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The impact of an automated learning component against a traditional lecturing environment

K.W. Maycock* **& J.G. Keating†**

*School of Computing, National College of Ireland, Ireland
†Computer Science, Maynooth University, Ireland

Abstract This experimental study investigates the effect on the examination performance of a cohort of first-year undergraduate learners undertaking a Unified Modelling Language (UML) course using an adaptive learning system against a control group of learners undertaking the same UML course through a traditional lecturing environment. The adaptive learning system uses two components for the creation of suitable content for individual learners: a content analyser that automatically generates metadata describing cognitive resources within instructional content and a selection model that utilizes a genetic algorithm to select and construct a course suited to the cognitive ability and pedagogic preference of an individual learner, defined by a digital profile. Using the Kruskal–Wallis H test, it was determined that there was a statistically significant difference between the control group of learners and the learners that participated in the UML course using the adaptive learning system following an examination once the UML course concluded, with p = 0.005, scoring on average 15.71% higher using the adaptive system. However, this observed statistically significant difference observed a small effect size of 20%.

Introduction and background

It is widely recognized that there is a need for a new digital driven pedagogy that leverages the emerging technology tools to bridge the gap between formal academic environments and the lifestyle of today's learners (Alvi, 2011; Sipilä, 2013). To build an automated approach capable of constructing suitable learning objects and promoting active participation for individual learners to online learning, consideration of the individual learner and the environmental contexts of the learning environment should be taken into consideration.

Current learning management systems (LMSs) like Moodle (Moodle, 2016), Sakai (Introducing Sakai 11, 2016), Blackboard (Blackboard | Reimagine Education | Education Technology and Services, 2016) and Desire2Learn (Desire2Learn Homepage, 2016) act as a framework for educational providers to organize and deliver their instructional content in a standard way. They also offer some blended learning facilities to promote a constructivist approach to learning, for example, using discussion forums. The approach used in many LMSs to support learning has been criticized for reinforcing the information transfer didactic style of delivering content, which does not promote knowledge creation or active learning (Littlejohn, 2003). Typically, no content adaptation is taken into consideration within LMSs; consequently, these platforms only act to transfer the educational sector into an online environment, including an easy-to-use interface to enable the management of educational material. Without an element of suitable adaptation embedded into these systems, these technologies could disadvantage learners as their learning would be constrained by the cognitive ability and pedagogical preference of the author of the instructional content compounded by the limitations of the LMS. Without appropriate interventions, these technologies could act as an interference to the learning experience. The influence of a lecturer's experience and

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Correspondence: Dr Keith W. Maycock, School of Computing, National College of Ireland, Mayor Street, Dublin 1, Ireland. Email: kmaycock@ncirl.ie

cognitive traits on the creation of instructional content for an online learning environment, coupled with the disconnect introduced by adopting an LMS between learners and educational providers, can lead to learners becoming autonomous, isolated, procrastinating and dropping out (Mazman & Usluel, 2010). The act of integrating information and communication technology into teaching and learning is a complex process (Bingimlas, 2009). Most practitioners would agree that the knowledge and use of information and communication technology within education should complement the experience and not act as a barrier, which is sometimes the case. Two primary issues have been identified through the literature to suggest challenges in the current LMS model. Firstly, retention rates for courses that are delivered through the use of a massively open online course have mixed results. It has been found that the completion rate for 90% of massively open online course courses was less than 14% (Breslow *et al.*, 2013; Liyanagunawardena, Adams, & Williams, 2013). Secondly, the rigidity of the systems, characterized by specificity, stability and transparency of function (Koehler & Mishra, 2009), results in these platforms acting as a transfer agent or reinforcing the information transfer didactic style of delivering content and not a replacement to the construction of knowledge transfer. Research suggests the learners themselves tend to use these platforms as content viewers (John, Thavavel, Jayaraj, Muthukumar, & Jeevanandam, 2016) and not every student profits from the learning assumed opportunities of LMSs (Lust, Collazo, Elen, & Clarebout, 2012).

There are many examples of learning technologies. They can be categorized into two broad categories: adaptive technologies for the delivery of individual content [e.g. adaptive hypermedia system (AHS; Brusilovsky, 2003)] and the technologies that help build competence [e.g. intelligent tutoring tools (Brown & Burton, 1978; Burton & Brown, 1979; Carbonell, 1970; Patel, Kinshuk, & Russell, 2000)]. The author of an AHS would create a student profile, using various approaches and then map pathways through the learning unit (Brusilovsky, 2003; Brusilovsky & Anderson, 1998; Brusilovsky, Eklund, & Schwarz, 1998; Conlan, O'Keeffe, & Tallon, 2006; Conlan, Wade, Bruen, & Gargan, 2002; De Bra & Calvi, 1998; Oppermann, Patel, & Kashihara, 1999; Specht, Kravcik, Pesin, & Klemke, 2001). This approach is not easily transferable across disparate subject domains and is constrained to the cognitive ability and pedagogical preference of the author of the AHS (Maycock & Keating, 2014). Intelligent tutoring tools were designed to enhance the skills of learners using the systems, typically constructed in specific nontransferable domains (Brown & Burton, 1978; Burton & Brown, 1979; Carbonell, 1970; Patel & Russell, 2000), for example, building competence in an accountancy domain (Patel & Russell, 2000). Traditional work carried out on intelligent tutoring in the 1970s and 1980s was restricted by the computational power of the time. Buggy (Brown & Burton, 1978) and West (Burton & Brown, 1979) were involved with the identification of shortcomings in the learning experience to infer strategies for increasing the learning experience, including the introduction of stimulus to ignite the experience. Scholar (Carbonell, 1970) was involved with a highly connected network of facts, concepts and procedures to aid in computer-assisted instruction. Currently, processing power is not an issue, and it is possible to implement strategies as seen in Buggy, West and Scholar as an on-demand strategy. Although these learning technologies have their strengths and weaknesses, they are constrained by the pedagogical preference of the author of the learning technology and are all subject to the specific system for which they are developed.

Modern approaches to adaptation allow for the learner to become the driver of the educational experience and personalize their own experience (Dolog *et al.*, 2007). Although these learning technologies have their strengths and weaknesses, they are constrained by the pedagogic preference of the author of the learning technology and are typically designed for integration into a custom built system and not transferable across multiple LMSs. Several researchers have identified the challenges of a standard approach to evaluating the effectiveness of adaptive systems considering the internal complexities and the usability issues raised by end users (Ricci & Del Missier, 2003; Weibelzahl & Weber, 2002). Research also suggests that the learners themselves tend to use LMSs as content viewers (John *et al.*, 2016) and not every student profits from the learning-assumed opportunities of LMSs (Lust *et al.*, 2012).

Against this background, this experimental study was designed to create and evaluate an adaptive learning system that is capable of creating instructional content suited to the cognitive ability and pedagogic preference of a learner, independent of domain. The approach used an experimental design to investigate the performance of students engaging in a Unified Modelling Language (UML) module delivered by an adaptive learning system against students engaging with the same module delivered through a control group (traditional lecturing approach). Students were randomly selected for each group. The null hypothesis for the study was that for first-year undergraduate students, utilizing a technology-driven adaptive approach has the same effect on student performance as participating in a traditional delivery of a UML module.

The following section introduces the theoretical framework that underpins the experimental study. In particular, the design of the adaptive system and a suitable digital personal profile are described.

Theoretical framework

This section describes the design requirements of the adaptive learning system and also defines a suitable digital personal profile that is required by the adaptive learning system to be able to automatically generate instructional content suited to the cognitive ability and pedagogic preference of a learner.

Designing an adaptive system for evolving instructional content

The core function of the adaptive learning system is to search an instructional repository and take chunks of instructional material to create courses suited to the needs of disparate learners. The classification of suitable algorithms for solving such problems is known as evolutionary algorithms. Evolutionary algorithms, unlike traditional methods like linear programming, scale extremely well. Additionally, the evolution process is not a linear evolution; during the initial phase (early epochs), the evolutionary strategy excels exponentially, and over time, the evolution rate degrades. The following techniques were considered when constructing the adaptive learning system: ant colony optimization (Dorigo, Maniezzo, & Colorni, 1996), simulated annealing (Kirkpatrick, 1984), cultural algorithms (Reynolds, 1994), reactive search optimization (Battiti, Brunato, & Mascia, 2008), external optimization (Boettcher & Percus, 2001) and genetic algorithms (GAs; Mitchell, 1998). The study used GAs as the core element of the adaptive learning system when creating instructional content. GAs are simplistic in design and mimic natural selection. The process can be defined as follows:

1. An initial population of candidate solutions is generated from the full solution space (typically, the solution space is not feasible to search linearly); these are referred to as individuals. Each of these individuals in this study was a sample course.
2. Following the initial creation of the sample population, each individual is evaluated. This evaluation scores the individuals by using a fitness function, which awards a numerical score associated with the fitness of the individual for solving the problem.
3. The algorithm then follows a cyclical approach until an exit strategy is met. This includes the following operations:

a. Selection: Individuals are randomly selected to proceed to future epochs of the evolutionary process according to their fitness value, with better individuals having a greater chance to proceed to future generations of the population.

b. Crossover: A number of individuals are randomly selected. Parts of the individuals are randomly swapped to created new individuals.

c. Mutation: This process is introduced to ensure that the algorithm does not arrive at a local minimum (crowding problem), where the initial population of individuals do not include sufficient content to generate a suitable course for an individual learner.

After each epoch of the algorithm, all individuals within the population are evaluated by using the fitness function prior to the next round of selection, crossover and mutation. To enable the adaptive learning system, the flexibility to adapt content by using multiple pedagogic approaches, the following conditions were identified as key requirements for the searching strategy:

- An author-controlled adaptive threshold metric should be included in the adaptive system to allow the author to set the exit requirement that should exist when constructing suitable courses [the minimum expected learning experience (MELE)]. The MELE is an approximation of the learner's capacity for a successful

learning experience measured as a percentage. The MELE is used by the GA as a threshold for the fitness function. On each epoch of the evolution process, the current generation of content is evaluated and measured against the MELE. If the content is not suitable (i.e. the fitness value of the most optimal course generated is less than the MELE), the evolutionary process continues until the GA constructs a suitable course for the learner.
- An author controlled adaptive metric to favour instructional content based on the cognitive resources within the content. With the expected growth in e-learning, this metric will allow authors using different pedagogic strategies the freedom to control the evolutionary strategy based on strengths of individual cognitive traits.
- The functionality should allow for fast identification of suitable objects, the dissemination of the instructional content and recombination of various components, while keeping track of the original authors of the instructional content.

Maycock and Keating found that, using rank and truncation selection, a single-point crossover strategy and a mutation rate of 8% were optimal for evolving instructional content by using GAs (Maycock & Keating, 2008).

Suitable digital profile

In order to develop personalized content for each individual interacting with the adaptive learning system, a suitable personal profile associated with the environmental contexts of an online environment is required. The profile should include the cognitive ability of the learner to ensure that adaptation can occur across multiple domains and not be constrained by domain adaptation typically found in AHS. The Cattell–Horn–Carroll definition project (McGrew, 2003) is involved with the classification of a taxonomy of human cognitive abilities, in terms of broad and narrow categories; these are auditory processing, fluid intelligence/reasoning, general (domain specific) knowledge, kinesthetic abilities, long-term storage and retrieval, olfactory abilities, psychomotor abilities, psychomotor speed, reading/writing abilities, short-term memory, tactile abilities and visual–spatial abilities. Taking the environmental contexts of an online learning environment into consideration, these categories are reduced to the following: auditory processing, fluid intelligence/reasoning, general (domain specific) knowledge, long-term storage and retrieval, reading/writing abilities, short-term memory and visual–spatial abilities.

Additional reductions can be applied to the initial list of categories as defined by the Cattell–Horn–Carroll definition project. Firstly, the general (domain specific) knowledge category removed as our proposed digital profile should be independent of domain experience or knowledge level allowing adaptations to learner profiles without the requirement of the educational history of the individual. Next, fluid reasoning was also eliminated from the requirements as it is associated with mental operations to solve problems and would be deemed more suitable to specific domains or gaming applications. Finally, auditory processing was also removed as the effects of robotic voices on online learning environments are unknown; however, it can be assumed that there would not exist enough robotic voices to suit each individual learner. The reduced set of categories is defined as the following: long-term storage and retrieval, reading/writing abilities, short-term memory and visual–spatial abilities.

Considering that the vast majority of Sharable Content Object Reference Model learning objects currently available in digital repositories do not have appropriate associated metadata (Friesen, Roberts, & Fisher, 2002), the classification process for the creation of metadata describing learning objects should be automated, and there should exist a mapping of this generated metadata against the cognitive ability and pedagogic preference of a learner independent of the domain content being constructed by the system. The long-term storage and retrieval category/long-term memory removed as the learning component will initially generate content that is independent of educational history. This category would have great benefit when considering the associative learning skill of the learner; however, as there does not exist any learning experience initially from each student, the associative learning skill cannot be used. The visual, aural, read/write and kinesthetic (VARK) (Fleming, 1995) element represents the visual–spatial category; as the learning environment conducts learning experiences within an online learning environment, the VARK learning style is restricted to suit the visual constructs of the learning unit. The reading/writing ability category is defined by the readability level and the information processing speed of a learner. These elements along with the working memory of the learner identify the constructs for determining a unit of memory ['chunk' as described by Miller (1956)] when interacting in an online learning environment. In particular, the readability level of instructional content is used as a minor indicator for the suitability of instructional content for a given learner.

The following section presents the adaptive learning system that was created to bridge our perceived gap between modern learners and archaic LMSs.

Adaptive learning system

The adaptive system that was designed for the study consisted of two individual components: content analyser and a selection model.

- Content analyser is designed to automatically generate metadata for instructional content that characterizes the cognitive resources found within the instructional material as defined by the digital profile (Maycock & Keating, 2014).
- Selection model is the nucleus of the learning system; it identifies and re-engineers instructional content from created learning object repositories by using a GA to produce mathemagenic content suited to the individual needs of each learner interacting with the learning component.

Figure 1 shows an overview of the adaptive system. It can be seen that raw instructional content is passed through the content analyser, which generates metadata files describing the instructional resources in terms of the cognitive impact that the resource would have on a learner. These metadata files form a repository of Sharable Content Object Reference Model metadata files. A specification of concepts is created by an author of a course within the adaptive learning system. During the creation of the specification, the MELE, as defined in the preceding texts and cognitive traits (the author sets the cognitive traits field, indicating which cognitive trait is of greater importance. For example, if the author needs to generate instructional content that is focused on the working memory of the learner, then the author would select the appropriate CT value to strengthen the evolutionary process towards WMC), values are set. The adaptive system creates an individual course consisting of interconnected HTML files. The content of each HTML file that is created and is supporting links is suited to the digital profile of the individual that the course is created for. Figure 2 shows an example of one of the HTML pages that were created by the system. As can be seen, the navigation to the next concept is located in the bottom right of the page with additional links to extra information highlighted by the information sign.

When a student is logged in and selects a specification, the system appends the learner's profile to the specification of concepts to create an ideal specification, suited to the learner. The selection model uses the repository created by the content analyser when constructing a new course for a learner. The evolutionary approach of generating content evaluates new courses against the ideal specification until the MELE has been satisfied, and the course is made available for the learner.

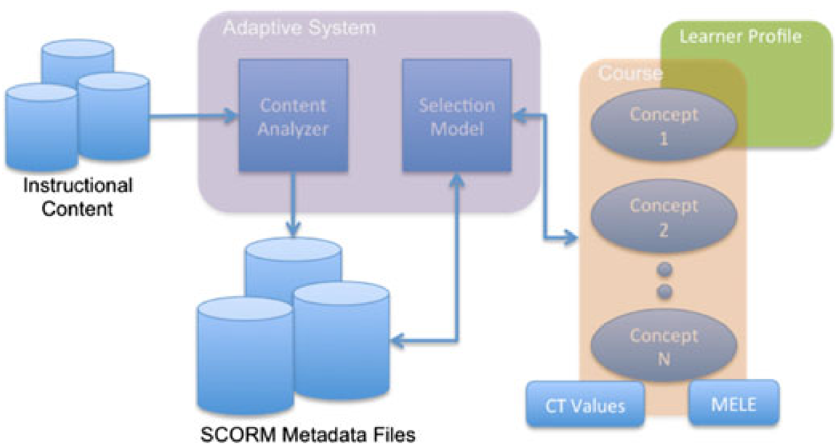

Figure 1 Protocol for adapted learning system. [Colour figure can be viewed at wileyonlinelibrary.com]

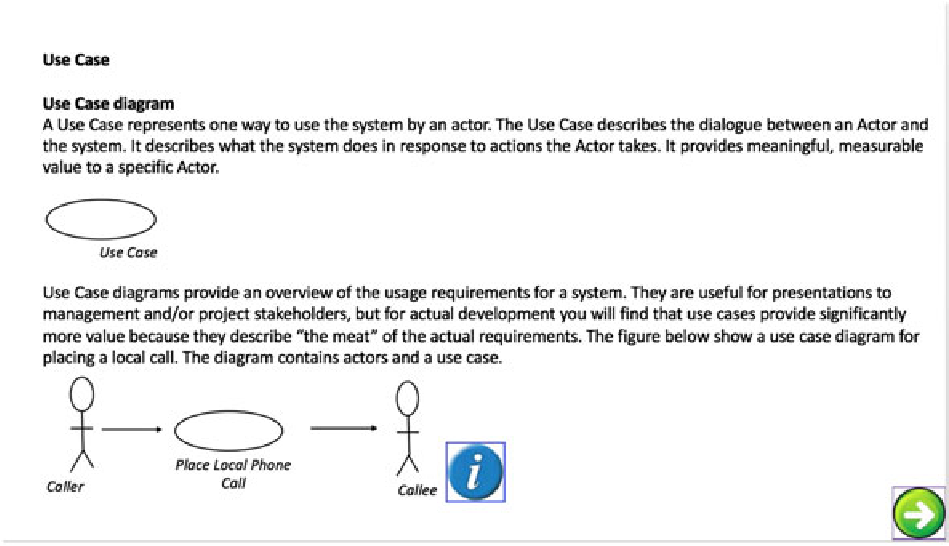

Figure 2 Sample output HTML page created to explain the concept of a UML Case. [Colour figure can be viewed at wileyonlinelibrary.com]

Evaluation of the adaptive system

This study required the creation of multiple digital resources encapsulating a module descriptor for an introductory course on UML. Eight instructional authors were involved in generating the instructional content. All selected authors held a PhD in Computer Science and had at least 3-year experience designing computer-related courses and lecturing prior to completing the resources for the study. Each author constructed content to describe each of the concepts within the module descriptor. The authors could link to external content when creating the resources. Following the creation of these resources, they were analysed by using the content analyser to generate a repository of metadata files associated with the cognitive resources found within the instructional content. This repository was available to the adaptive system for creating individual UML courses for learners.

The following section details the evaluation of students participating in a short UML course by using the adaptive learning system against students taking the same UML course delivered in a traditional lecturing environment.

Learning component evaluation

Thirty-nine students took part in the evaluation process of the learning component. Initially, all the students completed a survey to determine any previous experiential learning in relation to UML. The surveys showed that no student had any previous learning experience with UML content. The students were required to complete four tests to construct their personal profile. The evaluation tests were carried out in a studio classroom environment, where each student had ample room and access to their own computer for the duration of the experiments. Once the students completed the initial tests, the students were randomly divided into two cohorts: the control group was to be subjected to a traditional introductory lecture on UML, delivered by an experienced faculty member that had over 10 years of experience delivering UML modules, and the other group remained in the studio classroom to participate in an introductory lecture on UML developed by the adaptive learning system for each individual learner. The distribution of students between the groups was investigated to determine if there was a possible bias introduced by the random selection of the groups. The metrics that were considered were the readability level of the learners, the working memory capacity (WMC) and the VARK scores of the learners received after completing the initial preparation tests. Both the VARK scores and the readability of the learners were comparable in their distribution across groups. Within the distribution of scores for the WMC metric, there existed a large group of learners who scored a low score within the group selected for the automated component. It was expected that this grouping would have a negative impact on the learning potential of the cohort using the adaptive automated component. Students using the learning component were monitored by two laboratory attendants to ensure that once the student had completed the learning content, the monitor was switched off. Both groups were not allowed to take notes throughout the learning experience and completed the same exam on UML immediately following their learning experience.

Examination process

Two independent examiners marked all the completed UML tests for both groups. The examiners had no knowledge of the classification of the learner that completed the test, to ensure that the examination process was not reflective of a single examiner's interpretation of the examination scripts. A Persons' correlation between the two sets of results from both examiners was carried out to ensure the consistency and validity of the results obtained, which yielded a correlation of 0.806. Because there existed a strong correlation between both sets of results, no further investigation was conducted to determine the validity of the results obtained. All further investigations of the results obtained by the learners used the average of both results determined by the examiners.

Investigating the exam performance of students using an adaptive learning system against a traditional control group

The Kruskal–Wallis *H* test was identified as a suitable test to understand whether exam performance, measured on a continuous scale from 0 to 100, differed based on pedagogy design. The test selected as an investigation of homogeneity of variance (Levene's test of homogeneity) yielded $p = 0.24$, demonstrating that homogeneity of variance did not exist for the exam scores of the different populations, and consequently, a *t*-test was not suitable for investigating the differences between the groups.

The study design adhered to the assumptions of performing a Kruskal–Wallis *H* test, as follows:

- **Assumption 1:**
The dependent variable should be measured at the ordinal or continuous level. In this study, the dependent variable was measured on a continuous scale ranging from 0 to 100.
- **Assumption 2:**
The independent variable should consist of at least two categorically independent groups; these are traditional environment and adaptive learning system.
- **Assumption 3:**
There should be independence of observations. Once the students were randomly divided into their groups. Each group of students was separated for the duration of the experiment. No student participated in both cohorts.

The dependent variable was selected as the assessment component, while the independent variable was identified as the pedagogy design, with two distinct groups: traditional lecturing and adaptive learning system.

A Kruskal–Wallis *H* test showed, as seen in Table 1, that there was a statistically significant difference in examination score between the different groups of students based on pedagogy design ($X^2 = 7.823$, $p = 0.005$). The results differed on average by 15.71% between the populations. The effect size was calculated as 20%, meaning that 20% of the variability in exam scores can be accounted for by being associated within a particular group.

Correlation between the minimum expected learning experience and the actual results

The effectiveness of the fitness function within the GA is a measure of the correlation between the MELE for each learner and the actual result obtained after completing the learning experience. Throughout the evolutionary process, the MELE was initially set to 70%. However, due to the small repository that existed for the testing phase, a degrading element was incorporated into the evolutionary component to ensure that each evolutionary

Table 1. Kruskal–Wallis test, grouping by pedagogy design for examination component for a short course on Unified Modelling Language (UML)

	Examination scores
Chi-square	7.823
d.f.	1
Asymp. sig	0.005

process would produce a course for each individual learner interacting with the learning component. The correlation between the MELE and the actual results obtained was 0.274, which implies a weak positive correlation. Further investigation identified two possible outliers, which, when removed, yielded a correlation of 0.57. The potential outliers were not removed as both possible outliers were within two standard deviations of the mean of the results obtained. With additional resources for further studies, it would be expected that the MELE could be refined and a stronger correlation between the expected result and actual result from a learning experience be achieved.

Conclusion

This study investigated the performance of students participating in a UML course by using an adapted learning system against students taking the same UML course participating through a traditional lecturing environment. It was found that there exists a significant difference between the groups, $p = 0.005$, with the students that participated in the study using the adapted learning system scoring on average 15.7% higher in an examination following the delivery of the course. The size of the effect of the significant difference was small. It is recognized that the evolutionary process was limited due to the number of content developers that were involved in generating the initial raw instructional content, which had an impact on the adaptive system automatically generating instructional content to a predetermined expected learning outcome. A reasonable conclusion would be that the adaptive system outperformed the traditional lecturing approach; however, if more content was available to the evolutionary process, it would be expected that there would exist a larger effect size between the groups.

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