Personalised-adaptive learning – an operational framework for developing competency-based curricula in computer information technology

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Abstract: In this paper, we explore the intersection of grounded theory in cognition and learning with the operational frameworks needed to develop and evaluate adaptive learning systems. As a test case, we studied an online personalised competency-based CIT curriculum at Northern Arizona University (Flagstaff, Arizona, USA). Our approach focused on strategies for adding adaptive learning capacities to an extant learning management system, with particular attention to cost-effective yet evidence-based approaches for improving learning outcomes. We designed elements that would enhance feedback and remediation for students, which required developing software engines that could integrate data collection and analysis. Such capacities are essential to drive evidence-based educational practices for CIT undergraduate and graduate programmes. Research led to a conceptual model and the operational facets for personalised-adaptive learning CIT educational environments. The conceptual and operational model described herein is called SIGNAL CIT Education – Serial Integration of Guiding Nodes for Adaptive Learning in CIT Education.

Keywords: personalised learning; adaptive learning; competency-based learning; evidence-based learning; e-learning; e-teaching; learning assessment; misconception development; knowledge systems; CIT curricula; computer and information technology.

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Alison Leigh Brown is the Associate Vice President of Academic Affairs in Extended Campuses and Professor of Philosophy at Northern Arizona University. She has been charged with directing the academic development of personalised learning. Personalised learning enables motivated students to earn a respected university degree quickly and more affordably by customising online coursework to match students' learning preference, goals, and prior experience. She has authored four books and numerous articles in her field. She has worked with faculty to develop many degree programmes for time- and place-bound, highly motivated adult students. After receiving her PhD in Philosophy from the University of Massachusetts in Amherst, she came to NAU in 1989 and taught various subjects including philosophy, humanities and women's studies before joining NAU-Extended Campuses in 2000. She was appointed to her current position in 2012.

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1 Introduction

We describe the methodology and research foundation for a personalised and adaptive learning environment called *SIGNAL CIT Education* – serial integration of guiding nodes for adaptive learning in CIT education. The acronym of *SIGNAL* acknowledges emergence of inclusive and adaptive environments during a period of very aggressive implementation of hybrid and totally online courses at all levels of education and training. However, inclusive-adaptive hybrid and totally online environments have been elusive and understudied. Tashiro et al. (2010, 2011, 2013, 2014) and Garcia-Ruiz et al. (2011) described how the lack of evidence-based frameworks for hybrid and totally online learning results from complexity in studying and implementing such educational frameworks. Additional complexity results from disagreement about which theoretical frameworks should guide systematic studies of the enormous diversity in hybrid and totally online educational environments (Tashiro et al., 2011; Rudak and Sidor, 2011).

We previously analysed impacts of healthcare technologies on care planning and delivery and found important analogues between the transformation of healthcare and the transformation of evidence-based practices in education. Through these types of analyses, we identified a variety of problems within education. As we did in previous studies of healthcare, we sorted educational problems into one of three categories – micro, meso, and macro levels (Johnson and Tashiro, 2010).

Micro level problems tend to be those appearing at the individual level. For example, in education, the individual level would be the student. From our perspective, the critical micro level problems are the gaps in our knowledge related to educational environments and their effectiveness. To date, we feel confident that there are at least ten gaps in knowledge about how educational environments 'really work' to change an individual's learning outcomes and willingness as well as ability to sustain behaviours related to learning (Tashiro et al., 2014; Garcia-Ruiz et al., 2011). In brief, we argue strongly that there is scant empirical evidence on the structure and function of educational environments that will personalise education in ways that optimise individual learning outcomes.

For example, over a seven year period, we identified a critical micro-level set of knowledge gaps related to educational environments and their effectiveness. These gaps emerged from a review of a large and diverse research literature (Tashiro et al., 2014; Garcia-Ruiz et al., 2011). The US National Research Council (2005) offered a streamlined list of critical issues in developing expertise, which remain hallmarks of what educational methods and materials should provide. Extensive reviews also were published by the American Association for the Advancement of Science (2004) and Federation of American Scientists (2006).

Tashiro et al. (2011) studied the critical issues outlined by the US National Research Council (2005) and expanded the research literature review to discover a broader set of gaps, some that had been identified in the National Research Council analysis, but others that had not been identified. To date, we feel confident that there are at least ten gaps in knowledge about how educational materials 'really work' to change an individual's learning outcomes and willingness as well as ability to sustain behaviours related to learning:

1 How does an educational environment impact disposition to engage in a learning process?

2 What are the relationships between the level of realism in an educational environment and learning outcomes?

3 How do you define the threshold of experience within an educational environment that leads to measurable learning outcomes?

4 What are the knowledge domains being instantiated during learning?

5 In what knowledge domains are learning instantiations being retained and how stable is the retention?

6 What is the disposition to act on the knowledge gained during work within an educational environment?

7 How accurately can instantiated knowledge be transferred?

8 What learning outcomes (conceptual and performance competencies) are developed during the learning process while working within an educational environment?

9 How are misconceptions developed during and sustained after working within an educational environment?

10 How is learning impacted by teacher-student and student-student social networks or e-communities?

Since these gaps have not been adequately bridged for generalisable educational environments, truly inclusive and adaptive educational environments have been hard to build and evaluate. To complicate matters, and despite a rapid increase in use of hybrid and totally online courses, there are few sensible and empirically supported theoretical frameworks for design and implementation of hybrid (sometimes called 'blended') and totally online courses.

Students' formation of misconceptions is a keystone knowledge gap and we developed research models that allowed us identify how misconceptions become instantiated. Preliminary studies showed us how understanding misconception development would advance understanding of other knowledge gaps (Tashiro et al., 2014).

In contrast to micro-level problems, meso level problems occur at the level of course or learning environment organisation, such as educational materials and commercial learning management systems or other educational technology brought into teaching-learning-assessment environments. Meso level problems emerge when educational materials and learning management systems are used to provide singular solutions that seldom meet the idiosyncratic needs of diverse departments and other units within academic institutions. As an example, Tashiro (2009) identified unethical issues in ways faculty selected and used educational materials as well as issues with academic publishers' not producing evidence-based instructional materials (books, images, digital learning objects, test banks, content for learning management systems) and educational technologies (course cartridges and websites, learning management systems – some with a capacity for adaptive learning).

We argue one type of macro problem evolves at the level of institutional organisations. Examples include: department structures within a college; collaboration of colleges within a university; and the impact of government mandates typically found within state-funded universities as well as within city or county supported community colleges in the USA. A second type of macro problem evolves when an academic unit or institution decides to create a new model for a teaching-learning-assessment system. Problems become evident when developers must adhere to rigid external requirements (e.g., accreditation, licensing requirements for professional education). This second kind of problem inhibits development of innovative online learning models that are outside the norms of an educational institution's other course structures, even if the proposed model has strong evidence for actually improving students' educational outcomes. Not unrelated to this second macro problem we found a suite of related problems:

1 increased workload required of faculty and administrators to create evidence-based educational environments

2 lack of resources to create educational environments especially with mandates for integrating emerging educational technology (which may not be sufficiently studied to be called 'evidence-based')

3 accommodating new types of organisational relationships and change management when new models of education are being implemented within a department, college, or across an entire university.

Certainly, we do not make the claim that micro, meso, and macro problems are independent of each other, which adds to the complexity. However, we have made the argument in earlier papers that changes proposed for education should have some kind of empirical support for improving educational outcomes (see summary in Tashiro et al., 2014). Sadly, such empirical foundations are the exception rather than the rule.

In order to develop a rigorous framework for evidence-based education, we formed two educational teams to examine the problem areas listed above and explore ways to create and implement evidence-based models for online learning. One team was located at Northern Arizona University (NAU) (Flagstaff, Arizona, USA). The second team originated at the University of Ontario Institute of Technology (UOIT) (Oshawa, Ontario, Canada), subsequently working as part of a research and development group in the Incubation Programme at the Hong Kong Science and Technology Park and then with a research and development group called Maxit Systems in Tucson, Arizona (USA). A key difference from many online learning development collaborations is that these two teams both focus on competencies rather than credit hours or courses as defined in the traditional sense. Furthermore, before meeting each other these two teams had worked across the micro-meso-macro levels to examine how individuals learn, how misconceptions could be assessed in individual students, and how to build teaching-learning-assessment systems for online learning that were adaptive in the following ways:

1 personalising an educational experience for students

2 providing feedback and remediation pathways

3 building dynamic knowledge systems integrated into the many facets of any teaching-learning-assessment environment.

Finally, these two teams used concepts and technologies from the electronic patient record systems of healthcare to figure out how to create truly personalised-adaptive educational environments. As observed in many healthcare settings, our teams used combinations of commercially available software engines and software developed by academic teams to create the most appropriate educational systems for meeting the idiosyncratic needs of both the institutional operations base and the student populations served by the respective institution.

2 NAU personalised learning

NAU has a main campus in Flagstaff, Arizona (USA), as well as an extended campus educational system – a network of 34 satellite campuses spread throughout the State of Arizona. The NAU Flagstaff main campus and extended campuses have parallel administrative structures. Within the extended campus network, NAU faculty and staff built a personalised learning (PL) online educational environment. Dr. Alison Brown is the head of PL. She also serves as Associate Vice President of Extended Campuses. Dr. Brown helped develop the initial structure for PL.

PL development was partially funded by a $1 million grant from EDUCAUSE and the Bill and Melissa Gates Foundation. The online interface was designed in partnership with Pearson learning. PL officially launched on June 3, 2013 with three bachelor degree programmes: computer information technology, small business administration, and liberal arts. These programmes are entirely online and self-paced. All content is available to the student at the time of enrolment. Consequently, each student can progress as fast, or as slowly, as he or she would like. A student enrols for six-month subscriptions, and they are able to complete as many lessons as they would like during the subscription. The subscription is a flat USD$2,500 fee, which includes all fees and textbooks.

PL is a traditional degree programme that has been deconstructed and reconstructed around specific competencies. Reinforcing key concepts, activities, and assignments can address multiple yet related subjects at once. PL's aim has been to bring back the joy of learning by never treating material as mere information. Instead, everything a student studies will be relevant and interconnected. PL faculty members never want students to:

1 wonder why general education courses are essential

2 be discouraged because something is too hard

3 be bored because something is too easy.

In regards to the topic of competency-based learning, NAU faculty and administrators recognised that except in certain well-defined baccalaureate programmes leading to professional licensing (e.g., engineering, and nursing), there is no universally agreed upon strategy for developing competencies. Review of curricula with defined competencies will reveal that some competencies might come from established programme outcomes, others from professional organisations, some could be based on university-wide goals. Currently, Northern Arizona University's personalised learning (NAU-PL) has been developed around competencies for baccalaureate programmes.

Following best practices of curriculum mapping, a panel of faculty, experts working in the field, subject matter experts, and specialists in teaching and learning developed ten competencies for the computer information technology major. Ten competency domains were identified:

1 information technology foundations

2 data management and administration

3 IT business operations and leadership

4 information security and policy

5 enterprise architecture, network and telecommunications technology

6 software engineering and development

7 systems administration

8 business analysis and design

9 web-based systems and technologies

10 information technology.

However, below we show part of competency domain 1 – information technology foundations: Objective 1 > Lesson 1 (of five lessons) > Topic 1 (of seven topics). Note there are competency codes in red and course codes in blue. These codes are used for mapping competencies in the curriculum.

C1 Information technology foundations:/IT foundations/CITmnC1

Objective 1 Demonstrate knowledge of market trends and innovative technology in this fast changing technology industry and its many specialty areas as evidence the graduate has developed a clear understanding of information technology/trends and innovation/CITmn.C1.O1

Lesson 1 Examine the history of computers and early computing./history of computers/CITmn.C1.O1.L1 (CIT 294-0.3)

Topic 1 History of computing (hardware and software) – examine key theories on the history of computing and how it has evolved./history of computing/CITmn.C1.O1.L1.T1

As shown in Figure 1, each competency domain was expanded into one or more measurable objectives. In turn, each objective was analysed to develop lessons that would achieve the objective.

Figure 1 Competency mapping from competency domain to one or more specific objectives, and then for each objective mapping to one or more lessons, and for each lesson, sets of topic areas and respective learning activities and their associated learning assessments and diagnostic feedback (see online version for colours)

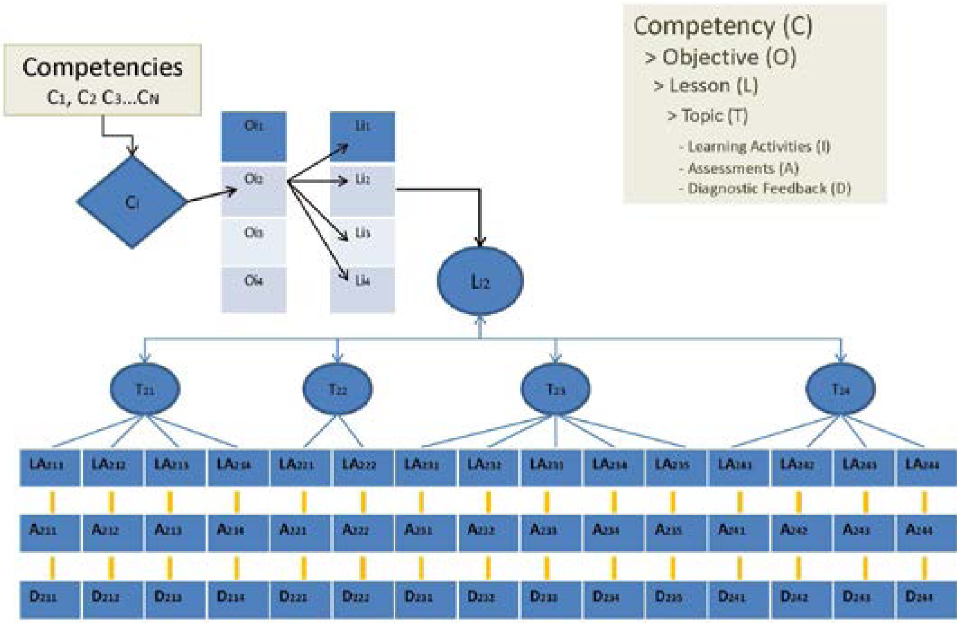
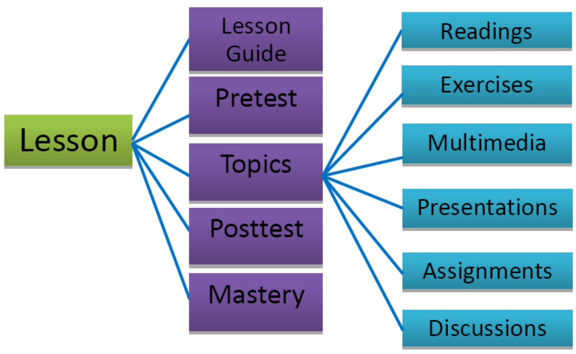


Figure 2 provides a schematic representation of how the NAU PL is expressed into an operational system from competency maps such as the one in Figure 1. Specifically, the NAU PL lesson environment wraps educational scaffolding around topic areas. In Figure 2, this scaffolding is shown as a lesson guide, a pretest, a posttest, and mastery. Each topic area has direct access to a suite of learning activities related to the topic. Each learning activity offers a variety of learning objects available to the student.

Figure 2 Lesson components and learning activities (see online version for colours)



To view elements of the NAU PL environment, please visit: http://pl.nau.edu/. The CIT major, as well as other NAU-PL degree programmes are tightly structured, with no electives in the curriculum. Each student proceeds on a defined path to graduation. The personalisation emerges as a learning plan developed for the student by a faculty mentor allowing each student to enter the lessons where he or she needs to be at any given time. This plan is not set in stone. Rather the plan is a good approximation of a reasonable path for the student, based on the respective student's past work experience and academic accomplishments. Students are freed from working on concepts they know and competencies they have acquired. They take a pre-test for each lesson and if they score an 86% or above, they may move on to the next lesson. If they score below that mark, they enter the exercises and activities as needed. No one spends time on topics and skills they already know so that the effort is placed where that effort affords the best progress through the CIT major.

The current number of students per faculty mentor is set at 150. Mentors meet with students once a week and on an as-needed basis, using the student's preferred environment. Subject-matter mentors meet in tutorials with a student based on the respective student's need related to specific content. Faculty mentors provide life-, academic-, and career-coaching. Lead faculty and faculty mentors are full-time faculty. Subject matter mentors are part-time faculty members.

3 Methodology for enhancing adaptive capacities of PL

3.1 Extant capacities of the NAU-PL/http://pl.nau.edu/

The NAU-PL environment is a well-built teaching-learning-assessment system. In July 2013, the adaptive learning research group from UOIT began a series of Gedanken experiments to study models for improving adaptive learning capacities for systems like the NAU-PL environment. The UOIT team had studied healthcare systems and the transformation of clinical systems for collecting, storing and analysing electronic patient data in electronic health records (EHRs). We realised an analogue to an EHR would be a student's electronic learning record (ELR). Research funded by the Social Sciences and Humanities Research Council of Canada allowed us to build middleware that could be layered into online environments to stream data into an ELR, analogously to the ways and means data stream into EHRs.

The NAU-PL was a good candidate for our studies of middleware that could enhance adaptive learning capacities to create an ELR. Specifically NAU-PL has a fairly extensive web of tools that are used to support learners and to assess other programmes. These programmes include Pearson's learning outcome manager (LOM) to track some student and course analytics. LOM also is an online repository of students' learning outcomes. Since NAU faculty had developed a sophisticated suite of competency domains, the competency maps allowed development of sensible competency-based learning outcomes as well as programmatic and institutional learning outcomes, all of which populate the LOM. Furthermore, the NAU-PL was built to take advantage of the Pearson LOM functionality coupled to a unique NAU user interface built by the IT unit at NAU serving the NAU-PL.

As part of the 'in-house' build, NAU staff created their own databases so data from students could be fed into NAU systems and Pearson systems, providing tremendous increases in data collection, management, and analysis without loss of functionality or compromising privacy. Using customised analytics and dashboards, the NAU-PL uses LOM to create reports as data arrays. These reports are available through 'enterprise reporting'. Individual student data, lesson data, or programme data can be easily gathered and analysed. For example, NAU faculty can monitor how long students take to complete a particular assessment, a particular lesson, or the entire programme, as well as tracking how many lessons students complete on average within a six-month subscription. Very specific data analyses are also possible, for example, item analysis on a particular assessment item related to a particular lesson-task-learning activity.

In other words, the NAU-PL environment is a very good example of a powerful competency-based online degree programme that is possible to build within the resource constraints now facing many US state universities. We analysed how to enhance adaptive learning capacities of such a system with middleware that are layered into the data collection and analysis flows of student outcome data. In addition, we studied how to add a powerful knowledge system that connected databases of learning objects in ways that a student could receive detailed feedback on their progress, as well as recommendations and remediation activities for improving their learning. During the period July 2013 to January 2014, we conducted two Gedanken experiments to study ways and means to add adaptive capacity to the NAU-PL environment.

3.2 Gedanken Experiment 1

A research platform we built provided a means to create a space-time mapping of each individual's conceptual and performance competencies to their decisions during engagement in educational and knowledge transfer activities (Gasparini et al., 2012; Tan et al., 2010; Khribi et al., 2009). Misconceptions identified during assessments of each individual could then be mapped to space-time moments in the individual's learning processes. These space-time moments could be analysed in the context of learning outcomes. Misconceptions could be identified then mapped to learning activities to help a student improve their learning [see a small sample of more than 40 virtual educational environments created by Tashiro and colleagues: (Kelly et al., 2000; Tashiro et. al., 2003; Mathers, 2006; Fulcher 2007)].

Gedanken Experiment 1 involved the creation of an abstraction of the NAU-PL environment for the CIT major. By 'abstraction' we mean a competency map: for each competency domain we delineated the objectives; for each objective its lessons; for each lesson its topics; for each topic its learning activities; and for each learning activity its learning objects. These were modelled abstractly as compartments that were dynamic in the sense of being able to send and receive signals that created database linkages. Such linkages could assemble components of a teaching-learning-assessment environment related to a particular learning activity nested in a particular topic of a lesson associated with an objective.

Our first Gedanken experiment used a research platform called MISSED – misconception instantiation as students study in educational domains, which allowed us to model students moving through the NAU-PL. On our early iterations within the NAU-PL, we realised the critical nature of signals received and sent by any compartment of the teaching-learning-assessment environment. We also realised that the dynamic nature of any given compartment would be critically important to building truly adaptive educational environments that could adapt to a student as he or she worked within a compartment. We use 'compartment' herein to represent a learning object for a learning activity associated with a specific topic of a specific lesson within a particular competency domain.

Gedanken Experiment 1 led to a refinement of MISSED. Basically, analyses of signals and dynamic features necessary for each compartment required layering monitoring middleware across compartments to record each student's navigational and engagement decisions as well as time spent in various activities. Using monitoring data coupled to learning assessment outcomes within the simulations, we could map students' learning and competency outcomes against expectations delineated by expert clinical panels (Fernandez et al., 2012; Fernandez, 2012; Regts et al., 2012; Regts, 2012).

A diagrammatic representation of MISSED is provided in Figure 3. Images show preliminary studies with Canadian health sciences students. Refinements resulting from our first Gedanken experiment allowed us to create a set of interconnected software engines that monitor educational activities of CIT students in the following manner:

1 A CIT student is working in the NAU-PL, engaging within a competency domain's lessons, topics, and their respective learning activities and associated learning objects – all their work is within a web-based interface, designed as a personalised inclusive-adaptive system that assesses a student's accessibility needs and preferences for a personalised educational environment.

2 The inclusive-adaptive interface collects data on the student's needs and preferences, creating a student profile database that becomes part of an ELR.

3 The student profile data stream to a MatchMaker system that selects an instructional deign template (IDT) based on a theory of cognition and behavioural change selected by a faculty member and consistent with the course content, but informed by the student's needs and preferences.

4 The MatchMaker engine then reads the metadata from the template.

5 The assembler engine reads the IDT and metadata brought to it by MatchMaker, searches learning object repositories to find and collate learning activities, resources, educational scaffolding, learning assessments, and feedback personalised for the learner, and then organises the assemblage to create a web-based personalised teaching-learning-assessment-diagnostic educational environment.

6 Students engage within the educational environment (and for some types of hybrid classes also engage in face-to-face settings, such as faculty mentoring, live skills labs, low-fidelity or high-fidelity simulations related to computer information technology).

7 Within the web-based educational environments, each student is constantly monitored by middleware called PathFinder that follows choices made within the educational environments and also times a student's engagement in learning activities, resources, assessments, and using diagnostic feedback.

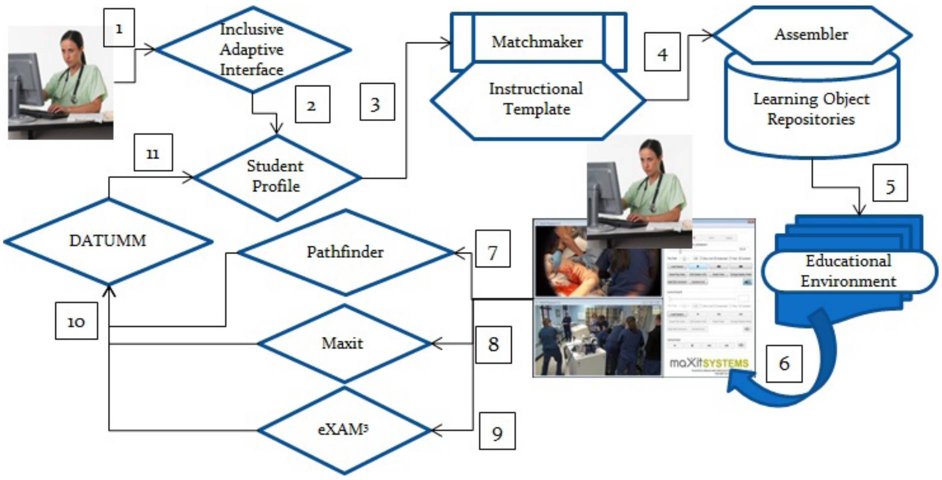
8 Within the face-to-face environments in some course types (e.g., live skills lab), a student is monitored during learning-demonstration activities, using a video-capture and analysis system called MAXIT EDUCATION (Tashiro and Hung, 2011; Vargas Martin et al., 2009; Tashiro et al., 2008) that efficiently collects assessment data on students' performance competencies.

9 Prior to, simultaneously with, or after learning-demonstration activities, students enter an assessment engine called eXAM[3] (Tashiro and Choate, 2004) which assesses their learning outcomes within a cognitive taxonomy selected by the faculty member (e.g., Bloom's revised taxonomy or a rubric for a CIT competency domain).

10 PathFinder, MAXIT EDUCATION, and eXAM[3] stream a student's data to a data analysis and knowledge system called DATUMM.

11 DATUMM, in turn, analyses the data, creates new information about the student, and sends this information back to the student profile. These new information sets are integrated into the student profile, with revised data and information facilitating adaptive changes to the flow beginning with the MatchMaker and ending in new configurations of the educational environment. Importantly, data from the student profile also stream into a subcomponent – the ELR, through time creating a longitudinal record of a student's progress.

Figure 3 Diagrammatic representation of the MISSED environment piloted in research on health sciences education (see online version for colours)



The MISSED research platform collects data on students' conceptual and performance competencies, creating a very detailed ELR. The ELR also can be constructed to receive data and information from multiple courses, and so create a much more detailed and informative multidimensional student transcript. Preliminary studies of this platform provide evidence that it will complement faculty efforts without increasing workload, while providing new tools and types of data for better assessing students' conceptual and performance competencies. The platform also will allow detailed analysis of cognitive processes and behavioural choices to trace development of misconceptions. Much of this work was based on extensive studies of learning and behavioural change in healthcare (Martin et al., 2010; Prochaska et al., 2008; Leventhal et al., 2004; Bensley et al., 2004; Baranowski et al., 2003; Fishbein et al., 2001).

3.3 Gedanken Experiment 2

In the second experiment, we studied the importance of signals received and sent by any compartment within an environment like the NAU-PL and we also explored the dynamic nature of compartments. For our modelling, we focused on the MISSED's engines called matchmaker, assembler, and the pathfinder. These engines have the most rigorous requirement for signal integrity and dynamic function.

- *MatchMaker engine*. MatchMaker bridges an individual learner to an instructor's educational goals for a course – in the case of the CIT curriculum, these goals are the competency domains, their respective objectives, lessons, topics, and learning activities. MatchMaker receives student profile data, making the first adaptive changes for individual students. NAU-PL has learning object repositories to accommodate many different types of learning objects for a particular learning activity. To be truly adaptive, the repositories must contain equivalent forms of learning objects that can be selected by MatchMaker, with selection based on student profile data. Different students have different needs. NAU-PL must be able to adapt to those needs by choosing different learning objects. Furthermore, some curricula may require multiple learning object repositories that could be integrated in ways that allow linked repositories to have all of the learning objects for a particular course. Our modelling in Gedanken Experiment 2 revealed the MatchMaker engine signal input-output must be able to acquire and interpret metadata for all of the elements comprising any learning object in order to identify that object's potential use for: PL, different knowledge or skills domains, diverse courses with specific types of educational goals, and choices of grounded theory for cognition and learning as well as behavioural expression of what has been learned.
- *Assembler engine*. MatchMaker provides metadata on the IDT for mapping to the metadata of learning objects within the learning object repositories. The assembler uses the IDT to select and organise specified learning objects, creating the personalised teaching-learning-assessment-diagnostic educational environment. Results of Gedanken Experiment 2 lead us to conclude that the IDT must be built as a multidimensional array that can be filled with metadata related to the diverse types of learning resources, activities, assessments, educational scaffolding and diagnostic feedback likely to optimise a student's learning. The assembler must be able to interpret the IDT and provide instructions to create the personalised education environment – the IDT is an organising framework. The assembler then loads into this framework learning activities, resources, educational scaffolding, learning assessments, and feedback for the student's personalised educational environment.
- *PathFinder*. Gedanken Experiment 2 refined our ideas about how PathFinder creates place-time stamps for every place in which the learner engages within the educational environment. Such engagement includes learning objects or sub-elements of a learning object nested within a learning activity, as well as with any resource or scaffolding element made available to a learner. PathFinder also monitors all assessment activities, collects data on each assessment, and retrieves sub-elements of any assessment in which the learner is working. This place-time data set is a record of decisional sequelae for the learner (sometimes called space-time worm). Basically, the data reveal the sequence of choices made, actions taken within

the educational environment, and time spent in such places and actions. In our modelling within Gedanken Experiment 2, we studied how space-time worms can be articulated with assessment data related to what a student actually learned during their the decisional sequelae of engaging with learning objects.

4 Analysis of key software nodes

This section describes analysis of key software nodes that are essential for adaptive capacities to function. More specifically, we examine three engine designs: MatchMaker, assembler, and the PathFinder. Rather than focus on software design, we take a more conceptual approach and examine the grounded theory for models of cognition and learning that must be understood in order to create an evidence-based adaptive learning capacity that will serve all students.

4.1 The MatchMaker engine

For over a decade, we studied educational simulations and serious games. One area of particular interest evolved from how cognitive and learning sciences inform instructional design in complex educational settings (Sorden, 2005; Mayer et al., 2004). Our early models for adaptive learning were specifically designed to improve clinical judgment of healthcare practitioners and students. Very interesting research by Patel et al. (2009) revealed that within care delivery settings cognition will be shaped by the situated encounters in that workplace, which are dynamic and strongly influenced by social contexts as well as by a diverse array of other elements in the setting. Such elements include technology, temporal and spatial heterogeneity in the patient's condition, changing shifts of providers caring for the same patient, and ongoing coordination of many different tasks and decisions as well as health information management (Patel et al., 2009). Effective action requires development of pattern recognition capabilities as providers move from novice to expert. Such pattern recognition capabilities are critical to clinical judgment and decision-making during planning and implementing care. Often, the decision making unfolds in a 'heuristically-guided' sequence [Patel et al., (2009), p.177]. Yet, we need to know what happens if pattern recognition development is incomplete. For example, what is the probability that exploring an educational environment, online or hand-on in a lab or skills setting, will actually lead students to tangential analyses and making decisions that are logical in the context of their analyses but are flawed as pattern recognition?

When we began working in disciplines other than healthcare education, similar issues emerged around pattern recognition and accuracy of patterns in representing the real world. One of the early versions of our adaptive-learning software was designed from models of cognition. However, there are a variety of models of cognition (Patel et al., 2009) as well as a variety of models of cognitive taxonomies that try to represent the intersection of cognitive processes and formation of knowledge and skills domains (e.g., Bloom's revised taxonomy; see Anderson and Krathwohl, 2001). As we examined nursing, computer science, and CIT curricular frameworks, we struggled with how to build an educational environment that overcame difficulties in assessing how cognitive processes result in knowledge domains instantiated as cognitive schema in learners. We were initially overwhelmed by trying to assess the probability of the relative stability of the knowledge instantiated. We could, of course, measure the realised stability by assessing the student's retention of what was learned at the end of a lesson or learning activity and then through time examine the stability of retained knowledge. However, through time a student is exposed to many new educational and life experiences. So, how could we tease out factors shaping knowledge gained and knowledge retained in the context of a particular situated learning experience?

The MatchMaker engine was one approach we explored. We realised there was no consensus theory of cognition and learning. For example, theoretical frameworks that have been proposed for cognition that appear with relatively high frequency in the educational literature include: cognitive load theory, cognitive flexibility theory, adaptive character of thought theory, and situated learning theory. Some of these theories cluster into more individualistic structured learning, such as adaptive character of thought and cognitive load theories. Others fit within the domain of what educators call constructivist learning theories such as cognitive flexibility theory and situated learning theory (Patel et al., 2009).

We built Matchmaker with access control management systems (ACMSs) that would allow setting a choice of a theory of cognition. As mentioned above, MatchMaker bridges an individual learner to an instructor's educational goals for a course. Certainly, most faculty members do not delineate course goals and objectives within a framework of grounded theory in cognition. However, we designed MatchMaker to allow our adaptive learning system to use a particular theory or theory cluster. So, for example, we could set key algorithms within the MatchMaker engine so that *the SIGNAL CIT Education* environment would shape the various facets of the environment in ways that were consistent with a constructivist learning theory, such as situated learning theory. Alternatively, our ACMS would allow selection of another set of algorithms that would set the environment to be consistent with more individualistic structured learning within a theoretical framework, such as adaptive character of thought.

In the case of the CIT curriculum, the competency domains would be mastered by students engaged in lessons, topics, and learning activities that were consistent with the theory of cognition and learning selected by a faculty member or academic programme. The NAU-PL has learning object repositories to accommodate many different types of learning objects for a particular learning activity. To be truly adaptive, we would have to build learning object repositories with forms of learning objects that can be selected by MatchMaker. Logically, MatchMaker must be able work at multiple levels. First, it must work at a grounded theory level. Second, it must work at the individual student level as informed by the student profile data. Different students have different needs. So systems like the NAU-PL must be able to adapt to those needs by choosing different learning objects. Again, we note that our modelling in Gedanken Experiment 2 revealed MatchMaker's signal input-output must, within a particular grounded theory framework for cognition, be able to acquire and interpret metadata for all of the elements comprising any learning object and validate that object's potential use for: PL, different knowledge or skills domains, diverse courses with specific types of educational goals, and choices of grounded theory for cognition and learning as well as behavioural expression of what has been learned.

We mentioned earlier that MatchMaker provides metadata on the IDT for mapping to the metadata of learning objects within the learning object repositories. The assembler uses the IDT to select and organise specified learning objects, creating the personalised teaching-learning-assessment-diagnostic educational environment. If MatchMaker has been set to a particular theory of cognition and learning, then there will be specific IDTs for each theory. How will the assembler engine function?

4.2 The assembler engine

The IDTs are instructional design templates. Our studies suggest each theory of cognition can be expressed as a set of IDTs. The assembler creates an environment based on the framework of a particular theory of learning and cognition and behavioural expression of learning. More particularly, the assembler builds a multidimensional array that can be filled with metadata related to the diverse types of learning resources, activities, assessments, educational scaffolding and diagnostic feedback that are consistent with the theory of cognition chosen and that are likely to optimise a student's learning.

The assembler basically interprets an IDT. Such an interpretation provides instructions to create the personalised education environment. Because the IDT is an organising framework, we can design IDTs to be consistent with different theories of cognition and learning. For the particular theory chosen, the assembler receives theory-specific IDTs which it uses to assemble and load activities, resources, educational scaffolding, learning assessments, and feedback for the student's personalised educational environment.

Of course, each IDT must be based around whatever theory of cognition has been chosen or must be adaptable in some kind of ACMS to switch from one theory to another. Such a switch will require there are learning objects consistent with each theoretical framework. Also, some learning objects may be used for more than one theoretical framework, and so care must be taken in the meta-tagging to assure any object is called up appropriately within different theoretical frameworks.

4.3 The PathFinder engine

The PathFinder engine is monitoring student activities within the educational environment. These data can be diverse, such as time on task in a particular engagement with a learning object, decisional sequelae in moving through a suite of learning objects, learning outcomes, and – an area we are particularly interested in exploring-monitoring for misconceptions (as inaccurate knowledge) that can be remediated. Even so, learning in a particular course in only a small fraction of an individual's experiential learning in any given day. So, how do you assess what has been learned and instantiated as part of neural networks that contain knowledge and skills (inaccurate or otherwise) that are related to a particular topic in a particular lesson falling under a particular competency objective? Linked data bases and big data analytics may provide a possible solution, if only partial solution. We can, for example, integrate serious games within the learning environment to engage students and probe what changes in learning have occurred since the end of their last excursion within the learning environment (e.g., new knowledge that has expanded what was learned, some of what was learned has not been retained, some of what was learned has been permuted in complex ways.).

Furthermore, PathFinder also will fall under the settings made when a particular theory of cognition is chosen. From a software perspective, Pathfinder is 'looking for and retrieving' data from a student's engagements within the educational environment and from any learning outcomes assessments the student encounters and completes (not completing an assessment is also recorded). We noted that Gedanken Experiment 2 helped us design PathFinder to create place-time stamps for every place in which the learner engages within the educational environment. PathFinder can manage such collections regardless of the theoretical framework chosen, although there might be different patterns of data collection for different theories of cognition.

Basically, PathFinder follow students in any engagement within the Educational Environment, including engagement with learning objects or sub-elements of a learning object nested within a learning activity. Pathfinder also monitors a student's usage patterns of any resource or scaffolding element made available to a learner. And, PathFinder monitors all assessment activities, collects data on each assessment, and retrieves sub-elements of any assessment in which the learner is working. The assembly of such data create a record of decisional sequelae we referred to as the learner's Space-Time worm).

5 Conclusions

We have studied how and why to add enhanced adaptive capacities to educational environments – our prototype was the NAU-PL environment. We used analogues of EHR systems' middleware and customisable graphic user interfaces to create student ELRs. Additionally, we have explored how to integrate different theories of cognition and learning into the design of the engines supporting a personalised-adaptive learning environment.

In times of limited resources, and without a clear evidence-based framework for education, there are significant advantages to building relatively cheaper solutions than to buying or leasing expensive learning management systems that are difficult to customise. Learning management systems and adaptive learning environments offered by academic publishers still have many weaknesses, often requiring loading of the respective publisher's learning objects. The NAU-PL environment represents an approach of combining commercial systems with in-house built systems that meets the needs of a university and its students.

The addition of adaptive capacities to the NAU-PL could provide cost-effective customisation that better serve the university, its students, and faculty. Our research has shown the possibility for building personalised adaptive learning environments for CIT curricula, although we already have demonstrated our model can be used with other curricular frameworks. Perhaps, the most exciting result of our work has been the conceptualisation and operationalisation of adaptive learning environments that can be sensibly built to accommodate different theories of cognition and learning. We look forward to continuing this area of research and proposing ways adaptive learning environments can be used in cross-theory studies of different theories of cognition and learning.

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