國立臺灣大學工學院工程科學及海洋工程學系

博士論文

Department of Engineering Science and Ocean Engineering
College of Engineering
National Taiwan University

Doctoral Dissertation

雲端教育科技對於學習經驗成效之研究

Analyzing the Effects of Cloud Educational Technology on the Learning Experience

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中華民國 106 年 11 月

November, 2017

doi:10.6342/NTU201704318

誌謝

本論文得以完成，首先要感謝指導教授張瑞益博士。感謝老師長久為學生在論文指導上所花費的心力與時間，謝謝老師耐心的教導，也給予很多鼓勵，使我有動力繼續往目標邁進，在未來，也會期許自己繼續實踐及遵循老師所給予的教誨。感謝諸位口試委員撥冗於論文口試時給予指正與建議，使本論文能夠更加完善，同時也給我許多啟發與收穫，也感謝老師們對學生的鼓勵，學生在此衷心感謝；感謝所有的家人、朋友、同儕、師長以及長官們，在準備論文的時間，給予本人許多包容和支持，本人謹致上十二萬分的謝意，感謝各位一路上的相伴，感謝你們的陪伴與鼓勵．

在就學的日子裡，有摯愛的家人們、朋友們、師長們，大家給予無盡的關愛與溫暖，讓本人有放鬆及傾訴的管道，謝謝父母、祖母、小姑姑、兄弟姊妹，心潔、品辰、冠惠這段時間的陪伴，讓我感覺到溫暖，但因為有你們，研究生活才得以充滿動力，在寫論文的過程中，由衷感謝一路上陪伴的人們。最後，僅將此論文與各位分享。

doi:10.6342/NTU201704318

中文摘要

隨著教育科技日新月異的發展，數位教材不斷地推陳出新，廣泛應用至各式學習系統中，個人化學習、教育資料探勘、教育物聯網、大規模開放式線上課程（MOOCs)等教育科技是目前熱門的創新技術，數位教育可藉由線上互動的方式提升學習效益，因此衍生出多樣化的教育技術與素材；對於學習者而言，個人特徵往往會影響對於教學素材的使用偏好，對於學習成效也有所差異；近年來，個人化學習被許多教育研究所重視的一個議題，相關研究在開發學習系統時，學習者的學習風格亦被當作設計考量之一，達到因材施教的效果，學習者特徵擷取扮演著重要的角色，對於教育科技而言，從教育技術之研發、個人特徵關聯調查、進階分析出個人特徵並進行適性化教學，每個階段都是環環相扣；藉由教育資料探勘進行個人化學習；在本研究中，我們開發各式教育技術並實際應用於教學活動中，如動畫、互動遊戲。為了確保系統品質與學習成效，本研究中提出的系統和現有教育技術被納入到評估系統績效中，而本研究的雲端學習資料，藉由數據挖掘技術分析個人特質與學習經驗、成效、與認知之間的關係。在教育素材開發部分，本研究所發展的系統，無論是問題解決遊戲系統，或是遊戲化資訊教育系統，皆能有效地提升學習者的動機和學習成效；在學習經驗方面，本研究針對目前的熱門素材進行學習經驗調查，其調查結果可幫助後續了解學習者對於雲端技術的看法與建議；在教育資料探勘方面，本研究採用詢問式分類機制，提供雲端個人化教育·

關鍵字：教育資料探勘、教育科技、遊戲化、雲端學習

doi:10.6342/NTU201704318

ABSTRACT

With the rapid development of educational technology, the new type of digital instructional material been widely applied in various learning management systems (LMS). Personalized learning, gamification, educational data mining, Internet of thing (IoT) and massive open online courses (MOOCs) are the popular cases of innovation in the education. E-learning takes advantage of the interactive abilities of the online digital media to enhance students' learning efficiency. It is critical to consider that educational technology can be designed with various types of instructional materials, and learning performance is improved depends on the kind of instructional materials provided to the learner. Personalized learning has received considerable attention, considering the learning styles when developing adaptive educational systems. In this study, we develop the various educational technologies in the different learning activity such as animation, the interactive game, and IoT solution. For ensuring the quality of learning activity, the usability of educational technology evaluation is needed. The proposed system and the existing educational technology were included in this study to evaluate system performance. Personalized learning has recently become a popular trend in e-learning. The cloud-based learning profile can be retrieved and maintained automatically based on the framework of information and communication technology (ICT) when learners interact with the LMS. This study also applied the data mining techniques in the learning profile to investigate the relationship between personal trait and learning experience, user's perception. The findings of this study demonstrate the relationship between tool, human behavior, and data. First, this study integrates game-based learning and personalized learning into a problem-solving activity and computer science education to maximize learner motivation and learning effects. Second, we explore the personal traits and learning preference on using the proposed system and the popular educational technology. Finally, the query-based classification was used to personalize the learning material.

Keyword: Educational data mining, Educational technology, Gamification, Cloud learning

doi:10.6342/NTU201704318

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Chapter 1 Introduction

E-learning, which typically means using a computer for a learning activity or in a learning environment, was proposed in the nineteenth century. A learning management system (LMS) was widely applied in the educational field to report, administer, and document courses. In the twentieth century, the development of educational technology was focused on computer-mediated communication between teachers and learners. In the twenty-first century, with the introduction of information and communications technology (ICT), educational technology has turned to cloud-based technology (see Figure 1-1).

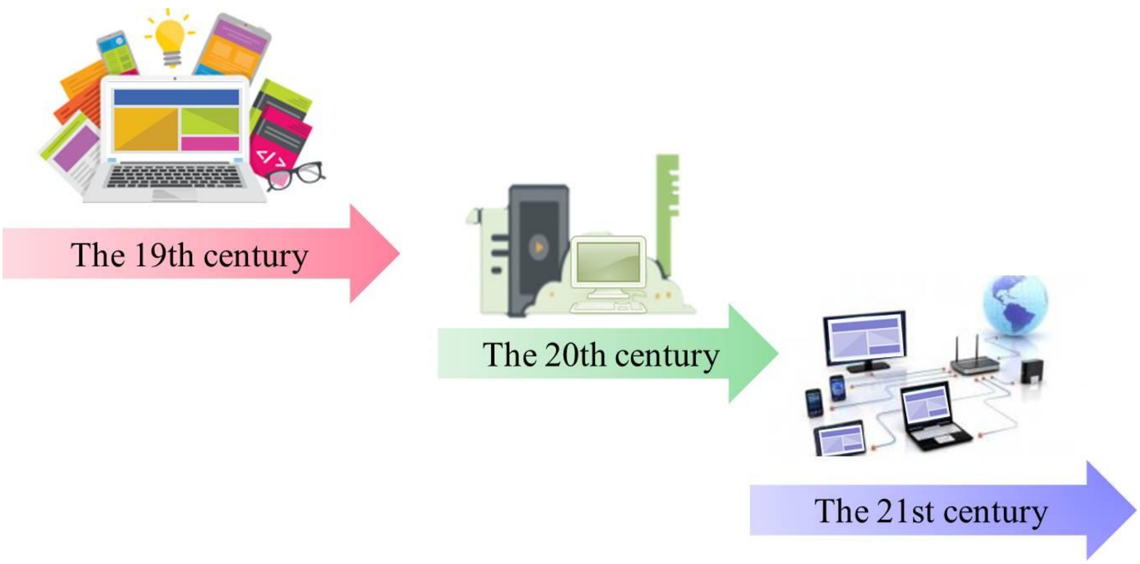

Figure 1-1 The evolution of educational technology.

Cloud-based technology has evolved dramatically in the 10 years, and this technology has become a critical tool in today's world of education. Cloud educational technology has benefits that include increasing accessibility, reducing information technology (IT) and infrastructure costs, enabling collaboration, and allowing learners more flexibility in personalizing their learning plan. In a flourishing e-learning industry,

doi:10.6342/NTU201704318

new educational technologies such as online games, massive online open courses (MOOCs), and cloud data mining have been gaining popularity. MOOCs provide an open-access curriculum to an unlimited number of learners and integrate social networking and interactive user forums. In MOOCs, learners can plan their participation according to their learning interests, learning goals, and prior knowledge. The present study investigates the influence that learning-style preferences have on learners' intentions to use MOOCs.

In a diverse learning environment, there are no fixed learning paths that are appropriate for all learners. Therefore, personalized learning is an important research issue for an LMS. Many researchers have focused on developing cloud-based personalized learning techniques that can be adapted to an individual's needs. The present study aims at enhancing learning efficiency and fit individual's needs. The study focuses on assessing the effects of different materials on learning performance and cognition, and the use of a mining algorithm to provide adaptive suggestions for the individual learner.

The remainder of the study is structured as follows. The related educational technologies are briefly introduced in Chapter 2. In Chapter 3, we present the main contributions of this thesis: different educational technologies that may be used in a problem-solving learning activity and in computer science education. In Chapter 4, we use the statistical analysis method to investigate the effect of personal traits on the use of MOOCs. In Chapter 5, the data mining technique is used to predict learning behavior in order to provide adaptive learning recommendations. Chapter 6 draws conclusions and discusses future studies.

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1.1 Motivation

The new educational technology is broadly applied in courses, programs, and other learning activities. However, not all popular learning materials are suitable for all learners. Each learner has a different attitude toward different forms of instruction. Therefore, it is necessary to understand learners' behavior and how to engage them in learning in order to develop educational technology. The term "reciprocal determinism" means that a person's behavior is determined by the individual, by the environment, and by their behavior. In the education field, learners have different responses to instructional practices and unique attitudes toward learning. This study is concerned with how to estimate a learner's response and provide a personalized context for learning. Therefore, the primary goal of the study is to enable a personalized, convenient, and intelligent learning environment. To facilitate a personalized learning environment, we assess the effects of different materials (e.g., static materials and animated games) on learners' behavior based on reciprocal determinism (see Figure 1-2).

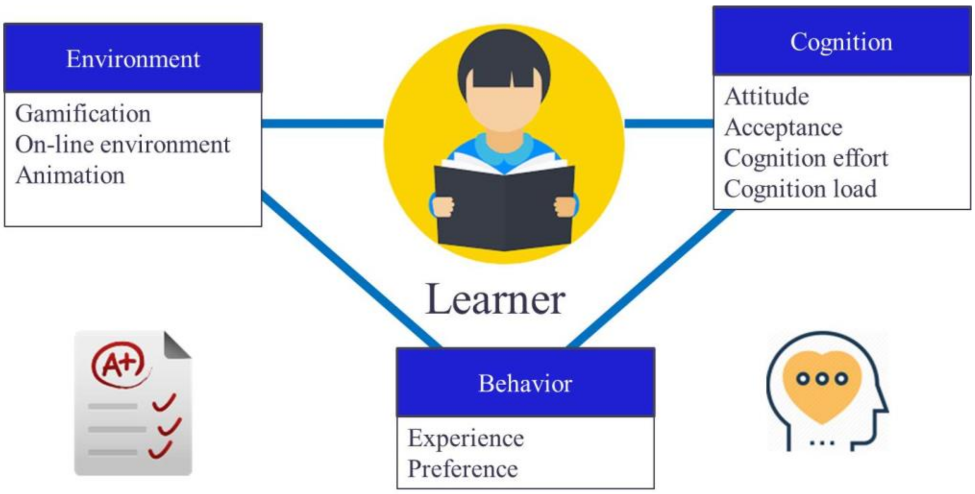

Figure 1-2 The behavior analysis of this study

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To make possible a convenient learning environment, this study develops animated gamified material and static material for use in problem-solving activities and computer education. We designed a problem-solving learning system (PSLS) and a computer science learning system (CSLS). The term "gamification" means applying game elements and game design concepts to a nongame context, with the aim of the learner reviewing the learning content via a gamified task. To enable an intelligent learning environment, we use data mining to estimate learning behaviors in online learning environments and to explore adaptive features for personalized learning.

1.2 Contribution

We contribute to the evolution of educational technology by developing various learning systems and providing adaptive learning suggestions for students. We also discuss how tools, behavior, and data analysis contribute to educational technology:

(1) Tools: These are the different materials that influence learner performance and perception. We demonstrate that gender differences exist: game-based material is more useful for males, and static-text material is more useful for females. Intuitive students perform better when using gamified material. Male students who use gamified material perceive solving a problem as easier in gameplay. Thus, a gamified learning system can enhance students' learning achievement and acceptance of technology as well as reduce cognitive load.

(2) Behavior: We investigate learners' experience using cloud educational technologies and a learning approach that can assist with this. The results show that the active and global learning style may influence the use of MOOCs and that visual learners are more likely to use gamification instructions.

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(3) Analysis: This is the classification algorithm for personalizing learning to engage learners in learning and to enhance their learning motivation and performance.

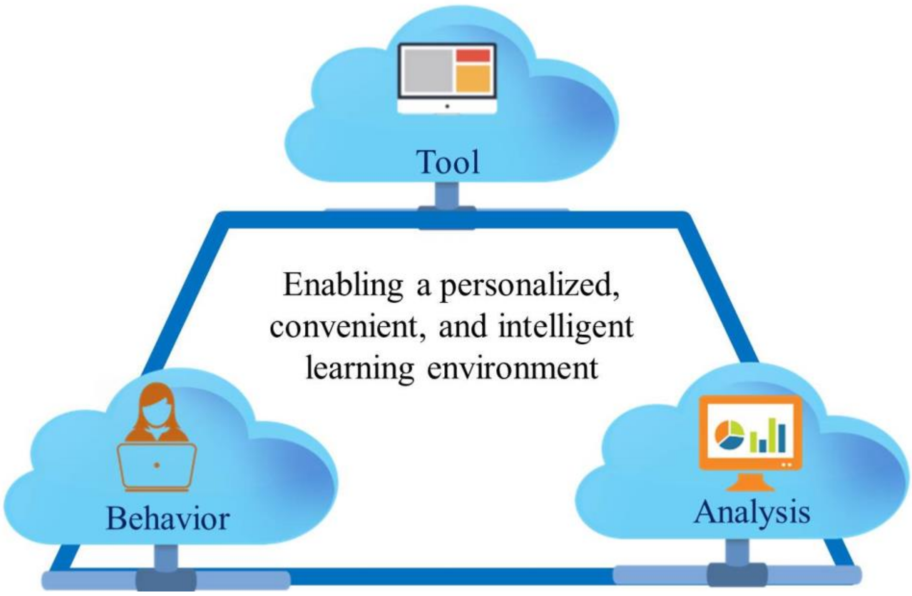

Figure 1-3 The contributions of this study

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Chapter 2 Related Works

The concept of student-centered learning has become increasingly important, owing to rapid advances in and the popularity of educational technologies. Numerous studies have reported the use of interactive instruction and technology-enhanced learning approaches in education. The present study provides two examples of e-learning and its integration into two facets of instruction: problem-solving learning and computer science education

2.1 Problem-Solving and Computer Science Education

Problem-solving and computer programming are considered as critical skills for people, and learning in this way is a popular trend in e-learning. Problem-solving employs cognitive processes: exploring and understanding, representing and formulating, planning and executing, monitoring and reflecting. The ability to solve problems is comprised of rule identification, rule knowledge, and rule application [1]. Learning through problem-solving is considered an effective learning paradigm, and there are various domain-general approaches to modeling problem-solving, such as computer programming [2], chemistry [3], and cognitive psychology [4]. In these cases, problem-solving has a substantial correlation with educational success, and it is considered an ability that allows knowledge to be acquired in different types of task [1]. Researchers have argued that problem-based learning is a student-centered pedagogy wherein knowledge can be available before the problem-solving process occurs, and that students learn through a facilitated experience of problem-solving [1][3][5][6]. In recent years, learning systems that are integrated with a web-based platform have attracted considerable attention from researchers [7][8]. For example, computerized

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adaptive tutorials have been applied to assess problem-solving skills [9] The ability to solve problems is the core of computer science, and problem-based learning is widely used in computer science education [6][10].

Computer programming is becoming increasingly important and is regarded as a core competency. In computer science education, instructors may face the challenge that their students perceive programming concepts as difficult. Factors that have an impact on students' learning motivation may be essential information for improving learning efficiency related to computer programming [11][12]. Games engage learners' imagination and curiosity [13][14], and also support them in engaging with a series of complex tasks. Some studies have shown that educational games are a good vehicle for learning because students find them entertaining and motivating [15][16][17], and games can be used to promote flow experience, which may improve problem-solving ability [15]. Game-based material is considered useful in improving learning performance, experience, attitudes, and behaviors [13]. Recently, games have been widely applied in learning procedures [13][18][19], and they are a convenient way to help students immediately learn via scenario feedback. Animation is also a good approach for assisting learners in imagining processes and performing mental representations [20].

2.2 The Effect of Personal Traits on Learning System

Learning materials are a complicated topic as everyone is unique in their learning experience. Personal traits such as learning style, gender, and self-efficacy may be related to the learner's preference for a certain type of instruction. The term "learning style" refers to the preferred way in which a learner processes, retains, and comprehends

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information and to an individual's habitual pattern of acquiring and processing information in learning situations. With the recent development of personalized learning, many researchers have used learning styles to develop LMSs [21][22][23].

2.2.1 Learning style

Felder and Silverman's learning styles model (Felder–Silverman model) has been widely used in the field of educational research, and classifies learners according to four learning style dimensions, with two types of learner preferences in each dimension. These eight learning styles are "visual–verbal," "sensing–intuitive," "active–reflective," and "sequential–global" [23]. Graf's showed that the "sensing–intuitive" dimension of a learning style can influence innovative thinking [22]. In other research, the visual–verbal learning style is associated with creativity. These learning styles may have an impact on the learning experience in different ways. For each learning style there is a unique learning preference and process [21]. Few studies, however, have investigated whether learning styles are associated with the learning experience in different learning environments. In this study, we employed the Felder–Silverman [23] model to investigate the effect of learning style on learning experience and perception in different learning environments (see Table 2-1).

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Table 2-1 The Felder-Silverman learning model

Dimension	Learning Style	Description
Visual–Verbal	Visual	Visual learners prefer pictures, diagrams, flowcharts, time lines, films, and demonstrations.
	Verbal	Verbal learners prefer spoken and written explanations.
Sensing–Intuitive	Sensing	Sensing learners have more interest in learning facts.
	Intuitive	Intuitive learners prefer exploring possibilities and relationships.
Active–Reflective	Active	Active learners understand information best through doing an activity.
	Reflective	Reflective learners tend first to think about information quietly.
Sequential–Global	Sequential	Sequential learners prefer linear steps, with each step following logically from the previous one.
	Global	Global learners prefer material that is presented randomly, without their seeing the order and the relationships between parts of the material.

2.2.2 Self-efficacy

Previous studies have indicated that self-efficacy increases problem-solving efficiency [24][25], and that learning performance can be attributed to self-efficacy [24]. An individual's perceptions of the environment are related to self-efficacy, and these perceptions are used as the basis for self-efficacy. In the current study, learners' perceptions, such as concerning technology acceptance and cognitive load, were included to access the effect of self-perception on different forms of learning instruction. Therefore, we also discuss the difference in personal traits as regards the perception of the difficulty of dynamic and static materials.

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2.2.3 Gender

Hoffman's study (2010) showed that differences exist between the genders—females have less self-efficacy than males. Penner's research indicated that gender influenced learners' performance in problem-solving learning activities [26]. Some studies have pointed out that male and female learners have different levels of learning motivation between different environments [27] or between types of instruction, such as static versus animated instruction. The difference in learning performance between genders exists in various environments [28]. As gender is considered a critical factor, we included it as a variable in analyzing learning performance or perception of the difficulty of a problem-solving activity.

2.3 Gamification in Education

Innovation in education has attracted much attention from researchers in recent years [29][30]. Gamification is the process of integrating game design elements into nongame content [31] to engage users [32][33]. Gamified educational technology has grown steadily in higher education [34][35][36], and recent studies have developed gamified platforms in computer science education [37][38] and demonstrated how gamified material is able to engage students in a learning activity. Some researchers have suggested that discretionary computing education games may improve efficiency in learning computing concepts in informal education [39] and help users understand computing content [40].

Some studies have shown that games are an integral part of the cultural and social environment, and that they have benefits in learning across age groups and content

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domains [41]. As described by Kinzie et al. (2008), “games are an immersive, voluntary, and enjoyable activity in which a challenging goal is pursued according to agreed-upon rules.” Games have been employed to motivate learners’ cognitive and psychomotor skills [42][43][44]. Some studies have found evidence that educational computer games used in learning activities can improve students’ learning performance [45] and perceptions (e.g., attitudes [40][41] and cognition[42]) of learning. Most of the existing game-based applications have been shown that the interactive characteristics of games can facilitate learning [44][45]. The related literature shows that an advantage of games is that they can use interactive scenarios to enhance learners’ motivation [40][46][47]. Previous studies have also supported this view. Prensky (2009) stated that digital games consist of elements that give learners enjoyment, encourage passionate involvement, and enhance their learning motivation [47][48]. In gamified scenarios, players received immediate rewards by solving a game task [47][48][49][50]. Therefore, educational games are frequently included as a positive component of personalized learning, and game-based learning is employed in various courses.

2.4 MOOCs and Users’ Perception

ICT has been widely applied in curricula. For example, learning portfolios can be automatically retrieved and maintained when learners interact through an LMS. MOOCs, which have recently gained popularity in the field of education, provide open access and allow for unlimited participation by learners. Downes and Siemens were the first to present an online teaching model (a MOOC) in their curriculum [51]. MOOCs have developed from the “cMOOC” (based on connectivism) to the “xMOOC” (based on instructionism) to further distinguish these classes. Coursera and edX are recent

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examples of providers of the “xMOOC.” Since 2012, MOOCs have been widely employed in distance education [52][53] through Facebook, Twitter, Wiki, forums, and other social networking sites [54][55]. The most significant innovation during this period has been the online courses offered by Stanford University, which was followed by several other educational institutions that began offering online courses through providers such as Coursera, Udacity, and edX (see Figure 1). In 2002, the Massachusetts Institute of Technology announced its OpenCourseWare (OCW) Consortium to provide free and open online courses with high-quality content. The online open-access course had a revolutionary impact on higher education worldwide. In Asia, the Taiwan OCW Consortium (TOCW) and the Japan OCW Consortium (JOCW) are popular local MOOC providers [56]. The TOCW offers diverse online courses from 27 universities, while the JOCW was launched to make such courses available through the top universities in Japan (University of Tokyo, Kyoto University, Keio University, Osaka University, the Tokyo Institute of Technology, and Waseda University). Open-access education can be considered as a form of social change that has been made possible by digital technology. Because students’ learning experiences and preferences may be influenced by their personal traits, the present study investigated the impact of learning-style preferences on learners’ intentions to use MOOCs.

2.5 Educational Data Mining

Data mining techniques can be categorized into four approaches: classification, association, clustering, and sequential pattern mining. Recently, educational data mining has attracted increasing interest, and it has been suggested that such data mining can inform adaptive learning programs to improve learning abilities. The application of data

doi:10.6342/NTU201704318

mining to an LMS has received considerable attention, as it is useful for optimizing personalized learning [57][58][59][61][62]. Educational data mining is the focus of a new and growing research community. Many studies have reported that a clustering algorithm can distinguish help-seeking behaviors and similar seeking strategies among learners in the same learning activity [58][61][62]. Romero et al. (2008) used data mining algorithms in course management systems [60][59].

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Chapter 3 Educational Technology on the Cloud

Instructional material can be designed in various forms for learning. Leopold et al. investigated the effects of verbal and pictorial material and found that the effect of spatial representations was facilitated by mental imagery activities [86]. Therefore, it appears that learning performance can be enhanced through the types of learning materials provided to learners. Identifying the different ways in which learning materials influence learning performance and learning cognition is essential for shaping learners' cognitive abilities and expectations related to learning [17][42]. Researchers have suggested that educational games are an effective means of learning, as learners may find such games entertaining and motivating.

With the rapid development of technology, problem-solving abilities and fundamental computer science skills are currently considered as core competencies that have become a popular trend in higher education. Students may aim at being well equipped with not only specialized knowledge in their field but also an understanding of basic computer science knowledge and excellent problem-solving ability. In the present study, a PSLS [63] and a CSLS [64] were included in the proposed system to engage learners in problem-solving education and computer science education.

ICT is currently flourishing, and web techniques have been applied widely to teaching and learning. The present study presents two learning systems, which are based on gamification and animation. The proposed systems were constructed around the architecture of ICT. Learners can interact via an e-learning platform, and learning portfolios can be retrieved automatically. A cloud-based learning system can be accessed through mobile devices and Internet browsers. The proposed system is based

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on the framework of responsive web design (RWD) and is compatible with mobile devices. The proposed system is also compatible with any cloud virtual machine, container, or server. Learners can learn anytime and anywhere. Learners or teachers also do not need to save their files in local storage devices. Figure 3-1 shows a learning scenario on the cloud. In the current study, learners can upload and administer their learning material on the cloud. When the learning content is updated, the system administrator notifies learners of their current status. Learners can also discuss issues that interest them collaboratively or individually on interactive platforms.

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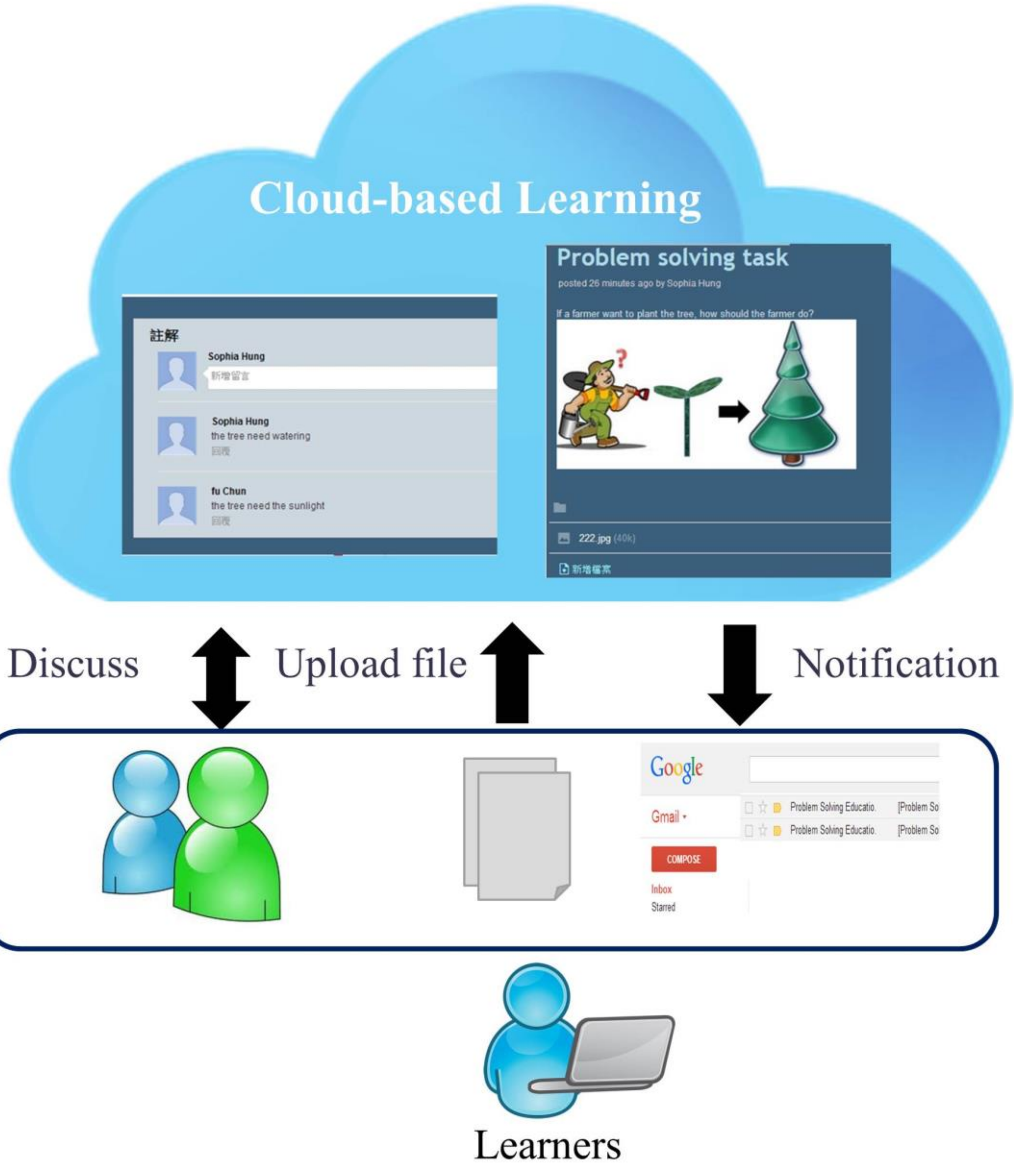

Figure 3-1 The cloud learning scenario on the cloud.

3.1 Cloud-based Problem-solving Learning

In recent years, the issue of developing a cloud-based PSLS has attracted

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considerable attention from researchers, because learning portfolios can be dynamically retrieved and maintained using web technology. The field of education has recently begun to focus on helping students improve their problem-solving skills. In the current study, we developed a PSLS, and gamified materials and problem-solving theory were included in the system design. The PSLS consists of a series of solution-inferring tasks that can be used to train a learner in problem-solving. This study was conducted with 134 undergraduate students to analyze differences in learners' self-perception and learning performance when using different learning materials. The study also investigated the relationship between instructional materials and personal traits [63]. Figure 3-2 shows the items of learners' behavior we investigated in this study.

Reciprocal determinism		
Environment	**Behavior**	**Cognition**
Gamification On-line environment Animation/ Static Gender	Learning performance Learning style	Self-perception

Figure 3-2 Items related to learners' behavior on cloud-based problem-solving.

3.1.1 Research objective(s)

The term "problem-solving" is defined as the most important cognitive activity, one in which people are required to apply knowledge to solve problems. Problem-solving also includes strategy shaping [1], and the learning experience related to problem-solving might be influenced by types of instruction such as strategies, systems, modeling, and coaching. Animated material is also a good approach for assisting learners in imagining processes and carrying out mental representations.

doi:10.6342/NTU201704318

Gamified learning programs constitute potentially powerful learning environments, and such instructional materials are considered an effective component of learning materials related to problem-solving activities. The current study develops a PSLS in which problem-solving theory and animation techniques are employed in the design of a cloud gamified learning system.

Males and females have unique ways of learning, and their different learning styles are associated with their particular performance. However, few studies have indicated whether learning style or gender has a direct relationship to the use of gamified learning materials in problem-solving learning activity. Accordingly, in the current study, both gender and learning style were included in the analysis of how personal traits might influence the use of static and dynamic materials. The goals of this research are

1. to investigate whether personal traits influence the use of learning materials and
2. to assess how different ways of presenting multimedia materials influence learners' performance and self-perception of difficulty

3.1.2 Applying the problem-solving model in gamification

In this study, the PSLS consists of problem-solving games, an interaction platform, and knowledge management. The problem-solving model was employed in the system design, and problem-solving theory was used a critical guide for developing an appropriate game scenario. The problem-solving model consists of a sequence of steps: identifying the problem, analyzing the problem, generating a possible strategy, implementing solutions, monitoring the process of solving the problem, and selecting the best solutions (see Table 3-1). In this study, we set up the topic and the learning goal

doi:10.6342/NTU201704318

(e.g., mathematical computation, logical analysis, observation). The PSLS consists of a series of solution-inferring tasks that can be used to train a learner in problem-solving. Each game task must have a defined topic and object. Observation analysis is an essential phase in the problem-solving model, and thus we designed the integral scenario and clues to train learners in observation ability. Learners therefore create their problem-solving solution through observation and knowledge. Monitoring the problem is another important phase of problem-solving, and thus the PSLS provides a learning board that records the process in which the problem occurs. Finally, learners respond by giving the solution on the interface. The results of the game are preserved in a learning database to provide learning support. The materials database and learning profile were established to collect information from experience sharing and from the results of brainstorming on the interaction platform.

doi:10.6342/NTU201704318

Table 3-1 The learning path of the PSLS

Step	Description
1	The game aims to motivate learners to improve their ability to observe, do logic analysis, do mathematical computation, and develop associative ability.
2	The problem type was identified and designed into the game scenario. The PSLS aims to enable the learner to identify when they have observed a clue. The procedure of the problem-solving game was well defined to enable the learner to understand the scenarios and discover the possible causal traits.
3	The information that was represented and organized, obtained by observing the situation, was applied during the game procedure. The problem-solving process was designed using the key information included in the brainstorming lists and fact files.
4	The essential information was designed as the clues which would enable the learner to solve the problem in the game and help him or her devise a strategy.
5	The useful clues were included in the game scenario to help the learner understand the environment and find the evidence. The learner explores the possible solution and allocates resources to implement the strategy, then starts to determine whether the solution will be effective or not.
6	The learner was focused on solving the problem by using the resources and knowledge.
7	After finishing the above steps, the learners had completed the procedures of the game.
8	The results of the game were collected in the learning database, which we analyzed to discover the relationship between personal traits (gender/learning styles), learning performance, and self-perception of difficulty with different materials.

doi:10.6342/NTU201704318

3.1.3 The animation-based problem-solving game

In the PSLS, animation-based problem-solving games consist of these four essential features (see Table 3-2): mathematical computation, logical analysis, observation, and associative ability [65][66]. Learners were asked to solve a problem by observing the game play. Each game had a learning board, which recorded the process of the game, and learners could monitor problems via the learning board.

Table 3-2 The list of the training targets in the PSLS

Unit	Training Target	Clue or Hint
1	The scenario is used to train the learner's mathematical computation, associative ability, and observation skills.	The farmer's friend is confused as to how 27 pigs can be allocated to four pigpens in odd numbers.
2	The scenario is used to train the learner's logical analysis, and observation skills.	The history of antiques and the label of antiques have the date contradiction between the years.
3	The scenario aims to train the learner's associative ability, logical inference, and observation skills.	The contradiction between the physics theory and the servant's testimony.
4	The solution requires associative ability, logical inference, and observation skills	According to the concept of geometric space, it is impossible for the paper money to be put between a single page

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Figure 3-3 The game scenario of the PSLS.

3.1.4 Design of the experiment

The purpose this study was to investigate the relationship between personal traits, learning performance, and cognition in two groups of participants.

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Table 3-3 shows the parameters of the present study. Figure 3-4 shows the procedure of the experiment. Participants were 134 college students who volunteered to take part in the experiment to compare the differences between the proposed learning material and static learning material for cloud-based problem-solving activities. Participants were randomly classified into two groups, each with 67 participants. The experiment group was assigned the gamification instruction, and the control group was assigned the static-text–based instruction. The experiment group was guided by animated interactions to complete the game, and the control group was guided by textual content. The Felder–Silverman model was used to estimate learners' learning style.

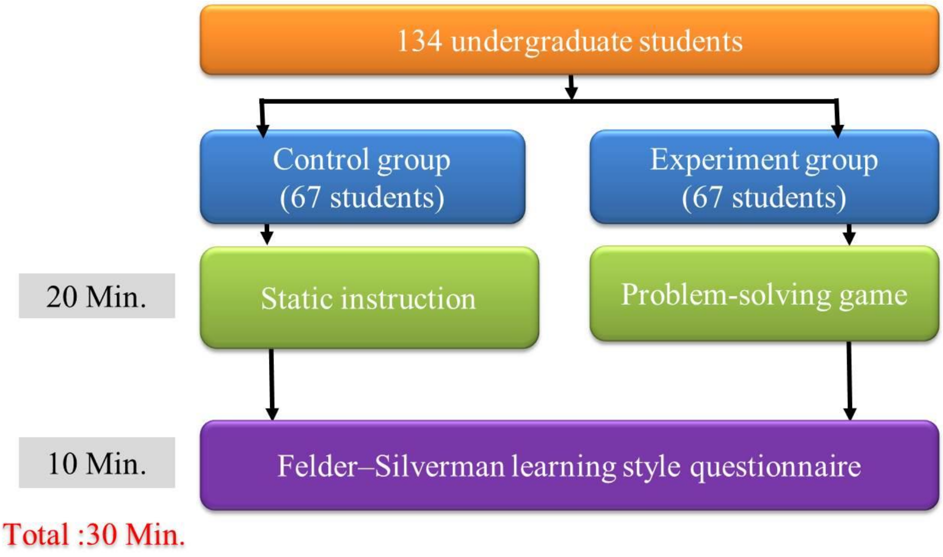

Figure 3-4 The procedure of the problem-solving experiment.

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Table 3-3 The parameters of the problem-solving study

Variables	Description	Type
ID	Identify sample (N=134)	Numerical
Group	1=Static text-based group (N=67) 2= Animation-based group (N=67)	Categorical
Age	18–25 years old (Mean = 21.5 years old, SD =4.6)	Numerical
Learning performance	Each scenario is rated (0 or 1), and the total score for each scenario is 4 points	Numerical
Self-perception of difficulty	The level of difficulty was evaluated on a 5-point Likert type scale: 1 = Very difficult; 2 = Difficult; 3 = Neutral; 4 = Easy; 5 = Very easy. Total score for each scenario is 20 points	Categorical
Gender	Male (N_{Male}=68); Female (N_{Female}=66)	Categorical
Learning style	Eight learning styles were assessed: active, reflective, sensing, intuitive, visual, verbal, sequential, and global (1–8).	Categorical
Level of learning styles	High (Top 50%) Low (Bottom 50%)	Categorical
Learning materials	Static text-based/Animation game-based	Categorical
Game scenario	Scenario$_1$: "A Confused Antique" (observation and logical analysis); Scenario$_2$: "The Mystery of the Rich Man's Death" (associative ability, logical inference, observation) Scenario$_3$: "The Missing Money" (logical inference on the geometric space) Scenario$_4$: "Magic Farm" (mathematic computation, associative ability, observation)	Categorical

3.1.5 Results

This study assesses the effects of personal traits and types of instructional materials on learning performance and self-perception of difficulty. The inter-rater reliability of

doi:10.6342/NTU201704318

the experiment included a Cronbach’s α value of 0.74. Reliability was acceptable for most domains (Cronbach’s α 0.64–0.92).

This study assesses gender difference in learning performance or self-perception when learners viewed the static and the gamified instruction. The hypotheses are as follows:

- $Hypothesis_1$: learning performance shows a significant difference between genders when learners use the static instruction.
- $Hypothesis_2$: learning performance shows a significant difference between genders when learners use the gamified instruction.
- $Hypothesis_3$: self-perception shows a significant difference between genders when learners use the static instruction.
- $Hypothesis_4$: self-perception shows a significant difference between genders when learners use the gamified instruction.

Table 3-4 shows that there is no difference in learning performance between genders in using the static instruction. However, female learners have better learning performance as compared to males ($Score_{\mathrm{Female}} = 1.48 > Score_{\mathrm{Male}} = 1.29$) in the control group. The results indicate that male learners perform significantly better when using gamified instruction ($F_{(1, 65)} = 6.131$, $p = 0.016 < 0.05$); thus, $Hypothesis_2$ is accepted. The study also examines the significance of self-perception of difficulty between the genders, and the difficulty level ranged from “very difficult” (1 point) to “very easy” (5 points).

doi:10.6342/NTU201704318

Table 3-5 shows that there is no significant gender difference between using the static instruction and the gamified instruction; thus, Hypothesis_3 and Hypothesis_4 are rejected.

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Table 3-6 shows that male learners had a significantly higher score on self-perception in Scenario 4 when they used the gamified instruction ($F_{(1, 65)}$ = 11.5, p = 0.002 < 0.05). The results demonstrated that male learners found it easier to solve the problem in Scenario 4. To summarize, the instruction type has different effects on learning performance and self-perception between the genders. Previous studies have indicated that female learners have less initial knowledge concerning computer memory, and that male learners develop greater familiarity with computing software and greater computer confidence and ability [13][17].

Table 3-4 Participants' performance correlated with two types of instructions

Learning performance					
	Mean	SD	N	$F_{(1,65)}$	Sig
The static instruction					
Male	1.29	1.03	34	0.626	.430
Female	1.48	0.93	33		
The gamified instruction					
Male	1.91	1.29	35	6.131	.016
Female	1.19	1.09	32		

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Table 3-5 Participants' self-perception correlated with two different instructions

Self-perception of difficulty					
	Mean	SD	N	$F_{(1,65)}$	Sig
The static instruction					
Male	10.94	1.79	34	0.06	.802
Female	10.81	2.31	33		
The gamified instruction					
Male	12.10	2.48	35	1.624	.211
Female	11.06	2.60	32		

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Table 3-6 Participants' self-perception correlated with two types of instructions for each scenario

The level of difficulty	The static instruction				The gamified instruction			
	Descriptive		ANOVA		Descriptive		ANOVA	
	Mean	SD	$F_{(1,65)}$	Sig.	M	SD	$F_{(1,65)}$	Sig.
Scenario$_1$								
Male	3.06	0.91	0.28	.600	3.14	0.91	0.08	.777
Female	2.94	0.99			3.06	0.99		
Scenario$_2$								
Male	2.88	0.75	0.11	.739	3.29	0.78	1.25	.269
Female	2.81	0.87			2.94	1.11		
Scenario$_3$								
Male	3.00	0.84	0.52	.474	3.05	0.92	0.58	.450
Female	2.84	0.93			3.28	0.95		
Scenario$_4$								
Male	2.00	0.95	0.82	.368	2.62	0.86	11.50	.002
Female	2.23	1.02			1.78	0.65		

The present study analyzed the impact of different types of material on learning style and how such materials affect learning performance (Felder et al., 1988). In the experiment, learners in each learning style were classified into two categories: high level (top 50%) and low level (bottom 50%). Prior research has shown that multimedia material has a stronger influence on learning performance and generates more positive emotions than does static material. Learners with high intuitive ability and those with high visual ability had better learning performance in using gamified instruction. In contrast, learners with high sensing ability and those with high verbal ability had better learning performance in using static instruction (see Table 3-7).

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Table 3-7 Results of learning performance based on different types of learning styles

The level of difficulty	The static instruction			The gamified instruction		
	Descriptive			Descriptive		
	Mean	SD	N	Mean	SD	N
Visual						
High	1.51	1.01	35	1.78	1.29	32
Low	1.25	0.95	32	1.37	1.19	35
Verbal						
High	1.25	0.95	32	1.37	1.19	35
Low	1.51	1.01	35	1.78	1.29	32
Sequential						
High	1.36	0.99	33	1.28	1.19	32
Low	1.41	0.98	34	1.83	1.24	35
Global						
High	1.41	0.98	34	1.83	1.24	35
Low	1.36	0.99	33	1.28	1.19	32
Active						
High	1.26	0.88	39	1.36	1.09	22
Low	1.57	1.1	28	1.67	1.31	45
Reflective						
High	1.57	1.1	28	1.67	1.31	45
Low	1.26	0.88	39	1.36	1.09	22
Sensing						
High	1.46	0.98	35	1.34	1.20	47
Low	1.31	0.99	32	2.1	1.21	20
Intuitive						
High	1.31	0.99	32	2.1	1.21	20
Low	1.46	0.98	35	1.34	1.20	47

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3.1.6 Summary

Some research studies have indicated that gender differences related to self-efficacy might be associated with problem-solving accuracy and efficiency. The experiment in the current study also supported this view. The results showed that both gender and learning style influence not only self-perception of difficulty but also learning performance with the gamified material in certain scenarios. To summarize, this study found that the unique personal traits of learners have different influences on their perception of difficulty and their learning performance in certain scenarios, which suggests that providing personalized material for learners with different personal traits might enhance their ability to solve problems. This study makes the following contributions:

- It confirms that various types of learning materials influence learning performance or self-perception of the difficulty of problem-solving activities.
- It develops of an animation-based game through which learners can accomplish tasks in an effective and interesting manner for problem-solving activities.
- It analyzes the differences in learning performance or cognition between various learning styles and gender.

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3.2 Cloud-based Computer Science Learning System

The computer is accessed through the Internet, which can be regarded as “the cloud.” The previous experiment showed that gamification has a positive effect on cloud-based problem-solving learning, providing an opportunity to actively learn through gamified mechanisms. Problem-solving learning and gamification were employed in the present study to enhance students’ engagement in learning computer science. The present study developed a CSLS consisting of three units: programming, database management, and data structure. Moreover, RWD allows web pages to adapt to the size of a screen. In this study, web technology and RWD were applied in the CSLS. Thus learners can use their mobile device or laptop to gain computer science knowledge wherever they are. Each unit of the CSLS has problem-solving games for students to play, to accomplish tasks using relevant knowledge. The study examined the learning performance, technology acceptance, and cognitive load among undergraduate students when they were using the CSLS [64]. Figure 3-5 shows the aspects related to learners’ behavior that we investigated in this study.

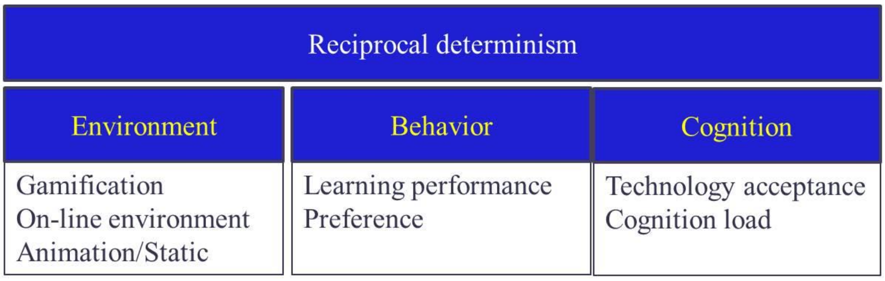

Figure 3-5 The aspects related to learners’ behavior on cloud-based problem-solving.

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3.2.1 Research objective(s)

Gamification is an educational innovation that involves incorporating game elements into nongaming content to increase user experience and engagement with the topic. Programming, data structure, and database management are considered prerequisite courses for most engineering colleges as a good fundamental knowledge of computer science is important for engineering students. The current study aims at capturing students' interest and reducing their cognitive load when learning computer science. In this study, we developed a gamified CSLS that has a series of problem-solving games. The research questions addressed in the survey are as follows:

(1). Investigating learners' perceptions of the gamified instruction when they are learning computer science concepts

(2). Estimating learners' cognitive load in relation to the gamified instruction when they are learning computer science concepts

(3). Determining the effect of the gamified material on learning performance in a computer science learning activity

3.2.2 The framework of the CSLS

The CSLS includes a series of computer science learning games related to programming, database management, and data structure (see Figure 3-6). In this study, game thinking and game mechanics were used to present computer science knowledge. Computer science education has recently been considered as a core competency. Students aim at being well equipped with the specialized knowledge in their field and a basic understanding of computing. Data structure, database management, and

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programming are the cornerstone of computer science knowledge (see Figure 3-6). A database is used for the manipulation of data, which is stored as various types, and computer programming can assist in a task by using the declared function. The data structure is a particular way of organizing data in a computer for efficient usage, while data searching and ordering play essential roles in the performance of programming. Useful systems with good data structures can enhance applications and services. To help students cultivate computer science knowledge, the CSLS focuses on providing learners with adaptive, easy-to-understand computer science concepts. The games used in the present study incorporated tasks that motivated students to apply their knowledge and thinking strategies in solving problems. Popular topics were included in the gamified material to engage learners in learning and give them a deeper understanding of computer science concepts.

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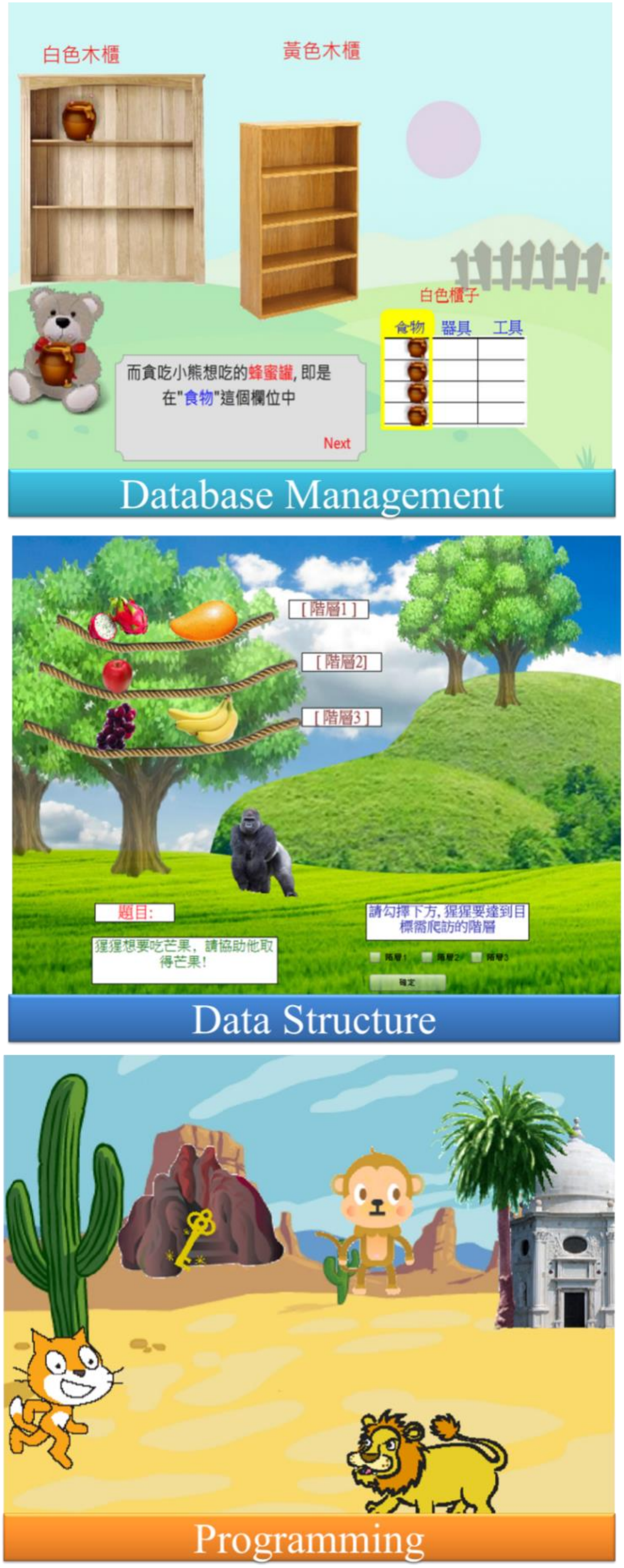

Figure 3-6 The game scenario of the CSLS.

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3.2.3 Design of the experiment

The CSLS consists of three units: database management, programming, and data structure. In each unit, participants were instructed to use the CSLS to learn fundamental knowledge. After completing the game-based activity, they were told to fill out technology acceptance and mental effort questionnaires. Finally, participants were asked to answer a system performance evaluation questionnaire and to rate their user satisfaction to measure the system performance. There are two experiments: a system performance evaluation and a measurement of students' learning achievement. In the first experiment, 46 participants' cognitive load and technology acceptance related to the proposed gamified system were examined (see Figure 3-7). In the second experiment, 98 participants were classified into two groups (see Figure 3-8). One group was assigned gamification instruction, and the other static-text–based instruction.

doi:10.6342/NTU201704318

Table 3-8 presents the parameters of the present study. The relevant questionnaire was employed to measure learners' cognition. The technology acceptance questionnaire was developed by Chu et al. [41] and the reliability of the questionnaire was 0.91. The cognitive load questionnaire was modified by Sung et al. [42] based on the cognitive load measures proposed by Paas (1992) [33] and Sweller et al. [34]. The Cronbach's α values of the cognitive load questionnaire were 0.90.

doi:10.6342/NTU201704318

Table 3-8 The parameters of the computer science education study

Variables	Description	Type
ID	Identify sample (N_{exp1}=46/ N_{exp2}=98) Not major in computer science	Numerical
Acceptance of technology	Acceptance of technology is consisted of “Perceived ease of use” and “Perceived usefulness” evaluation. A total of 13 items in this questionnaire, each item determined by Likert’s 5-point scale [41].	Categorical
Cognitive load	A total of 8 items in this questionnaire, each item determined by Likert’s 5-point scale [42].	Categorical
User satisfaction	The satisfaction degree of using system determined by Likert’s 5-point scale.	Categorical
Game scenario	1=Database management unit 2=Programming unit 3=Data structure unit	Categorical

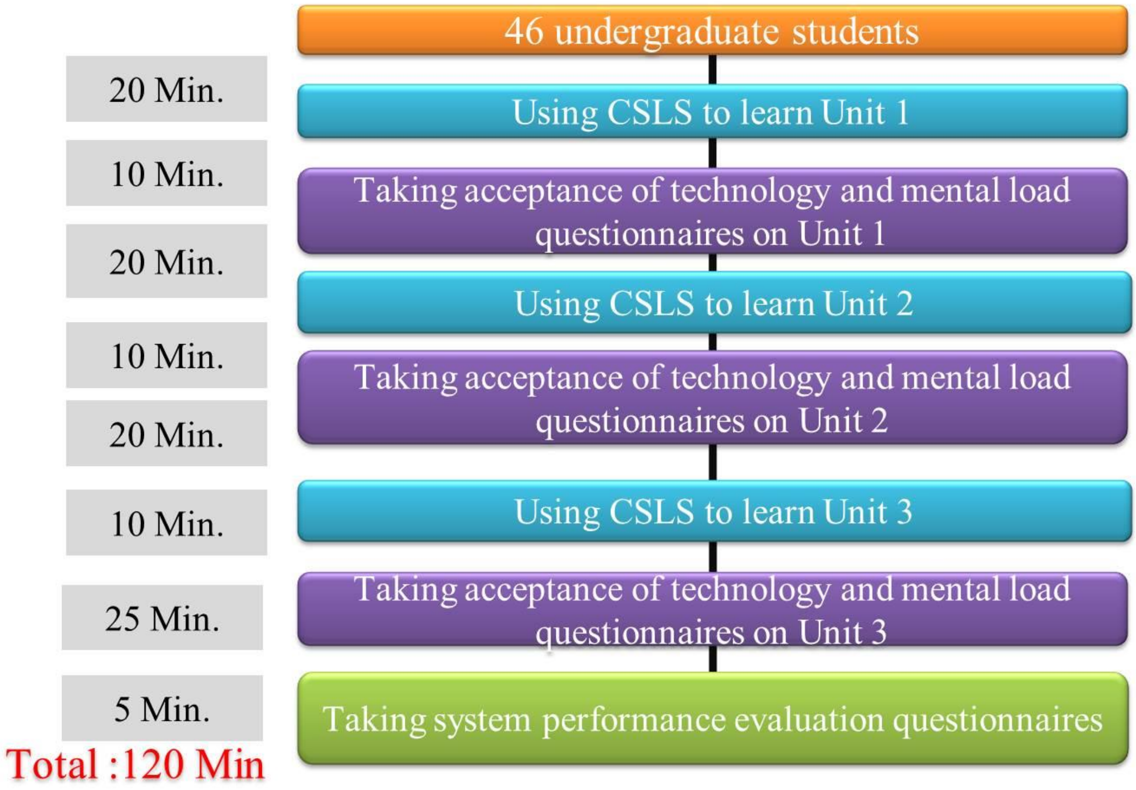

Figure 3-7 The procedure for experiment1 in the computer science education study.

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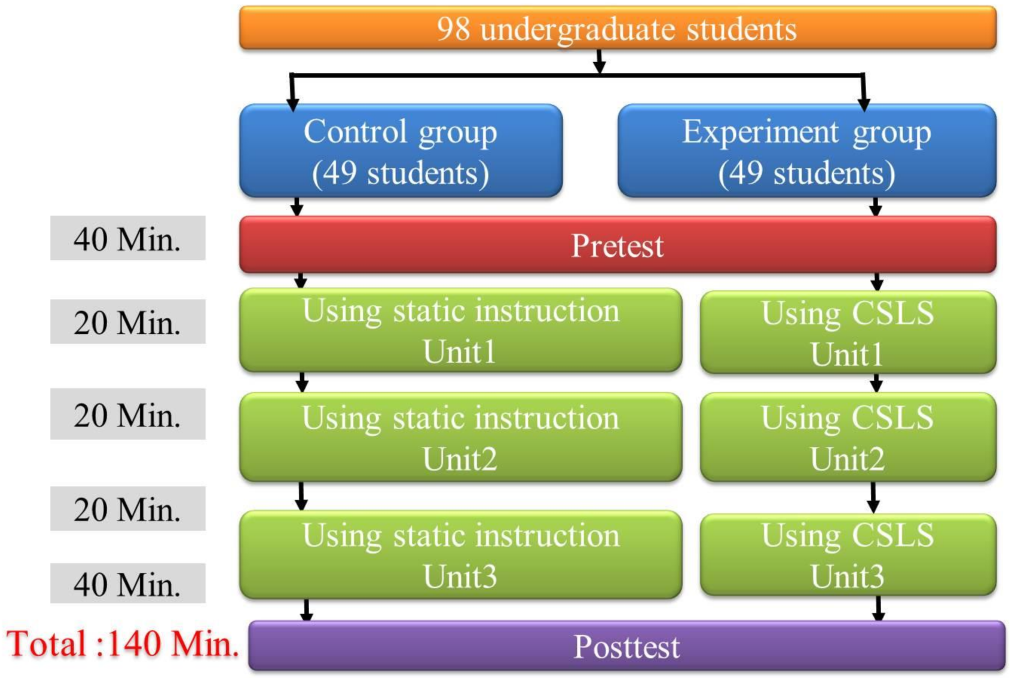

Figure 3-8 The procedure for experiment2 in the computer science education study.

3.2.4 Results

Previous studies have indicated that digital games contribute to motivating students and increasing their learning performance [31][35][48]. The current study assesses the effects of gamification material on computer science education.

Table 3-9 shows that learners' cognitive load was below average, and that the CSLS also received better technology acceptance than average.

Table 3-9 Results of Using CSLS

	N	Unit1	Unit2	Unit3
Technology acceptance				
Perceived usefulness	46	4.01	3.86	4.07
Perceived ease of use		4.38	3.76	4.24

doi:10.6342/NTU201704318

Cognitive load				
Mental load		1.79	1.96	1.81
Mental effort		1.85	2.05	1.75

Concerning learning performance, Table 3-10 showed that these two groups did not significantly differ before the pretest experiment. The results of the posttest showed that the students in the experimental group had significantly better achievement than those in the control group ($F = 6.93$, $p < 0.05$).

Table 3-10 The difference of learning performance between two groups

		N	Means	S.D.	Adjust mean	Std. error	F value
Posttest	Experiment Group	49	77.35	13.15	78.37	1.48	6.93
	Control Group	49	73.88	15.04	72.86	1.48	

3.2.5 Summary

Learners' cognition as a result of using digital games has begun to attract considerable attention [42]. The results showed that the CSLS has a positive effect on students' cognition for learning computer science. The present study showed that gamification as applied to programming, data structure, and database management benefits technology acceptance and cognitive load, and that animated games engage students in learning computer science knowledge. Some past studies supported the view that animation facilitates learning enjoyment [17][13][47]. Collaborative learning is perceived as an efficient vehicle for students to communicate with one another because it allows them to learn together by exploring questions or creating meaningful projects.

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The game scenario lacked collaboration, which is a limitation of the CSLS. In future studies, we will aim at developing multiplayer games that can be connected with social media (i.e., Facebook and Twitter).

3.3 MOOC Learning Experience

Technology is a powerful tool that continues to change education in many ways. MOOCs are a typical example of innovation in the area of education that can transform learning behavior. MOOCs have recently received great attention from researchers and education professionals. As online courses designed to support an unlimited number of student enrollees from anywhere in the world, MOOCs are a flexible and open platform that can allow a diverse population of learners to create and execute personalized study plans. MOOCs providers such as Coursera, OCW, Udacity, and edX offer platforms for universities to provide online versions of regular courses to hundreds of thousands of learners worldwide. Yet despite the dramatic growth in MOOCs, to date, the face-to-face classroom is still the primary teaching environment. Individuals have unique behavioral features, and they have different preferences regarding MOOCs and regular courses. The current study conducted a survey regarding learners' learning experience with, and motivation and intention to use, MOOCs. Moreover, learning styles involve various types of behavioral features that can be analyzed to provide a learning strategy [57]. Figure 3-9 shows the aspects related to learners' behavior that we investigated in this study.

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Reciprocal determinism		
Environment	Behavior	Cognition
MOOCs	Enrollment Status (e.g., interrupted) Learning style Assisted approach	Using intentions

Figure 3-9 The aspects related to learners' behavior on the MOOCs learning experience survey.

3.3.1 Research objective(s)

MOOCs provide a flexible structure, and therefore they can help students learn when their learning may be otherwise limited by the lack of moderation associated with a regular course. Learning style refers to an individual's approach to learning based on their preferences, strengths, and weaknesses. Different learning styles can influence learners' preferences for MOOCs. However, only a limited number studies have indicated whether learning styles have a direct relation to user intention toward MOOCs. The present study examined the learning styles of 185 undergraduate students to determine the way in which they have an effect on learners' utilization of MOOCs. The goals of this study were

1. to investigate a learning approach that can assist learning in MOOCs and enhance learners' motivation;
2. to explore whether learning styles can influence the use of MOOCs and determine the learning style related to use intentions; and

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3. to survey learning experiences, motivation, and suggestions as valuable information for using MOOCs.

3.3.2 Design of the experiment

Every learner possesses a unique combination of needs and abilities that influence his/her learning. Various types of learning materials may lead to different learning outcomes. This study aims at investigating the correlation between learning style and user intention, analyzing the learning approach that can assist in learning through MOOCs, and exploring reasons for learners to use MOOCs. The participants were 185 undergraduate students, who were surveyed regarding their learning experiences, motivation, and intentions to use MOOCs. Figure 3-10 shows the experimental procedure of the MOOCs learning experience study.

doi:10.6342/NTU201704318

Table 3-11 shows the parameters of the present study. In this study, the relevant questionnaires were employed to measure learners' cognition. This study administered questionnaires to estimate participants' learning styles. Based on the score guidelines of the ILS Questionnaire, each participant's learning style was classified into two categories (Felder et al., 2001): high level (greater than the mean) and low level (less than or equal to the mean). In this study, the reliability of the ILS Questionnaire showed a Cronbach's α value of 0.73.

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Table 3-11 The parameters of the computer science education study

Variables	Description	Type
ID	Identify sample (N=185)	Numerical
Gender	Male (N_{Male}=95; 51%); Female (N_{Female}=90; 49%)	Categorical
College Major	Science ($N_{Science}$ =33; 18%) Engineering ($N_{Engineering}$ =30; 16%) Liberal arts ($N_{Liberal\ arts}$ =23; 12%) Social Science ($N_{Social\ Science}$ =35; 19%) Business ($N_{Business}$ =30; 16%) Management ($N_{Management}$ =34; 18%)	
The reasons why MOOCs were used by the participants	Habit=1 Special project requirements=2 The cultivation of professional skills =3 The instructor asked them to enroll in the course =4	Categorical
The reasons why MOOCs were not used by the participants	Unfamiliar with online environments=1 Prefer a physical classroom=2 Lack of face-to-face interaction= 3 No real-time group discussions=4 Fear about the operation of MOOCs=5	Categorical
The reasons why MOOCs were interrupted by the participants	Time Management =1 Overloading =2 Particular subject have learned =3 Others = 4 Delay self-study plan = 5	Categorical
Learning approach	Collaborative learning =1 Query based learning =2 Game-based learning =3	Categorical

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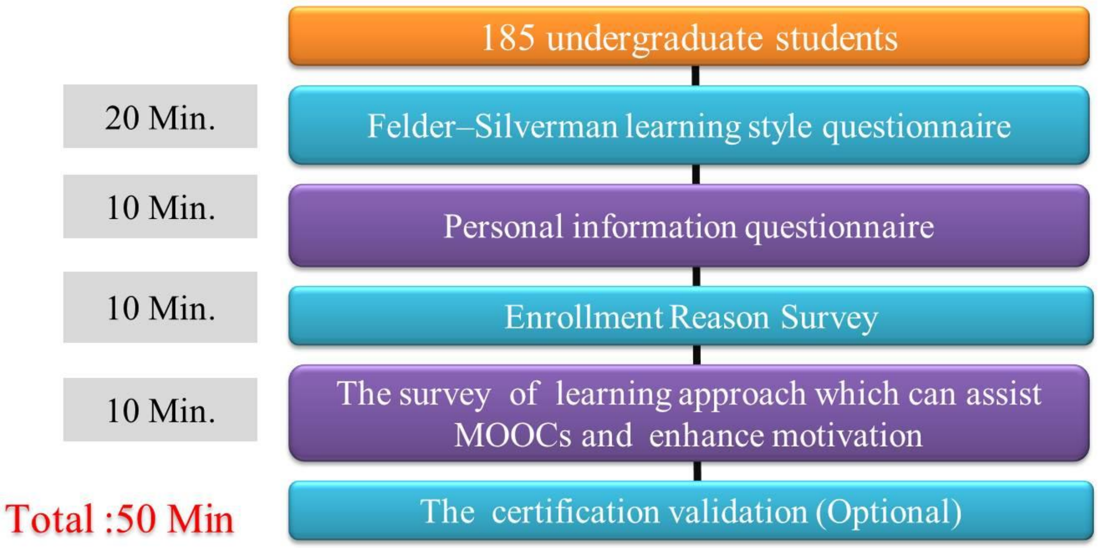

Figure 3-10 The procedure of the MOOCs learning experience study

3.3.3 The effects of learning styles on use of MOOCs

Each participant's learning style was classified into two categories based on the scoring guideline of the ILS Questionnaire (Felder et al., 2001): high level and low level. For students familiar with MOOCs, those with high intuitive, high global learner and high active ability have a greater probability of using MOOCs (see Table 3-12). Intuitive learners prefer innovation, so the new instruction offered by MOOCs is suitable for them. Active learners prefer to understand information and knowledge by actively engaging in action, and MOOCs are a good tool for helping them learn in this way. In the case of reflective learners, the learning content of MOOCs should include new information or short summaries for them to spend some time thinking or writing about on their own. Global learners prefer to learn by absorbing, large jumps material, so MOOCs provide flexibility to help them retain and understand information.

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Table 3-12 Results of learning experience based on learning style

Learning style		Have used MOOCs	
		No	Yes
Active	High	44	34
	Low	77	30
Reflective	High	77	30
	Low	44	34
Sensing	High	30	17
	Low	91	47
Intuitive	High	91	47
	Low	30	17
Visual	High	25	11
	Low	96	53
Verbal	High	96	53
	Low	25	11
Sequential	High	59	27
	Low	62	37
Global	High	62	37
	Low	59	27
High (greater than the mean) Low (less than or equal to the mean).			

3.3.4 Learning experience analysis

The purpose this study was to investigate the relationship between personal traits, learning performance, and cognition in the two groups. In this survey, the MOOCs providers used by the participants were TOCW (32%), Coursera (29%), Udacity (29%), edX (9%), and others (JOCW) (1%). The result shows the top five reasons why the

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participants in this study did not use MOOCs. Most of the participants who had never used MOOCs stated that they were unfamiliar with online environments. Thus, for such students, providing detailed information about MOOCs is a necessary part of school education. The physical classroom is a general learning environment, and learners are familiar with such an environment and may experience difficulties in changing their original learning behavior to use unfamiliar material. Therefore, it is critical to provide pertinent information regarding this online approach to learning. The majority of participants stated that time management was the reason why they interrupted their involvement in MOOCs (see Table 3-13). Moreover, selective learning was applied, perhaps to avoid overload or to simply complete a special task. The result shows the top four reasons why the participants used MOOCs: invitation from instructor to enroll in the course (31%), habit (29%), special project requirements (21%), and cultivation of professional skills (19%).

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Table 3-13 The survey of MOOCs learning experience

	Never Used		Interrupted	
Rank	Descriptions	Portion	Descriptions	Portion
1	Time management	57.9%	Unfamiliar with online environments	34.1%
2	Overload (heavy workload in school)	15.8%	Prefer a physical classroom	24.0%
3	Particular subject has been learned	10.5%	No face-to-face interactions	19.2%
4	Others (personal reasons)	10.5%	Lack of real-time group discussions	17.4%
5	Delay self-study plan	5.3%	Fear about the operation of MOOCs	4.8%

.

Various approaches employed in learning systems may enhance motivation and engagement. Query-based learning actively and repeatedly trains students as well as provides them with learning suggestions, and it is an active learning approach in which teachers provide useful information in response to learners' questions. Game-based learning is a method that engages learners and improves their problem-solving abilities. For collaborative learning, students learn together to explore questions or create meaningful projects. MOOCs provide ways for students to collaborate through online

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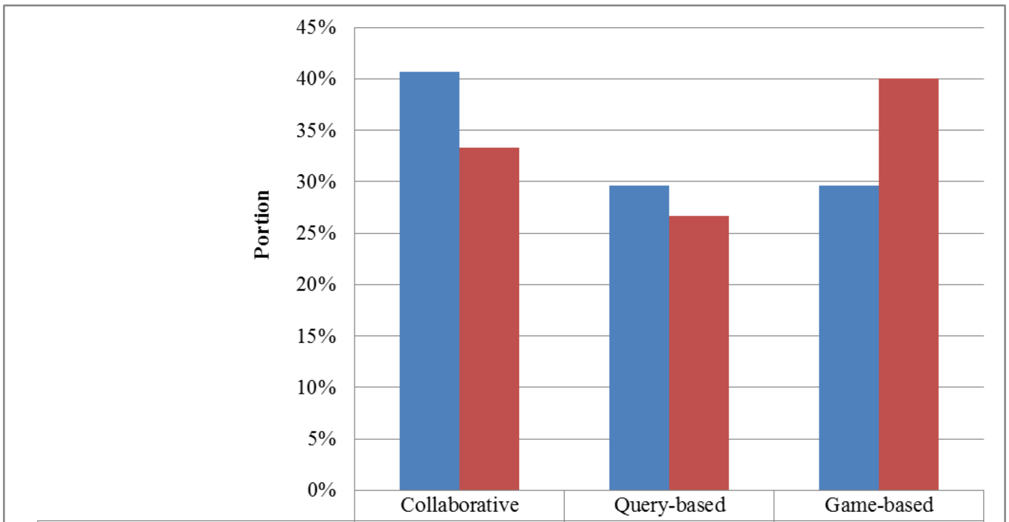
forums and social networking tools; thus, they are a useful approach for students to interact with others.

The present study investigated which learning approach can assist MOOCs in enhancing learning motivation. Figure 3-11 shows the different preferences in learning approaches between learners who have used MOOCs and those who have never used them. Participants who have used MOOCs perceive that collaborative learning can offer more appropriate opportunities for them to communicate with one another, and their motivation could also be strengthened through this learning approach. For learners who have no related learning experience and may be unfamiliar with such an environment, games can help them adapt to the presented learning activities.



	Collaborative	Query-based	Game-based
Learners who have used MOOCs	40.70%	29.60%	29.60%
Learners who have never used MOOCs	33.30%	26.70%	40.00%

Figure 3-11 The learning approach that can assist learners in using MOOCs.

Students with different majors have different requirements for MOOCs. The College of Management focuses on organizational ability and cross-domain expertise. Some of the participants in the present study selected relevant courses such as computer

doi:10.6342/NTU201704318

applications software, programming, and knowledge management. Participants from the College of Management had the highest proportion of students using MOOCs (28.8%) (see Table 3-14). The second highest was the College of Liberal Arts (23.1%), in which participants are enrolled in courses related to economics, law, and even computer science. The College of Engineering (19.2%) and the College of Science (15.4%) were the third and fourth highest colleges, respectively, and a majority of the participants from these colleges preferred advanced courses (e.g., artificial intelligence, computer networks, and quantum physics). Finally, the percentages for the College of Social Science and the College of Business were 7.7% and 5.8%, respectively, and these participants concentrated on expanding their professional knowledge, such as financial management and supply chain management.

Table 3-14 Proportion of college students who had used MOOCs

College	Proportion
Business	5.8%
Management	28.8%
Engineering	19.2%
Social Science	7.7%
Science	15.4%
Liberal	23.1%

Table 3-15 shows a list of courses in which learners were enrolled. MOOCs can fit not only with individuals' particular academic needs but can also offer flexibility that is not found in other learning activities. As shown in the table, participants had used

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MOOCs to gain general knowledge (e.g., musicology, public speaking). Table 3-16 shows a summary of learners' suggestions as they relate to MOOCs. Most of the participants suggested that interaction is important for learning through MOOCs, and that having the courses provide documentation and high-quality instructional video is also critical when they are studying with MOOCs.

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Table 3-15 List of MOOCs in which learners had been enrolled

Course Type	Course Name
Engineering	Artificial Intelligence
	Machine learning
	Introduction to computer science
	Computer programming
	Web application architectures
	Multimedia
	Learning to program: The fundamentals (Python)
	Web application architectures
	Data structure
	Introduction to computer networks
	Automatic control
Business	Microeconomics principles
	Econometrics
	Supply chain management
	Business financial management
Mathematic	Calculus
	Theory of probability
	Statistics
General	Public speaking
	Traditional medicine and modern life
	Film and Video Design course
	Musicology
	General physics
	General chemistry
Social Science	Social statistics
	Social psychology
	Advertising psychology
	Introduction to legal science
	Intellectual property rights
	Knowledge management
	The constitution and government of the Republic of China
	Educational administration
Science	Quantum physics
	Brain research
Liberal arts	Philosophy
	Chinese I-Ching
	The pedagogies of the Chinese language
	Introduction to Taiwanese languages
	History of Western art

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Table 3-16 Summary of learners' suggestions for MOOCs

Suggestion Type	Learners' suggestion
Document related	A MOOCs manual can assist learners in enrolling in a course
	Providing an operation video can help learners learn on MOOCs
Interaction related	More Group discussion
	More Online discussion
	More Real-time response
	Face-to-face communication
	A social forum like Facebook
Material related	Material maintenance is needed
	The security of the material database is important for the learning environment
	The high-quality video is needed

3.3.5 Summary

MOOCs provide options for learners with various needs and interests. Learning styles might influence the learning experience in different environments, and the results of this study showed that the active, intuitive, and global learning styles may be related to using MOOCs. A student's attitude toward learning is important for distance education, and most participants suggested that interacting with other students has a

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positive effect on learning motivation. Collaborative, query-based, and game-based learning can be considered effective methods for enhancing motivation. Query-based learning offers students learning suggestions and information related to the presented content. Approximately 29% of the participants believed that query-based learning was helpful for those enrolled in MOOCs.

doi:10.6342/NTU201704318

Chapter 4 Cloud Personalized Learning and Cloud Data Visualization

LMSs are increasingly being engineered to capture and store data on users' interactions with a system. How the learning profile from a learning activity or a learning system is applied, is important in the field of education. Learning analytics is a closely related concept with an emphasis on investigating the collected data along with learning observations about the teaching and learning content. The learning profile can be analyzed using statistical, machine-learning, and data mining techniques. Data mining encompasses a broad range of research techniques that includes association analysis, clustering, classification, and sequential analysis. The use of data mining to investigate learning profiles within educational research is termed "educational data mining," and it is used to discover novel and potentially useful information from large amounts of data [67][60]. When a data mining algorithm it used to analyze the raw data from an LMS, the results can inform design decisions and provide helpful learning suggestions. Educational data mining can support learning by adapting learning resources to fit the individual's needs and by providing educators with instructional suggestions based on investigation of the effects of different pedagogical enhancements on student learning. The most useful patterns have been those obtained by using a classification algorithm, which has been widely applied in various LMSs, such as examination systems and intelligent tutoring systems. Investigating the effect of personal traits on diverse environments or instructions is critical, as learners deserve the opportunity to use the appropriate learning tools to make the most of their strengths and to help them overcome their weaknesses. The present study developed a query-based

doi:10.6342/NTU201704318

classification for cloud personalized learning.

4.1 Cloud Personalized Learning

This study presented that different learners have different preferences for certain materials in problem-solving learning. Recently, cloud personalized learning and the inference system [68] have received a considerable amount of attention in the field of education. The use of a query mechanism can be viewed as interactive learning. Oates et al. (1997) reported that training data can be applied as partially representative to improve the degree of correctness and save time [69]. In the current study, we present a query-based classification technique for personalized learning. The learning profile was applied in a decision tree algorithm to classify the learning path, and the training result is considered as a learning oracle for system query. Students can obtain adaptive learning material, though the system actively queries the oracle to get the estimate criteria.

Table 4-1 The parameter of training dataset

Parameter	Type	Description	Attribute
Learning performance	Numeric	The learning performance in the problem –solving activity (Toal Score= 4)	Input
Gender	Categorical	Male (NMale=68); Female (NFemale=66)	Input
Material Type	Categorical	Static material (N_{static}=67) Gamified material ($N_{gamified}$=67)	Predict Only

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- Training data set: In this study, we used 154 undergraduate students' problem-solving learning profiles as the training data set. Table 4-1 presents the parameters of classification.
- Training method: A decision tree algorithm was used to personalize the learning path [70]. A decision tree algorithm is nonparametric supervised machine algorithm for classification. A decision tree algorithm is used to predict the value of a target variable by learning simple decision rules inferred from the training data set. Learning from data to infer approximates with a set of if-then-else decision rules is the functionality of a decision tree. The training results showed that male learners with high learning performance prefer gamified material, while female learners with high learning performance prefer static material. The analysis results were considered as the oracle provides a relevant suggestion and the personalized learning material for learners to learn (see Figure 4-1).

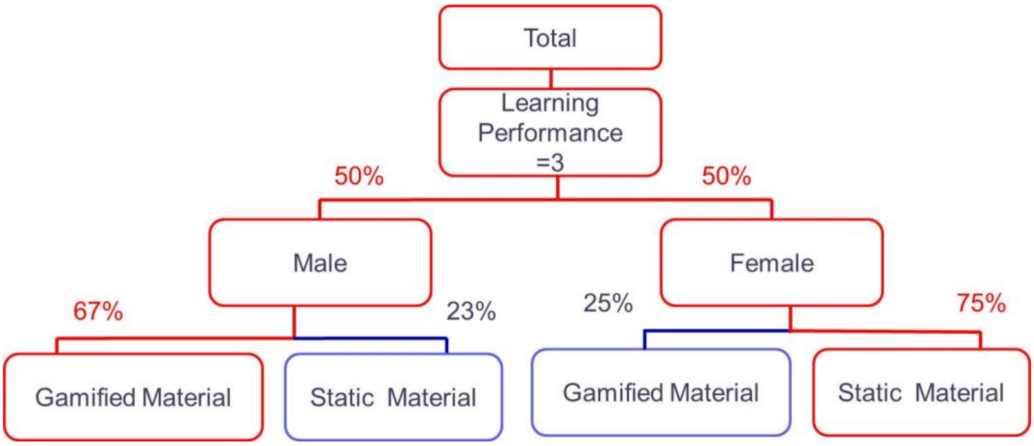

Figure 4-1 The decision tree of personalized learning.

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■ Personalized learning:

Figure 4-2 shows the framework of cloud personalized learning. A query-based mechanism was used to inquire about the training results and obtain personalized learning suggestions. The query mechanism was applied in a training algorithm or a system model to enhance the performance of the analysis [71]. For the concept of query, system performance or computation efficiency can be improved by actively querying the "oracle" to get useful information. An "oracle" is defined as a data source that can provide a relevant example, and it also can take the form of a natural system, artificial simulation, a mathematical equation, experts' experience, and so on. An oracle can be in the form of an inquiry, with the goal of finding clear learning cases, to help the system learn correctly.

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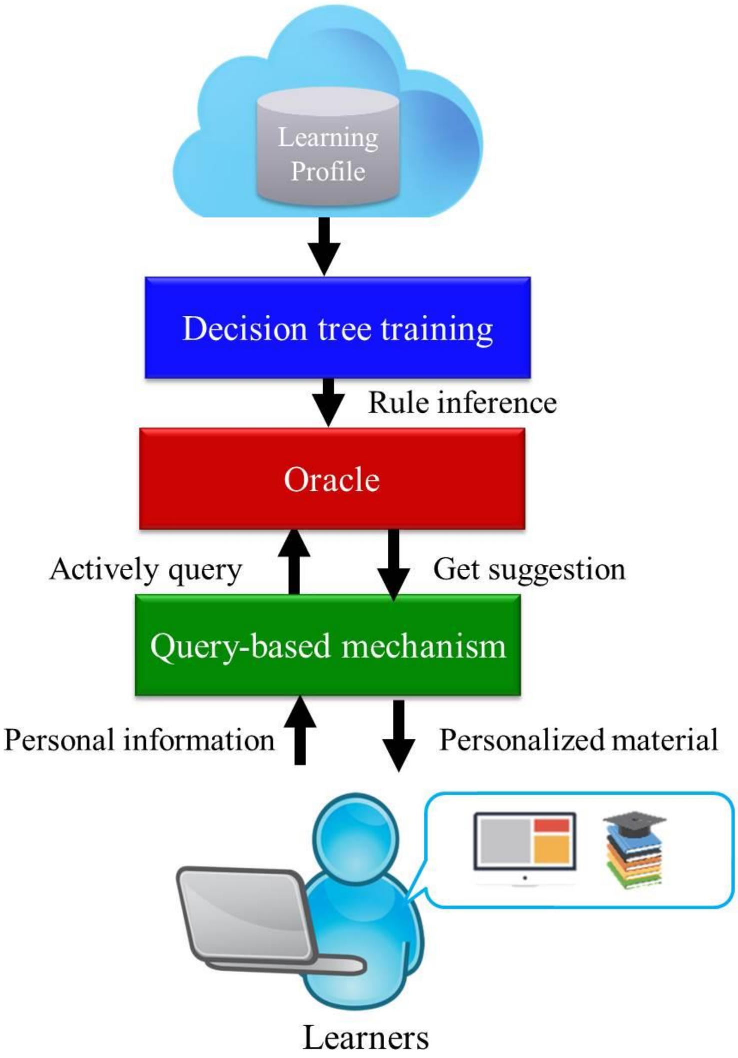

Figure 4-2 The architecture of cloud personalized learning.

4.2 The Visualization of Analytics Results

The presentation of the analytics results in a graphical format plays a critical role in educational data mining. In this study, we used D3.js (see Figure 4-5), and the Highcharts JavaScript plug-in to display the analytics results (see Figure 4-3). The D3.js allows the user to bind data to the document object model and then apply data-driven transformations to the document (see Figure 4-4). The Highcharts JavaScript plug-in is an SVG-based, multiplatform charting library. The interface can easily add interactive,

doi:10.6342/NTU201704318

mobile-optimized charts by using the Highcharts JavaScript plug-in. Highcharts features robust documentation, advanced responsiveness, and industry-leading accessibility support. Facebook, IBM, and Microsoft have used Highcharts products. Figure 4-3 shows the visualization of analytics results.

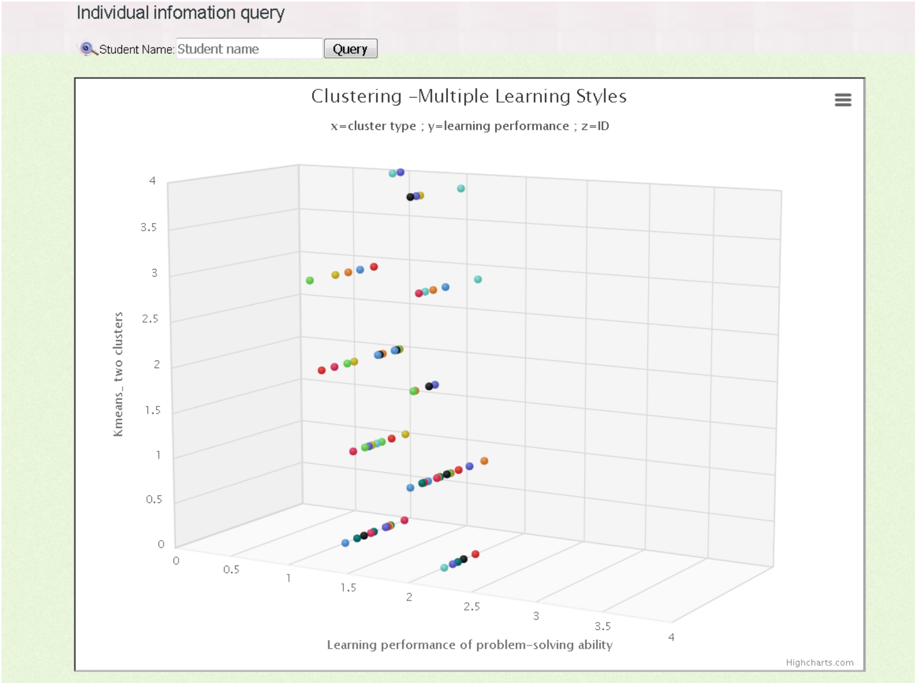

Figure 4-3 A visualization of analytics results.

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Figure 4-4 The 3D interactive visualization.

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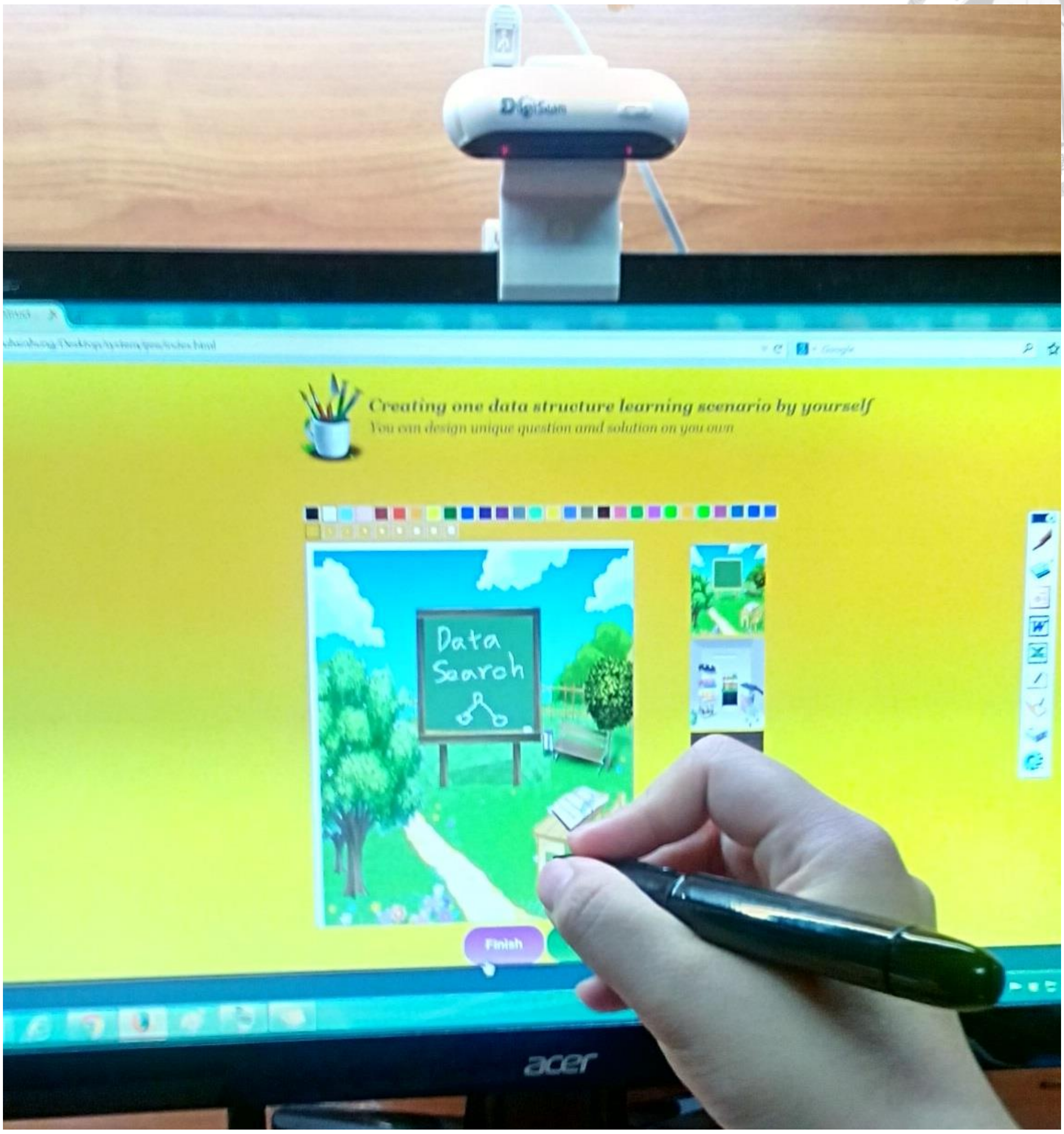

Figure 4-5 The interactive interface.

doi:10.6342/NTU201704318

Chapter 5 Conclusion and Discussion

Popular applications such as gamification, MOOCs, and personalized learning were examined in this study, which investigates learners' learning experience. Gamification and problem-based learning were employed in the development of problem-solving learning and computer science education. In this study, we investigated learners' perceptions of innovation tools (e.g., MOOCs). Finally, the data mining algorithm was used to analyze the learning profile and to personalize learning material. This study demonstrated various research results and was aimed at improving learners' learning performance and learning experience. In personalized learning, personal traits play an essential role in adapting material to the individual learners' needs, and this study focuses on exploring the personal traits necessary to achieve the goal of adaptive learning, to enhance learning performance and cognition.

5.1 Conclusion

This study investigates the fundamental question of how to take advantage of various tools so that instruction and learning can be more efficient, and also considers whether educational technology affects the learning experience. Many researchers have indicated that learners who use their unique strengths might achieve better performance. Training learners to create their own strategy can have a positive effect on their problem-solving abilities. Cognitive load theory, the learning-style model, technology acceptance, and information system evaluation models were included in this study to assess learners' traits and learning achievement. The survey results are shown in

Table 5-1.

doi:10.6342/NTU201704318

Table 5-1 Conclusions of this study

Type	Research results
Gamified problem-solving learning system	■ Males perform better when using gamified material, and females perform better using static-text material. ■ Male learners using game-based material perceive a problem as easier in a specified scenario.
Gamified computer science learning system	■ The students who used a gamified learning system had better achievement than those who used static material in computer science education. ■ Gamified computer science learning received the high acceptance of technology and reduced cognitive load.
MOOCs	■ TOCW and Coursera are the main course providers through which user had been enrolled in MOOCs. ■ Most users interrupt their learning due to time management problems. ■ Most participants who have never used MOOCs stated that they were unfamiliar with online environments. ■ Learners who never used MOOCs recognized that game-based learning can assist them in using MOOCs, and that collaborative learning was a good approach for learners who have used MOOCs. ■ Interaction with other learners, documentation, and the quality of material are issues that learners are concerned with.
Cloud personalized learning	■ A query-based classification was applied in the cloud personalized learning. ■ Popular visualization tools were used to cloud data visualization.

Learners have unique learning preferences, cognitive abilities, and attitudes, and the learning experience may be influenced by their personal traits in different environments. This study demonstrated that learning style, gender, and perception have different effects on learners' experience in gamification, MOOCs, and computer science education. Educational technology is already universal. The LMS was designed for storing instructional content, delivering it to students, and facilitating interaction between learners and instructors. Educational data mining can be used in the LMS to provide the user with learning suggestions and personalized learning paths. Data visualization benefits instructors and allows learners to have a greater understanding of

doi:10.6342/NTU201704318

their current learning status and to make a flexible and helpful learning plan.

5.2 Discussion

Educational technology approaches to support learning have become an increasing focus of both research and practice in recent years. Within this field, gamification, whether games are played on computers, tablets, mobile phones, or other mobile devices, has received significant attention for several reasons. Games are seen as having the potential to address barriers to learning and to promote inclusion. However, games may be more distracting than a typical learning tool, and an educator must determine whether this method is appropriate for particular students. Technology has been applied widely to teaching and learning and will continue to change education. Through the architecture of ICT, everything can interact via an e-learning platform. Learners can learn anywhere on cloud-based learning systems. However, of even greater use are learning materials that are presented in different forms, particularly gamified materials, mobile devices, and sensors. MOOCs and personalized learning are powerful tools that can support and transform education, ranging from instructional materials design to interactive learning. Every year, the New Media Consortium releases the *Horizon Report* on the future of technology in higher education. Adaptive learning technologies are a future trend in educational technology. With the worldwide reach of ubiquitous mobile devices, sensors, and wearable devices that can connect to the Internet, a new age of anytime-anywhere education is dawning. The cloud-based learning system is considered as the innovations that can make education open to everyone, everywhere. The growing appreciation in the field of education for individual aptitudes and preferences has led to “student-centered” education, in which the focus is on adapting

doi:10.6342/NTU201704318

teaching to the student's individual needs: from personalized learning that students can master at their own pace to programs designed to match content and presentation style with the learner's personality.

5.3 Future Work

Many studies have indicated that instruction can be adaptive based on learning styles, achievement, attitude, and interests to make learning more likely to occur. Through an understanding of learning materials and personal traits, educators can provide learners with an adaptive approach to learning, with personalized instruction that is available to every individual in a given class. In future studies, we aim to implement the goal of the educational Internet of Everything (IoE) [72][73][74][75] in which everything (e.g., learners' biology signals and mobile devices) can be connected and communicated everywhere, anytime. The educational IoE not only brings together learners, teachers, processes, data, and sensors to make networked connections more relevant and valuable but also turns information into actions that create personalized capabilities (see Figure 5-1). Neuroscience studies have provided new insights into the intricacies of the neural processes underlying learning. Developing teaching methods to fit the diversity of individual preferences is a major challenge for the field of educational technology in the future. Deep learning, artificial intelligence, and data mining applied in the educational IoE are the key to developing personalized learning. Future studies should employ a machine-learning technique to discover important personal traits that contribute to personalizing learning.

doi:10.6342/NTU201704318

Figure 5-1 The educational IoE.

doi:10.6342/NTU201704318

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doi:10.6342/NTU201704318