

# Intelligent Learning Systems Where are They Now?

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**Abstract**— This paper documents the work in progress in creating a new Intelligent Learning System. The paper introduces the issues of relevance when developing such systems. It examines briefly the state of the art followed by key approaches to addressing the major research questions in the field. We introduce the *Realise<sup>it</sup>* system outlining the philosophy behind the system, and also the novel approach which we are taking to its implementation. Following this we explore the as yet unanswered research questions which must be addressed in order to develop what we believe is a truly intelligent learning system; one which can appropriately and intelligently guide learners (students) along their individual learning paths throughout their lives.

**Keywords**— Intelligent Learning, ITS, Artificial Intelligence, Data Mining, Knowledge Management.

## I. INTRODUCTION

Over the last twenty years we have seen an explosion in the number of computer based training systems (also: VLE, LMS, LCMS, ITS and e-learning). With the internet we have a plethora of web based learning systems, all of which can utilise a variety of ways to present the material to students: text, graphics, audio and movies. The majority of educational institutions at third level have now implemented some form of managed learning environment comprising a backbone Virtual Learning Environment [1] of Moodle, Blackboard, Caroline, etc. These systems essentially provide knowledge management of the educational content, assessment and also a level of administrative assistance. To increase the attractiveness of these systems to learners, over the last few years these systems have embraced new educational technologies. The use of this technology has long been questioned, particularly around issues of relevance such as - to what extent do these new technologies assist the student in gaining the required knowledge?

A number of education technology researchers have investigated this issue, for example Clark and Mayer [2] have investigated an *interaction enhanced* e-Learning system (using natural language, first and second person pronouns for assessment and feedback). Their approach to using novel technology was benefit driven, not just because it was

available but because following scientific investigation it was found to be superior to other (evaluated) approaches.

However, adding new technology to a learning system that does not contain any real intelligence raises many questions. Many of the aforementioned VLEs utilise homogeneous learning paths for all learners. These systems achieve an economical educational approach both in terms of finance and educational benefit to all students. More flexible approaches which adapt to individual learners' needs have been attempted. One of the primary research areas is Intelligent Learning Systems [3, 4] (sometimes referred to as Intelligent Tutoring Systems). This is an area of AI research which fundamentally highlights where cognitive interaction of man and machine are critical for the best performance of both systems.

Some researchers have suggested that further work is required to improve issues around homogenised e-Learning systems together with poor support and feedback for the individual learners.

## II. INTELLIGENT TUTORING SYSTEM

An Intelligent Tutoring System (ITS) as defined by the AAAI [5] is “educational software containing an artificial intelligence component. The software tracks students' work, tailoring feedback and hints along the way. By collecting information on a particular student's performance, the software can make inferences about strengths and weaknesses, and can suggest additional work.” The AI element is the key component to individualised learning systems. Over the last ten years a number of different systems have been developed which provide intelligent tutoring. These systems, however, have developed along very narrow lines in terms of subject area and educational objectives. An example is algebra for first year university Mathematics students. Tom Murray a significant researcher and author in the ITS and adaptive learning systems field, was critical that the ITS field lacked vision [6]. In 1999 he summarised the focus of research in ITS as applying to: particular subject domains (like algebra or calculus), learning environments which embodied either an instructional metaphor or a traditional curriculum metaphor only and those which were pedagogy or performance oriented solely. His 1999 summary of the state of the art sadly remains largely unchanged today. Murray identified a number of areas which he felt were important for future research in order to

move the field forward. He noted that these were neglected in the work up to 1999, and today they remain largely uninvestigated.

One central element of research which has been identified as requiring significant exploration is the human computer interaction in learning systems. How information is presented to the learner is a complex problem, requiring the direct input from a number of interdisciplinary specialists such as: HCI, Educationalists (both pedagogical and androgogical), Cognitive Science and Software Engineering.

### III. MAN & MACHINE

Understanding the needs of both man & machine is critical when creating an effective intelligent and adaptive learning system. It is *relatively* straightforward to assess the state of knowledge in an artificial system. However, it is somewhat more *complex* to assess the current state of knowledge in a human learner. From a human psychology perspective, through profiling and observation of the individual, an estimation of the knowledge profile of the user is possible. The degree of belief one places in this is influenced by a number of correlated factors including: the level of profiling, and the techniques used in this profiling [7]. Effective user profiling is closely associated with the development of a highly coupled human computer interaction [8]. Many studies have identified differing profiling techniques (e.g. learning style profiles [9, 10, 11]), all of which can profile particular elements of the user, using questions ranging from 10 in number to 1000 or more. New approaches that have been used to successfully assess the interaction of users and systems, include those which combine traditional profiling with theories of *Cognitive Load* [12] on a student as he/she interacts with the system. Measuring passive interactions with the systems through various techniques such as head and eye tracking, or EEG, can assist in improving our understanding

of the HCI process and what most suitably works with individual learners [13].

### IV. REALISE<sup>IT</sup> INTELLIGENT LEARNING SYSTEMS

The Realiseit Intelligent Learning System is currently a work in progress, (see Figure 1, which depicts a typical view in the system). A number of key modules have been completed including the Artificial Intelligence Engine (AIE), see Figure 2. The AIE is tasked with providing the differing system modules with the specific intelligence to dynamically modify and develop each student's learning path.

The approach builds upon the current state of knowledge concerning expert systems. This is achieved through the use of *evidence based decision (EBD)* making. Our EBD approach utilises proactive and passive assessments coupled with profiling to create an evidence profile which can feed into an innovative blend of allied algorithms such as: Bayesian Reasoning [14], Simulated Annealing [15], Information Theory [16], Graph Theory [17], Fuzzy Logic [18], Classification Trees [19], Nonlinear and Ordinal regression techniques [20].

The Realise<sup>it</sup> system attempts to embrace the issues raised by Murray. The learning system is enhanced with a blend of methodological approaches including instructional metaphor, traditional curriculum metaphors, pedagogy-oriented and performance oriented metaphors, all united in a single environment. This approach facilitates the larger objective of enabling the system to be applicable across a variety of differing subject areas such as Math, Science, Languages, Business, History and Social Sciences.

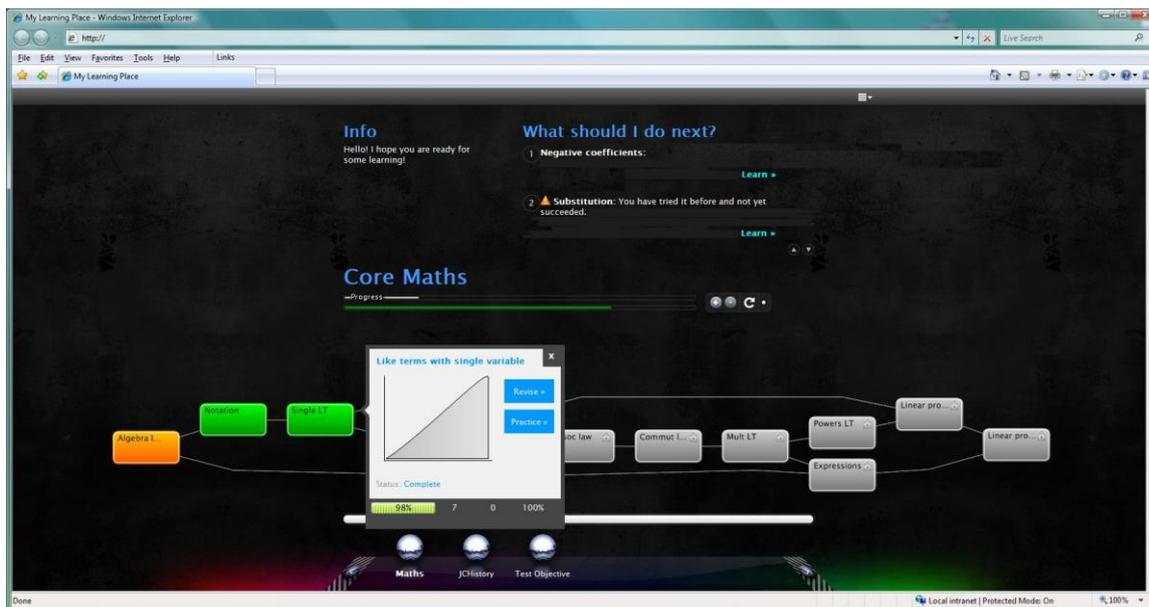
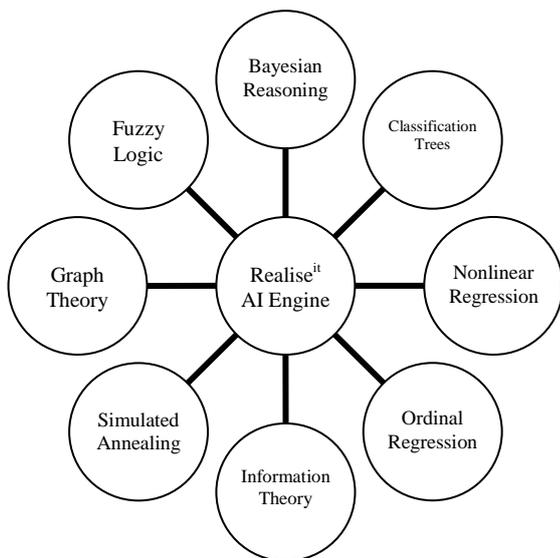


Figure 1 Screenshot of Realise-it Intelligent Learning System



**Figure 2 Artificial Intelligence Engine**

The primary goals of the Realise<sup>it</sup> project that have been achieved so far provide the following core design features:

- Multi disciplinary learning approach. The system provides a single environment for the student to learn a broad range of subjects such as Languages, Math, Science and History. A learning objective for one individual may include learning items drawn from different subjects. This novel approach is as a result of trials which have shown that individual student learning paths typically require skills drawn from a broad range of disciplines.
- Individual dynamic learning paths. Each individual learner has a dynamic learning path for their particular learning objective. The learning path is integral to the navigation through the educational material and is consulted (and possibly modified) continuously during a learning session. This technique is one of our approaches to ensure that the user can always determine “where am I?” in relation to their progress towards intended learning objectives.
- Focus on individual learning and appropriate learning designs. The system is designed to reduce the technology noise that is often present in eLearning applications. This is particularly acute when significant amounts of valuable “learning time” are devoted to solving technology problems, instead of addressing learning problems.
- Flexible and adaptable learning environments. The system has been designed to embrace Cognitive load theory [21] and its impact upon Learning Design, creating a modern flexible learning system. Using the Learning Design approaches and standards of IMS Global (IMS-LD) [22] as a foundation, our system is self-intelligent. This provides intelligent flexibility to an individual learner’s desired pedagogical (or androgogical) approach.

Trials of the system are currently underway and it is expected that further publications will document the results of these trial when they have been completed (expected later in 2009).

## V. FUTURE WORK

At present we have identified two key areas of further research which we expect will significantly enhance the understanding of intelligent learning systems. Initially we will focus on how intelligent learning systems can become even more intelligent and how they can best be utilised in an efficient *man and machine* manner. To achieve this a more full understanding of the profile of both the learner and the content is required. We will focus on:

- Behavioural assessment & modelling
- Cognitive assessment & modelling
- Learning style assessment & modelling

This will enhance our approach to developing a suite of tools to accurately instruct and assess the individual learner across a range of differing specialist fields, subject areas and multi disciplinary learning path objectives. This will ensure that the system continuously adapts (a) assessment methods, (b) content delivery vehicles and (c) the learning paths for a wider range of subjects and individual learners.

A second key area of work is *how* to fully embrace interoperability and usage of differing educational content. Content presentation and navigation is tightly coupled with the advantages of technology drive education and also cognitive loading. Improper usage of technology may purely divert attention away from the learning objective. Equally it is likely that cognitive profiling may indicate where novel usage of new technology may be more effective, for example with special case learners such as those who have an intellectual disorder or an attention deficit disorder.

It is the marrying of cognitive psychological techniques and artificial intelligence techniques that, we suggest, will bring about the next generation of intelligent learning systems.

## VI. SUMMARY

In this paper we have briefly explored the work in progress in creating the Realise<sup>it</sup> Intelligent Learning System. The paper introduced the issues of relevance in developing such a system. It examined briefly the state of the art followed by key approaches to addressing the major research questions in the field. We introduced the Realise<sup>it</sup> system outlining the philosophy behind the system and also the novel approach which we are taking to its implementation. Following this we identified the outstanding research questions which must be addressed to ensure a truly intelligent learning system which can appropriately guide learners along their individual learning paths.

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