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Experience beyond knowledge: Pragmatic e-learning systems design with learning experience ☆

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ABSTRACT

With the growing demand in e-learning system, traditional e-learning systems have dramatically evolved to provide more adaptive ways of learning, in terms of learning objectives, courses, individual learning processes, and so on. This paper reports on differences in learning experience from the learner's perspectives when using an adaptive e-learning system, where the learner's knowledge or skill level is used to configure the learning path. Central to this study is the evaluation of a dynamic content sequencing system (DCSS), with empirical outcomes being interpreted using Csikszentmihalyi's flow theory (i.e., Flow, Boredom, and Anxiety). A total of 80 participants carried out a one-way between-subject study controlled by the type of e-learning system (i.e., the DCSS vs. the non-DCSS). The results indicated that the lower or medium achievers gained certain benefits from the DCSS, whilst the high achievers in learning performance might suffer from boredom when using the DCSS. These contrasting findings can be suggested as a pragmatic design guideline for developing more engaging computer-based learning systems for unsupervised learning situations.

1. Introduction

No man's knowledge here can go beyond his experience (John Locke, An Essay Concerning Human Understanding, 1690)

Electronic learning (e-learning) or computer-based learning is widely seen as a key mode of pedagogy in higher education and professional training today, given the convenience and flexibility offered by these systems in comparison to traditional face-to-face learning activities (Song, Singleton, Hill, & Koh, 2004). Though this popularity seems to demonstrate the utility of computer-based learning systems, this seems to be in stark contrast to some assessments of usability or effectiveness (Chiu, Hsu, Sun, Lin, & Sun, 2005; Georges, Alfred, Catherine, Ben, & John, 2003; Hubona & Blanton, 1996).

Of course, there have been constant improvements in the usability of e-learning systems, but in essence they are still compared relatively poorly with traditional face-to-face learning activities (Allen, Bourhis, Burrell, & Mabry, 2002; Bernard et al., 2004; Levenberg & Caspi, 2010) thanks to the nature of unsupervised learning. This issue becomes the driving force of learners' needs, by which they seek to experience more enjoyable, easy-to-use, and effective learning tools. The on-going needs have prompted the evolution of introducing new e-learning systems and/or pedagogical theories, for instance, from simple electronic books (e-books) to game-based learning and adaptive learning systems.

Despite these advances, it seems that the assessment of these new e-learning systems has primarily been made by measuring the knowledge acquired through them, employing learning performance data such as retention (Packham, Jones, Miller, & Thomas, 2004; She & Chen, 2009) or transfer tests (Harskamp, Mayer, & Suhre, 2007; Mayer, 1997). Even some studies on game-based learning (e.g., Ebner & Holzinger, 2007) have adopted learning performance data to examine the effects of the game-based learning activity, aiming to show equal learning performance outcomes to traditional face-to-face learning. Contrary to this approach, Liu et al. (2009) and Sun, Tsai, Finger, Chen, and Yeh (2008) contended that learner's psychological satisfaction should be the ideal alternative measure of any e-learning systems, rather than learning performance, since this would have significant effects on the learner's ongoing intention to use e-learning systems in the future (Chiu et al., 2005; Lee, 2010; Lin, 2011).

Indeed, learner's psychological satisfaction has been to a greater extent included in many recent studies (Liaw, 2008; Lin, 2011; Paechter, Maier, & Macher, 2010; Sun et al., 2008), user satisfaction

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and learning experience having been interchangeably used in the context of usability (Chiu et al., 2005; Lee, 2010; Liaw, 2008; Sun et al., 2008). Lee (2010), for instance, claimed that usability, including the user's perception of learning experience, would be the essential factor in measuring the success of e-learning, but its subjective variance would make it hard to embed the necessary quality in e-learning systems design. Further, Alexander and Golja (2007) examined that the very quality of the e-learning system is the user experience that comes from the holistic perception of the system given throughout every learning activity including usability (e.g. easy of use, effectiveness) and usefulness (in terms of learning outcomes).

These perspectives suggest that the learner's experience with e-learning systems should be one of our primary research interests. Note that learning performance, which is related to learner's knowledge or skill level, can be measured in a quantitative way; in comparison, its corresponding learning experience, which generally involves user's learning conditions and internal cognitive states whilst engaging in learning activities, is still open to question about whether it can condition learning performance.

Of course, it is the case that learning performance with e-learning systems is the most important learning outcome; thereby it cannot be overlooked entirely. However, some studies (Mitchell, Chen, & Macredie, 2005; Koehler, Thompson, & Phye, 2011; Kopcha & Sullivan, 2008) have shown that some user groups (i.e., those who have relatively high skills or knowledge in the learning subject domain) tend not to take in e-learning systems, partly because of the lack of flexibility but mostly because of boredom whilst using them. Hence, a disclaimer of this article is that learning performance alone might not tell the full story. Instead, learning experience in conjunction with learning performance might indicate how to assess an e-learning system, and as a consequence, the designer could find an integrated way to embody both performance and experience quality into a computer-based learning system, and know what should be considered in this multi-dimensional process.

That being said, the primary aim of this article is to empirically demonstrate this issue, from the well-known perspective of optimal '*flow*' experience theory as suggested by Csikszentmihalyi (1990). A generally accepted definition of '*flow*' is a holistically controlled feeling where one acts with total involvement or engagement with a particular activity. Prior research on e-learning systems (Roca, Chiu, & Martínez, 2006) has proven that students who had enjoyed a good e-learning experience would readily adopt the computer-based or mobile-based technology and intend to use the learning application again in the future. In this article, the optimal flow experience theory in conjunction with learning performance is applied on the assumption that it can establish a solid approach to analyse computer-based non-formal and unsupervised learning processes.

As to the context of e-learning system, it is noted that few studies have considered an individual's optimal learning experience against his or her learning performance. This issue seems to be important due to the fact that a learner would have rather different learning experiences as their knowledge or skill level grows. Entry-level learners might have great interest in an e-learning system that is adaptable to their limited understanding, but experts might show a preference for an e-learning system that enables them to easily navigate through the system to selectively learn what they need. In this regard, the experiment in this present study takes into consideration a *dynamic content sequencing system* (DCSS), which is capable of self-organising learning content depending on learning performance or skill level. This dynamic content sequencing system fits well into the focus of our study in that it can reveal how different learning experiences might relate to levels of learning performance.

Yet, this paper does not intend to comprehensively investigate all the possible benefits of learning activities with e-learning systems, since this is rather too broad a scope. Instead, we narrow down our study to explore the benefits and limitations of an adaptive e-learning system, comparing it with a more traditional e-learning system activity. This will give an insight into how effectively the adaptive e-learning environment may cope with learning experience, extending the unsupervised learning experience and helping e-learning designers to make explicit the assumptions they are making when specifying how a user should interact with e-learning content.

2. Learning experience in computer-based learning

The nature of interaction and experience in learning activity has been advanced with the advent of computer-mediated communication. For instance, interaction modes adapting to computer-based learning are seen as learner–content, learner–teacher, and learner–learner interaction, respectively (Moore, 1989). The notion of community also comprises learning experience in conjunction with cognitive presence, teacher presence, and social presence together (Garrison, Anderson, & Archer, 2001). Both perspectives emphasize the importance of interactions among learners and between learners and teachers, as integral to the development of an effective learning experience (Buraphadeja & Dawson, 2008).

However, many studies in the area of computer-based learning have tended to focus on the development of courses and tend to emphasise what could be done online by teachers and what students would get from the computer-based learning application (Alexander, 2001). In contrast, our empirical study examined learner experience with a dynamic content sequencing system (DCSS) from learner's perspectives to see if it led to different learning outcomes against a non-dynamic system. If learning outcomes are not in parallel between DCSS and its counterpart, it would be interesting to further explore how to deal with individual's learning experience against his or her learning performance. The possible learning experience is outlined here for purposes of discussion.

2.1. Learning experience in the optimal flow channel

In previous literature about e-learning experience, learning experience has been examined two distinct perspectives. On the one hand, for instance, Deepwell and Malik (2008) investigated the experience of e-learning from the perspective of e-learning providers; so their main concerns were not for the students but for the teachers, addressing issues such as the technical usability and how the technology might support processes of pedagogical transition in higher education. On the other hand, as Paechter et al. (2010) claimed, the e-learning experience should be subject to the e-learning users, and it is imperative to consider the learner's experience of course content, interaction with the instructors, interaction with peer students, individual learning processes and course outcomes. Likewise, Liaw (2008), Song et al. (2004) and Sun et al. (2008) also saw how a learner perceives the design of a course, user interface, interaction with tutors, interaction with other students, learning processes and learning outcomes would be more important than what teachers would perceive.

Indeed, the studies mentioned above give a broad definition of *learner's experience*, but a more specific definition is needed for correct usage in this article. We relate learning experience to some cognitive states or conditions which a learner might undergo during individual computer-based learning processes and interactions. This would be examined by collecting their learning conditions and internal cognitive states whilst engaging in a learning activity, in particular assessing *how much an individual learner engages in a* *particular learning activity*. However, assessing internal cognitive states is easier said than done. No widely accepted instruments to assess them have been fully proposed yet.

In the traditional classroom context, this could be quickly done by the teacher. An experienced teacher was readily able to know whether or not a student is engaged in a learning activity by their learning performance and attitudes in the classroom. Unlike the traditional classroom setting, observing a learner's engagement in a computer-based learning activity is limited by the nature of unsupervised learning. Hence, it is much harder to regulate individual learner's engagement, in particular without any internal motivation (Clark, 2002). Furthermore, the increasing complexity of technological advances in the learning environment, for instance, hypermedia, hypertext, collaborative learning, and web-based learning environment, causes self-regulated learning difficult (Azevedo & Hadwin, 2005). In this regard, the investigation of the motivational aspects of self-regulation (e.g., self-efficacy) has been to the fore of learning experience study. Several studies suggested the effective ways to promote self-regulated learning such as scaffolding techniques in computer-based learning (e.g., Azevedo & Hadwin, 2005; Dinsmore, Alexander, & Loughlin, 2008).

That is, in the current computer-based learning environment, an individual learner's engagement appears to be highly dependent of the learner's intrinsic motivation (e.g., self-regulation), thereby computer-based learning applications (with perhaps the exception of game-based learning) lack the means to control and manipulate a learner's engagement to maintain optimal learning experience. It can thus be said that the absence of this mechanism is a major challenge in ensuring the future sustainability of computer-based learning (DeRouin, Fritzsche, & Salas, 2005; Lim, 2004).

To strengthen learner's engagement, it has been noted that dynamic content sequencing is a possible way forward to provide learners with different paths through learning content (Liu et al., 2009; Stern & Woolf, 1998). Learning contents are dynamically generated based on individual learning parameters; for instance, each learner will be presented with a set of learning content that meets his or her current knowledge and skill level. Adaptive e-learning systems such as ELM-ART (Brusilovsky, Schwarz, & Weber, 1996; Weber & Brusilovsky, 2001) for example make learners learn more efficiently and effectively with personalised, goal-oriented contents. In light of this previous work, a dynamic content sequencing system was adopted for the empirical study in this present study, in order to see the relationship between learner's engagement and his or her learning experience.

In essence, *learner's experience* that is measured as "*how much an individual learner engages in a particular learning activity*", would actually lead to somewhat subjective answers. One may say that he or she was fully engaged, though actually they were not. The states of engagement (or disengagement), are thus very elusive and difficult to quantify.

Perhaps this is the main reason why some prior research described engagement through combinations of a few relevant characteristics such as cognitive attention, concentration, control, enjoyment and many more (Finneran & Zhang, 2003; Shin, 2006; Webster, Trevino, & Ryan, 1993). On the other hand, several other studies measured engagement or disengagement through the use of some possible cognitive or behavioural states such as self-consciousness, happiness and endurance (Burleson, 2005; Choo, 2005; Liaw, 2008; O'Brien & Toms, 2008; Richter, 2008).

Again, to examine the level of engagement, it is essential to see that individual engagement in a learning activity is forced by either extrinsic or intrinsic factors (O'Brien & Toms, 2008). That is, it is deemed that learner's motivation to participate in a learning activity is influenced by external or internal rewards a person may obtain from the learning activity. For instance, participation in a learning activity that is driven by the intention to get good grades, or other material rewards and recognition, can be described as external motivation. On the other hand, participation in a learning activity for the sake of the learning goal itself is mostly driven by intrinsic motivation, where there are no apparent external forces to cause a person to participate in the activity (Teo, Lim, & Lai, 1999). Both extrinsic and intrinsic motivations are found to be very important in ensuring high engagement in learning activities. However, Graef et al. (1983) suggest that intrinsic motivation is a more influential and longer-term construct of behaviour than extrinsic motivation because it gives a feeling of enjoyment to the person and encourages that person to engage in the activity again in the future.

On the basis of the merits of internal motivation, Csikszentmihalyi (1990) studied engagement and enjoyment in different daily life activities such as playing sports, describing engagement and enjoyment in the subjective flow of experience. His theory claims that intrinsic motivation is the fundamental component in achieving an optimal engagement that underlies optimal experience in doing a particular activity (Csikszentmihalyi, 1975). Hence, flow of experience is achieved when a person is capable of controlling the given challenges in the activity in a progressive and spiral manner, otherwise he or she will suffer from anxiety or boredom in performing an activity. Having said that, the learning process itself is dynamic and growing in nature. In this regard, this optimal flow theory is able to pinpoint how people can manage their learning activities, positioning themselves against optimal flow experience, and the improvement in knowledge and skills is accordingly evolving in conjunction with increasing levels of difficulty. Therefore, the three cognitive states (i.e., flow, boredom and anxiety) that occur with regard to individual knowledge and skills against the given level of challenges by a dynamic content sequencing system could be a good indicator to assess whether or not the learner enjoys a core learning experience with e-learning systems.

2.2. Optimal learning experience and e-learning systems design

For several reasons, we chose to examine optimal flow experience in learning by means of a rather reductionist approach. That means that we only considered the three cognitive states in learning activities (i.e., flow experience, boredom and anxiety or frustration) with focusing on conscious balance between a person's skills and the challenges in that particular learning activity. Of course, there are many other cognitive states (e.g., happiness, social connection, conflicts and so forth) relevant to learning activities. However, the reductionist approach taken in this article can be justified by the fact that our theoretical stance is quick to interpret the value of learning experience in conjunction with learning performance in individual e-learning activities and we do not intend to determine all the other types of user experience (e.g., arousal, tensions among learners and so on) by the same manner. This can thus be said that authentic e-learning experience is to reduce the complexity of an unsupervised learning task. When authenticity is compromised too much, this may lead to adverse effects. Examples are, students getting board, or a superficial approach, since students perceive the learning task to be less difficult than it actually is. Nevertheless, when learning tasks are presented in their full complexity, this may have other adverse effects, like for example, students experiencing difficulties in getting started, or having difficulties in activating their prior knowledge, or students losing confidence and feeling lost. We have thus adopted the notion of scaffolding as pivotal in e-learning experience since each element of the learning content should be ruggedizedly designable.

A note of practical challenges to secure such learning experience in conjunction with learning performance is further discussed here. Most of the studies with regard to e-learning content design in our view contribute to developing the necessary design guidelines to respond to these challenges. For instance, the study of design patterns for e-learning environments (e.g., Zitter, Kinkhorst, Simons, & Cate, 2009) proposed that task conceptualisation of a learning activity would help e-learning practitioners to develop an appropriate design process for better learning experience. Further, Evans (2009) demonstrated that e-learning experience should be differently styled by the learner's mental efforts to be voluntarily made (e.g., visually impaired learners enjoyed the same e-learning task more than the sighted learners did). In sum, both studies claimed that the balance between task complexity and individual's intended effort would achieve a better learning experience and new design guidelines that would trigger this learning experience would be of urgent necessity. Hence, we hypothesised that the three states of learning experience (i.e., flow, anxiety and boredom) would dominate the learning performance with e-learning systems. Our theoretical framework proposed in this study is thus sketched out as shown in Fig. 1, consisting of three stages: flow antecedents (i.e., preconditions of flow experience), flow experience, and flow consequences (i.e., lifting learning performance).

In detail, flow antecedents are much concerned about what would trigger flow in a particular e-learning environment. They include four flow dimensions (control, attention focus, curiosity, intrinsic interest), prior knowledge (domain knowledge and/or skills that a learner has) and the preferred learning style that might dictate the organisation of learning contents. With regard to the preferred learning style, the dynamic content sequencing system (e.g., AHA!, DeBra et al., 2003; ELM-ART, Brusilovsky et al., 1996; Weber & Brusilovsky, 2001) has been suggested as a way to handle the dynamic mapping of challenge and skill. Though these novel learning systems revealed advantages over non-adaptive learning systems, there is still a lack of understanding about how dynamic content sequencing systems can best be built upon what design guidelines, which is the central research question of this article. As to the four dimensions of flow, we employed Webster et al.'s (1993) study that assessed flow experience in the operative level. To be noted, Hoffman and Novak (1996) further advanced it by both structural properties of the flow activity (seamless sequence of responses facilitated by interactivity with the computer and self-reinforcement), and antecedents of flow (skill/challenge balance, focused attention, and tele-presence), but they were more applicable to general web activities rather than e-learning.

As discussed above, our study considers three cognitive states of flow experience: *anxiety*, *optimal flow*, and *boredom*. Fig. 2 depicts the four points of cognitive states (A_1, A_2, A_3, and A_4) that a learner may have in the context of computer-based learning.

Looking at Fig. 2, at Point A_1, a learner could virtually be in a *flow* state as the challenge given is low and the learner can cope with this challenge with his or her current knowledge. Hence, it can be seen that this learning activity itself holds the learner's attention and focus to that learning activity. However, as learning activities advance, there occur two possible cases to be considered. One is that the challenges given do not meet with their current knowledge level (depicted in A_2), where it might cause boredom. This perhaps can be easily observed when the learner is an expert, so their skills are much higher than what the learning system can do for them. A rather different situation happens at A_3, where the level of challenges is higher but the learner's level of skill is too low to cope with this challenge. Here, at this point (i.e., A_3), the learner would experience anxiety that causes disengagement from the learning activity, resulting in feelings of lost and difficulties in focussing on the learning activity. To handle this correctly, the learning system should be able to adjust to a difficulty level that can be handled by the learner, either heightening their knowledge level (advance to A_4) or lowering the challenges given to them (take them down to around A_1). The dynamic content sequencing system considered in this article is expected to have this mechanism based on the learner's current knowledge level, so if they are not ready to go ahead to the higher skill level (e.g., A_4) the system will lower the level of difficulty for the learner to build their confidence (e.g., around A_1 or somewhere between A_1 and A_4 in the optimal flow channel). This simplified approach would aim to move the learner into an optimal *flow* state, where there is a balance between challenges and skills depicted in points A_1 and A_4 or the flow channel represented by the white area.

This article empirically tested the dynamic content sequencing system from two perspectives: *learning performance* and its corresponding *learning experience*. An early assumption was made prior to the empirical study. We hypothesised that the learner's perfor-

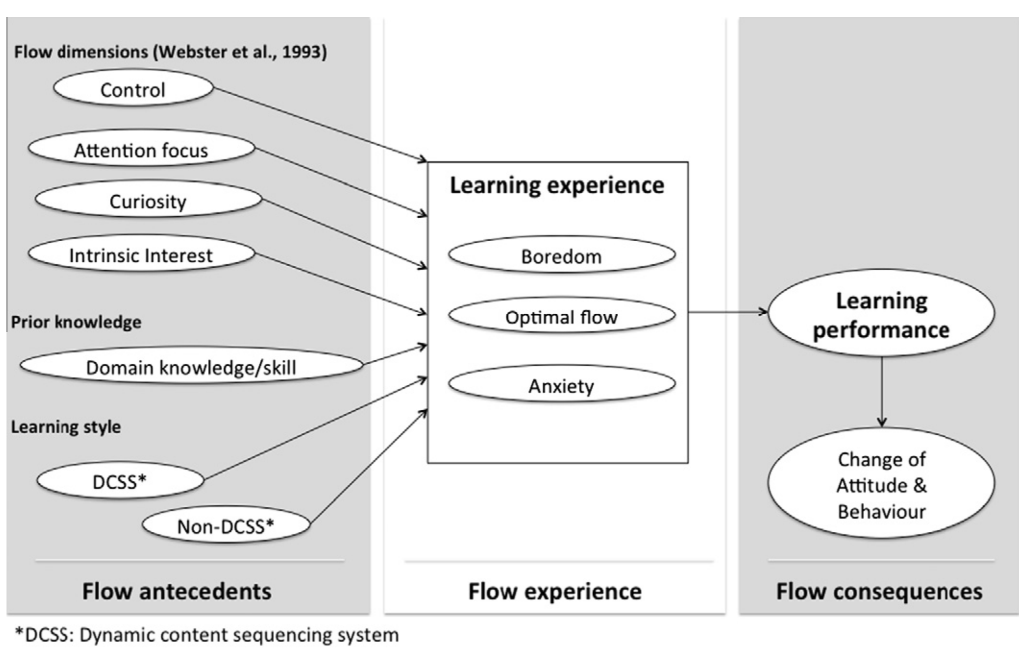

Fig. 1. Flow design framework for e-learning in this study.

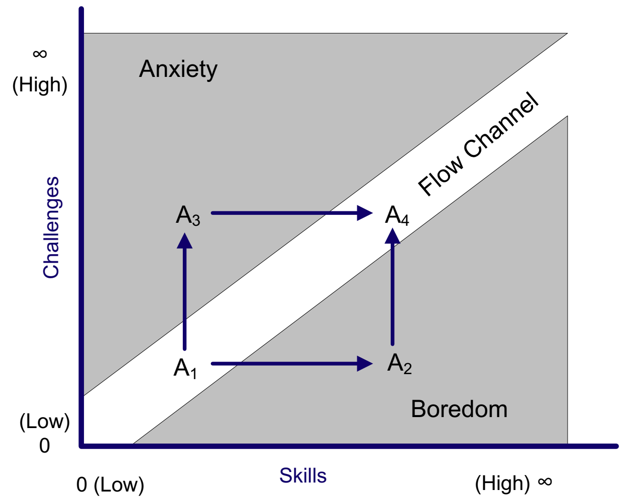

Fig. 2. Cognitive states of flow theory (extended from Csikszentmihalyi, 1990). Moving around A_1, A_2, A_3, and A_4 is essential in learning experience. Hence, the dynamic content sequencing system should be able to locate the learners into the optimal flow channel.

mance and experience with the dynamic content sequencing system would be higher than those with the non-dynamic system, thanks to its capability to match the challenge levels to each learner's learning performance. However, it was also likely, from the work of Mitchell et al. (2005), Koehler et al. (2011) and Kopcha and Sullivan (2008) that expert learners would not favour the dynamic content sequencing system due to its rigidity, quickly resulting in boredom. We proposed to examine these propositions by means of evaluating learning experience.

3. Method

The discussion above suggests that the dynamic content sequencing system might be better off than the non-dynamic content sequencing system, as the former might ensure a learner's optimal flow experience in its design. To empirically test this proposition, an experiment with an arbitrary e-learning system was carried out. The flow measures considered in this study are based on the work proposed by Webster et al. (1993), an *activity-followed-by-survey* method where participants completed the questionnaire as soon as they completed the e-learning activity. Total 12 item scales were used to measure the flow experience as a combination of control, attention focus, curiosity, and intrinsic interest. The original statements proposed by Webster et al. (1993) were modified to our adaptive e-learning environment.

3.1. Participants

A total of 125 students from Massey University (New Zealand) were invited to participate in this study. Only 94 participants completed all the learning sessions and the data from these participants were only used for the following analysis. This high drop-off rate was examined by two independent educational technologists who have at least 10 years experience in providing e-learning services. The primary reason behind the high attrition rate was that the participants were voluntarily enrolled in this experimental online course and their interests on the subject matter were varied, so that they were not much internally motivated. Most of the participants who did not complete the course (28 students) were from non-CS (Computer Sciences), non-IT (Information Technology) disciplines. Hence, the analyses in the present study were only carried out with the CS/IT degree course students (sample size = 80; 40 subjects who used the dynamic content sequencing system, and 40 for the non-dynamic content sequencing system). The average age of the participants was 20.13 years. Around half of them were the first year students (38) and the rest of them were the second or third year undergraduate students.

3.2. Experimental design

A one-way between-subject design was used for this study. The independent variable was the type of e-learning system (i.e., the dynamic vs. the non-dynamic content sequencing system). Each participant was assigned randomly to one of the two conditions. Two dependent variables, learning performance (assessed by retention test and transfer test) and the four dimensions of learning experience (control, attention focus, curiosity, and intrinsic interests), were considered. We also identified two nuisance variables, the learner's prior knowledge and the type of learning style of each individual, which were accordingly considered in the following analyses.

3.3. Apparatus/materials

The materials used for this empirical study were comprised of four components: e-learning applications (the dynamic content sequencing system and the non-dynamic content sequencing system), the tutorial session with pre-learning quizzes, post-learning quizzes, and the learning experience questionnaire.

The two different e-learning applications were the main apparatus of this experiment. The e-learning systems are derived from '*IT-Tutor*' originally developed for teaching non-IT students from Massey University about computer networks. The original version of IT-Tutor was built upon a non-dynamic content sequencing approach, where all the contents were given in a pre-defined way irrespective of the student's current knowledge level. Hence, the learners must follow the fixed path of the learning contents. In contrast, the dynamic content sequencing version of IT-Tutor, newly designed for this empirical study, employed a user modelling to infer the forthcoming learning content comparing to his or her current knowledge level based on his or her previous learning outcomes. For this reason, we found that Bayesian models (Pearl, 1988) can be effective in diagnosing a user's needs and can provide useful enhancements to dynamic content sequencing (Conati, Gertner, VanLehn, & Druzdzel, 1997). However, moving from a high-level specification of the problem of Bayesian user modelling to specific domains and prototypes requires a detailed consideration of distinctions and relationships for particular learning contents and settings. In so doing, the studies with two novice and two expert learners helped us to identify several important classes of evidential distinctions. These observational clues appeared to be valuable for making inferences about a user's problems and for making an assessment of the user's need for assistance, therefore to implement the dynamic content sequencing system. The classes of evidence include:

- *Search*: Repetitive, scanning patterns associated with attempts to search for or access a learning item.
- *Focus of attention*: Selection and/or dwelling on portions of a document or on specific subtext after scrolling through the document.
- *Introspection*: A sudden pause after a period of activity or a significant slowing of the rate of interaction.
- *Undesired effects*: Attempts to return to a prior learning content after an action. These observations include quickly returning to the previous learning contents.

Given the results of the user studies, particularly for the classes above, we set out Bayesian models with the ability to predict the

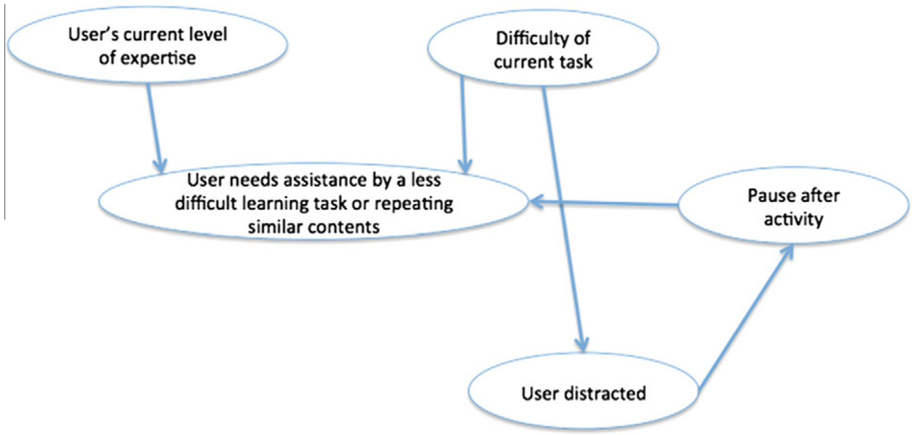

Fig. 3. A portion of a Bayesian user model for inferring the likelihood that a user needs assistance by dynamic content sequencing, considering previous history of learning performance as well as observations of recent activity.

forthcoming content. Fig. 3 displays a small Bayesian network model that represents the dependency between a long pause after activity and the likelihood that a user would welcome the forthcoming learning content that gives a less difficult learning action or repeating similar difficulty level of learning content. The detail of the Bayesian network user model is not fully described in this article, which is far beyond the objective of the present study. Figs. 4a and 4b show the apparatus used in this study.

As briefly discussed above, IT-Tutor was intended to teach '*Basic Computer Networks*' at the university level. It consists of two learning sessions: '*Introduction to Computer Networks*' and '*Network Devices and Transmission Media*'. Fig. 5 shows what each learning session covered. Each learning session was designed using multimedia text and images.

Prior to the main learning session, each learner was given a tutorial session. This was intended to remove some *participant effects*, such as different prior knowledge on the topics to be learnt. The tutorial consisted of four stages. The first two stages were to identify learners' current knowledge about the topics being taught whilst the last two stages were to reinforce learning obtained during the first two stages.

Fig. 6 depicts how each tutorial was administered. At the beginning, learners were presented with eight multiple-choice questions. Each question corresponded to the sub-topics as shown in

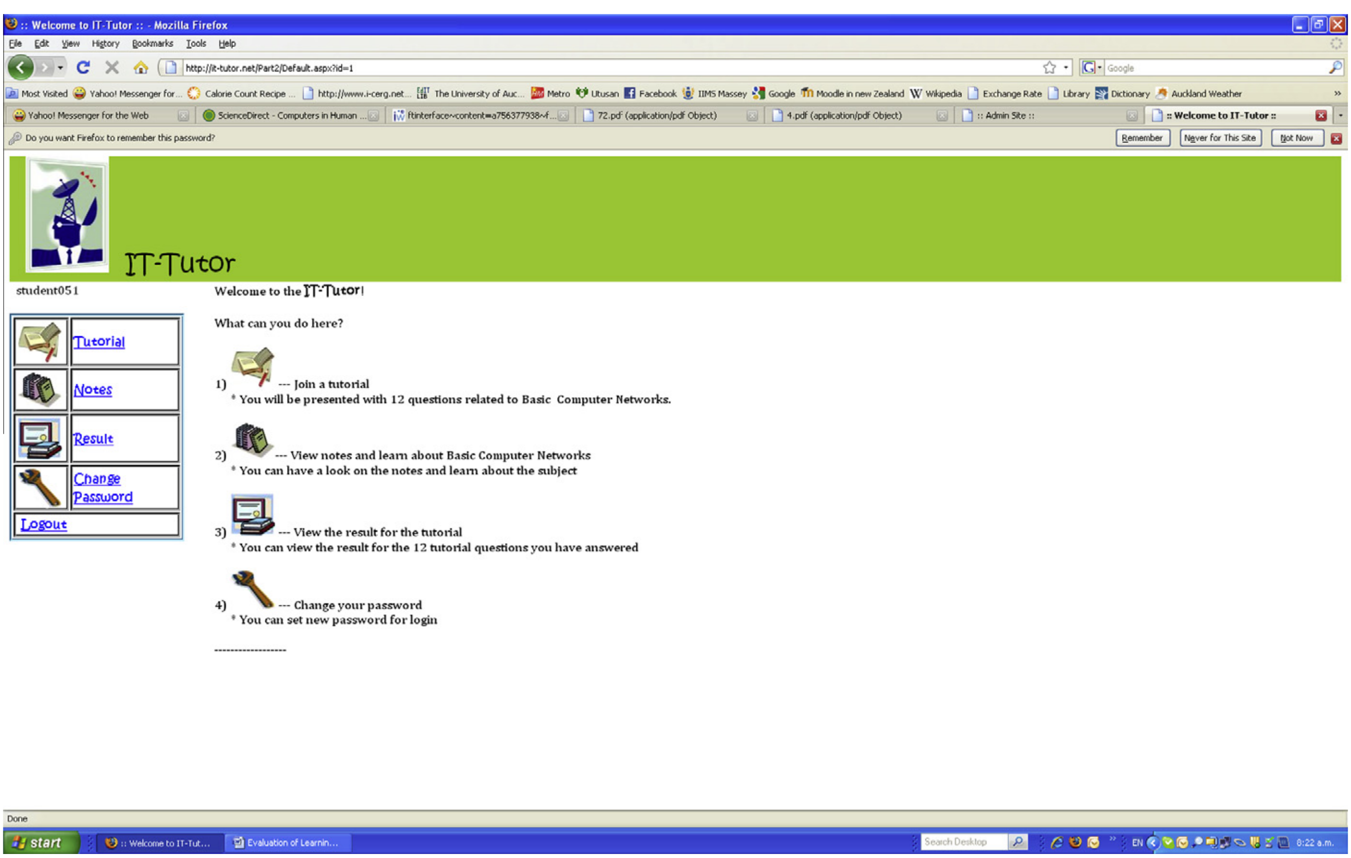

Fig. 4a. The original IT-Tutor – The main page.

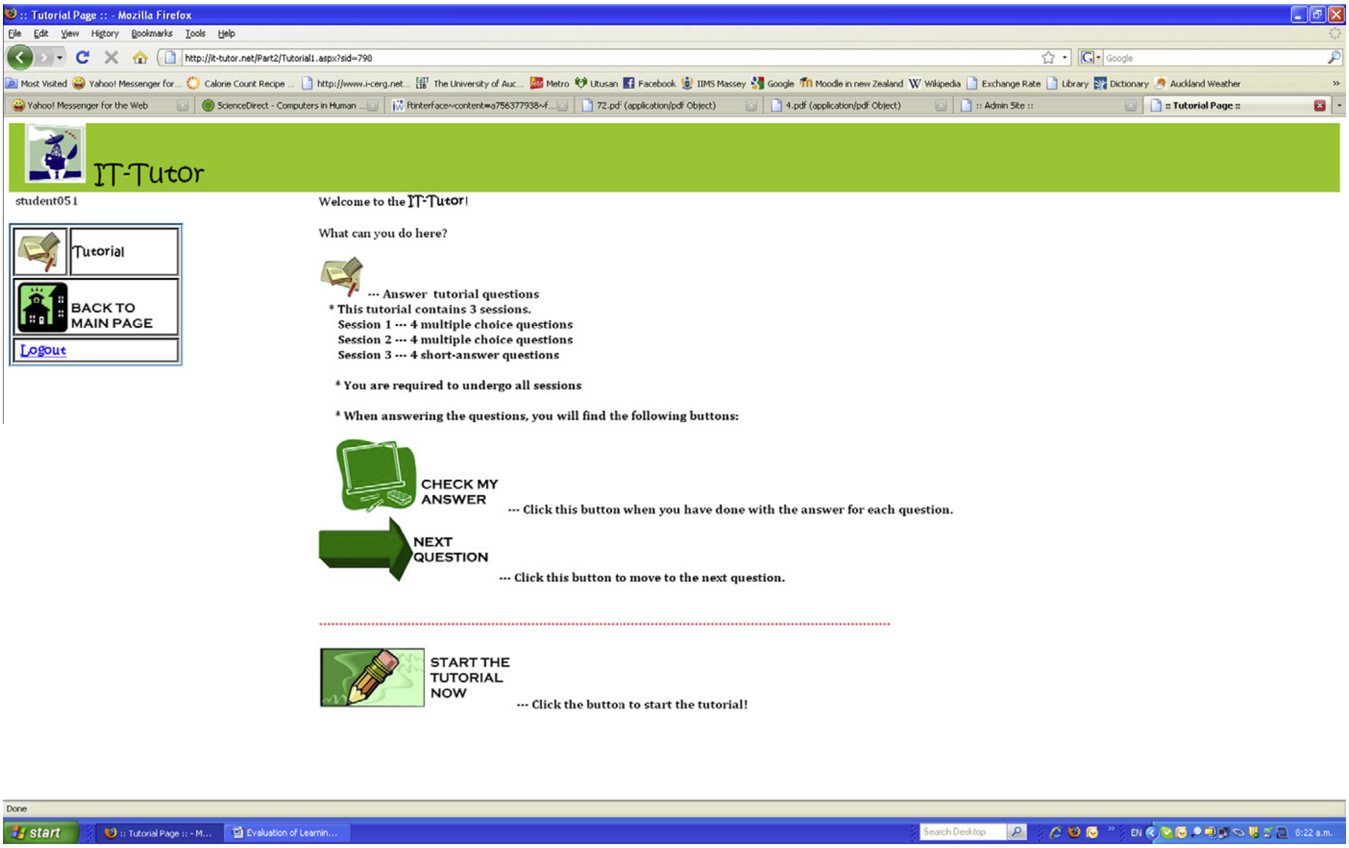

Fig. 4b. The original IT-Tutor – The tutorial page.

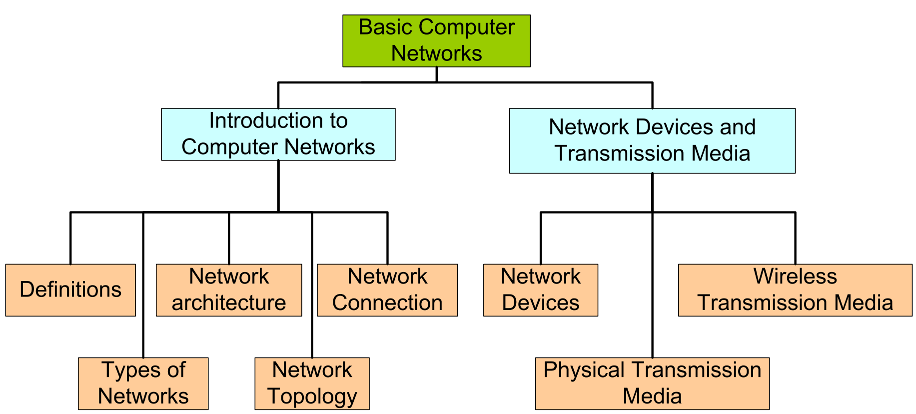

Fig. 5. The structure of Basic Computer Networks module.

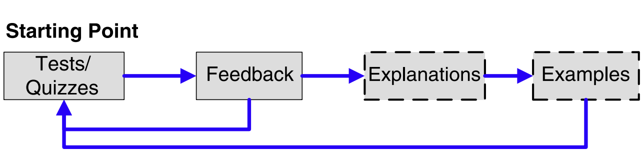

Fig. 6. The sequence of tutorial in IT-Tutor with DCSS.

Fig. 5, i.e., definitions of computer networks, types of computer networks, network architecture, topology, connection, devices, physical and wireless transmission media. The answers to these questions were used to assess the learners' current knowledge. As to the dynamic content sequencing system, these were employed to reorganise the initial sequence of the learning content in the main experimental configuration. A note of this mechanism is needed here. Thanks to this variation, the dynamic content sequencing system might have rather different learning paths against the non-dynamic content sequencing system and be individually different at the early stage of learning session, though the overall contents are exactly the same. This manipulation would be able to contrast the effect of the order of learning sequencing for the individual's optimal learning experience, between the dynamic and the non-dynamic content sequencing system.

The tutorial session also served to manage group homogeneity in the main experimental setting. To avoid issues such as students with a high GPA being assigned only to a particular experimental condition, two groups of the participants (knowledgeable learners vs. entry-level learners) were made based on the outcomes of the

Table 1
Retention and transfer questions.

Retention questions	Transfer questions
_______ is a network that covers a large geographic area using many types of media.	"A network officer at a primary school has been assigned by the school principal to create a computer network for the new computer laboratory. There are 12 computers which need to be connected to each other. The network officer needs a type of network which can be easily expandable in the future and has better performance in routing data, instructions and information among the computers." What type of network topology is the best for the computer laboratory?
_______ is a type of network in which one or more computers act as host computers and other computers access the host computer.	"A network officer is required to setup a small network consists of four computers. He needs to create a network so that all computers can share files and resources among them and as well as sharing access to the Internet. To enable this setting, he must ensure that each computer has equal capabilities and responsibilities." What type of network architecture that he needs to choose?
_______ network uses a cable that forms closed loop with all computers and devices arranged along the cable.	"A network consultant is required to setup a small office network consists of two computers. Each of the computers has been installed with modem, but no network cards. All computers should have access to the internet." What type of network connection appropriate for this setting?
_______ allows access to the Web wirelessly from a notebook computer, a smart phone, or other mobile device	"A network consultant is required to setup a network for a public library in North Shore. There are 10 computers within 100 m^2 of the library building. All computers have been installed with TCP/IP standard network cards. He needs to think of the cheapest cable that is appropriate for connecting all computers in the building. The cable must also thin and easy to string between walls." What type of network cable appropriate for this setting?
_______ consists of a single copper wire and often used for cable television wiring	"A network consultant is required to setup a wireless network at the ground level of Westfield Mall in Albany. The wireless network will be used by customers who are having their meals at the food court area of the mall. The new wireless network will be connected to the existing local area network (LAN) in the building. He is thinking of investigating a network device for the wireless network." What is the most appropriate wireless network device he should think of?

quizzes in the tutorial session. They were later randomly assigned into either the control (i.e., the non-dynamic sequencing system) or the treatment condition (i.e., the dynamic sequencing system), only to find that knowledgeable and entry-level learners were around equally distributed to each experimental condition. Hence, within the limits of sampling error, the effect of learning experience will be distributed as it is in the sampled population.

At the end of the experiment, they were also given ten post-learning quizzes, although the written instructions at the beginning of the experiment had emphasised that no questions would be asked in this respect. This was deliberately administered in order to give an impression of their learning that was as natural as possible. The questions were made up of two parts: a retention test and a transfer test (Mayer, 2005). The question set used in this experiment is detailed in Table 1.

The last instrument was the *learning experience questionnaire*. The questionnaire was adapted from Park, Parsons, and Ryu (2010), as shown in Table 2. It was designed to measure four dimensions of experience based on flow theory (Csikszentmihalyi, 1990): *control*, *attention focus*, *curiosity*, and *intrinsic interests*. *Control* refers to the situation in which a learner feels in control of the learning activities. In this situation he/she is capable of keeping the interactions between himself/herself with IT-Tutor on track. *Attention focus* refers to the situation in which a learner is absorbed by the e-learning activities. *Curiosity* is the situation in which a learner is excited and eager to find out about the domain knowledge. The *intrinsic interests* dimension is where a learner feels enjoyment in the learning activities. Participants were asked to rate their learning experience using a five-point Likert scale on the 12 statements at the end of the experiment, though the written instructions at the beginning of the experiment clearly indicated there would be no assessment of their learning experience. This was deliberately administered so as not to bias our participants to their other prior learning experience.

3.4. Procedure

The participants were firstly given an information sheet about the study. It included what the study was about and how the experiment would be performed. Then they were given a consent form and the data protection policy. Next, the participants were required to attend the tutorial session with the pre-learning quizzes. Based on their performance in the quizzes, they were first grouped and then randomly assigned to one of two experimental groups, i.e., the dynamic content sequencing and non-dynamic content sequencing. After taking a five-minute break, they were again invited to the laboratory to complete the main experimental session. Having done this, the participants were asked to complete the learning experience questionnaire and do the post-learning quizzes.

In completing all the experimental tasks, the participants were free to work at their own pace. In order to maintain the reliability of the data, the application was suspended when a participant was inactive[1] for 5 min and these data were not included in the analyses.

4. Results

Table 3 shows the means of the two learning performance measures: *Retention test* and *Transfer test*. The *Kolmogorov–Smirnov* (K–S) test showed that the sample population data did not meet the normal distribution assumption, thereby all statistical tests were carried out by non-parametric tests. The *Mann–Whitney U* tests were respectively performed to analyse the differences, which were not statistically significant.

The learning experience was measured through their ratings on the Likert scale. The *Cronbach's alpha coefficient* for the questionnaire data was 0.85 in average, suggesting that the three items on each dimension had relatively high internal consistency. The means for all the four dimensions of learning experience are presented in Table 4. Looking at Table 4, no significant differences between the dynamic and the non-dynamic content sequencing system were found, and the *Mann–Whitney U* tests confirmed this interpretation.

A further analysis on '*who was engaged in the learning experience and gained the optimal learning experience?*' was made. In so doing, we first carried out a cluster analysis (Everitt, Landau, & Leese,

[1] *Inactive* is defined by the situation in which there were no interactions had happened between participants and the application for a certain period of time. Interactions include mouse moving and clicking, and page scrolling.

Table 2
Learning experience questionnaire.

Dimensions of learning experience	The associated questions
Control	(Q1) When using IT-Tutor, I felt in control over everything (Q2) I felt that I had no control over my learning process with IT-Tutor (Q3) IT-Tutor allowed me to control the whole learning process
Attention Focus	(Q4) When using IT-Tutor, I thought about other things (Q5) When using IT-Tutor, I was aware of distractions (Q6) When using IT-Tutor, I was totally absorbed in what I was doing
Curiosity	(Q7) Using IT-Tutor excited my curiosity (Q8) Interacting with IT-Tutor made me curious (Q9) Using IT-Tutor aroused my imagination
Intrinsic interests	(Q10) Using IT-Tutor bored me (Q11) Using IT-Tutor was intrinsically interesting (Q12) IT-Tutor was fun for me to use

Table 3
Learning performance (mean/sd, max: 5).

	Dynamic content sequencing ($n = 40$)	Non-dynamic content sequencing ($n = 40$)	p
Retention test	3.12 (1.90)	2.73 (1.58)	n.s.
Transfer test	1.64 (1.21)	1.37 (1.14)	n.s.

Table 4
The four dimensional learning experience (mean/sd).

Learning experience	Dynamic content sequencing	Non-dynamic content sequencing	p
Control	3.50 (1.12)	3.01 (0.99)	n.s.
Attention Focus	3.13 (1.04)	3.00 (0.88)	n.s.
Curiosity	3.67 (1.00)	3.36 (0.89)	n.s.
Intrinsic Interests	3.54 (0.96)	3.18 (0.93)	n.s.

Table 5
Types of learners based on the post-learning quiz by the cluster analysis.

Types of learners	Range score	Dynamic	Non-dynamic
Low achievers	0–2	11	15
Medium achievers	3–5	17	12
High achievers	6–10	12	13

2001; Hair, Anderson, Tatham, & Black, 1995), to classify learners into the different groups based on the homogeneity in their learning performance. This analysis divided all the participants into three groups – *Low, Medium,* and *High achievers*.[2] Fisher's algorithm (Fisher, 1958) identified three group centroids, and Table 5 shows the range of scores based on the centroids and the number of learners clustered into each group.

Table Next, with the three cluster groups, we further analysed their learning experience. Table 6 shows the means for each dimension of learning experience. The pairwise comparisons within the same cluster groups, i.e., low achievers, medium achievers and high achievers, against each experience dimension show some contrasting results. That is, in terms of curiosity, the low-achievers (mean 4.24) and medium-achievers (mean 3.76) with the dynamic content sequencing system seemed to have higher ratings against those with the non-dynamic content sequencing system (mean 3.43 for the low achievers and 2.69 for the medium achievers). As to intrinsic interest, low achievers (mean 3.98) showed higher intrinsic interest with the dynamic content sequencing system than the other system. However, in general, the high achievers showed no preference for either dynamic or non-dynamic sequencing in their own learning experience. The *Mann–Whitney U* tests confirmed these interpretations. This suggested that, from the perspective of curiosity and intrinsic interests, both low and medium achievers seem to have gained certain benefits from the dynamic content sequencing system. Also, it is striking that the high achievers did not have significant benefits in terms of the four dimensional learning experience, which would be in line with Mitchell et al. (2005), Koehler et al. (2011) and Kopcha and Sullivan (2008).

A further analysis to predict the three cognitive states of the flow theory (i.e., flow, boredom and anxiety), in conjunction with the learning performance and their learning experience ratings, was carried out with a discriminant function analysis. This analysis is considered to be of great value for classifying a set of observations into predefined classes in our study, e.g., *flow*, *boredom*, and *anxiety*. To do so, we employed the Csikszentmihalyi's account that the learners who rated their learning experience highly (i.e., the mean of the ratings of the four dimensions in learning experience is greater than the neutral value = 3) regardless of their learning performance during the post-learning quizzes were classified into a *flow* group. In contrast, the learners with high scores in the post-learning quizzes but low ratings on the learning experience questionnaire were classified as a *boredom* group. The remainder were classified as an *anxiety* group. See Fig. 1 for the three cognitive states.

Table 7 shows the number of the participants in terms of this classification. Using the dynamic content sequencing system, three quarters of the subjects (30 out of 40) were in the optimal flow state; by comparison, around a half of the subjects (19 out of 40) using the non-dynamic content sequencing system were in the optimal flow state. This clearly indicates that the dynamic content sequencing system used in this study was able to well predict the forthcoming learning content based on a subject's past learning outcome; as a consequence, his or her learning experience was posited on the optimal learning experience channel shown in Fig. 1. This was confirmed by a Fisher's exact test (p-value $\leqslant .05$).

Markedly interesting is that none of the learners using the dynamic content sequencing system felt any anxiety. This implies, at the very least, anxiety is not the typical cognitive state that the dynamic content sequencing system would create, and the benefit of the dynamic content sequencing system seems obvious in this light too. It also suggests that the algorithm to predict the forthcoming content in the dynamic content sequencing system seems to work out, presenting an appropriate learning content based on their current knowledge level. However, similar to the learning experience data by the high achievers, as shown in Table 6, it is again striking that around 42% of the high achievers (5 out of 12) had felt bored using the dynamic content sequencing system, which also implies the content sequencing algorithm did not perfectly capture the expert learner's knowledge level at some learning points. On the other hand, nine expert learners using the non-dynamic content sequencing system felt anxiety. This again confirms that the non-dynamic content sequencing system was not in parallel with a learner's current knowledge level. Clearly, the Fisher's exact tests supported the general

[2] The use of this categorisation is very common in classifying learners into groups. See Konstantopoulos and Chung (2009) for an example.

Table 6
Means and standard deviations of learning experience based on different types of learners.

Learning experience	Dynamic sequencing			Non-dynamic sequencing		
	High achiever	Medium achiever	Low achiever	High achiever	Medium achiever	Low achiever
Control	3.41 (1.01)	3.40 (1.23)	3.74 (1.09)	3.02 (0.78)	2.91 (1.03)	3.09 (1.12)
Attention focus	3.09 (0.94)	2.97 (1.06)	3.41 (1.11)	3.29 (0.69)	2.55 (0.97)	3.11 (0.98)
Curiosity	3.01 (0.95)	3.76 (0.97)*	4.24 (1.13)*	3.90 (0.78)	2.69 (0.84)	3.43 (1.00)
Intrinsic interests	3.25 (0.85)	3.45 (1.02)	3.98 (0.98)*	3.98 (0.76)	2.73 (0.91)	2.85 (1.08)

* Significant at $p \leqslant 05$.

Table 7
Classification of the participants in terms of the cognitive state.

	Dynamic content sequencing				Non-dynamic content sequencing			
	Low achiever	Medium achiever	High achiever	Total	Low achiever	Medium achiever	High achiever	Total
Flow	11	12	7	30	12	5	2	19
Anxiety	0	0	0	0	3	2	9	14
Boredom	0	5	5	10	0	5	2	7

interpretation that the dynamic content sequencing system might ensure the higher level of learner's experience.

5. Conclusions and discussion

Taken together the analyses presented above seem to demonstrate that the learning performance and learning experience should be juxtaposed in the analysis of the learning outcomes of e-learning systems. In particular, learning experience as a new parameter for adaptive e-learning systems could be warranted. Though it is not possible to present all learners with the same optimal learning experience, the fact that both low- and medium achievers might have less boredom or anxiety with the dynamic content sequencing system might be indicative. None of these possibilities has been demonstrated empirically before.

It is of course difficult to generalise from the conditions of the experiment to more comprehensive conditions in which the user may have optimal learning experiences on every e-learning system, and many other studies would be thus needed to confirm this interpretation. However, the data can be taken to suggest that, at the very least, care is needed when designing e-learning systems and that both learning performance (i.e., the level of the student's learning performance) and its matching level of learning difficulty need to be considered for the optimal learning experience. In particular, its predictive matching algorithm can take into consideration the learning experience parameter in its user modelling for effective adaptation.

5.1. Lesson learnt and limitations of the study

In this empirical study, we developed and evaluated an e-learning system called IT-Tutor. The apparatus devised for this study provided a reductionist e-learning situation, but in the context of the different learning activities: dynamic vs. non-dynamic. Comparisons of the two configurations in the present study allowed us to assess the potential value of the dynamic content sequencing in terms of learning experience available in this experimental context.

Looking at the flow states identified in each e-learning system (i.e., Table 7) some insights as to what the two systems are good or bad at arise. In particular, the fact that anxiety was not observed in the dynamic content sequencing system would hint some benefits of adaptive e-learning systems in terms of learning experience, at the very least.

Newly developing e-learning systems have been drawing much attention to the connection between the user's level of understanding and presenting the appropriate forthcoming learning content, as a primary direction of the future e-learning environment development (Mitchell et al., 2005). Our empirical study points out that the underlying driver of this approach should consider a new parameter, that is the optimal learning experience from the user's perspective rather than their learning performance only, which has been the norm in many adaptation processes.

However, implementing with learning experience is hard, because many prior studies have proposed no generally acceptable methodology for how to optimally locate the learner's cognitive states to the right learning experience. In fact, the empirical study in the present article was not able to answer these questions either. Instead, we noted that the dynamic content sequencing system, as a promising e-learning system, might be able to better support optimal learning experience thanks to its ability to adjust the forthcoming content for the learner's current knowledge level. This was the main motivation for this research, but it was not that clear for the expert learners.

The fact that some medium- and expert learners did not have the optimal learning experience with the dynamic content sequencing system was highly dependent on the matching algorithm that determines the forthcoming content. Our algorithm was one of the best predictive content-based learning methods, which are suitable for situations where users tend to exhibit an idiosyncratic behaviour (Zukerman & Albrecht, 2001). Several different statistical models have been proposed, but Breese, Heckerman, and Kadie's (1998) comparative study on the predictive performance of several predictive models indicated that Bayesian Network outperform the other models for a wide range of conditions. This technique is particularly useful when building an initial model on the basis of limited data and homogeneous subjects groups, since only a few learning contents are required to identify possible topics of interest for each subject group. In addition, we collected accuracy of the forthcoming learning content for the purpose of evaluation, counting the number of user attempts to return to a prior learning content after an action (*undesired effect*, see Section 3.3). It showed that only around 15% of the learners tried to return to the previous learning contents, which implies that our algorithm was not at critical issue.

That being said, the first evaluation in this paper suggested learning performance would not be the major determinant of seeing the difference between the adaptive e-learning system and the non-adaptive e-learning system. This perhaps indicates that the learning performance measures that are widely being used for assessing e-learning systems would not be very effective. Learning experience measurements alone, shown in Table 4, did not provide

Table 8
Feature analysis of the DCSS (dynamic content sequencing system) and the non-DCSS based on the findings from the experiment.

Feature	DCSS	Non-DCSS
Sequencing of learning contents (*supported by* Table 7)	Self-enforced learning and automatic sequencing is best for learners who lack prior knowledge. The mechanism helps the learners to concentrate on the contents rather than thinking about how to choose the appropriate learning	Non-DCSS is good for learners with high prior knowledge as they are free to browse the learning materials in their own way. However, beginners might suffer from anxiety, as they are unable to determine their own learning paths
Control over learning process (*supported by* Tables 5 and 6)	DCSS applications are good for low-achieving learners as the predetermined learning path helps them to take control over their learning activities	Non-DCSS is good for high achievers because learners have control over the learning path
Attention and concentration (*supported by* Tables 5 and 6)	DCSS applications give moderate levels of attention and concentration to all learners	Non-DCSS is not suitable for learners with high attention focus but low performance as they could suffer from anxiety
Learners' curiosity towards new knowledge (supported by Tables 5 and 6)	DCSS applications increase low achievers' curiosity about the domain of study	Non-DCSS helps in increasing curiosity among high achievers
Optimal learning experience (*supported by* Table 7)	DCSS applications could give an enjoyable learning experience to low achievers as they obtain a fully guided learning path, thus reducing feelings of anxiety	Non-DCSS is good for high achievers as they can freely navigate their own learning path, which could reduce the feeling of boredom

much indication of the benefits of the adaptive e-learning system. However, when both *learning performance* and its corresponding *learning experience* were considered together (see Tables 5–7), it can be seen that the lower or medium achievers would have gained certain benefits from the dynamic content sequencing system rather than the non-dynamic content sequencing system. These benefits may be seen as particularly important since the lower-to-medium achievers would be the primary target users of many e-learning systems (Johnson, 2005).

Of course, other samples in other contexts may give different results and the generality of these results can only be tested by further studies, which are now being planned. For instance, it is important in learning experience design to investigate how the adaptive Bayesian Networks systems themselves would learn from the learner's performance (i.e., machine learning process) and how they might determine the learner's flow states without reflective measures such as learning experience questionnaires. Also, one of the main benefits of the e-learning system would be collaborative learning (i.e., collaborative prediction method), and the flow experience from this social interaction should be also discussed (Ryu, Parsons, & Cui, 2012). Furthermore, given that our empirical domain in this article was only limited to Computer Science (CS) and Information Technology (IT), the sample population and context of the experiment might not warrant the interpretations made above. However, taken at face values, the results are encouraging. According to a widely agreed classification of discipline-specific teaching–learning approaches (Neumann, Parry, & Becher, 2002), the CS/IT discipline is classified as the 'hard-applied' field. Our findings can thus be quickly applicable to other 'hard-applied' disciplines, such as engineering. Of course, further studies are needed to rehearse similar interpretations in other disciplines, but our empirical findings are suggestive of the benefits of *'IT-Tutor'*.

Finally, there is a methodological limitation of this study in measuring learning experience. Several studies showed that learning experience is very subjective; hence a simple quantitative method might not be able to interpret the levels of engagement of learners as claimed in this study. In this sense, a hybrid approach of quantitative, qualitative (e.g., observation, interview, think-aloud protocol), or mixed methodologies (Johnson & Onwuegbuzie, 2004) are to be considered.

5.2. Using the results for future e-learning systems design and further work

In the case of adaptive e-learning system design, by the spirit of Mitchell et al. (2005), Koehler et al. (2011) and Kopcha and Sullivan (2008), it was agreed that expert learners might not favour the adaptive e-learning system for its rigidity, resulting in boredom. In this regard, we outlined the merits of this case based on our empirical findings. Table 8 below codes the above conclusions as guidelines to be applied in designing e-learning systems.

Considering learning experience in designing e-learning systems is very useful in deciding how learning materials should be organised and presented to the different types of learners. The use of an effective and appropriate organisation method is thus important to accommodate the different types of learners so that they obtain better learning experiences through highly engaging computer-based learning. This research suggests that the learning experience is a crucial factor in improving the quality and effectiveness of e-learning, but we have seen that not all learner groups would have equal merits. That is why Table 8 differently coded the design guidelines in terms of the two user groups. Of course, these two user groups are arbitrary in our analysis, so we may need further examination on the different learning styles rather than the classification by learning performance too (e.g., Al-Dujaily, Kim, & Ryu, in press).

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