Engine............................................................................................... 58
4.8 Distribution of the DOM events produced by 10 students in a 
lecture.............................................................................................. 59
4.9 Highlight hotspot objects and time slots while playing a lecture 
recording............................................................................................ 61
4.10 Popularity Dashboard: a graphic visualized monitor tool for 
instructor........................................................................................... 63
4.11 Comparison of student’s performance with different delivery 
methods (the Department of Financial Management)........................ 68
4.12 Comparison of student’s performance with different delivery methods (the Department of Computer Science) ........................................ 69
4.13 Participants’ attendance in virtual classroom throughout the course ........................................................................................................ 72
4.14 Interactivity by instructors in the virtual classroom throughout the course ........................................................................................................ 73
4.15 Interactivities by learners in the virtual classroom throughout the course ........................................................................................................ 73
4.16 Popularity observation in the virtual classroom throughout the course ........................................................................................................ 74
5.1 The overview of FishBuddy system .......................................................... 81
5.2 Snapshot of the SPLS: (a) an exercise result; (b) an exercise in progress; (c) question review; and (d) summary of exercises ......................... 82
5.3 The e-Fish running on an Apple Watch ....................................................... 84
5.4 Comparison of total engagement times for students in the experimental group and control group ......................................................... 92
5.5 Comparison of the average correctness rate of the control group and experimental group in the exercises ..................................................... 94
List of Tables

3.1 Heuristic rules in post extraction phase................................. 32
3.2 Definitions of the data features in classification......................... 33
3.3 Data source used in the experiment.................................. 36
3.4 Results of the experiment with machine data.............................. 37
3.5 Comparison of Page Segmentation....................................... 38
3.6 Overall Comparison of Data Extracting.................................. 39
3.7 Comparison of Time Consumption........................................ 39
3.8 The details of the posts to each topic in the topic list page............. 40
4.1 The definitions of learning object elements................................ 57
4.2 Results of the Satisfaction Questionnaire (n=464)....................... 67
5.1 Physiological-state-aware performance reference metric set........... 86
5.2 Questionnaire result.......................................................... 93
Chapter 1 Introduction

1.1 Background & Motivations

E-learning refers to computer-based learning experiences, self-paced or instructor-led, supported and enabled by information technology (Van, Erik & Jeroen, 2008). Virtual learning environments (VLEs), as the major form of e-learning environments, are widely adopted by many universities for both on-site teaching and distance education (Mahanta & Ahmed, 2012). A typical VLE usually consists of (1) learning management module, (2) learning materials services, (3) and a set of pedagogical tools and features (e.g., online course forums, shared whiteboard, learning tracking, text chat, lecture recording, etc.) (Cheung et al., 2009).

Currently, e-learning does significantly improve the learning experience by facilitating a flexible learning environment that supports various kinds of interactions and collaborations in e-learning activities, with the distinguished advantage of eliminating location and time barriers (Au et al. 2009). However, there are a number of weaknesses of current e-learning environments: (1) content-centric, not learner-centric or interaction oriented; (2) lack of instant feedback on learning activities; (3) lack of interoperability, the interaction with learning content from different interfaces is difficult and costly (Weller, 2006; Bulger, Mayer, Almeroth & Blau, 2008; Davis & White, 2011). Towards these goals, in this thesis, we develop a number of e-learning approaches and tools to enhance student engagement and interaction in e-learning environments.

1.1.1 Page Segmentation-based Information Extraction from Online Course Forums

There are much less communications and interactions among the participants in VLEs than in traditional classroom-based learning, where knowledge is delivered by the instructor to the learners face to face at a physical place within a specific time. A lot of literatures covering
e-learning theory and practice emphasize that effective interaction, in which both teachers and students should be mutually oriented in teaching and learning activities, is a critical factor for successful teaching and learning (Plantamura et al., 2010; Beliad, Talon & Kerkeni, 2013; Head, 2014; Bosanquet, Radford & Webster, 2015; Kim, Jeong, Ji, Lee, Kwon & Jeon, 2015). A number of researchers argue that insufficient supervision and intervention by the instructors often results in poor engagement in learning activities (Breunig, Kriegel, Ng, & Sander, 2000; Liaw, Huang & Chen, 2007; Mason, Shuman & Cook, 2013). This lack of interaction usually results in a negative impact on the total learning outcome. It is agreed by many researchers that future e-learning technology should address the issues such as emotional illiteracy and lack of interaction (Bråten & Strømsø, 2006; D’Mello, Picard & Graesser, 2007). The possible ways of doing this are (1) providing efficient guidance and assistant to students while attending learning activities; (2) monitoring and augmenting students’ interaction in learning activities and (3) reducing students’ anxiety and enhancing emotional engagement in learning activities.

The course forum is an appropriate venue for information exchange and knowledge sharing regarding the courses in an e-learning environment (Davis & White, 2011). As an important feature of a VLE, online course forum are designed for answering frequently asked questions and asynchronous communications between the learners and instructors. Currently, as a massive online open course, the number of learners in a course usually exceeds 1,000, which suggests that there can be thousands of posts in the course forum everyday. Consequently, it accumulates plenty of valuable information (Yang, Cai, Wang, Zhu, Zhang & Ma, 2009). If the frequently discussed topics on every page of a course forum can be identified and highlighted, the learners could easily catch the common questions, and the instructor could be accurately aware of the questions the learners are interested in or confused in the course forum.

In the e-learning context, considerable research efforts have been made to extract valuable information from the online course forums to provide guidance and assistance to students and improve their learning outcomes, e.g., hotspot analysis and monitoring, intelligent tutoring
services (Zhang, Ackerman & Adamic, 2007; Cong, Wang, Lin, Song & Sun, 2008). However, extracting information from an online course forum is still one of the most challenging tasks. Firstly, a page in the course forum is usually congested with noisy information, e.g., site title, banner, navigation, advertisement, decoration, etc., which significantly skews the performance of knowledge discovery (Cai, Yu, Wen & Ma, 2004). Furthermore, online course forums not only suffer from noise data (as illustrated in Fig. 1.1), but also allow for external advertisements. Due to the diverse representation of e-learning content, current data extraction tools do not work efficiently. For example, in Fig. 1.1, the content highlighted by orange rectangles are targets for data extraction, and the content highlighted by red rectangles are noise that should be disposed.
Fig. 1.1 An example of online course forum

In this thesis, we present an online course forum wrapper – eCF-wrapper designed for structural information extraction from web...
It aims to extract all valid student-produced content, with which we can accurately identify (1) frequently discussed topics/questions and (2) topics/questions with little discussion or without answers. With the identified information, we can advise on the content re-organization of the web pages in a course forum, so that the students can easily catch the hotspots in the course forum and the teachers can be aware of the content the students are interested in but confused of.

1.1.2 Interaction-aware Virtual Learning Environments

In a typical e-learning setting, learning interaction and engagement are carried out solely through the user interface. The design of a flexible interface that suits the needs and preferences of different users is increasingly important for a successful e-learning environment because the users have diverse learning skills, styles and goals. This motivates an exploration of ubiquitous interactive interfaces and its intelligent augmentation in order to support different interaction models and learning contexts. The learner-to-instructor interaction is often less active in existing VLEs than in traditional classroom-based learning (Angelino, Williams & Natvig, 2007; Kim et al., 2015). Instructors are not aware of the continual feedback on the learning content from learners due to the “linear and monotonous” interactive patterns in current e-learning systems (Zhang, Zhou, Briggs & Nunamaker, 2006; Gasparini, Pimenta & de Oliveira, 2011). Many studies suggest that learning interaction in VLEs should be monitored continuously and augmented dynamically by orchestrating the interaction between participants (instructors and learners) and learning services in an automated manner (Carter, 2009; Juan, Daradoumis, Faulin & Xhafa, 2009; Plantamura et al., 2010; Dyckhoff, Zielke, Bültmann, Chatti & Schroeder, 2012; Beliad et al., 2013). This requires the development of a set of learning analytics tools that can instantly provide the information of each learner’s interaction in VLEs.

Furthermore, in order to improve the quality of e-learning courses and assist the learners to easily catch the core content while they watch the course recordings, tracking and analysing learners’ interactions towards the VLE should be carried out (Brooks, Epp, Logan & Greer, 2011; Vatrapu,
Teplov, Fujita & Bull, 2011; Head, 2014). If we can identify and highlight the hotspots that most of previous learners have focused on, we might provide the learners efficient assistance on the key content of the lecture recordings. The challenge to achieving this goal is how to effectively identify and highlight the hotspots in a lecture recording. We present a high-granularity Learning Analytics Engine (hgLAE), which can automatically analyze the hotspot contents in lecture recordings.

Learning activity refers to the collaboration of a set of learning objects and participants of an e-learning environment to promote learners in receiving knowledge and achieving learning objectives. A learner interacts with various types of learning activities in the learning process, performing a series of interactions and collaborations. The monitoring in an e-learning environment refers to the observation on any interaction a learner produced within the learning process, and dynamic interventions by the instructor are required to ensure the learner to be on the right way to achieve learning objectives. An efficient monitoring and intervention mechanism is expected to be capable of instantly providing support and feedback to the instructors and eventually enhance the learners’ engagement in learning activities.

In traditional classroom-based learning, the teaching/learning runs in the face-to-face manner, in which the instructor can efficiently intervene the learners’ learning process. The learners’ interactions are conducted under the instructor’s supervision (e.g., the attendance, learning process, response to the pedagogy, etc.). Recent VLEs are capable of monitoring, analyzing, and summarizing learners’ interactions in learning activities (Mazza & Dimitrova 2007; Adesina & Molloy, 2012). For example, the Blackboard\(^1\) has a monitoring tool showing the summarized information regarding a student’s behavioral engagement of learning activities (including the time the student spent on questions and how much typing they did, the number of students attending the course, the number of times the lecture recording was played, and the time spent on each unit, etc.). These kinds of information are indicators of behavioral engagement, and can be harnessed to improve and personalize a student’s learning.

\(^1\) http://www.blackboard.com/
experience (Tanes, Arnold, King & Remnet, 2011). However, the above engagement information cannot be instantly provided in the current VLEs. To address this issue, we present a web-based interaction-aware VLE, with which the learners’ interactions in learning activities can be continuously tracked and instantly provided to the instructors by using a learning analytics tool.

1.1.3 Promoting Student Engagement in Self-Paced Learning

There are an increasing number of e-learning environments such as Benchprep\(^2\) and TenMarks\(^3\) that are adopted for self-paced learning. A student who is actively engaged and intrinsically motivated in a learning environment is more likely to meet established learning goals (Fredricks, Blumenfeld & Paris, 2004). Learning in isolation in self-paced learning may cause negative emotions, such as anxiety, which may significantly weaken students’ motivation to engage in learning activities (Picard, R. W., & Picard, R., 1997; Shute, 2008; Handri, Nomura, Yajima, Ogawa, Fukumura & Nakamura, 2011; Üğur, 2013; Bower, Dalgarno, Kennedy, Lee, & Kenney, 2015). Fredricks et al. and Liu M et al. argue for the importance of emotional and behavioral engagement in the context of learning (Fredricks, Blumenfeld & Paris, 2004; Liu, Calvo, Pardo & Martin, 2015). Emotional engagement here refers to emotions and interests in self-paced learning (e.g., affective reactions during a learning activity and attitudinal responses toward learning materials).

Emotional engagement is difficult to measure and utilize, and it is a hot research topic in the area of affect-aware computing technologies (Calvo & D'Mello, 2012). Many studies have explored behavioral and physiological factors that affect learning. Modern computing and sensing technologies are capable of observing academic performance and, to some degree, psychological status during a learning activity (Bulger, Mayer, Almeroth & Blau, 2008). Biosensors can also be utilized for simple physiological measures of heart rate as well as more complex

\(^2\) http://www.benchprep.com

\(^3\) http://www.tenmarks.com
neuropsychological relevant measures (e.g., EEG and fMRI) that are effective in tracking a student’s learning processes, but require specialized setups. Those more advanced sensors are often intrusive and distract students’ attentions from learning activities and negatively affect the learning process (Schall, 2014).

In this thesis, we advocate a non-intrusive approach to facilitate anxiety reduction, based on visualizing simple heart rate data. We present a web-based self-paced learning environment - FishBuddy for detecting and promoting student engagement in learning activities. In a between-groups experiment, two groups of students with or without the FishBuddy system completed exercises on English grammar in a self-paced learning environment. Computer-generated tracking of exercise performance was instantly processed and combined with physiological data provided by the Apple Watch to create a biofeedback-generated visualization of a moving fish for the experimental group. These visualizations were displayed on the Apple Watches of students whose physiological measures indicated that they were anxious. The computer-observed results of student engagement were compared with self-reported levels of student engagement for cross-validation to determine whether FishBuddy was useful for promoting student engagement. The experiments demonstrate that FishBuddy is helpful for reducing anxiety and experience of isolation during the self-paced learning exercises.

1.2 Thesis Outline

This section provides a summary of the subsequent chapters in this thesis:

- Chapter 2: Literature Review
  This chapter gives the definitions of e-learning and the major types of e-learning modes. The definition and types of e-learning environments are described. This chapter also investigates the learning interaction and student engagement. Besides, in this chapter we introduce the data extraction, learning analytics and
wearable technology.

- **Chapter 3: A Wrapper for Extracting Information Records from Forums based on Page Segmentation**
  In this Chapter, we describe the design and implementation of a content wrapper for e-learning course forums (eCF-wrapper), specially designed for structural information extraction, which is used to address frequently asked questions in e-learning environments. This chapter introduces a novel page segmentation algorithm, which is designed to detect hotspot content in a page. It also describes a decision tree classifier, which is adopted to parse and identify the details of each record. The evaluation on eCF-wrapper and an example of content re-organization with the suggestion from eCF-wrapper is also given in this chapter.

- **Chapter 4: WebIntera-classroom: An Interaction-aware Virtual Learning Environment for Augmenting Learning Interactions**
  This chapter presents a web-based interaction-aware VLE that is designed to monitor and enhance learners’ interactions in learning activities. This chapter describes the details of a ubiquitous interface and a graphical tool, which are designed to enhance interactions in a learning activity. The instruction effect and user satisfaction level on WebIntera-classroom are also presented in this chapter.

- **Chapter 5: The FishBuddy: An Exploration of Promoting Student Engagement in Self-Paced Learning through Wearable Sensing and Visualized Intervention Technology**
  This chapter presents the design and implementation of a web-based self-paced learning environment – FishBuddy, which is designed for detecting and promoting student engagement. This chapter also describes a between-groups experiment, in which two groups of students with or without the FishBuddy system completed exercises on English grammar in a self-paced learning environment. The comparison of the computer-observed results of
student engagement and the self-reported levels of student engagement is presented for cross-validation to determine whether FishBuddy is useful for promoting student engagement.

- Chapter 6: Conclusion
  This chapter describes the conclusion, major contributions of the thesis and discusses the future work.
Chapter 2 Literature Review

2.1 Introduction to E-learning

Over decades, the advancement of Information and Communication Technology (ICT) has brought significant impact to education, and promotes lots of innovative learning technologies (Cardinali, 2003). Lin (2007) and Clark & Tomic et al. (2011) describe these new learning technologies as electronic learning (e-learning), which involves the engagement of various kinds of information technologies. A number of literatures present different definitions of e-learning that describe the relationships between educational context and information technologies. Hasibuan & Santoso (2005) and Ma et al. (2010) argue that e-learning is a type of learning conducted by using technologies to enhance the teaching/learning process. Meyen et al. (2002) define e-learning as the delivering and acquisition of the knowledge that is dispensed and facilitated essentially by electronic tools and media. Van, Erik & Jeroen (2008) define “e-learning” as computer-based learning experiences, self-paced or instructor-led, supported and enabled by information technology, and it is a new method for knowledge delivery in the synchronous/asynchronous manner by using digital media (e.g. Internet, Compact Disc, Television, etc.). Besides, according to Zimmermann (2011) and Hayakawa et al. (2012), the term “e-learning” could be further generalized as the way for knowledge delivery by electronic media.

E-learning provides facilities to participants, allowing them to learn anywhere, anytime and at their most convenience. This advantage makes the learners flexible in knowledge acquisition. Ivan Mahanta & Ahmed (2012) argue that the e-learning systems should be more flexible in assisting all participants during the learning process, and should be designed with more facilities that support learning process in an efficient way. Currently, e-learning systems have been widely adopted by many universities, institutions and industries for educational purposes and
professional training (Beliad, Talon & Kerkeni, 2013). Using e-learning technology can enhance the learning process and learner-centric learning. Furthermore, with well-designed strategies, e-learning could make the participants (i.e., learners and instructors) in the center of the learning process, and promote effective interactions in learning activities (Zhang et al. 2007; Plantamura et al., 2010; Dyckhoff et al., 2012).

2.1.1 Instructor-led e-learning

The term “instructor-led e-learning” is interchangeable with other terms (e.g., synchronous learning, on-site learning, etc.), and it is usually instructor-centric. It is capable of enabling all the participants (i.e., the learners and instructors) to interact with each other in a real-time manner and supporting the interactions between the participants and the learning contents in e-learning environments. Various kinds of virtual classrooms (e.g., shared whiteboard, video conference system, etc.) are set up to conducted in synchronous teaching/learning activities. With these kinds of virtual classrooms, participants can share content and interact real-time with each other within the e-learning environment. In instructor-led e-learning, the instructors own the absolute control over the learning process and can dynamically intervene the learners’ learning activities. In summary, the instructor-led e-learning supports various types of learning activities, absolute supervision on learning process, synchronous collaboration and interactions among participants.

2.1.2 Self-paced e-learning

Self-paced e-learning is also called asynchronous e-learning, in which various digital media technologies are employed to enable the learner-centric learning process. There is an increasing number of self-paced e-learning systems (e.g., Benchprep, TenMarks, etc.) that are adopted. In particular, for higher education, self-paced e-learning systems are widely adopted for the practice and preparation of the course examinations. Self-paced e-learning is so flexible that learners can take part in it at their most convenient. In addition, current self-paced
e-learning systems support various types of learning materials (e.g., handout, PPT, lecture recordings, etc.) (Alghamdi, Zedan & Alzahrani, 2011).

Castek, Jacobs, Pendell, Pizzolato, Reder & Withers (2015) argue that self-paced e-learning could reduce the pressure within the e-learning environment and increase the feeling of comfort. They also argue that self-paced e-learning can reduce fear and anxiety, which are major barriers the learners face in a self-paced learning environment. This is because in synchronous learning, attempting to keep pace with other participants can increase the already-existing anxiety. A few “slow” learners need more time to accumulate skills and experiences before obtaining enough confidence to formally take part in the learning activities.

2.1.3 Blended Learning

Collis & Moonen (2001) describe the blended learning as a mixed learning environment, in which the learning process is conducted in both physical classrooms and on the Internet. Valia (2002) defines the blended learning as the combination of different types of learning (i.e., traditional classroom-based learning, synchronous e-learning and self-paced e-learning. Garrison & Vaughan (2007) further define the blended learning as a novel way to conduct teaching/learning that involves traditional teaching/learning activities (e.g., use hardware-based blackboard, etc.) and information technologies (e.g., e-learning systems, Internet, etc.). Blended learning facilitates lots of existing pedagogical tools and methodologies to provide very flexible learning environments.

Blended learning is designed to address the problems existing in the traditional learning and e-learning contexts in many educational institutions and universities (Cheung et al. 2010): 1) it provides more opportunities for learners to recall the learning content they missed in the traditional classroom-based learning; 2) there are more pedagogical strategies available for delivering content for different types of learning content (e.g., some learning materials are appropriate for traditional classrooms, some digital materials are appropriate for e-learning); 3) with blended learning the instructors could dynamically employ different
learning styles to improve the effectiveness of the learning process and learners’ learning outcome.

However, So & Brush (2008) argue that even though the blended learning could provide a flexible and effective experience of a learning process, the blended learning would not completely replace the traditional classroom-based learning nor web-based e-learning.

2.2 E-learning Environments

Nowadays, with the evolvement of information technology and communication, teaching and learning via the Internet have become increasingly popular in universities and educational institutions world-wide, and the demands for e-learning systems are significantly increasing (Buendia et al. 2009).

Al-Ajlan & Zedan (2008) define e-learning environments as the combination of information infrastructures and Internet-based applications, which are usually complex systems requiring the contributions from a variety of areas (e.g., databases, system engineering, psychology, education, etc.). E-learning environments are designed to help the participants in e-learning activities to achieve their goals: 1) delivering learning contents to target learners; 2) attempting to learn and understand the knowledge delivered by the instructors. In a typical e-learning environment, instructors, learners, coordinators and other expertise from other fields are required to join together to support an effective learning process. A typical e-learning environment usually consists of several basic services: (1) learning process management; (2) learning materials affordance and (3) pedagogical strategies and tools. Current research on the e-learning environments works towards the direction that e-learning environment will provide more dynamism and flexibility (Dong & Li 2005; Graven et al. 2006; Jeroen, 2008; Clow, 2013).

2.2.1 Learning Management Systems (LMSs)
Carliner (2005) describes the learning management system (LMS) as a technology enhanced e-learning platform that conducts various types of tasks related to a set of traditional educational affairs in universities: 1) sign up; 2) course enrolment; 3) track the engagement of learning activities; 4) conclude academic performance; 5) provide statistical reports regarding a course. Roqueta (2008) defines the LMS as a type of educational application designed to support individual learning process, as well as the analytics on the learning performance and outcome achieved by the learners. LMSs provide automated mechanisms to make the course delivery and management of learning process more convenient and effective. For example, some LMSs can automatically notify the learners of the performance of the learning activities they have attended. A common LMS is Moodle⁴, which is open source and increasingly adopted for submitting and managing the students’ assignments in universities all around the world.

2.2.2 Virtual Learning Environments (VLEs)

Virtual learning environments (VLEs) have been emerging as a tool for distant education. Compared to the LMS, which focuses on the management of learning tasks, VLE focuses on the management of learning process. It consists of a number of pedagogical tools designed to enhance the effectiveness and experiences within teaching/learning processes. VLEs include some basic features: 1) remote communication; 2) support for online collaboration among participants; 3) recourse management and 4) tracking of learners’ learning process (Dillenbourg, 2000; Weller, 2007). Currently, VLE as a major form of e-learning systems is being increasingly adopted in universities and higher educational institutions (Mahanta & Ahmed, 2012). The most valuable benefit it provides is the elimination to the time and location barriers from attending an e-learning activity.

⁴ https://moodle.com/
2.2.3 Wearable-based Enhanced Learning Environments (WELEs)

Wearable-based enhanced learning environments (WELEs), which are closely related to wearable technology and ubiquitous computing, can be defined as a type of learning in a state of physical mobility with support of body-worn devices (Bowskill & Dyer, 1999; Buchem, Klamma & Wild, 2014). WELE is easily confused with the term “mobile learning”. The major differences between the WELE and mobile learning are: 1) in a WELE, the device used for learning is body-worn, whereas the device is not attached to the learner’s body in mobile learning; 2) the learner needs to take a state of temporal stationary for learning with mobile devices, whereas there is no need to keep temporal stationary in WELEs.

2.3 Learning Interactions

Alghamdi, Zedan & Alzahrani (2011) define the learning activities as the interactions and collaborations among different types of learning objects and participants to make the learners better understand the learning content and achieve the learning objectives within the learning process. Interaction is an integral part of the learning process, whereby instructors, learners and the learning content share a common learning environment. Moore (1989) identified three major interaction types in a learning process: learner-to-learner, learner-to-content and learner-to-instructor. The interactions within these learning activities indicate that, to what extent, the knowledge could be acquired by the learners. In this thesis, our study focuses on the major learning activities that occur in the typical e-learning settings, which include learner-to-instructor interaction, the collaboration among learners and learner-content interaction.

Interactive papers are designed to augment conventional (physical) papers to enhance reading and writing experience, and to provide distinctive opportunities for participants to engage in learner-to-content interaction in a VLE, not only because of their nature but also because of their mobile interactional flexibility (Signer, Norrie, Weibel & Ispas, 2014). TAP & PLAY is a tool supporting language activities for children, and it
plays audio content and recognizes handwriting and gestures on (digital) paper to augment learner-to-content interaction (Piper, Weilbel & Hollan, 2012). Physical paper supports various forms of content highlighting and annotation. It is not easy to provide the same richness to users engaged in learning interactions in a VLE. In contrast, in this thesis, we propose a ubiquitous user interface that integrates regular paper and Anoto® digital pen with a web-based whiteboard to augment learner-to-content interaction in VLEs.

Tracer is a tool used to measure user engagement in writing, and analyze and generate visualizations of the quantitative measures of user engagement (Bransford, John, Ann & Rodney, 1999). AAT is a learning analytics tool used to analyze students’ behavior in VLEs (Graf, Ives, Rahman & Ferri, 2011), and it provides information regarding students’ engagement during learning, enabling the identification of confusing learning content. LOCO-Analyst was developed to provide educators with feedback on students’ learning performance and learning activities (Ali, Hatala, Gašević & Jovanović, 2012). Gómez-Aguilar, Hernández-García, García-Peñalvo & Therón (2015) proposed a visualized tool to identify the objective factors related to the interaction between the student and the VLE (e.g., the number of resources accesses, and the number of forum posted and viewed). These studies aim to augment learner-to-instructor interactions by tracking and analyzing large-scale user-produced behavioral data and log data, but the feedback is not instant. The ex-post-facto provision of the information about learners’ activities in VLEs does not help instructors to take runtime actions in response to learners’ performance. In contrast, the graphical tool developed in this thesis can instantly provide this information, enabling instructors to take dynamic actions for optimal supervision and encouragement of learner-to-instructor interaction.

5 http://www.anoto.com/
2.4 Student Engagement

The data collection as characterized in the research literature on student engagement in learning is typically based on the teachers’ observations and/or student self-reports (Venkatesh, Morris, Davis, G. & Davis, F. 2003; Liu, 2008). For example, in the student engagement walkthrough process, teachers assess the degree of student engagement through overt behaviors such as answers to questions, verbal participation, as well as frequency of student interaction with learning materials (Gewnhi, Bavel, Vasey & Thayer, 2013). The ratings are then compared to the student ratings of the extent to which the learning activities are interesting and challenging, and the degree to which they understand why and what they are learning. It has been concluded that a general description of student engagement should include three aspects: (1) emotional engagement, (2) cognitive engagement and (3) behavioral engagement.

Dynamic, individualized intervention is required to further help each student’s engagement adequately. In this thesis, we focus on the consistency of engagement and develop an approach for intervening the learning of the students whose behavioral engagement or emotional engagement is low. Previous research focuses on engagement in traditional classrooms (Sheldon & Biddle, 1998), web-based learning activities (Chen, Lambert & Guidry, 2010), learning activities using smart interactive devices (Piper, Weibel & Hollan, 2012) and virtual learning environments. Various “clicker” systems have enabled students to give live feedback with respect to learning materials. The responses can be recorded, and analyzed by e-learning systems to generate feedback-oriented visualizations (Blasco-Arcas, Buil, Hernández-Ortega & Sese, 2013). However, teacher-led online courses are much different from self-paced learning. In this thesis, we employ an alternative approach for automatic monitoring and intervention to promote student engagement (without teacher’s supervision) based on Jones’ general model of student engagement (Jones, 2009).

Universities are increasingly using systems that integrate student interactions with physiological data gathering to perform learning
interventions that reduce student anxiety in self-paced learning (Uğur, 2013; Clow, 2013). In such systems, a variety of intelligent agents may analyze the data with regard to additional factors (e.g., grades, gender, etc.) to produce learning feedback (Mattingly, Rice & Berge, 2012). Researchers have recommended that teachers suggest appropriate actions to students for optimizing their learning processes through learning interventions in the form of instant feedback on learning activities (Liu, Calvo, Pardo & Martin, 2015). Various visualization techniques have been used in this context to give instant feedback and promote student engagement (Santos, Govaerts, Verbert & Duval, 2012).

Many visualizations of learning processes are based on a dashboard to display student performance on learning activities and messages to guide the students through learning activities (Verbert, Govaerts, Duval, Santos, Van Assche, Parra & Klerkx, 2014). A simple dashboard in a traffic-light-style form can indicate student performance (Romero-Zaldivar, Pardo, Burgos & Kloos, 2012) while a complex dashboard can show more detailed information regarding various dimensions of the learning activities (Luo & Xia, 2014). CourseVis is an e-learning system capable of visualizing peer-to-peer interactions in a web-based course (Mazza & Dimitrova, 2007). These systems focus on the measurement of learning performance and do not include physiological factors to help support student motivation for learning activities.

2.5 Data Extraction

Due to its wide adoption in various types of application contexts (e.g., e-learning context, etc.), data extraction technologies have attracted lots of attention from researchers all around the world. Feng, Haffner & Gilbert (2005) proposed that the popular approaches used for data extracting could be categorized into two groups: (1) duplicated sub-tree pattern detection approaches; and (2) machine learning based approaches.

Duplicated sub-tree pattern detection approaches are widely applied to extract information from web pages. Generally, they utilize the
structural information of Document Object Model (DOM) tree to generate a wrapper (Kushmerick, 2010; Zheng, Song, Wen & Wu, 2007). The assumption is that sub-trees with frequently repeated structures are used to carry data records. However, diverse layout styles make it difficult to identify the repeated structures in the DOM tree (Kushmerick, 2010), and thus additional manual interactions are needed to assist these data extraction approaches to improve the performance (Zheng et al., 2007). Moreover, only a few web sites are designed to have duplicated structure patterns, which make structure pattern detection based approach inappropriate. As a frequently used approach in machine learning, Hidden Markov model-based data extraction is treated as a generalized approach for data extraction on web pages (Barros, Silva, Prudêncio, Filho & Nascimento, 2008). In this thesis, we propose an approach based on the Hidden Markov model to analyze web pages of course forums, and extract data records from each web page. In order to accurately train a Hidden Markov model, it requires a lot of efforts to prepare the training data as well as a longer learning process of the system parameters. Feng et al. presented the assumption that there usually exist 12 fields in a record (Feng Haffner & Gilbert, 2005). We can employ a support vector machine (SVM) to classify the DOM nodes into the 12 fields pre-defined by Feng et al. (2005). It is obvious that the pre-defined categories significantly restrict the flexibility of this approach.

In order to develop a generalized and effective tool for data extraction on web forums, lots of attempts have been conducted. For example, data extraction is treated as duplicated sub-tree pattern detection problem (Yang, Cai, Wang, Zhu, Zhang & Ma, 2009). It shows the feasibility of handling post data according to their types of layout styles, which can work effectively on static web sites generated by fixed page templates, but not appropriate for e-learning course forums generated by unfixed page templates. Besides, machine learning and ontology-based approaches have been successfully applied to an e-learning course forum (Yang & Zhu, 2011).

---

6 https://developer.mozilla.org/zh-CN/docs/DOM
2.6 Learning Analytics

Siemens (2012) defines learning analytics (LA) as “the use of learner-produced data, intelligent approaches, and analytical models to discover valuable information and social connections, and to predict and advise on learning activities”. The emergence of learning analytics to improve the teaching and learning process is inspired by many existing analytic services such as Google analytics and business intelligence (Dyckhoff et al., 2012). It has been suggested that educational datasets should be used to support various kinds of learning processes (Chatti, Dyckhoff, Schroeder & Thüs, 2012). Van Barneveld, Arnold & Campbell (2012) further proposed a conceptual framework that describes different types of analytics in educational contexts as well as their relationships.

Recently, there are increasing interests in improving the online pedagogical designs using learning analytics. As mentioned in Section 2.1, LOCO-Analyst, Tracer and ATT are learning analytics tools for monitoring learners’ interactions. In addition to these, CourseVis is a tool that analyzes web logs from course management systems (CMSs), enabling instructors to follow what is happening in remote classrooms (Mazza & Dimitrova, 2007). SAMOS automatically generates weekly monitoring reports of students’ and groups’ activities in online learning environments, which are derived from the data archived in server log files (Juan et al., 2009). Moodog tracks students’ online learning activities and runs as a CMS log analysis tool (Graf, Ives, Rahman & Ferri, 2011). CourseVis and Moodog are both log analysis tools for CMSs. ELAT is used to handle large-scale monitoring data in microseconds to help instructors to reflect on pedagogical processes, and to identify appropriate interventions and improvements (Dyckhoff et al., 2012). Cruz-Benito, Therón, García-Peñalvo & Lucas (2015) explored the data retrieved from an educational virtual world to identify and validate user behaviors. But there are still barriers that prevent these studies from working efficiently. One such barrier is that as a consequence of the increasing volume of learning objects and learner-produced behavioral data, data processing is

---

7 https://analytics.google.com/
unacceptably time-consuming. As such, learners’ runtime information cannot be instantly provided to instructors. Thus, it is difficult to make runtime decisions in response to students’ activities during the learning process.

Watching course videos is a popular approach for self-paced learning, and more and more studies are conducted for the improvement of course design by performing data analytics on learners’ watching history (Wieling & Hofman, 2010; Kizilcec, Piech & Schneider, 2013; Kim, Li, Cai, Gajos & Miller, 2014). Wieling & Hofman (2010) invited 474 students to participate in an experiment evaluating the impact of self-paced learning through watching course videos and the automated feedback on learning performance. Kizilcec et al. (2013) presented a simple and scalable classification method to identify learners according to their patterns of interaction with video lectures and assessments. They used the K-means clustering algorithm to analyse students’ interaction with MOOCs, and divided the student engagement to four categories: “completing”, “auditing”, “disengaging” and “sampling”. Kim et al. (2014) collected user behavioral data regarding pausing and resuming videos, and navigating between points during playback. They also analyzed video content to identify points of interest and content that are confusing for users, and to advise on improvements to video designs. These studies inspired us to discover knowledge from users’ watching history. But there are still barriers to effectively apply discovered knowledge to improve the learning experience while watching the lecture recordings. These barriers include the fact that existing lecture recordings are based on video stream, which is difficult to edit once published, and the data analysis on it is also unacceptably time-consuming. Furthermore, video-based recordings are not specially designed for an educational purpose, and hence it is difficult to extract knowledge.

2.7 Wearable Technology

Wearable technology can enable transparent interaction that allows a
person to move freely. The design of wearable technologies increasingly allows for measuring psycho-physiological factors (Uğur, 2013).

Wearable-device-based health monitoring, which continuously tracks body statuses, is a typical example for health and wellbeing that may be used for psycho-physiological measurements such as detecting stress. Buchem et al. proposed an extension of a typical learning environment with the level of engagement made available through utilizing body-worn devices (Buchem, Merceron, Kreutel, Haesner & Steinert, 2015). The emergence of new wearable devices, such as smart watches and smart glasses support capturing live data from individual learning activities, and identifying appropriate moments for carrying out learning interventions in a wide variety of scenarios. Wearable devices used for student interaction in learning activities (Mistry, Maes & Chang, 2009) typically maintain connections with external information systems, capable of tracking learning activities, measuring physiological data and delivering feedback to students. By collecting physiological data in learning activities for feedback visualization, wearable devices can play an important role in enhancing students’ learning experiences (Nakasugi & Yamauchi, 2002).

Anxiety is a negative emotion that may occur when students experience discouragement during learning activities (e.g., when faced with difficult learning materials), and it typically impairs consistency of engagement in learning (Chiu & Wang, 2008). There are many possibilities for utilizing physiological measurements to assess student anxiety. An electroencephalogram (EEG) device can measure continuous electrical activities in the human brain through a set of electrodes placed on the scalp. The physiological signals captured can be represented in waveforms that reflect minute voltage variations resulting from gross neural activities over time (Niedermeyer & da Silva, 2005). The electroencephalogram device is usually considered intrusive and is typically used only in laboratory environments. Picard (2001) proposed to use galvanic skin response (GSR) for measuring physiological arousal that could, depending on context, likely indicate increased levels of anxiety. The results of GSR, however, cannot be made available in real-time. Eye tracking is used for measurements that are meaningful only if analyzed within scope of what
the user observes (Bergstrom & Schall, 2014). These relatively complex biometric devices and methods cannot be readily deployed in everyday learning contexts.

In this thesis, we use the Apple Watch for simple, unobtrusive physiological measurements. The Apple Watch is capable of measuring and tracking change of heart rate, which can be used, in conjunction with contextual data, as a rough, albeit imperfect indicator of anxiety (Schirmer & Escoffier, 2010). It is an imperfect measurement since, depending on context, someone may well experience the increased heart rate without anxiety. However, within our context and for our purposes of online learning, increased heart rate is sufficiently associated with anxiety. In this thesis, we adopt a wearable health-monitoring platform termed HealthKit for the Apple Watch that measures physiological dimensions. Developers can use the Application Programming Interfaces (APIs) provided by HealthKit to access physiological data. The Apple Watch is capable of non-intrusive measurements (without user interruption) and has been successfully applied in health management (Lutze & Waldhor, 2015) and medical monitoring in hospitals (Shin, D. M., Shin, D. & Shin, D., 2013).

2.8 Summary

In this chapter, we gave a brief introduction to the conception of e-learning and discussed the definitions of e-learning. Then we reviewed the history and definitions of e-learning environments, and described three types of e-learning environments concerned in this thesis. The critical review on learning interactions and student engagement showed that there were still challenges to instantly monitor and intervene the learners’ interaction and engagement in a learning process in most VLEs. Within a learning process, the learner-to-instructor interaction and the learner-to-content interaction are our concerns, and by well-designed pedagogical tools, there is still room to enhance these two types of

https://developer.apple.com/healthkit
interactions. Using the approaches from data mining and other areas could possibly address these limitations that current VLEs face. Hence, the review on data extraction, data analytics and wearable technology has also been covered.
Chapter 3

eCF-Wrapper - A Wrapper for Extracting Information Records from E-learning Course Forums

In this chapter, we present a page-segmentation based wrapper (called eCF-wrapper) specially designed for structural information, which exists in the course forums of e-learning environments. Aiming to accurately extract valid student-produced post records, eCF-wrapper combines a page-segmentation algorithm and a decision tree classifier to extract the structural information in course forums. In the segmentation phase, a novel page-segmentation algorithm is proposed to detect the valid data area, where there are valid learner-produced records in each web page of an online course forum. In the extraction phase, the decision tree classifier is used to identify and analyze the details of each record. With this two-phase approach, the learner-produced post in each web page of a course forum could be accurately identified and parsed. This chapter is organized as follows. We briefly introduce and clarify some basic concepts in Section 3.1. The design rationales and implementation of eCF-wrapper is introduced in Section 3.2. Experiment and evaluation is presented in Section 3.3. A case study, which illustrates the content re-organization of a web page of an online course forum with the suggestion from eCF-wrapper, is presented in Section 3.4. Finally, the chapter summary is presented in Section 3.5.

3.1 Preliminaries and Concepts

As an essential module of an e-learning system, the online course forum plays an important role for exchanging information and sharing knowledge regarding the course in an e-learning environment. In a typical online course forum, there are thousands of posts produced by the learners, as well as the post from external services (e.g., advertisement services, etc.) every day. It attracts considerable research efforts to extract
valuable information from the course forums for improving the learning experience. With well-designed analytics on these learner-produced data, we may reveal many interesting and meaningful facts (e.g., the learners' learning trend, the difficulties they face, the hotspot questions the learners frequently discussed in the course forums, etc.), which are significantly helpful to improve the efficiency of learning. Besides, with the collaboration with external services, these posts can be used for content optimization of the course forums, automated question-answer system and tutoring services (Zhang et al, 2007; Cong et al, 2008). However, there are still barriers preventing us from carrying out effective data analytics on these posts, for example, accurately extracting valid learner-produced records in a course forum is a challenge.

Extracting information from an e-learning course forum is still one of the most challenging information retrieval issues due to the fact that a web page consists of auto-generated page content and learner-produced content, which is unpredictable and always consists of non-structural content. Traditional information extraction methods employ either duplicated sub-tree pattern detection methods, or machine learning methods. Due to the periodical update of forum templates and diversity of page contents, the aforementioned approaches cannot work efficiently for the course forums.

In a typical e-learning course forum, a web page is usually congested with much noisy data (e.g., course title, course introduction, content navigation, advertisement from sponsors, external hyperlinks, etc.), which significantly skews the performance of knowledge discovery and should be discarded in the process of data analytics (Cai, Yu, Wen & Ma, 2004). Furthermore, a course forum not only suffers from noise data, but also includes lots of repeated contents. For example, posts may contain a repeated block of textual descriptions, images or a fragment of random HTML code. Existing data extracting approaches are not designed for the diverse representations of learners’ posts. Fig. 3.1 shows an example web page of a course forum. In Fig. 3.1, page areas highlighted by orange rectangles are data blocks to be extracted, and areas in red rectangles are noise that should be discarded in the data extracting process.
Fig. 3.1: A web page of an online course forum with noises
A number of attempts have been carried out to develop a generalized and accurate tool for data extracting on web page. For example, Yang, Cai, Wang, Zhu, Zhang, Ma (2009) applied the solution for the duplicated sub-tree pattern detection problem to the data extracting. These approaches are appropriate for the web forums consisting of web pages generated by fixed template, but not valid for those web forums consisting of web pages without fixed templates. In addition, Yang & Zhu (2011) have applied some machine learning and ontology-based approaches to some specific web forums concerning the problem of data extracting. However, these existing approaches can only be valid in some web forums consisting of static web pages, but cannot be adopted for current dynamic e-learning course forums.

3.1.1 Concept Definition

In order to clearly formulate the problem and facilitate the description of
the system, we briefly define several basic concepts in our research context.

Course Forum: a learner-oriented discussion venue within an e-learning environment, where learners and instructors could exchange their opinions and sharing their knowledge regarding courses. A course forum can be visible to any visitor or only accessible for registered ones. In a course forum, users (i.e., learners, instructors) can view a topic and the posts included in it, comment on a topic, reply to a specific post and initiate a new topic. Typically, a course forum includes lots of web pages.

- Topic: it is the title of a discussion, which represents the main idea in a discussion. In a course forum, a topic implies a question that learners face in an e-learning course.
- Topic List: an independent web page in a forum, which includes the topics created by users in the course forum, and each topic record includes a unique hyperlink to its correspondent post list page.
- Post: a user-produced record in a course forum and it usually represents a user’s opinion to a specific topic or a response to a specific post.
- Post List: an independent web page in a forum, which usually represents users’ discussion on a specific topic. It may consist of several posts.

In Fig. 3.3, there is an abstract page module illustrating a post, a topic, and a reply to a post. And each post consists of the author information, the time it created, and the content, which are the target content of the eCF-wrapper.

3.2 Design Rationale & Implementation

In this section, we will describe the details of the system architecture and the implementation of the major modules.
Our system incorporates two phases, as depicted in Fig. 3.4: (1) segmentation phase, and (2) extraction phase. The goal of the segmentation phase is to automatically identify valid records from the
HTML code. In practice, the first step will segment a forum page into several independent page modules. Then, the structural data including explicit semantic structures could be identified from those posts. In Fig. 3.4, and each phase is denoted by a dash-lined box.

3.2.1 Page Segmentation

In a course forum, a post page not only contains a number of user posts, but also contains noise data. Therefore, it is necessary to segment post pages into independent semantic structures, then the post area and noise area could be distinguished. Inspired by the traditional segmentation methods, we assume posts are generated in such a way that contents of independent topics are encapsulated in a close sub-tree of DOM tree and have similar layout.

There is an assumption illustrated in Fig. 3.2: the post areas in left of Fig. 3.2 are highlighted in bold rectangle, and the DOM tree in the right of the Fig. 3.2 is the simplified model of these post areas. With this assumption, we can build a mapping relationship between the post areas and the sub-trees of a DOM tree. The second assumption is that a post is generated by only one learner in a fixed style. As illustrated in Fig. 3.1, the two records in the post page have different visual styles (i.e., module size and text font).

Based on these two assumptions, a set of heuristic rules can be proposed to judge whether a node of a DOM tree is a user post or not. If a node is a post node, then this post is to be extracted. In order to accurately identify user posts, a novel page segmentation algorithm is proposed in terms of: (1) DOM tree structure; (2) visual style and (3) additional information regarding a user. The heuristic rules are described in Table 3.1.

<table>
<thead>
<tr>
<th>DOM tree rules</th>
<th>Rule 1</th>
<th>In a post page, a post should consist of either a “DIV” tag, or a “TABLE” tag.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule</td>
<td>Visual rules</td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Rule 2</td>
<td>The nodes in a sub-tree of a post node should consist of similar tag, such as “A”, “UL”, “SPAN”, etc. If the types of all the tags appearing in node 1 are the same with the types in node 2, we can conclude that the node 1 and 2 are similar.</td>
<td></td>
</tr>
<tr>
<td>Rule 3</td>
<td>The width of post module should exceed 480 pixels, and the height of post module should exceed 20 pixels.</td>
<td></td>
</tr>
<tr>
<td>Rule 4</td>
<td>The difference of two posts’ width should be smaller than 20 pixels.</td>
<td></td>
</tr>
<tr>
<td>Rule 5</td>
<td>A user post should include a timestamp.</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: Heuristic rules in post extraction phase

### 3.2.2 Classification

With the operation of page segmentation, the target posts in a course forum can be identified accurately. Then these identified posts will be parsed to form information records. According to the semantic structure of a post, a record contains four fields (i.e. “author”, “time”, “content” and “additional information”). We extract the text nodes in the posts. The data extraction on these records is a typical classification problem, in which text nodes in the posts can be used as samples and the four fields mentioned above can be used as labels. In the current context, we summarize eight attributes, which are closely related to the classification label. These attributes are defined in Table 3.2.
Table 3.2: Definitions of the data features in classification

<table>
<thead>
<tr>
<th>Id</th>
<th>Definition</th>
<th>Description</th>
</tr>
</thead>
</table>
| 1  | width = \[
\begin{align*}
1 & \text{ v<200} \\
2 & \text{ 500>v\leq200} \\
3 & \text{ v\geq500}
\end{align*}
\] | The width of node v |
| 2  | height = \[
\begin{align*}
1 & \text{ v<40} \\
2 & \text{ 400>v\geq40} \\
3 & \text{ v\geq400}
\end{align*}
\] | The height of v |
| 3  | class = \[
\begin{align*}
1 & \text{ v=’class’} \\
2 & \text{ other}
\end{align*}
\] | The parent of v has the ’class’ attribute |
| 4  | time = \[
\begin{align*}
1 & \text{ v=’time stamp’} \\
2 & \text{ other}
\end{align*}
\] | The text in v contains time stamp |
| 5  | parent = \[
\begin{align*}
1 & \text{ v=’A’} \\
2 & \text{ v=’H’} \\
3 & \text{ v=’SPAN’} \\
4 & \text{ v=’DIV’} \\
5 & \text{ v=’B’} \\
6 & \text{ v=’FONT’} \\
7 & \text{ other}
\end{align*}
\] | The type of parent or grandparent |
| 6  | category = \[
\begin{align*}
1 & \text{ v=’author’} \\
2 & \text{ v=’time’} \\
3 & \text{ v=’content’} \\
4 & \text{ v=’additional information’}
\end{align*}
\] | The categories of v |
| 7  | space = \[
\begin{align*}
1 & \text{ v=’space’} \\
2 & \text{ other}
\end{align*}
\] | The text in v contains space. |
| 8  | Integer | The depth of v |

Decision tree algorithm (DT) is used in this phase to classify each text node into a predefined category (Breiman, Friedman, Olshen, & Stone, 1984), and the C4.5 algorithm is adopted. A decision tree initiates with a set of training samples according to the normalized criteria of information. The training data is denoted as a set \( S = \{s_1, s_2, \ldots, s_n\} \). Each sample is denoted as a vector \( s = (x_1, x_2, \ldots) \), in which \( x_1, x_2, \ldots \) represent the attributes or features of the sample. The training data is augmented with a
vector \( \mathbf{C} = (c_1, c_2, \cdots) \), in which \( c_1, c_2, \cdots \) represent the class that each sample belongs to.

For each node of the tree, C4.5 takes an attribute of the data, with which the set of samples can be split most efficiently. We take the ratio of normalized information gain that results from choosing an attribute to split the samples set, as the criterion. The attribute with the best ratio of normalized information gain will be used to split the DOM tree.

Equations 1-5 explain how to work out the information gain ratio of an attribute with the following steps:

- (1) the entropy of the sample set \( \mathbf{D} \) with category information is computed by Equation 1.
- (2) the expectation of samples will be computed, where value of the attributes \( \alpha \) is \( i \).
- (3) normalized information gain of the attribute \( \alpha \) can be obtained by Equation 3.
- (4) the entropy of sample set with split attribute \( \alpha \) is computed using Equation 4
- (5) the information gain ratio of the attribute \( \alpha \) can be computed by Equation 5.

\[
\text{entropy}(\mathbf{D}) = -\sum_{k=1}^{m} \frac{|D_k|}{|\mathbf{D}|} \times \log_2 \left( \frac{|D_k|}{|\mathbf{D}|} \right) \quad (1)
\]

where \( \mathbf{D} \) is the training set, \( D_k \) is the training data set of class \( k \) and \( m \) is the number of categories.

\[
\text{expectation}_{\alpha}(\mathbf{D}) = -\sum_{i=1}^{A} \frac{|D_{\alpha i}|}{|\mathbf{D}|} \times \text{entropy}(D_{\alpha i}) \quad (2)
\]

where \( \alpha \) represents an attribute, \( A \) is the number of possible values of attribute \( \alpha \) and \( |D_{\alpha i}| \) indicates the number of samples in which the value of attribute \( \alpha \) equals to \( i \).

\[
\text{gain}_{\alpha}(\mathbf{D}) = \text{entropy}(\mathbf{D}) - \text{expectation}_{\alpha}(\mathbf{D}) \quad (3)
\]
\[ \text{splitEntropy}_a(D) = -\sum_{i=1}^{A} \frac{|D_{ai}|}{|D|} \times \log_2 \frac{|D_{ai}|}{|D|} \]  

(4)

\[ \text{gainRate}_a(D) = \frac{\text{gain}_a(D)}{\text{splitEntropy}_a(D)} \]  

(5)

With the completion of the classification, all the text nodes in a post are associated with semantic information types. Actually, the category of “additional information” has limited explicit semantic meaning and will be discarded. Finally, the target records are labeled with “author”, “time” and “content” attributes.

### 3.3 Experiments and Evaluation

In order to evaluate the effectiveness of eCF-wrapper, experiments are carried out with various kinds of datasets. The segmentation algorithm PS-STS and classification algorithm naive Bayes (NB) are adopted for the comparison (Yun, Bicheng & Chen, 2009). Experimental results show that eCF-wrapper acquires a better segmentation and extraction performance than PS-STS and NB.

The PS-STS algorithm can split a post page based on a similarity of the DOM sub-tree structure (Yun, Bicheng & Chen, 2009). Equation 6 shows the similarity function for PS-STS. In order to acquire better performance, the parameters of PS-STS are initialized as \( N = 3, \omega = \{0.6, 0.3, 0.1\} \).

\[ \text{Sim}(x, y) = \sum_{i=1}^{N} w_i \sum_{j=1}^{M_i} \frac{1}{M_i} S_y \]  

(6)

where \( x, y \) are two sub-trees, \( N \) is the maximum depth of the sub-tree, which means the similarity function only considers nodes in top \( N \) layers of \( x, y \). \( w \) is weight that indicates the layer \( i \)’s influence on the calculation of similarity, \( M_i \) is the number of nodes in layer \( i \), and \( S_{ij} = 1 \) if nodes \( i \) and \( j \)
are of the same types or attributes, and 0 otherwise.

3.3.1 Experimental Settings

As there is no benchmark dataset available, we collect data from different data sources as the dataset for experiments. In order to validate the robustness, two types of dataset are adopted: 1) post pages and user posts generated by forum generating program; (2) post pages crawled from course forums in the e-learning environments. Table 3.3 shows the details of course forums used in the experiments. Semantic objects in each page and data records are manually labeled. If the result of using eCF-wrapper or any one of the two baseline algorithms is the same as the manual label, the result is positive, and vice versa.

<table>
<thead>
<tr>
<th>Id</th>
<th>Forum Site</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PhpBB</td>
<td>forum creating program</td>
</tr>
<tr>
<td>2</td>
<td>Discuz</td>
<td>forum creating program</td>
</tr>
<tr>
<td>3</td>
<td>PhpWind</td>
<td>forum creating program</td>
</tr>
<tr>
<td>4</td>
<td>IPB</td>
<td>forum creating program</td>
</tr>
<tr>
<td>5</td>
<td>LeadBBS</td>
<td>forum creating program</td>
</tr>
<tr>
<td>6</td>
<td>tieba.baidu.com</td>
<td>general forum</td>
</tr>
<tr>
<td>7</td>
<td><a href="http://www.tianya.cn">www.tianya.cn</a></td>
<td>social events discussion</td>
</tr>
<tr>
<td>8</td>
<td><a href="http://www.xcar.com.cn">www.xcar.com.cn</a></td>
<td>car clubs</td>
</tr>
<tr>
<td>9</td>
<td><a href="http://www.xici.net">www.xici.net</a></td>
<td>citizen clubs</td>
</tr>
<tr>
<td>10</td>
<td>bbs.163.com</td>
<td>general forum</td>
</tr>
<tr>
<td>11</td>
<td><a href="http://www.19lou.com">www.19lou.com</a></td>
<td>travel information</td>
</tr>
<tr>
<td>12</td>
<td>club.pchome.net</td>
<td>mobile phones</td>
</tr>
</tbody>
</table>
3.3.2 Performance Comparison of Page Segmentation

In order to evaluate the performance, three classical criteria are adopted in the experiments: Precision (P), Recall (R) and F-score. Let S denote the semantic objects set acquired by FPPS/PS-STS, M denote the semantic objects set, which is manually labeled as the ground truth label. Then Precision, Recall and F-score can be defined as Equation 7.

\[
P = \frac{|S \cap M|}{|S|}, \quad R = \frac{|S \cap M|}{|M|}, \quad F_{\text{score}} = \frac{2PR}{P+R}
\]  

(7)

Firstly, the experiment is performed on the dataset from forum 1-5, and the experimental result of FPPS algorithm is described in Table 3.4. The result shows that the eCF-wrapper can accurately identify all semantic objects, which match the labels.

<table>
<thead>
<tr>
<th>Forum Id</th>
<th>Manual</th>
<th>FPPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2359</td>
<td>2359</td>
</tr>
<tr>
<td>2</td>
<td>3743</td>
<td>3743</td>
</tr>
<tr>
<td>3</td>
<td>2728</td>
<td>2728</td>
</tr>
<tr>
<td>4</td>
<td>1457</td>
<td>1457</td>
</tr>
<tr>
<td>5</td>
<td>2003</td>
<td>2003</td>
</tr>
</tbody>
</table>

Table 3.4: Results of the experiment with machine data

Secondly, the comparative experiment is carried out with the dataset from forum 6-10. The result (shown in Table 3.5) shows that FPPS outperforms PS-STS in terms of Precision, Recall and F-score. A possible reason is that the PS-STS algorithm only takes the sub-tree structure for
consideration and ignores the information hidden in visual clues and the content of a post. For example, there exist several post pages that only include one post. In these cases, the PS-STS algorithm cannot work as expected, whereas FPPS works properly in these two situations.

<table>
<thead>
<tr>
<th>Forum Id</th>
<th>Precision</th>
<th>Recall</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FPPS</td>
<td>PS-STS</td>
<td>FPPS</td>
</tr>
<tr>
<td>6</td>
<td>1.000</td>
<td>0.835</td>
<td>1.000</td>
</tr>
<tr>
<td>7</td>
<td>0.974</td>
<td>0.861</td>
<td>0.974</td>
</tr>
<tr>
<td>8</td>
<td>1.000</td>
<td>0.955</td>
<td>1.000</td>
</tr>
<tr>
<td>9</td>
<td>1.000</td>
<td>0.943</td>
<td>1.000</td>
</tr>
<tr>
<td>10</td>
<td>0.945</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 3.5: Comparison of Page Segmentation

3.3.3. Comparison of Data Extraction

We design an experiment to evaluate the performance of data extraction with the use of a Naive Bayes classifier. It has two distinguished features: (1) Naive Bayes classifier works quite effectively in many complex application contexts; (2) it only requires a small amount of training data to estimate the parameters.

The experimental data is from forum 11-14. It contains 9383 samples, in which 128 samples are used for training; the others are used for testing. All samples will be generated based on FPPS. Table 3.6 shows the result of the performance comparison between the Decision Tree classifier (DT) and Naive Bayes classifier. As shown in Table 3.6, the two algorithms work properly on data extraction. The performance of NB is quite close to DT in the categories of “author” and “time”. However, the NB classifier confuses the samples in categories of “content” and “additional information”. The recall values of the two categories are poor, and the DT obtains a better value. It is clear that DT outperforms NB in this setting.
<table>
<thead>
<tr>
<th>Category</th>
<th>Precision</th>
<th>Recall</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DT</td>
<td>NB</td>
<td>DT</td>
</tr>
<tr>
<td>Additional information</td>
<td>0.935</td>
<td>0.857</td>
<td>0.993</td>
</tr>
<tr>
<td>Author</td>
<td>0.985</td>
<td>0.988</td>
<td>0.994</td>
</tr>
<tr>
<td>Time</td>
<td>0.993</td>
<td>0.927</td>
<td>1.000</td>
</tr>
<tr>
<td>Content</td>
<td>0.996</td>
<td>0.545</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 3.6: Overall Comparison of Data Extracting

3.3.4 Comparison of Time Consumption

It is also noticed that the DT classifier is a more efficient approach and is more suitable in wide application contexts where a large-scale data set is commonly used. Table 3.7 shows the result of the comparison of time consumption between the DT and NB classifier from 2000 samples to 9200 samples. DT classifier is 2 times faster than NB. A possible reason is that the average height of DT classifier is 3.2.

<table>
<thead>
<tr>
<th></th>
<th>2000</th>
<th>4000</th>
<th>6000</th>
<th>8000</th>
<th>9200</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>3.87</td>
<td>6.04</td>
<td>9.75</td>
<td>12.2</td>
<td>14.59</td>
</tr>
<tr>
<td>NB</td>
<td>5.7</td>
<td>12.6</td>
<td>18.24</td>
<td>22.08</td>
<td>27.11</td>
</tr>
</tbody>
</table>

Table 3.7: Comparison of Time Consumption

3.4 Case Study

In this case, we take the course forum of the online course “Python In Actions” as an example. In the original topic list page, the topic list displays in the order of “created time”. By executing the extracting program to the HTML files crawled from the course forum website, the details of the posts to each topic in the topic list pages are described as
The details of the posts to each topic in the topic list page

In order to make the content frequently discussed and confused to be easily identified, we define a set of policies for content re-organization of the web page:

- The frequently discussed topics, which include more learner-produced content should be placed at the top of the web page, and properly highlighted.
- The topics without any answers from learners or instructors should be displayed at a priority place, and properly highlighted.
- The advertisements should be placed at the bottom of the web page. The auto-generated content should be discard or removed from the web page.

We applied the abovementioned policies to the original web page, and
made some changes in the HTML code, and the comparison between the optimized web page and the original one is illustrated as Fig. 3.5 and Fig. 3.6, respectively. With the optimized web page, users can easily identify the content the students are interested in, as well as the topics requiring the intervention from the teachers.

![Comparison of optimized and original web pages](image)

**Fig. 3.5** The comparison of the optimized post list page (based on the information provided by eCF-wrapper) and the original one.
Fig. 3.6 The comparison of the optimized topic list page (based on the information provided by eCF-wrapper) and the original one

In this case, the content re-organization is carried out by manually updating the HTML code with regards to the “Learner-produced Content” described in Table 3.8. In the future, we will develop an integrated tool, with which is capable of both efficiently extracting a web page and re-organizing the content of the web page with the extracted information.

3.5 Summary

In this chapter, we presented a novel page segmentation based wrapper – eCF-wrapper, to extract structural data from post page in online course forums. Existing approaches either depend on simple heuristics rules or learning algorithms with a pre-defined data template. Facing with complex layouts and diverse user created posts, the performance of those approaches is poor. By combining the DOM-tree features and visual clues,
our proposed page segmentation method can successfully extract post modules. Furthermore, a decision tree algorithm is employed to extract structured data. Experimental results show that eCF-wraper is effective for extracting data from course forums, and a case study is also presented to illustrate the effect.
Chapter 4

WebIntera-classroom: An Interaction-aware Virtual Learning Environment for Augmenting Learning Interactions

Interaction is critical for successful teaching and learning in a virtual learning environment (VLE). This chapter presents a web-based interaction-aware VLE (called WebIntera-classroom), which aims to enhance the learning interactions by increasing the learner-to-content and learner-to-instructor interactions. We propose a ubiquitous interface, which integrates the pen-and-paper interface with a web-based whiteboard to promote the effective learner-to-content interactions. Besides, we develop a learning-analytics tool that instantly shows the learners’ learning interactions, with which instructors can supervise the learner-to-instructor interactions. We implement a high-granularity Learning Analytics Engine (hgLAE) to broadcast, record and play a lecture recording. The hgLAE identifies hotspots in a lecture recording and raises students’ awareness of these hotspots when they watch the lecture recording. The WebIntera-classroom has been deployed in 11 universities in China, and has obtained high satisfaction in the questionnaires (N=464) and face-to-face interviews (N=60) conducted with the users from China Jiliang University. We compare the students’ performance respectively achieved in traditional classroom-based learning and in the WebIntera-classroom at China Jiliang University during 2012-2013. The result demonstrates that the students could gain performance improvement by using the WebIntera-classroom.

The remainder of this chapter is organized as follows: we give a brief introduction of this chapter in Section 4.1; the design rationale and system components of the WebIntera-classroom are described in Section 4.2; the evaluation of the system effectiveness is presented in Section 4.3; a case study is introduced in Section 4.4, and the summary of the chapter is presented in Section 4.5.
4.1 Introduction

In traditional classroom-based learning, when a learner has a question, he/she could raise hand to the instructor for the answer. The instructor can directly talk to the learner and answer the question, and in the case that the answer is complex and cannot be clearly explained by talking, the instructor would present the answers on the whiteboard. In summary, in traditional classroom-based learning, interactions between the learner and the instructor and the supervision from the instructor are efficient because that the learner can be monitored by the instructors in a face-face-face manner and the interventions can be provided immediately. As such, the problems that the learners face could be solved in an efficient and swift manner.

The massive online open courses (MOOCs) are increasingly popular in higher education, and MOOCs are always delivered by VLEs in educational institutions and universities (Head, 2014). Tracking and analysing learners’ interactions while they watch the lecture recordings of the MOOCs can significantly help to improve the quality of the MOOCs and the learners’ learning outcomes (Brooks, Epp, Logan & Greer, 2011; Vatrapu, Teplovs, Fujita & Bull, 2011). If we can identify and highlight the hotspots that most of previous learners have focused on, we might augment learner-content interactions such that future learners can easily catch the key content in the lecture recordings and improve the learners’ learning outcomes. The challenge to achieving this goal is how to identify the hotspots in a lecture recording and highlight these hotspots when the learners watch the lecture recordings. In addition, the traditional lecture recordings of the MOOCs are based on video format, which is hard to edit once it is published.

This chapter describes the details of the WebIntera-classroom to address the issues mentioned above.
4.2 Design rationale & system components

Existing tools aiming to augment learner-to-instructor interactions are usually designed to track user behaviors and analyze large-scale log data, but these tools cannot run in runtime. The ex-post-facto provision of the information about learners’ activities in VLEs does not help instructors to take runtime actions in response to learners’ performance. In contrast, the tools developed in our proposed VLE can instantly provide this information, enabling instructors to take dynamic actions for optimal supervision and encouragement of learner-to-instructor interaction.

Nokelainen (2006) proposed a set of criteria for the design of an effective e-learning tool. We address these criteria in our design. In addition, we provide a set of features that augment interactions and improve instruction effect in types of learning contexts, which are the highlights of our research. The overview of the combination of instructor-led and self-paced learning contexts is illustrated in Fig. 4.1: An instructor performs a lecture in a traditional classroom, and communicates with on-site learners. Meanwhile, the instructor creates a virtual classroom to share the lecture with online learners. If a learner does not attend the instructor-led lecture, he/she could watch lecture recordings in self-paced manner later on. The major components of WebIntera-classroom are introduced in the following subsections.
4.2.1 Integrating the Interactive Paper Interface

Signer et al., 2014 emphasize that the interactive papers can augment physical papers to enhance the reading and writing experience, and to provide distinctive opportunities for participants to engage in learner-to-content interaction in a VLE, not only because of their nature but also because of their mobile interactional flexibility. For example, the TAP & PLAY, which is developed by Piper et al. (2012), is a tool supporting language activities for children. It plays audio content and recognizes handwriting and gestures on physical paper to augment learner-to-content interaction. Physical paper is still the dominant media in knowledge sharing and delivery, and supports various forms of content highlighting and annotation. It is not easy to provide the same richness to users engaged in learning interactions in a VLE. Existing VLEs fail to incorporate physical paper to facilitate a natural interaction between participants and e-learning environments, the main challenge is how to
track user behavior on physical paper such as users’ paging (Signer et al., 2014). Aiming to apply the richness of the interaction supported by the physical paper to our proposed VLE, we propose a ubiquitous user interface that integrates physical paper and Anoto digital pen with a web-based whiteboard to augment learner-to-content interaction. Based on the Anoto digital pen, we develop a non-intrusive pen-and-paper interface to map the digital materials from an e-learning environment to physical paper without restricting natural interaction. It works as follows (illustrated in Fig. 4.2):

(1) In preparation for a lecture, learning materials (e.g., PDF, image, hand out, etc.) are uploaded to the teacher’s learning materials repository. The teacher also prints out the selected learning material with a special printer provided by Anoto.

(2) In the beginning of a lecture session, the teacher picks up the learning material (e.g., a previous hand out) from the repository and loads it to the whiteboard. Then, the students can view the learning material on the clients of WebIntera-classroom. The teacher also distributes the printed copies to the on-site students.

(3) The ink traces on a printed copy of the learning material, produced by the teacher or a student who has been granted the privilege of presenting on the canvas of the whiteboard (in Fig. 4.3), will be recorded and transformed to digital traces by the Anoto pen.

(4) The Anoto pen is always connected to a computer running a client of WebIntera-classroom. The digital traces in step (3) are instantly transmitted to the server and broadcast to other clients.

(5) Finally, these digital traces are sent to a database and merged into the learning material.
Fig. 4.2 Workflow of the pen-and-paper Interface

Fig. 4.3 A teacher/student uses the Anoto pen to write on the paper in WebIntera-classroom
4.2.2 Web-based Interactive Whiteboard

The whiteboard is the major user interface for learning activities in an educational context (Heemskerk, Kuiper & Meijer, 2014), and it is defined as a synchronous collaborative tool used to increase knowledge sharing and to support interactive communication (Zhang & Almeroth, 2010). We implement a web-based interactive whiteboard for collaboration in VLEs, which is a low-cost and highly effective alternative to traditional whiteboards. It consists of 3 components: (1) the online user list; (2) the shared canvas area and (3) the learning tool panel.

Fig. 4.4 Interface for learners: (a) Webpage running on a plain browser; (b) Webpage running on a mobile browser; (c) iPad App; (d) iPhone App

The “online user list” shows the statuses of online students attending a course. The canvas area supports 3 types of content presentations: (1)
Khan-style tablet drawing, (2) slide-style presentation and (3) plain-text presentation, and the content presented in the canvas area is always shared to the participants in a course. The learning tool panel includes: (1) a real-time voice chat tool, (2) a text chat tool, (3) an annotation tool and (4) a learning material loader. Markett, Sánchez, Weber & Tangney (2006) recommended the real-time voice chat tool and text chat tool for promoting learner-to-instructor interaction. In traditional classroom-based learning, the supervision from the instructor and interactions between the learner and the instructor are in face-to-face manner. But there are two limitations: (1) some students are embarrassed to directly ask questions to the teacher in instructor-led courses (Ho et al., 2004; Markett et al., 2006); (2) the discussion regarding the questions/answers between the student and the teacher cannot be recorded, which is important for the student to review the question (e.g., the answer to a complex question usually requires more time to understand clearly). With the learning tools provided by our proposed system, when a learner needs to ask a question to the teacher in instructor-led learning, he/she can just submit his/her question in the text chat area, where the content is visible to anyone in the same virtual classroom and the instructor can immediately be aware of the questions the learner submitted and respond to him/her. The learner can directly answer the questions in the text chat area if the answers are simple enough (described in Fig. 4.5).
Fig. 4.5 A student communicated with the teacher by text chat tool

For a complex question, which cannot be clearly described by lines of text, the learner and the instructor can directly communicate via the real-time voice chat tool, or further present the details of the questions/answers on the shared canvas area (described in Fig. 4.6) with the following steps:

- A learner clicks the “voice chat” icon to request a real-time voice chat with the instructor.
- The request is immediately sent to the instructor’s interface, and the instructor can immediately see the request and approve or deny it.
- If the instructor approves the request, the learner will be granted the privileges of using the voice chat tool and presenting content on the canvas area of the whiteboard. Thus, the learner can use the voice chat tool to directly discuss questions with the teacher.
- The instructor and the learner both can present content on the canvas area of the whiteboard, and the learner can easily understand the answers from the teacher.
- After the completion of question session, the learner revokes the privileges of using the voice chat tool and presenting content on the canvas area of the whiteboard from the learner.
Fig. 4.6 An example of the discussion between a learner and the instructor

4.2.3 Data Schema

MOOCs is a popular approach for self-paced learning, more and more studies are conducted for the improvements of course design of MOOCs using data analytics on the course recordings (Wieling et al., 2010; Kizilcec et al., 2013; Kim et al., 2014). For example, Kim et al. (2014) perform data analytics on collected data of user behaviors while playing the course videos (e.g. pausing, resuming and navigating between points during playback, etc.) However, there are still barriers to effectively applying the discovered knowledge to the content of the lecture recordings. These
barriers include the fact that existing lecture recordings are based on a video stream, which is single-stream and difficult to edit once published, and the data analysis on it is also unacceptably time-consuming. In summary, video-based recordings are not specially designed for an educational purpose, and it is difficult to extract knowledge (e.g., the attractive content and learners’ interests, etc.)

We propose a new schema to store the lecture recordings, which consists of 5 types of learning object elements (described in Table 4.1): (1) track, (2) text, (3) file, (4) audio and (5) event. The new schema is specially designed for data analytics in a learning context, and allows editing and reorganizing elements in a lecture recording.

<table>
<thead>
<tr>
<th>Learning Object</th>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Track</td>
<td>trackType</td>
<td>Normal mode or highlight mode</td>
</tr>
<tr>
<td></td>
<td>penColour</td>
<td>Specific colour picked from colour panel</td>
</tr>
<tr>
<td></td>
<td>userId</td>
<td>User to whom current track belongs</td>
</tr>
<tr>
<td></td>
<td>frameId</td>
<td>Page to which current track belongs</td>
</tr>
<tr>
<td></td>
<td>penSize</td>
<td>Specific size of ink</td>
</tr>
<tr>
<td></td>
<td>traceArray</td>
<td>A group of points in the format [X,Y]</td>
</tr>
<tr>
<td></td>
<td>penOpacity</td>
<td>Degree of pen opacity [0, 100%]</td>
</tr>
<tr>
<td></td>
<td>classroomId</td>
<td>Specific classroom to which the current track belongs</td>
</tr>
<tr>
<td></td>
<td>timestamp</td>
<td>Time at which current track occurred</td>
</tr>
<tr>
<td></td>
<td>penWidth</td>
<td>Width of pen in highlight mode</td>
</tr>
<tr>
<td>File</td>
<td>originalName</td>
<td>The original name of the document</td>
</tr>
<tr>
<td></td>
<td>urlPath</td>
<td>Absolute file path in the file system</td>
</tr>
<tr>
<td>Attribute</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>--------------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>referred to by one page on the whiteboard</td>
<td>Text: Text is defined as any text information on the whiteboard, including chat messages, users’ notes, and text included in presentations.</td>
<td></td>
</tr>
<tr>
<td>hashCode</td>
<td>The hashed value of file content</td>
<td></td>
</tr>
<tr>
<td>classroomId</td>
<td>Classroom to which current file belongs</td>
<td></td>
</tr>
<tr>
<td>frameId</td>
<td>Page to which current file belongs</td>
<td></td>
</tr>
<tr>
<td>fileType</td>
<td>Type of document</td>
<td></td>
</tr>
<tr>
<td>timestamp</td>
<td>Time at which the document was loaded</td>
<td></td>
</tr>
<tr>
<td>textType</td>
<td>Type of text</td>
<td></td>
</tr>
<tr>
<td>senderId</td>
<td>User to whom current text belongs</td>
<td></td>
</tr>
<tr>
<td>classroomId</td>
<td>Classroom to which current text belongs</td>
<td></td>
</tr>
<tr>
<td>panelWidth</td>
<td>The width of the text area</td>
<td></td>
</tr>
<tr>
<td>content</td>
<td>The content of the text</td>
<td></td>
</tr>
<tr>
<td>frameId</td>
<td>Page to which current text belongs</td>
<td></td>
</tr>
<tr>
<td>fontSize</td>
<td>Font size of the text content</td>
<td></td>
</tr>
<tr>
<td>coordinateStart</td>
<td>The start coordinate of context area</td>
<td></td>
</tr>
<tr>
<td>coordinateEnd</td>
<td>The end coordinate of context area</td>
<td></td>
</tr>
<tr>
<td>timestamp</td>
<td>Time at which the text was created</td>
<td></td>
</tr>
<tr>
<td>classroomId</td>
<td>Classroom to which current voice clip belongs</td>
<td></td>
</tr>
<tr>
<td>userId</td>
<td>User to whom current voice clip belongs</td>
<td></td>
</tr>
<tr>
<td>voiceSpan</td>
<td>The duration of a voice clip</td>
<td></td>
</tr>
<tr>
<td>timestamp</td>
<td>Time at which the voice clip starts</td>
<td></td>
</tr>
<tr>
<td>eventType</td>
<td>DOM event or user-defined event</td>
<td></td>
</tr>
<tr>
<td>eventInstruction</td>
<td>Details describing the steps of event</td>
<td></td>
</tr>
</tbody>
</table>

Audio: Audio is defined as a continuous voice clip broadcast to participants in the same virtual classroom.

Event: Event is defined as user operation on the
whiteboard, and can be recorded and reproduced in time sequence.

- **classroomId**: Classroom to which current event belongs
- **frameId**: Page to which current event belongs
- **userId**: User to whom current event belongs
- **timestamp**: Time at which current event occurred

Table 4.1. The definitions of learning object elements

### 4.2.4 High-granularity Learning Analytics Engine

A number of studies have been conducted for the improvements of design of MOOCs using learning analytics (Kirkpatrick, 2006; Wieling et al., 2010; Kizilcec et al., 2013; Kim et al., 2014). For example, Kim et al. (2014) analysed video content to identify points of interest and content that is confusing for users, and to advise on improvements to video design. These studies inspired us on discovering knowledge from users’ behaviors history. We developed a high-granularity Learning Analytics Engine (hgLAE), with which the system could perform data analysis on individual learning object elements (cf. a whole lecture recording). The hgLAE consists of two modules: (1) hotspots related learning analytics (detailed in this section) and (2) popularity dashboard related learning analytics (detailed in Section 4.2.6).
Fig. 4.7 The overview of the high-granularity Learning Analytics Engine

The hotspots related learning analytics module (as illustrated in Fig. 4.7) works in the following steps: (1) data collection, (2) data analytics, and (3) content enhancement.

Data Collection: We enclose the visible objects in the recordings (e.g., a handwriting trace, an image or a text, etc.) by HTML tags. The clients (i.e., webpage, app) will capture the DOM events (e.g., blur, click, focus, mouse down, etc.) occurred on HTML tags and send them to the server. Each event record will be attached with the information indicating when and in which learning mode the event occurred.

Data Analytics: The learning objects (e.g., text, track, file, etc.) created in a lecture are saved in different repositories according to their types. The analytics engine of hgLAE runs at midnight everyday to perform statistical analytics on the event records:

(1) Extract and validate event records from the event repository: it will determine whether the analytics process should proceed according to two criteria: (a) there must be at least 100 new students who have watched the recording since the last data analytics, and (b) there must be at least 2000
new event records produced since the last data analytics. If it fails to fulfill any one of the two criteria, the engine will abort the analytics process.

(2) Perform statistical analytics on these records to identify the hotspots in the recordings that students have focused on when they watched the recordings in the past: the analytics engine will traverse all the event records (including the old ones and new ones produced since the last data analytics) in a lecture recording. We distinguish between hotspot objects and hotspot time slots:

- **Hotspot Objects**: A learning object in the current recording, on which over half of the students have produced DOM events, would be identified as hotspot object.

- **Hotspot Time Slot**: It refers to a time slot during which (1) over half of students produced DOM events and (2) the number of events exceeds the average number of events in all time slots of the current recording. For example, in Fig. 4.8, the colorful dots represent different events (i.e., one color represents one type of event) falling into different time slots, and those slots (i.e., the 2nd, 25th-26th, 30th-32nd minutes) in which there are obviously denser dots compared to other time slots are identified as hotspot time slots.

![Distribution of the DOM events produced by 10 students in a lecture](image)

**Algorithm 1. Identify a lecture recording from DOM events repository**

**Input**: a set of DOM events $X = \{e_1, \ldots, e_N\}$ from $N$ students.
Each DOM event data $e_i$ consists of the event location $(x,y)$, the event time $t$ (t is normalized by a shift from the lecture video starting time $t_0$) and the student ID sid, denoted by $e = \{x,y,t,sid\}$; parameters $(P,Q)$, the grid size of the video screen and $M$ (seconds) the time period for every time step, and threshold $\gamma$; video screen size $W$ and $H$.

Output: 1) hotspot objects $\{c_1, ..., c_C\}$, where $c = \{p,q,m\}$.

2) hotspot time slots $\{m_1, ..., m_M\}$.

Algorithm:

1. Initial 3D matrix $U$ of $P \times Q \times T = (T_0/M) \times N$, where $T_0$ is the total length of the video with zeros; initial $U$ of $P \times Q \times T$

2. For every $e$ in $X$

3. Quantilize $e$ by $P Q T$ as $e' = (p,q,m) = \text{floor}(x/P, y/Q, t/T)$

4. $U(p,q,m,e(4)) = 1$

5. End for, and then we have $U$

6. Initial $C = \Phi$, $M = \Phi$

7. Calculate a histogram according to student ID dimension, that is $H(p,q,m) = \sum_{all_s} U(p,q,m,s) \, / \, N$

8. For every element $h$ of $H$, denote the subscript indices of $h$ as $(p,q,m)$, that is $h = H(p,q,m)$

9. If $h > \gamma$, then we have $C = C \cup \{p*W/P, q*H/Q, m\}$

10. End for, and then we have output 1)

11. Margin $U$ with respect to the $P$ and $Q$ as follows

12. $U_{T,S}(m,sid) = \sum_{all_{p,q}} U(p,q,m,s)$

13. Calculate a new histogram as $H(m) = \sum_{sid} \delta(U_{T,S}(m,sid))$ where

$\delta(x) = \begin{cases} 1, & x \neq 0 \\ 0, & x = 0 \end{cases}$

14. For every element $h$ of $H$, denote the subscript index of $h$ as $m$, that is $h = H(m)$

15. If $h > \gamma$, then we have $M = M \cup \{m\}$

16. End for, and then we have output 2

| Content Enhancement: after data analytics, hgLAE would generate content-enhancing instructions at the server side. Upon request, the content of the recording as well as its content-enhancing instructions |
would be sent to the client. The client would parse and execute the content-enhancing instructions to highlight the hotspots while playing the recording. Two strategies are used to highlight the hotspots: (1) these hotspot objects will be highlighted in yellow color (shown in Fig. 4.9 (a)); (2) when the recording play approaches a hotspot time slot, the player would prompt an alert message to raise students’ awareness on the hotspot time slot (shown in Fig. 4.9 (b)).

Fig. 4.9 Highlight hotspot objects and time slots while playing a lecture recording
Learning Analytics is defined as the use of learner-produced data, intelligent approaches and mathematic models to discover helpful information, and to predict learning behavior and optimize on learning process (Siemens, 2012). In this thesis, using the learning analytics to improve the teaching and learning process is inspired by many existing tools, which are used to support and enhance the various kinds of learning process (Chatti et al., 2012). For example, Bransford et al. (1999) proposed the Tracer tool, which is used to measure user engagement in writing, and analyzes and generates visualizations of the quantitative measures of user engagement. LOCO-Analyst was developed to provide educators with feedback on students’ learning performance and learning activities (Ali et al., 2012). In addition to these, CourseVis proposed by Mazza & Dimitrova (2007) and SAMOS proposed by Juan et al. (2009) both are used to monitor students’ and groups’ activities in online learning environments by using the data analytics of the log files archived in server.

However, there are barriers that prevent existing learning analytics tools from working efficiently. One such barrier is that as a consequence of the increasing volume of learning objects and interaction data produced by learners, data processing is unacceptably time-consuming. As such, learners’ runtime information cannot be provided instantly to instructors. Thus, it is difficult to make runtime decisions according to students’ activities during the learning process. In order to address this issue, a novel learning analytics tool, which can handle large-scale monitoring data in microseconds to help instructors to reflect on pedagogical processes, and to identify appropriate interventions and improvements, is proposed in our research.

We developed a graphical learning analytics tool (called popularity dashboard), which is used to monitor each learner’s interactions and identify appropriate moments to make pedagogical decisions in instructor-led learning. As illustrated in Fig. 4.10, each bar of the popularity dashboard represents one student and each column represents the student’s level of interaction in a 3-minute time slot. The duration for a lecture is typically 40 minutes in most of universities of China. Thus, we
use 12 columns to visualize the levels of interaction for each student in the past 36 minutes. The dashboard periodically updates: for each bar, a new column represents a student’s level of interaction in the past 3 minutes will be inserted to the right end of the bar. If a bar had included 12 columns, the oldest column at the left side of the bar will be removed from the bar, and the other columns will move a place towards the left side.

Fig. 4.10 Popularity Dashboard: a graphic visualized monitor tool for instructor

We consider the number of DOM events as an indicator of the level of interactions. The webpage running on a plain browser (in Fig. 4.4 (a)) captures frequently used mouse events: (1) click, (2) mousedown, (3)mousemove, (4) mouseup, (5) scrollup and (6) scrolldown. The webpage running on the mobile device (in Fig. 4.4 (b)) captures touch events, which are alternatives of mouse events on mobile devices: (1) click, (2) touchstart, (3) touchmove, (4) touchend and (5) touchswipe. And the native app running on the mobile devices (in Fig. 4.4 (c) and Fig. 4.4 (d)) captures touch events mentioned above too. We treat a mouse event and a touch event equally concerning the level of interactions.

In an instructor-led learning mode, the events generated by students will be immediately sent to the hgLAE. Periodically, the analytics engine of hgLAE traverses these data and counts the number of events for each
client. Then the result will be returned to the clients to update their popularity dashboard indexes as illustrated in Fig. 4.10. According to the existing study (Silfverberg, Mackenzie & Korhonen, 2000), we set the maximum number of the DOM events produced by students as 150. If the number of events is in the range (0, 50) implies that the level of interactions is low. If the number of events is in the range (51, 100) implies that the level of interactions is medium. If the number of events is in the range (101, 150) implies that the level of interactions is high.

Instructors can easily identify the learners whose levels of interaction are low. For example (in Fig. 4.10), the instructor had high interaction, so did student 2 and 3. In contrast, the other students were less active; in particular, Student 5 and 8 were very passive and with the lowest level of interactions. The instructor can use the real-time voice chat tool to carry out interventions to make those students at lowest levels of interactions be actively involved in learning activities (Croft, Dalton & Grant, 2010; Santarosa, Conforto & Machado, 2014).

4.3. Evaluation of system effectiveness

4.3.1 Material & Setting

WebIntera-classroom has been deployed in 11 universities in China for providing online teaching and learning services. We conducted a survey with 464 participants from China Jiliang University. The participants took three courses delivered by WebIntera-classroom. There were 80 students and three teachers in the course “Advanced Topics in Mathematics”, 177 students and seven teachers in the course “University Mathematics”, and 190 students and seven teachers in the course “Fundamentals in C Programming”. Each participant was invited to answer an online questionnaire, and a few of them joined a 10-minutes face-to-face interview (60 interviewees). The teachers perform teaching in WebIntera-classroom. The students can attend the instructor-led course, or
watch the lecture recordings in WebIntera-classroom.

We also compared the students’ performance respectively achieved in traditional classroom and in WebIntera-classroom to validate the instruction effect of the system. We considered the course “Fundamentals in C Programming” delivered by the same teacher to 4 classes from China Jiliang University during 2012-2013. There were 36 students in each class, and Classes 1 & 2 were from the Department of Financial Management and Classes 3 & 4 were from the Department of Computer Science. The students from the same department had similar academic backgrounds when they entered university. The students in Class 1 and Class 3 took the course in traditional classroom in 2012. The students in Class 2 and Class 4 took the course in WebIntera-classroom in 2013.

4.3.2 Questionnaire Design

Liaw, Huang & Chen (2007) surveyed learners’ and instructors’ attitudes to e-learning technology, and showed that (1) “teacher-led”, (2) “multimedia instruction”, (3) “learner attitudes” and (4) “self-paced” are the main impact factors affecting participants’ attitudes to e-learning technology as an effective tool. The “teacher-led” and “learner attitudes” are closely related to learner-to-instructor interaction. The “multimedia instruction” and “self-paced” are closely related to learner-to-content interaction. Besides, Graham et al. (2012) proposed seven principles (including “Instructors should provide clear guidelines for interaction with students”, “Well-designed discussion assignments facilitate meaningful cooperation among students”, “Students should present course projects”, “Instructors need to provide two types of feedback: information feedback and acknowledgment feedback”, “Online courses need deadlines”, “Challenging tasks, sample cases, and praise for quality work communicate high expectations”, “Allowing students to choose project topics incorporates diverse views into online courses”) are helpful to significantly improve learning outcomes. WebIntera-classroom can perfectly meet 4 principles (including “Instructors should provide clear guidelines for interaction with students”, “Well-designed discussion
assignments facilitate meaningful cooperation among students”, “Students should present course projects”, “Allowing students to choose project topics incorporates diverse views into online courses”) out of these principles. With regard to these impact factors and the analysis regarding the learning interactions, we designed a questionnaire to evaluate the satisfaction on WebIntera-classroom.

The questionnaire consists of 24 items, each of which includes 1 to 5 questions. Each participant should answer “YES” or “NO”. An item corresponds to a feature provided by the WebIntera-classroom to augment learning interactions. The items are categorized into four groups, and each group represents one of the impact factors mentioned above.

4.3.3 Experimental Results

As shown in Table 4.2, these major features of WebIntera-classroom obtained high user satisfaction. The “Popularity Dashboard” gained 89.4% satisfaction (i.e., 415 from a total of 464 participants), and the “Online User List” gained 60.7% satisfaction. The “Real-time Voice Chat” gained 79.8% satisfaction, and was the most preferred communication tool by users. 60.5% of the interviewees reported that the “Shared Whiteboard” was a good choice for interactions requiring complicated description and collaboration. The “Pen-and-Paper Interface” gained 78.5% satisfaction. The “Hotspots Highlight” gained 75% satisfaction.

<table>
<thead>
<tr>
<th>Impact Factor</th>
<th>Satisfaction (Mean)</th>
<th>Item</th>
<th>Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instructor-led</td>
<td>58.95%</td>
<td>1. Instant Text Chat</td>
<td>36.6%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Discussion Management</td>
<td>28.2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Online Students List</td>
<td>60.7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Internal Notification</td>
<td>52.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5. Popularity Dashboard</td>
<td>89.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6. Real-time Voice Chat</td>
<td>79.8%</td>
</tr>
<tr>
<td>Learners‘</td>
<td></td>
<td>7. Shared Whiteboard</td>
<td>60.5%</td>
</tr>
</tbody>
</table>
Table 4.2 Results of the Satisfaction Questionnaire (n=464)

Regarding the comparison of students’ performance using WebIntera-classroom vs. traditional classroom, the full marks of the final examination were 100. For those students from the Department of Financial Management (in Fig. 4.11), the average score of students in Class 2 (i.e., 66.75) is higher than that of student in Class 1 (i.e., 62.14) by 7.4%.
For those students from the Department of Computer Science (in Fig. 4.12), the average score of students in Class 4 (i.e., 83.63) is higher than that of students in Class 3 (i.e., 79.5) by 5.2%. Overall, the result demonstrates that students could gain better performance improvement by using WebIntera-classroom. Note that the students’ average scores from the Department of Financial Management, either in traditional classroom or WebIntera-classroom, were lower than that from the Department of Computer Science. This might be due to the fact that computer science students are usually better at science courses. And this also might be because the course “Fundamentals in C Programming” was one of the core courses for the students from the Department of Computer Science.

Fig. 4.11 Comparison of student’s performance with different delivery methods (the Department of Financial Management)

Fig. 4.12 Comparison of student’s performance with different delivery methods (the Department of Computer Science)
4.3.4 Discussions

In the interviews with participants, some students reported that in an instructor-led lecture, they were always required to answer a question, so the students can concentrate on the lecturing. Some students preferred watching lecture recordings because they could control the learning pace. Furthermore, some teachers reported that they usually watched the lecture recordings to reflect on the pedagogical process and identify the questions frequently asked. Many teachers reported that those students, who were too shy to a face-to-face interact in traditional classroom, could actively interact with the teacher by the text chat tool or the real-time voice chat tool in our system.

4.4 Case study

In this section, we will take the course MATH7090 - “The high-precision Numeric Calculation” as a case study to illustrate the learning process using WebIntera-classroom. MATH7090 is the first online open course provided by the Department of Mathematics with Hong Kong Baptist University, and this course was delivered to science students in the Semester 2013-2014-1. The course included 12 sessions, and the duration for a session is two hours. 29 students enrolled the course from the academic office, and totally 53 students subscribed the course in the WebIntera-classroom. That means there are 24 students attending the course only via Internet. The design of the course includes three major processes: (1) preparation for the online course learning activities, (2) teaching & learning activities and (3) assessment & feedback. Due to the regulations regarding privacy protection, we did not reveal students’ performance in this course.

4.4.1 Conceptions
In the case study, we conduct a comparative analysis of interactions from four aspects: (1) Participants’ attendance, (2) Interaction by instructor, (3) Interaction by learners, and (4) Popularity. The figures are based on the data produced in the course MATH7090.

There are kinds of measure metrics used to evaluate the performance of online courses. In order to clarify how the learners attended the open course (i.e., the way, the manner), we define four measure metrics:

- “Device used – Mobile” describes the number of the learners use mobile device in each lecture;
- “Device used - PC” describes the number of the learners use PC in each lecture;
- “Participants - Synchronous” describes the number of the learners attend the virtual classroom synchronously;
- “Participants - Asynchronous” describes the number of the learners attend the virtual classroom asynchronously.

Analyzing the interactions among the participants helps to understand to what extent the learners interact with the teachers and the learning content. Based on the possible activities within a typical learning activity in WebIntera-classroom, we define eight measure metrics to indicate the interactions:

- “Handwriting” describes the use of the whiteboard-based handwriting tool in each lecture;
- “Document Sharing” describes the usage of the document sharing via the whiteboard;
- “Notes” describes the use of the note tool in each lecture;
- “Hands up” describes the number of the actions - handing up in the synchronous learning in each lecture;
- “Comments” describe the number of the comments produced by a learner in each lecture;
- “Text chat” describes the use of the text chat tool in each lecture;
- “Popularity of instructor” describes the change of the average value of the popularity in each lecture;
- “Popularity of learner” describes the change of the average value of the popularity of all the learners in each lecture.
4.4.2 Settings

Prior to the beginning of the online course, the course syllabus and user instructions regarding the WebIntera-classroom was automatically sent to the subscribers of the course by the system. The course syllabus describes the session topics and learning objectives. The instructions explained how to conduct teaching and learning activities. Prior to the beginning of each lecture, the Teaching Assistants (TAs) will upload the learning materials to the virtual classroom. The TAs are expected to attend the virtual classroom ahead and help to solve possible problems the students may face while attending the online course. The instructor can join the virtual classroom from any location, as long as the Internet is available. And a remainder message will be automatically sent to the subscribers of the course six hour ahead of the beginning of the course, and they can join the virtual classroom with mobile devices from any location too.

4.4.3 Data Analysis

The following figures show the engagements and interactions of the participants throughout all the 12 lectures of the course.
Fig. 4.13 Participants’ attendance in virtual classroom throughout the course

As illustrated in Fig. 4.13, it shows that the learners gradually prefer to attend the online course via mobile device. With regard to this fact, we would advise that the instructor should consider the size and format of the materials while preparing the learning materials. We observed that most of the students attending the synchronous learning would be present in all the 12 lectures, but the students attending the asynchronous learning gradually drop out the online course over time. A possible reason for this phenomenon is due to the feeling of being isolated in asynchronous learning.
As illustrated in Fig. 4.14, it shows that the instructor prefers using the handwriting, which is a simple but efficient tool appropriate for

Fig. 4.14 Interactivity by instructors in the virtual classroom throughout the course

Fig. 4.15 Interactivities by learners in the virtual classroom throughout the course
explaining complicated problems. The handwriting is frequently used in the 8th lecture, which is regarding the topic “Temporal discretization and FFT” and contains a lot of mathematical formulae. The same observation is also found in Fig. 4.13 on the measure metric “Note”. Fig. 4.15 shows that the note tool is the most frequently used tool for learners, then followed by text chat tool, comment tool, and “hands up”. The text chat tool is frequently used and gets the highest record in the 12th lecture, which included the course review. In the 12th lecture, the learners preferred asking questions via the text chat tool instead of the “hands up” tool, and that means the instructor should instantly pay more attention to the contents in the public text chat area.

As illustrated in Fig. 4.16, it describes the change of the mean value of instructor’s popularity (represented by the red trace) throughout each lecture, as well as the change of the mean value of all the learners’ popularity (represented by the blue trace) throughout each session. As shown, the popularity of the instructor is always active throughout the course. The popularity of the learners increases over time, which implies

---

![Graph showing popularity change](image_url)
that if the instructor could better monitor learners’ engagement in a learning activity, it is more likely to keep the learners actively engaged in the learning activity.

4.5 Summary

Interaction is critical for successful VLEs. In order to effectively augment learning interactions in VLEs, we identified two major issues in existing VLEs: (a) the learner-to-content interaction is limited by obsolete interaction interfaces; (b) in an instructor-led lecture, a teacher cannot instantly monitor learner-to-instructor interaction.

To overcome issue (a), we proposed a ubiquitous interactive interface that integrates a pen-and-paper interface with a web-based whiteboard to make learner-to-content interactions to be easily obtained. We implemented a learning analytics engine to broadcast, record and play a lecture recording. The engine can identify the hotspots in a lecture recording, and raise students’ awareness on the potential importance of key contents as learned from historical data. To overcome issue (b), we developed a graphical dashboard to instantly monitor students’ learner-to-instructor interactions in an instructor-led lecture session.

The system has been deployed in 11 universities in China as a teaching and learning platform. We conducted a survey (n=464) and face-to-face interview (n=60) to investigate the users satisfaction on the WebIntera-classroom. The result of the questionnaire showed that the major features of WebIntera-classroom gained high user satisfaction. Besides, we compared the students’ performance for the same course using WebIntera-classroom vs traditional classroom. The result demonstrated that the students could gain performance improvement by using WebIntera-classroom.

We also included a case study, which is an online open course provided by the Department of Mathematics with Hong Kong Baptist University. With the carefully analytics on the course, we found many interesting and meaningful facts, which could be used to improve the
course design delivered by WebIntera-classroom.
Chapter 5

The FishBuddy: An Exploration of Promoting student engagement in Self-Paced Learning through Wearable Sensing and Visualized Intervention Technology

Student engagement is crucial for successful self-paced learning. Feeling isolated during self-paced learning with neither adequate supervision nor intervention by teachers may cause negative emotions such as anxiety. Such emotions may in turn significantly weaken students’ motivation to engage in learning activities. In this chapter, we develop a self-paced learning environment (FishBuddy) that aims to reduce anxiety and promote student engagement during poor learning performance. We design and implement a physiologically-aware performance-evaluation model for identifying potentially fruitful moments of intervention when a student shows frustration during learning activities using an Apple Watch application that measures the heart rate. It can alert the student to watch a visualization of his or her own physiological state. We conduct an experiment with 20 first-year undergraduate students, randomly separated into an experimental and control group, who carried out online, self-paced English grammar exercises. The students in the experimental group used FishBuddy and those in the control group did not. The self-reports from both groups show that FishBuddy significantly reduces reported experiences of anxiety and isolation in the experiment.

The remainder of this chapter is organized as follows. Section 5.1 gives a brief introduction to this chapter. Section 5.2 presents the design rationale and system implementation. In Section 5.3, we discuss the experiment and findings. We summarize this chapter in Section 5.4.

5.1 Introduction
Liu et al. (2015) emphasize the importance of emotional and behavioral engagement in the educational contexts. Behavioral engagement is defined as the participation in learning activities and overt involvement in them (e.g., exercises completed online, etc.), and can be measured through self-reporting or technical observation. Behavioral patterns can be easily defined, tracked and visualized. For example, keystroke logging (Leijten & Van Waes, 2013) allows a detailed record of behavioral engagement, including the time students spend on online questions and how much typing they do. These kinds of records are indicators of behavioral engagement, and can be harnessed to improve and personalize a student’s learning experience (Tanes et al., 2011). Besides, Jones (2009) also proposed three measure metrics to describe the extent of engagement: (1) Breadth of engagement: how broadly the class as a whole is engaged; (2) Consistency of engagement: how long students remain engaged at high levels throughout a learning activity; (3) Intensity of engagement: the general level of engagement.

Emotional engagement is more difficult to measure and utilize for educational purpose, and it is already a hot research topic in the area of affect-aware computing technologies (Calvo & D’Mello, 2012). A number of literatures explored the physiological factors that affect learning. Modern computer and sensing technology is capable of observing academic performance and, to some degree, psychological status during a learning activity (Bulger et al., 2008). Biosensors can be utilized for simple physiological measures of, e.g., heart rate as well as for more complex neuropsychological relevant measures (e.g., EEG and fMRI) that can be effective in tracking a student’s learning process, but require specialized setups. Schall (2014) argue that those more advanced sensors are often intrusive and distract student attention from learning activities and negatively affect the learning process. Hence, in our research, we use a non-intrusive approach to facilitate anxiety reduction, based on visualizing simple heart rate data.

In this chapter, we present the details of the FishBuddy, which is a self-paced learning environment for tracking and evaluating student engagement in learning activities. Besides, we introduce the experiment conducted with students from a university in China to investigate the
impact of the FishBuddy on their self-paced learning.

5.2 Design Rationales and System Implementation

Data collection in the e-learning context on student engagement in self-paced learning is typically based on the human observations or the students’ self-reports (Liu, 2008; Venkatesh et al., 2003). For example, in the student engagement walkthrough process, teachers assess the degree of student engagement through overt behaviors such as the answers to questions, verbal participation, as well as the frequency of students’ interactions with the learning materials within a learning process (Gewnhi et al., 2013). The ratings are then compared to student ratings of the extent to which the learning activities are interesting and challenging, and the degree to which they understand why and what they are learning.

Dynamic, individualized intervention is required to help further each student’s engagement adequately. In this study, we focus on the consistency of engagement and develop an approach for intervening in the learning of the students whose consistency is low. Previous research has focused on engagement in traditional classrooms (Sheldon & Biddle, 1998), web-based learning activities (Chen et al., 2010), learning activities using smart interactive devices (Piper et al., 2012) and virtual learning environments (Chen et al., 2014). The “clicker” system has enabled students to give live feedback with respect to learning materials, and the responses can be recorded, and e-learning systems are deployed to intelligently analyze them and generate feedback-oriented visualizations (Blasco-Arcas et al., 2013). The interaction-aware virtual learning systems, such as the WebIntera-classroom introduced in Section 4.4, have been used in many universities and educational institutions for supporting distance learning through monitoring and visualizing student engagement.

In Section 4.4, we analyzed a mathematics course delivered in the VLE WebIntera-classroom to examine the degree to which the WebIntera-classroom can promote student engagement in an
instructor-led online course (Chen et al., 2014). However, the instructor-led learning is much different from the self-paced learning: there is no any supervision or intervention from the instructors. In our study, we adopt an automatic approach to make up the supervision and intervention in self-paced learning, and it also aims to promote student engagement, such as the consistency of engagement, which is a major measure metric of engagement proposed by Jones (2009).

Our proposed system is designed to promote student engagement in self-paced learning by intervening in the learning process to reduce anxiety when students show weak learning performance in conjunction with stress or anxiety (detected through heart rate analysis). FishBuddy consists of three major components (as illustrated in Fig. 5.1): (1) a self-paced learning system (SPLS); (2) an application running on the Apple Watch called e-Fish, and (3) a physiologically-state-aware performance evaluation model. The SPLS provides online exercise services where students complete a set of multiple-choice questions per exercise in a given time while wearing the Apple Watch running the e-Fish application.
5.2.1 Web-based Self-Paced Learning System

The SPLS runs as a web-based service providing self-paced exercises to students without the limitation of the location and time. Its goal is to encourage students to complete as many exercises as possible, and achieve better performance. The data regarding the student’s performance on the questions and exercises are collected for learning analytics. The performance details include:

- Time spent on completing questions in an exercise;
- Time spent on completing questions in one sitting;
- Correctness of a student’s completed questions in an exercise;
- Percentage of correct answers from the completed questions so far.

A student uses an account, which is associated with the worn Apple Watch to login to the SPLS and complete one or more exercises. The students can pick exercises appropriate for their levels. All completed tasks and new exercises tasks, as well as the chart regarding the student’s achievements are listed on the exercise homepage (depicted in Fig. 5.2 (a)). An exercise consisting of a set of multiple-choice questions will be completed in a given time. A timer component displays the time used for the current question and the time left for the whole exercise (depicted in Fig. 5.2 (b)). After the completion of an exercise, a student can receive the performance result of the exercise and review details of his/her performance one question by one question (depicted in Fig. 5.2 (c)). Students can comment on the difficulty of the questions by assigning a value (i.e. hard, medium, easy) to current question (depicted in Fig. 5.2 (d)).
Fig. 5.2 Snapshot of the SPLS: (a) an exercise result; (b) an exercise in progress; (c) question review; and (d) summary of exercises

5.2.2 Wearable Application - e-Fish

Wearable technology can enable transparent interaction that allows a person to move freely. The design of wearable technologies increasingly allows for measuring psycho-physiological factors (Uğur, 2013). The Apple Watch for health monitoring that continuously tracks body statuses, is a typical example. Buchem (2015) proposed an extension of a typical learning environment with the level of engagement made available through utilizing body-worn devices. The emergence of new wearable devices, such as smart watches and smart glasses support capturing live data from individual learning activities, and identifying appropriate moments for carrying out learning interventions in a wide variety of scenarios. Mistry et al., (2009) argue that wearable devices used for student’s interaction in learning activities typically maintain connections with external information systems, capable of tracking learning activities, measuring physiological data and delivering feedback to students. By collecting physiological data in learning activities for the visualizations of
feedback, wearable devices play an important role in enhancing student’s learning experiences (Nakasugi & Yamauchi, 2002).

Universities are increasingly using systems that integrate student interactions with physiological data gathering to perform learning interventions that reduce student anxiety in self-paced learning (Uğur, 2013; Clow, 2013). In such systems an intelligent agent may analyze the data with regards to additional factors, e.g., grades and gender, to produce learning feedback (Mattingly, Rice & Berge, 2012). Researchers have recommended that teachers suggest appropriate actions to students for optimizing their learning process through learning interventions in the form of instant feedback on learning activities (Liu et al., 2015). Various visualization techniques have been used in this context to give instant feedback and promote student engagement (Santos et al., 2012).

Many visualizations of learning processes are based on a dashboard display with student performance on learning activities and messages to guide the student through learning activities (Verbert et al., 2014). A simple dashboard in a traffic-light-style form can indicate student performance (Romero-Zaldivar et al., 2012) while a complex dashboard can show more detailed information regarding various dimensions of the learning activities (Luo & Xia, 2014). CourseVis is an e-learning system capable of visualizing peer-to-peer interactions in a web-based course (Mazza & Dimitrova, 2007). In our previous work as mentioned in Section 4.2.3, we developed a thermometer-style dashboard to visualize live student engagement, which enabled teachers to identify appropriate moments to intervene in the learning processes. That system focused on learning performance and did not include physiological factors to help promote student motivation for learning activities, as does our FishBuddy system reported here.

The goal of e-Fish is to (1) instantly measure heart rate and perform analysis to detect stress and anxiety during an exercise (Picard, R. W., & Picard, R., 1997; Han, 2011; Chiu & Wang, 2008); and (2) intervene in the student’s learning process through reminding the student to watch the fish when stress and anxiety is detected. Heart rate is measured unobtrusively as the watch is worn. When the student shows low performance and drastic change of heart rate, e-Fish will remind the
student to turn to it on the Apple Watch. As an anxiety-reducing strategy, the fish swims freely in a rhythm inversely related to the student’s heart rate variability (Üğur, 2013; Novak & Johnson, 2012). The design of the e-Fish is rooted in Chinese philosophy and aesthetics according to which the fish represents tranquility and inner peace, and can be used to relax one’s mood and to reduce anxiety (Liu, 2008). Fig. 5.3 illustrates continuous changes in the swimming of the Chinese fish on an Apple Watch.

![Fig. 5.3 The e-Fish running on an Apple Watch](image)

### 5.2.3 Performance Evaluation Model

Our model depends on student performance data, collected during the use of FishBuddy and algorithms to process that data. As described in Table 5.1, we use a physiologically-state-aware performance reference metric set (PsaPRms) to evaluate a student’s performance and physiological state instantly. It consists of nine averaged metrics: (1) time spent on a question, (2) time spent on an exercise, (3) correctness rate of a question, (4) correctness rate of an exercise, (5) time spent on a wrong answer for a question, (6) time spent on an exercise with a weak result, (7) rated difficulty of a given question, (8) heart rate variability associated with a question and (9) heart rate change associated with an exercise with a weak result. These metrics can be categorized into two groups: those having to do with academic performance and those having to do with physiological state. Metrics (8) and (9) are physiological state metrics, and the others are academic performance metrics.
<table>
<thead>
<tr>
<th>Dimension</th>
<th>Metric Name</th>
<th>Metric Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic performance of each question</td>
<td>At_q</td>
<td>Average time spent on a given question</td>
</tr>
<tr>
<td></td>
<td>Cr_q</td>
<td>Correctness rate of a given question</td>
</tr>
<tr>
<td></td>
<td>At_wa_q</td>
<td>Average time spent on a wrong answer for a given question</td>
</tr>
<tr>
<td></td>
<td>Ad_q</td>
<td>Average difficulty of a given question</td>
</tr>
<tr>
<td>Academic performance of each exercise</td>
<td>At_e</td>
<td>Average time spent on a given exercise</td>
</tr>
<tr>
<td></td>
<td>Acr_e</td>
<td>Average correctness rate of a given exercise</td>
</tr>
<tr>
<td></td>
<td>At_wr_e</td>
<td>Average time spent on a given exercise with weak result</td>
</tr>
<tr>
<td>Physiological state</td>
<td>Ahrc_q</td>
<td>Average heart rate change of a given question</td>
</tr>
<tr>
<td></td>
<td>Ahrc_wr_e</td>
<td>Average heart rate change of a given exercise with weak result</td>
</tr>
</tbody>
</table>

Table 5.1 Physiological-state-aware performance reference metric set

Using these metrics, we propose a hybrid performance-evaluation model for identifying student academic performance in a self-paced learning environment. Periodically, average student academic performance and physiological signals collected during exercises will be used to update the PsaPRms. These averages in PsaPRms are then compared with measurements from individual students during the use of FishBuddy. As baseline heart rates during rest differ among individuals, each student’s baseline heart rate at rest is established prior to using FishBuddy and subsequently taken into account when comparing to collected averages during the use of FishBuddy. Thus FishBuddy utilizes baseline-corrected, relative heart rate measures.
5.2.4 Performance identifier algorithm

Our Physiologically-state-aware Weak Performance Identifier algorithm (PsaWPI) identifies when students experience anxiety and perform poorly. We use two kinds of input data: student academic performance on exercises and heart rate variation to this aim. We measure heart rate denoted as \( P \), and we measure academic performance on questions denoted as \( Q \). Details of these measures are described in Table 5.1.

\( P \) is sampled every 10 minutes because of technical limitations in our platform, and ideally it would be sampled continuously. For \( Q \), we collect two values: the score for the current question, \( Q_c(t) \), and the cumulative scores for the questions completed by the student, \( Q_a(t) \).

It is easy to find that:

\[
Q_a(t_0) = \int_0^{t_0} Q_c(t) dt
\]

For every \( P \), \( Q_c \) and \( Q_a \), we adopt a Gaussian model as prior knowledge to describe the previous data. Thus we have three Gaussian models for \( P \), \( Q_c \) and \( Q_a \) respectively. These models can be used for detecting outliers. For example, given data \( P \), we can use a z-test as follows:

\[
\text{prob}(P) = \text{prob}(P|G_P(\mu, \phi)) = e^{-\frac{(P-\mu)^2}{2\phi^2}}
\]

To detect the outlier, we use the modified local outlier factor (LOF) by Breuning et al. (2000). The basic idea of LOF is to calculate the local density of a given dataset, using the KNN classifier, whose distance is measured to estimate the density. Generally speaking, if data is far away from its KNN neighborhood, it will be considered as an outlier. In the current study, we consider such data as anxiety, and we believe that the student will be in anxiety.

For a given set of data, \([X_1, \ldots, X_k]\), each \( X_i \) consists of three pieces of data \((P(t), Q_c(t) \text{ and } Q_a(t))\). We calculate the reachability-distance of two pieces of data as follows:

\[
\text{rd}(X_i, X_j) = \max \left( \text{kd}(X_i), \left| X_i - X_j \right|_2 \right)
\]

where \( \text{kd}(X) \) is the k-distance of the data point \( X \). We define a simplified LOF (SLOF) as follows:
where $X_k$ is the $k$-th nearest neighborhood of $X_i$, and $X_n$ goes through all $K$ nearest neighborhoods of $X_i$. The SLOF measure of the local characteristics of a given data set could identify which $X_i$ is far away from the major data. In our setting, the KNN neighborhood is defined with respect to time ($t$).

Based on the SLOF, we can detect if a student’s physiological state is abnormal. Further details are outlined below:

**Algorithm:** identifying individuals who deviate from normal state with regard to PsaPRms.

**Input:**
- $P(t)$: student’s heart rate.
- $Q_a(t)$: cumulative score for questions completed by the student.
- $Q_c(t)$: score for current question completed by the student (as the $P$, $Q_c$ and $Q_a$ will be recorded in different time stamps, we adopt a linear interpolation to align the time frame to get three measurements at one time stamp). ($t$ is from 0, $t_1$, $t_2$, … and $t_n$, while $t_i$ is the time required for the student to complete question $i$).
- $T_0$: the time interval for searching the neighborhood.
- $K$: the KNN neighborhood.
- $Th_1$: the threshold for probability testing (index1).
- $Th_2$: the threshold for SLOF testing (index2).

**Output:** whether the student is in an abnormal state or not.

**Algorithm:**

For time $t$,

1. Calculate $\text{prob}(P)$, $\text{prob}(Q_a)$ and $\text{prob}(Q_c)$ by Eq(1).

2. Define $\text{index1} = \max(\text{prob}(P), \text{prob}(Q_a) \text{ and } \text{prob}(Q_c))$.

3. Denote $X(t)$ as $(P(t), Q_a(t) \text{ and } Q_c(t))$.

4. Calculate SLOF by Eq(4) with a time interval from $(t-T_0, t)$, as $\text{index2}$.

5. If ($\text{index1} > 0$) or ($\text{index2}$), the output student is in an abnormal
state; otherwise, the student is in a normal state.

6. If t<D, go to the next time stamp, and repeat steps 1-5.

5.3 Experiment and Findings

The goal of the experiment is to investigate the impact of the use of FishBuddy on the students’ continuous engagement in self-paced learning.

5.3.1 Experimental Settings

20 first-year undergraduate students from China Jiliang University, who were healthy and did not report any physiological disease, participated in the experiment. They had all achieved an A-level (best academic performance) in the course “English – Level 1” of the last semester and had just enrolled in the course “English – Level 2” for the current semester. The age of these students ranged from 18 to 21 years old and there were 11 male students and 9 female students. They did not have any prior experience with FishBuddy, nor had they participated in any other research regarding learning and engagement in self-paced learning environments. The students were randomly assigned to two groups (10 students in each group):

- The control group, in which the students carried out online self-paced exercises without FishBuddy; and
- The experimental group, in which students used FishBuddy while carrying out the same exercises.

The content of the exercises was chosen from questions that had been on the College English Test – Level 6 in the past three years.
5.3.2 Experimental Hypotheses

Our hypotheses are: Experienced anxiety and isolation will be both significantly reduced for the group using FishBuddy in comparison to the group without using FishBuddy. Academic performance will be significantly increased for the group using FishBuddy in comparison to the group without FishBuddy.

Venkatesh et al. proposed the unified theory of acceptance and use of technology (UTAUT) model for evaluating user readiness to adopt information technology in a general setting (Venkatesh et al., 2003). Chiu et al. (2008) further applied the UTAUT in the context of web-based learning environment and concluded that expectancy of academic performance is a positive determinant of the intention to continue engaging in web-based learning. Isolation, anxiety and delayed feedback are negative determinants that weaken user intention to continue engaging in web-based learning.

In the current study, anxiety is understood as an affective response, an emotional fear toward potential negative outcomes (i.e., failing in an examination). Chiu et al. (2008) concluded that negative feelings detract students from academic tasks and usually result in significant negative impacts on a student’s intention to continue engaging in self-paced learning. Anxiety is the main negative factor that we aimed to reduce in a self-paced learning environment.

We define isolation as markedly few interactions between a student and other students/teachers. Breunig et al. (2000) argued that experienced isolation was a direct factor leading to the dissatisfaction with web-based self-paced learning. Handri et al. (2011) concluded that students participating in learning activities via web-based self-paced learning often suffer from experienced isolation, which frequently results in their withdrawal from the learning activity, and it is difficult to bring them back. We understand delayed feedback as responses within an e-learning system to a student’s actions that come too late to be experienced as timely. Vonderwell (2003) asserted that lack of timely feedback from the instructor in web-based learning was a serious drawback that caused frustration for students.

In the current study, the expectancy of performance is understood as
the extent to which a student expects to improve performance within the adopted e-learning system. Venkatesh et al. (2003) argued that expectancy of performance was another critical factor for a student’s intention to continue to use the new e-learning system. Bahli’s study (2005) found a positive correlation between a student’s intentions to adopt new learning technology and its usefulness for improving performance in the context of self-paced learning.

5.3.3 Experimental Procedures

We conducted the experiment in an independent environment without Internet connection, so that each student could only complete the exercises individually, thus avoiding any possible plagiarism. The setting was similar for the experimental and control group: each student used the SPLS to participate in the exercises, but the students in the experimental group wore the Apple Watch with e-Fish during the experiment, while the students in the control group did not. The SPLS provided 10 English grammar exercises with 40 multiple-choice questions per exercise and allowed a maximum of 60 minutes for each student to answer them. Students were asked to complete as many exercises as possible. At the end of the experiment, all students in the experiment were required to answer a questionnaire regarding his/her intention to continue engaging in our self-paced learning environment (FishBuddy), in which score 1 represented strongly disagree and score 5 represented strongly agree. The questions were as follows:

- Q1: Did you experience anxiety while you were doing exercises?
- Q2: Did you have the feeling of isolation while you were doing exercises?
- Q3: Did you receive instant feedback on your performance while doing exercises?
- Q4: Do you agree that the self-paced learning environment could improve your academic performance?
5.3.4 Results and Findings

Our experiment aimed to investigate the impact of FishBuddy on the intention to continue engaging in self-paced learning using the SPLS among students. The results of the experiment include the following:

- The comparison of students’ total engagement time in the two groups;
- The comparison of the self-reports from the two groups;
- The comparison of the students’ performance on exercises from the two groups.

These comparisons were conducted in order to test the hypotheses proposed earlier.

To compare students’ total engagement time in learning activities between the groups, we analyzed the data, which included when the students began the exercises and when they quit the experiment. In Fig. 5.4, the horizontal axis represents total engagement time for each student in the experiment while the vertical axis represents the percentage of the students staying in the experiment in each group. We found that in the first 30 minutes of the experiment, all students in the two groups were fully engaged with exercises. In the control group, most of students quit the experiment between 33 and 98 minutes, the earliest quit the experiment after 31 minutes, and the longest engagement time was 122 minutes. The average engagement time was 65.5 minutes. In the experimental group, most quit the experiment between 40 and 151 minutes. The first quit after 41 minutes and the longest engagement time was 163 minutes. The average engagement time of the experimental group was 111.4 minutes, which was much longer than the average engagement time in the control group and evidence in support of the hypothesis that FishBuddy was significant in promoting student engagement in our SPLS.
In order to investigate students’ subjective attitudes toward the FishBuddy, we designed a questionnaire that included four questions (as described in Table 5.2) to gather feedback from the two groups. Regarding the answers to Question 1, the students in the experimental group reported less anxiety as compared to the students in the control group. This result accorded with the result illustrated in Fig. 5.4, that students in the experimental group engaged longer with the SPLS than those in the control group. Regarding the answers to Question 2, the students in the experimental group reported less experienced isolation than those in the control group. The hypothesis that FishBuddy is useful for reducing student anxiety and feelings of isolation in our SPLS was supported by the results of the questionnaire. Regarding the answers to Question 3, most students in the experimental group agreed (4.1/5) that they received instant feedback; in comparison, the students in the control group strongly disagreed (1.4/5). A possible explanation for this result is that students in the experimental group treated the e-Fish as providing instant feedback from the SPLS just in virtue of being there.
Questionnaire | Exp. Group (N=10) | Ctrl. Group (N=10)
---|---|---
Q1: Did you experience anxiety while you were doing the exercises? | M=2.1, SD=0.87 | M=4.2, SD=0.91 |
Q2: Did you have the feeling of isolation while you were doing an exercise? | M=2.6, SD=1.26 | M=3.9, SD=1.28 |
Q3: Did you receive the instant feedback on your performance while you were doing an exercise? | M=4.1, SD=1.19 | M=1.4, SD=0.69 |
Q4: Do you agree that the self-paced learning environment could improve your academic performance? | M=4, SD=1.05 | M=1.9, SD=0.99 |

Table 5.2 Questionnaire result

Regarding the self-reports from the students, we found that those in the experimental group agreed (4/5) that FishBuddy was useful for improving their performance. Furthermore, in order to quantitatively evaluate the usefulness of improving performance, we created a scatter plot to display the results of the average correctness rate achieved by each student on each exercise for the two groups. This scatter plot can be used as a direct indicator of academic performance.
Fig. 5.5 Comparison of the average correctness rate of the control group and experimental group in the exercises

Fig. 5.5 shows that students in both groups achieved a high correctness rate in the first exercise even though these questions were difficult for first-year undergraduate students, and then the correctness rate rapidly decreased until the third exercise. Since the fourth exercise, the correctness rates of the two groups went in different directions. We suggest that this is due to that many students were guessing. The average correctness rate students achieved for all exercises in the experimental group were 46% and the corresponding average correctness rate in the control group was 47%.

According to the result \( t = -0.21198, \text{ df } = 18, \text{ p-value } = 0.4173 \) of t-test on the performance of two groups, we failed to reject the null hypothesis, which means that there is no enough evidence showing that the participant’s average correctness rates between experimental group and control group are different at significant level 0.05. This result conflicted with students’ answers to Question 4 in the questionnaire, but it is in accordance with that all participants had the same level of English grammar knowledge prior to engaging in the experiment. Thus the hypothesis that FishBuddy was significant for improving performance was not supported in our experiment. However, it only makes sense that academic performance would not be improved in such a short timeframe,
even if the students in the experimental condition had more positive learning experiences during the trial.

5.4 Summary

In this chapter, we presented a self-paced learning environment (FishBuddy), which consists of a web-based SPLS and a wearable application (e-Fish). We used FishBuddy in an attempt to unobtrusively track student exercise performance during a learning activity and regularly measure students’ heart rate variations.

We proposed the use of a physiologically-state-aware performance evaluation model, which includes a performance reference metric set and a weak performance identifier algorithm, to instantly determine if a student was feeling anxious during a learning activity. The e-Fish application would generate a visualization: a fish would appear on the screen of the Apple Watch to mirror the student’s physiological state through an inverse mapping of the speed of the fish to heart rate so the fish swam more slowly as monitored heart rate increased. The design of the fish was inspired by Chinese aesthetics according to which it represents tranquility and inner peace (Liu, 2008).

In a between-groups experiment, two groups of students with or without the FishBuddy system completed exercises on English grammar in a self-paced learning environment. Computer-generated tracking of exercise performance was instantly processed and combined with physiological data provided by the Apple Watch to create a biofeedback-generated visualizations of a moving fish that we term (hence the name FishBuddy), for the experimental group. These visualizations were displayed on the Apple Watches of students whose physiological measures indicated that they were anxious. The computer-observed results of student engagement were compared with self-reported levels of
student engagement to validate that FishBuddy is useful for promoting student engagement.
Chapter 6 Conclusion

6.1 Research Conclusion

Since the commencement of my Ph. D. study, I was much interested in the argument that “regardless what pedagogical approaches are adopted in e-learning systems, many questions still remain: to what extent are learners’ interactions with the learning materials, instructors and other learners effective? How can online pedagogical designs be improved?” (Lias & Elias, 2011). This thesis reports the attempts towards answering some of these questions in e-learning environments by using disciplinary approaches.

In Chapter 2, we reviewed the literatures on education, physiology, e-learning, data mining, learning analytics, wearable computing, affect computing, etc. We identified two major issues in existing e-learning environments:

- The learner-to-content interaction is limited by obsolete interaction interfaces;
- The learner-to-instructor interaction is poor due to the fact that the face-to-face communication is not available in most of e-learning environments.
- The supervision and intervention from the teachers are insufficient in e-learning environments.

In order to improve the efficiency of the learner-to-content interaction in an online course forum, we attempted to identify the questions frequently asked (including valid learner-produced posts) and those questions without valid answers in online course forums by analysing DOM elements, so that the frequently asked questions (including most valid learner-produced posts) and those questions for answers for a long time could be highlighted. In Chapter 3, we presented a novel page segmentation based wrapper (called eCF-wrapper), to extract structural data from the post pages in online course forums. By combining the DOM-tree features and visual clues, our proposed page segmentation
method can successfully extract post modules. And then with simple statistics, an optimization of the content display can be easily obtained. Experimental results show that eCF-wrapper is effective for extracting data from course forums and helpful for suggesting the content display in online course forums.

In order to effectively augment learning interactions, in Chapter 4, we proposed an interaction-aware VLE (called WebIntera-classroom). In WebIntera-classroom, we proposed a ubiquitous interactive interface that integrates a pen-and-paper interface with a web-based whiteboard to make learner-to-content interactions to be easily obtained. We implemented a learning analytics engine to broadcast, record and play a lecture recording. The engine can identify the hotspots in a lecture recording, and raise students’ awareness on the potential importance of key contents as learned from historical data. Besides, we developed a graphical dashboard to monitor students’ learner-to-instructor interactions in the instructor-led learning. We conducted a survey (n=464) and face-to-face interviews (n=60) to investigate the users satisfaction on the WebIntera-classroom. The result of the questionnaire showed that the major features of WebIntera-classroom gained high user satisfaction. A case study regarding the use of WebIntera-classroom was also introduced, and we compared the students’ performance for the same course using WebIntera-classroom vs a traditional classroom. The result demonstrated that the students could gain performance improvement by using WebIntera-classroom.

Student engagement is crucial for successful self-paced learning. Learning in isolation without supervision and intervention by teachers in self-paced learning may significantly weaken students’ intentions to continue engaging in learning activities. In Chapter 5, we developed a self-paced learning environment (called FishBuddy), which consists of a web-based SPLS and a wearable application (e-Fish). We proposed the use of a physiologically-state-aware performance evaluation model, to determine if a student was feeling anxious during a learning activity. The e-Fish application would generate a visualization: a fish would appear on the screen of the Apple Watch to mirror the student’s physiological state through an inverse mapping of the speed of the fish to heart rate so the
fish swam more slowly as the monitored heart rate increased. The result of between-groups experiments shows that the average engagement time of the experimental group was 111.4 minutes, which was significantly longer than in the control group (65.5 minutes). This provided evidence that FishBuddy was significant in promoting student engagement (i.e. the consistency of engagement) in our SPLS. The students’ self-reports indicated that FishBuddy was useful for reducing student anxiety and experience of isolation during the self-paced learning exercises. Additionally, we found that students in the experimental group experienced FishBuddy as improving their performance; but a quantitatively comparison indicated no difference between the groups with respect to student performance. This latter result should not come as surprising as academic improvement can only be expected to take some time. That students in the experimental group had more positive experiences during the short trial and developed stronger intentions to continue using the learning environment speaks for that FishBuddy ought to lead to such academic improvement in the long run.

6.2 Summary of Research Contributions

In this thesis, we proposed a set of approaches, and developed a number of e-learning tools, to enhance the interaction and engagement in e-learning environments, and the contributions we achieved are summarized as follows:

- **C1.** A page-segmentation based data extracting approach – eCF-wrapper, specially designed for structural information extracting from online course forums, which is desired to extract generalized, robust and accurate data records.

- **C2.** An interaction-aware VLE – WebIntera-classroom, with which we can achieve better instruction effect than in traditional classroom-based learning. And it is capable of:
  - Integrating the pen-and-paper interface;
  - Providing real-time tracking on learners’ interaction and
engagement in learning processes;
- Raising the learners’ awareness on the hotspot time slots and contents when watching the lecture recordings.
- C3. A high-granularity learning analytics engine - hgLAE, which is based on a novel data schema for the storage of learning objects, hgLAE could efficiently record and deliver a lecture recording in VLEs, and to identify the hotspots in a lecture recording.
- C4. A self-paced learning environment - FishBuddy, which consists of a web-based learning system and an Apple Watch application. It tracks behavioral and physiological data of students participating in learning activities, and using a physiological performance-evaluation model, it identifies appropriate moments for providing biofeedback-based visualizations that reduce the learners’ anxiety.

6.3 Future Work

For these approaches and tools we proposed to enhance the interaction and engagement in e-learning environments in this thesis, there are still some limitations, and further effort should be carried out to improve these approaches and tools in the future.

For example, the eCF-wrapper can only provide suggestions on the display of the content in the course forums, but it cannot directly update the display of the content in the web page. A possible way to address this issue is to develop a plugin for the browser, with which the content of the web page can be automatically updated with regard to the suggestions from eCF-wrapper.

Currently, the WebIntera-classroom is not able to distinguish between the difficulty and curiosity when it detects a hotspot in a lecture recording. It would be certainly interesting yet challenging to distinguish between different types of hotspots. This will be an important work for us to investigate in the future.

A limitation of FishBuddy is that the sampling of students’ heart rate
occurred every 10 minutes due to technical limitations of the WatchKit. In the future, we will attempt new approaches to immediately detect a student’s heart rate after he/she completes a question. Additionally, as presented in Section 5.4.4, the quantitatively comparison in the between-groups experiment indicated no difference between the groups with respect to student performance. We do believe that academic improvement can only be expected to take some time. In the future, we will continuously investigate the impact of the FishBuddy on the students’ academic performance.

Finally, in order to support the interoperability of the e-learning services argued by Bulger et al. (2008), in the future we will develop a set of application program interfaces (APIs), with which the e-learning tools proposed in this thesis could be connected and interoperate with other existing e-learning systems (e.g., learning management system, content management system, etc.) to provide a holistic e-learning environment.
References


relating to achievement. Educational Psychology An International Journal of Experimental Educational Psychology, 57(1-2), 867-869.
of General Education, 63(4), 244-255.


Luo, B., & Xia, J. (2014). A novel intrusion detection system based on
gamification. Cybernetics and Statistics, Babes-Bolyai University, Romania.


Yun, W., Bicheng, L. I., & Chen, L. (2009). Data Extraction from Web
CURRICULUM VITAE

Academic qualifications of the thesis author, Mr. CHEN Jingjing:

• Received the degree of Bachelor of Science from China Jiliang University, September 2006.

• Received the degree of Master of Engineer from Zhejiang University, November 2012.

August 2016