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Ubiquitous Learning Environments and Technologies

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Ubiquitous Learning Environments and Technologies

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Preface

The exponential growth in handheld devices and wireless technology in recent years, and increasing availability of high bandwidth network infrastructures, have opened up new accessibility opportunities for education. As a result, ubiquitous learning environments have started to emerge with potential to support life-long learning. These environments break the boundaries of the classroom and enable learning to take place in the contexts where learners are able to relate with the learning scenarios in their own living and work environments, leading to better learning experience. This book focuses on the design and architecture of ubiquitous learning environments, associated technologies, various learning scenarios supported by these environments, and various contexts that arise in such environments where seamless immersion of formal and informal activities and interactions has potential to contribute to the learning process. With particular focus on adaptivity for individual learners, this book explores various dimensions of ubiquitous learning environments and technologies.

Kinshuk provides a possible roadmap for adaptive and personalized learning in ubiquitous environments and looks at the vision for advancements in research in future. Starting with various pertinent research issues, he looks at overall research direction and provides sample roadmap with examples and anecdotes.

Jon Dron and Terry Anderson first explain their typology of social forms, categorizing social groupings as sets, nets, and groups, along with an emergent entity, the collective, which arises from them. Then they describe the pedagogies, benefits, problems faced, and tools for learning using each social form, and after that they conclude with some suggestions about how social media may best be constructed to support each form and the likely future shape of social learning.

Vive Kumar, Kinshuk, Clayton Clemens, and Steven Harris discusses the core ideas of causality and modeling of causality in the context of educational research with big data analytics as the underlying data supply mechanism. Their chapter provides results from studies that illustrate the need for causal modeling and how learning analytics could enhance the accuracy of causal models.

Chris Lu, Maiga Chang, Kinshuk, Echo Huang, and Ching-Wen Chen reveal the design of a story generation engine for mobile educational role-playing game and the use of decorating mobile learning activities with the generated story fragments. The results from an experiment show that the stories play an important role in terms of increasing student perceptions toward the mobile educational game's effectiveness and making students more satisfied with the game.

Tingwen Chang, Jeffrey Kurcz, Moushir M. EL-BISHOUTY, Kinshuk, and Sabine Graf introduce a general approach to automatically identify working memory capacity (WMC) from students' behaviour in a learning system which can provide teachers meaningful recommendations to support students with low and high WMC by the recommendation mechanism created by them.

Nian-Shing Chen, I-Chun Hung, and Wei-Chieh Fang introduce an augmentation-enhanced learning context with an integration of digital content into paper-based materials in order to facilitate learning. Constructive feedback, scaffolding questioning, and procedural scaffolding are three strategies applied into the instructional designs and learning system. Quasi-experiments for personal learning and collaborative learning were also conducted to evaluate the effects on learning performance, the results of which suggest that the three instructional designs had significantly positive effects on individual's learning performance.

Dunwei Wen, Yan Gao, and Guangbing Yang introduces how natural language processing (NLP) technologies can be employed to help build and improve NLI that can support ubiquitous learning. Through emphasizing semantic analysis such as semantic role labeling, semantic similarity, of natural language, and develop and use them to enhance question and answer processing, automated question answering, and automatic text summarization in educational system, they propose approaches to improve the technology of natural language processing and help develop different NLI systems in the ubiquitous learning environments.

Vive Kumar, Kinshuk, Thamarai Selvi Somasundaram, David Boulanger, Jérémie Seanosky, and Marcello Vilela offer a new perspective on learning and instructional attainments with big data analytics as the underlying framework, discuss approaches to this framework with evidences from the literature, and offer a case study that illustrates the need to pursue research directions arising from this new perspective.

Mohamed Koutheaïr Khribi, Mohamed Jemni, and Olfa Nasraoui provide a generic meta-level framework for a common description of TEL recommendation systems and present an analysis of several existing TEL recommendation systems with respect to their defined framework.

Alex Mottus, Kinshuk, Sabine Graf, and Nian-Shing Chen propose visualization mechanisms to support teachers to function effectively in ubiquitous learning environments, which provides one potential solution for unlocking the full potential of ubiquitous learning environments and allowing students to follow their own learning which being fully supported and encouraged.

Chun Chang, Maiga Chang, and Jia-Sheng Heh reveal the design of mobile educational role-playing game for doing informal learning in museum and then explains the game-play with mocked user's experience so readers can have clear idea of how the things work.

Moushir M. El-Bishouty, Kevin Saito, Tingwen Chang, Kinshuk, and Sabine Graf present an interactive tool for analyzing existing course contents in learning management systems based on learning styles, which allows teachers to be aware of the course support level for different learning styles. It aims at supporting teachers in adaptive and personalized learning environments to decide making efficient modifications in the course structure in order to meet the needs of different students' learning styles.

Ronghuai Huang, Yongbin Hu, and Junfeng Yang first define the learner experience in technology rich classroom as learners' perceptions and responses that resulted from physical environment changes, and they also propose the five elements of learner experience: value, usability, adaptability, desirability, comfortability. Finally, they identify the indicators for evaluating learner experience in TRC by deeply investigating the changing factors of classroom and the five elements of learner experience.

Kinshuk
Ronghuai Huang

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Chapter 1
Roadmap for Adaptive and Personalized Learning in Ubiquitous Environments

Kinshuk

Abstract There is greater awareness in educational system regarding benefits authentic learning experiences bring to the learning process. As a result, ubiquitous educational environments have started to gain acceptance in mainstream education. These environments break the boundaries of the classroom and enable learning to take place in the contexts where learners are able to relate with the learning scenarios in their own living and work environments, leading to better learning experience. This chapter focuses on various contexts that arise in such environments where seamless immersion of formal and informal activities and interactions has potential to contribute to the learning process. With particular focus on adaptivity for individual learners, the chapter explores the diminishing boundaries of formal and informal learning, and the potential of location-aware context-sensitive approaches that are emerging as successor of Web 2.0 paradigm.

1.1 Introduction

The exponential growth of wireless technology in recent years, increasing availability of high bandwidth network infrastructures, advances in mobile technologies, and the popularity of handheld devices have opened up new accessibility opportunities for education. Mobile learning environments overcome the restrictions of classroom or workplace-restricted learning and extend e-learning by bringing the concepts of anytime and anywhere to reality, aiming at providing people with better educational experience in their daily living environments. Use of devices such as mobile phones and personal digital assistants allows new opportunities for learners by being intensely connected. Therefore, educational content can be accessed and interaction can take place whenever learners need it, in different areas of life, regardless of space and time.

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While “mobile learning” is a growing research area, aspects of adaptivity and personalization become more and more important. Incorporating adaptivity and personalization issues in mobile learning systems allows these systems to provide learners with an environment that is not only accessible anytime and anywhere, but also accommodating to the individual preferences and needs of learners. Being aware of and considering the current context of the learners as well as, for example, their different knowledge, interests, learning styles, and so on, leads to a more effective, convenient, and successful learning experience in a mobile learning environment.

This chapter first takes a look at current state of e-learning, the issues learners encounter in existing e-learning solutions, and considers a roadmap for moving toward mobile learning, and subsequently to ubiquitous learning. Particular focus is given on how to provide adaptive and personalized learning in ubiquitous environments. Online Learning has been around for quite some time. Every academic institution has embraced some form or shape of online learning. Taking it further to cater for people who are travelling, who are trying to learn from wherever they can, brings us to mobile learning or m-learning. The question then remains, how we can bring authentic context in learning process, where the ubiquitous learning starts to make sense. This chapter investigates that question.

1.2 Research Issues in Current e-Learning Approaches

Learners in online education have somewhat different requirements compared to traditional brick and mortar institutions. Online learners are not present on campus. Teachers do not see them face to face, and most of the time, face-to-face interaction takes place only when these students actually come to their degree-awarding institution for graduation at the end of their studies, if they come at all. So, trying to teach learners who are at a distance, and facilitating for them the kind of learning experience that will be called good learning experience or even better learning experience than what traditional universities could perhaps provide in the situation where large classrooms are becoming reality, various research issues need to be investigated in order to provide learners the kind of learning experience they deserve. Several research issues are identified where learners demand or expect certain functionality in online learning environments.

1.2.1 Social Interaction

First research issue is that the learners in current online learning environments feel very isolated. When they are engaging in learning process, they are perhaps at their home or their work, and they do not see the same kind of peer exposure as campus-based students see. A lot of research is going on under the umbrella of social networking area looking at how to facilitate learning communities to enhance the social presence or social learning aspect. A major research area under social networking is to provide social learning community. While there are multitudes of social platforms available, research is ongoing to find solutions that can comply with the privacy issues formal educational institutions experience. An example implementation of such research is Athabasca University's Landing platform (Rahman and Dron 2012) that tries to combine different functionality that is available in various publicly available social platforms, and tries to provide that within the confines of the educational environment, within the secure platform that is required for providing learning experience, and not something that is accessible by anyone who is not part of that particular educational community.

1.2.2 Immersive Environments

Research is also ongoing to provide learning platforms using immersive environments for learning. Many of such immersive environments are now becoming available as open-source platforms, providing opportunities for teachers to configure them to their particular requirements. These platforms enable students to collaborate while gaining hands-on experience for the kind of activities that are typically not possible in traditional online environments, for example, laboratories. It is important to note that these environments are not to replace what used to be done in a physical hands-on environment, but to provide initial practice or initial experience, and also to provide the kind of experience that otherwise would be very costly or prohibitive in certain situations where that affects either public safety or affects production lines, or something similar. So, how can that kind of experience be provided to the learners is another research area that has attracted attention of researchers focusing on ubiquitous learning.

1.2.3 Mobile Learning

Third, online learners are typically not fresh students coming out of high school. They are generally people who are already working. They have their jobs, their families, and other similar reasons why education is not their first priority. They have many other priorities that they have to take care of, and therefore, they learn whenever they can, whichever way they can, and they expect that they will be able to access the content, access the learning activities, and have social interaction through various means. This has garnered a lot of attention of researchers, and the whole area of mobile learning has emerged to support these needs of the students. In particular, research is on-going toward using wide variety of wireless devices and applications, with focus on widening access to education to remote and isolated communities. The idea is to provide content and interaction accessible through different devices, wherever learners are and wherever they would like to access these on devices of different sizes and functionality. One of the major aims of the research on mobile learning is to remove communication and educational barriers and make learning convenient and available anytime and anywhere. Communities such as immigrants and their families, disabled people, people working and living in remote areas, and others in situations that prevent them from attending education at a prescribed time and location can particularly benefit from mobile learning research.

1.2.4 Adaptivity and Personalization

Since online learners come from different backgrounds, they have different work, life, and learning experiences, they are working at different places, coming from different places, and they also need personalized support that is typically nonexistent in existing online learning environments. The question then is, how we can support them by understanding them, by understanding what their needs are, at that particular moment when they are trying to learn, and provide the learning experience accordingly. This has resulted in the research area which has evolved under the umbrella of adaptivity and personalization. Efforts are underway to identify how we can design different paradigms and architectures for personalized learning, and then implement learning systems that take into account different characteristics of learners, the kind of technologies that are available, in the physical environment these learners are trying to learn, and then consider the context in which the learning is taking place. Researchers are also focusing on combining all that with the authentic experience learners can get within the physical environment they are learning, so as to take advantage of real-life objects that are available in such environment and combining them with virtual or electronic information to provide suitable learning experience.

The basic idea behind these research approaches is to empower learners, knowing that these are the learners who are learning within their own environment, within their own restrictions or confinements of their own life style. How can we provide them the kind of experience where they feel that they have the options to choose and to take decisions on how they think they can make their learning experience better?

1.3 Overall Research Direction

The focus of the overall research in adaptive and personalized learning in ubiquitous environments is on improving learning experience of learners, whether they are online or in classroom. The aim is to increase the accessibility to education for all different types of learners in such kind of global environment that we currently have. And then, the next question is, how can we bridge the gap between different learners? Different learners learn differently. Different learners have different backgrounds. They are at different stages of learning. How can we bridge the gap and how can we know about them as much as we need to? Subsequently, how can we provide the kind of learning that can bring the learners who are at lower stages to the same level or even higher than where typical educational environment would take them?

Next is to provide support for mobile and life-long learners. Online learners are generally working adults. In fact, nowadays regardless of any university or any educational environment, learners are engaged in different types of activities, and the question is, how can we, first of all, accommodate learning within their environment, and second, how can we harness the benefits they get from different types of activities they are involved in, to improve learning?

In terms of how can we change the educational system, so that it is something that is actually what learners start to like, that is the aim of this research: just-in-time learning, on-demand learning, and quite importantly, context adaptation, because learners are in different environments. Learners have different backgrounds. Not everybody learns in the same way. Not everybody learns, or understands, or has perspective in the same way. How can we understand them first, and then provide learning that works for that one particular student, and, then another student, and, then another student…? And, how do we do that, while not overburdening the teacher? There is no way that a teacher himself or herself can provide such kind of individualized learning to large number of learners. So, how can technology help in that process, so that without overloading the teacher, we can provide such kind of adaptive and personalized learning?

The vision is to make learning omnipresent and highly contextual. Learning does not remain just a classroom phenomenon. Because learning happens everywhere, so the definition of learning also needs to change, to include those components which are currently not count as actual as learning. These components have a rather significant impact on the learning process. For example, any informal discussions that take place during the course of day to day living, while they provide significant learning, are not treated as the moments of learning as such. Problem is that there is no record of what is learned in such situations, and when such knowledge is needed in other situations, without any formal records, the assumption would be that the learner did not have that knowledge.

Next issue is how do we use that information into future learning process, future learning experience? The term “learning experience” is used here to encompass various aspects of the learning process, and not just the learning content. Content is just one component of the overall learning process. Learning activity itself is not full learning either. A lot more goes around, both in forefront and in background that contributes to learning process, and learners—they do, regardless of the generation, a lot of different activities that contributes to learning process. How can we actually take account of that and use that to provide further learning?

First and foremost, we need to identify as much information as possible about our learners. Extensive modeling of what they are doing at any given time, what interactions they are having with others, with the learning system, and with the content. In what kind of mood they are? Mood is something that changes very fast, but that also affects very significantly the way we learn or how much we learn. We also need to know their trends of preferences. People have different preferences but people actually change preferences also as fast. So it is important to understand their trends of preferences, so as to infer their possible preferences in near future. Another important piece of information is the kind of skills and knowledge levels learners have. People have changes in the levels of their skills and knowledge all the time. Some changes are explicit, such as in the classroom where learners are learning and the teacher is noting “OK, I have taught this”, and some changes are implicit, such as those that happen during informal chat outside classrooms. The question is how to identify those changes that are implicit.

All these issues require real-time monitoring of a number of different parameters, such as learners’ location, and learners’ technology use—what technologies are available to the learners, and what technologies exist in the surroundings of the learners that can provide information about the learners’ environment. Another parameter is the changes in learners’ situational aspects—the changes in the context. Changes in the situation describe better what context means here, since it can provide us enough information to at least start working on providing adaptivity, providing customized learning, and providing personalized learning.

1.4 Learner Awareness

While there are several aspects that can provide insight about the learners, an important aspect is to know about the knowledge and skills sets possessed by the learners. What does the learner know about a certain topic? What does he/she know about the overall area in which that topic is situated? What kind of skill levels he/she have? What kind of knowledge decay there has been since the topic was learned last time? When was the last time the learner learned that topic? All those kinds of things are part of performance based model.

Performance based models have been researched extensively for more than 40 years (Self 1974). A number of very efficient and effective student modeling techniques have become available since then that can provide comprehensive information about students’ domain expertise.

Another area of learner awareness is cognitive traits, which provide information about cognitive or mental capabilities of the learners. These capabilities are built-in; they are hard-wired. They are rather persistent and the rate of change is very slow. It can take decades to see any real changes in these capabilities. So, if we can identify somebody’s, say, working memory capacity, which is one of the cognitive traits, we can personalize learning experience accordingly. Working memory capacity allows keeping active a limited amount of information (7 ± 2 chunks) for a short time (Miller 1956). Further analysis of this suggests that some people can keep $7 - 2 = 5$ chunks, while others can keep almost double of that number ($7 + 2 = 9$ chunks). So, the question is, whether both types of learners should be given same kind of content and same kind of learning activities? Or, should we take advantage of this information and customize learning content and interaction to suit their working memory capacity? Similarly, there are many other cognitive traits, such as inductive reasoning ability which is the ability to construct concepts from examples, associative learning skills to link new knowledge to existing knowledge, and information processing speed that determines how fast learners acquire the information correctly. These are just some examples of cognitive traits that influence the learning process. There are many more cognitive traits that can be measured and used to customize the learning process. If we identify that someone has, say, low working memory capacity, high inductive reasoning ability, medium information processing speed, and high associative learning skills, we could probably provide them a package of instruction that works effectively for that particular set, compared to somebody who may be at the exactly same performance level, but has different levels of cognitive traits.

Learners also have different learning styles, and knowing about individual students' learning styles enables educational systems to personalized learning. Benefits of learning styles have been open to debate for decades. Majority of learning style models that exist in the literature attempt to classify learners into a particular type of category, such as active, visual, etc. However, people do not behave in one particular manner all the time. What people have is different tendencies that they exhibit as and when choices are available. So, a person with active tendency would still behave as reflective when needed. For example, Felder Silverman Learning Style Model (FSLSM) promotes the concept of tendencies by putting learners' preferences on four dimensions, namely, Active-Reflective, Sensing-Intuitive, Visual-Verbal, and Sequential-Global, where each learner has strong or moderate tendency toward one of the extremes of each dimension, or the learner may exhibit equal tendency for both extremes (Felder and Silverman 1988). FSLSM goes one step further by also analyzing what kind of learning activities and learning experience would work better for a particular learner with particular learning style tendencies. The teacher can then use this analysis to decide what to do. Teacher then has possibility to make informed decision whether to provide learning to suit a learner's learning style, or to provide content and interaction in a way that challenges learner's learning style tendencies, so as to encourage him/her to excel even outside of his/her comfort zone.

So, the first step is to identify those learning style tendencies. There are different methods available to analyze them. Typically, learning style models require completion of some sort of questionnaires to measure people's learning styles. For example, Felder and Silverman (1988) use 44-item questionnaire, where each of the four dimensions (Active-reflective, sensing-intuitive, visual-verbal, and sequential-global) is measured through 11 questions of the questionnaire. While questionnaires can provide a fairly accurate estimate of the learners' learning style tendencies, they suffer from two major drawbacks. First, they take time away from actual learning tasks. Second, they provide a snapshot in time, and any changes that may have occurred since the learner completed the questionnaire need re-completion of questionnaire at regular interval, taking further time away from the learning process.

Research has been done to identify learners' learning style tendencies by observing their actions in the learning systems when learners are engaged in actual learning process. If we can identify learners' characteristics and tendencies through that observation, that would provide more reliable information. For example, Bayesian networks have been used to detect learning styles by monitoring learner action in learning management systems while they are learning the actual content (Graf 2007).

It is important to note that the application of pedagogy guides the learning process, but detection of attributes, such as learning styles, allow for finer interventions. Ubiquitous learning technologies play a significant role in such determination, as they allow teachers to understand learners' characteristics by analyzing learners' actions regardless of learners' location, time of study, and other similar parameters.

A dynamic learner modeling platform has been created as an example using various components of learner awareness, which mines the historical data of the learners and the real-time data of their activities to provide real-time adaptivity. The monitoring of learners' activities in the platform takes place in a very heterogeneous environment. It is not an environment where learners are sitting in a lab, or sitting at home. The learning is supposed to happen where learning actually happens. What it means is that learning happens when learners can relate to the learning. Learning happens in authentic environments. For example, for an arts student who is trying to learn about certain paintings, sitting at home and trying to learn about it, or sitting in a class and trying to learn about it, perhaps is not the best way to do it, compared to if the learner actually goes to a painting exhibition, or a museum or something like that.

In such kind of authentic environments, it is not possible to bring and use devices such as desktop computers. Even laptops would not be very comfortable. But with technical advancements, many other kinds of devices have become available, such as smartphones and tablets that are now so ubiquitously available. These scenarios are taking instruction into more complex learning environments where complexity is increasing not just by who the individual learners are, but also what kind of device they have, and what kind of technology they have available at their disposal? Are there any sensors which can help in learning process? How can they actually learn from real objects available in authentic environments if there is no teacher available at hand who can help there and then by looking at what the learner is currently looking at?

Several different parameters are used in the dynamic learner modeling platform to provide such kind of authentic learning. These include learning activities, learning styles, interests and knowledge, problem solving activities, what kind of learning objects and learning activities the learner has used, what kind of social activities he/she has engaged in as a learner, where he/she is now, where he/she has been, and what he/she did in previous locations so that the platform can analyze what he/she should do in the current location. So for that we need to know about learners' location.

1.5 Location Awareness

If learners are using one of the newer cellphones, then it is very easy to identify their locations, because nowadays most of these devices come with Global Positioning System (GPS) navigation chip. Even if a cellphone does not have such navigation chip, it is still possible to identify its location, since all cellphones are connected to 'cellular network base stations' to facilitate users to make calls. At any time, the cellphone phone connects to multiple cellular network base stations. By doing so, it can provide connectivity even when the user is moving long distances, by seamlessly hopping from one base station to another. By identifying the intensity of the connection, it is possible to pinpoint learner's location. If the phone also has GPS, the information from GPS can be combined that with the information from cellular network base stations in order to triangulate learner's location even more precisely. Of course, GPS technology does not work well inside the buildings. There are other technologies available that can work inside. For example, if there are Wi-Fi access points nearby and/or the device is connected to Internet, there are other location calculation methods that can be used. Google maps, for example, use such methods to identify users' location.

Once the learners' locations are known, various methods can be used to improve learning experiences of the learners. For example, location based optimal groups of the learners can be created. Such learning groups or study groups can be based on a number of different parameters that are available about different learners, for example, learners' location information can be combined with their learning profiles, learning styles, and their learning interests to create different types of groups. An example is the complimentary groups, where learners with different knowledge and skills come together and help each other; or learners with a similar kind of information but at different levels, so that they can mentor each other (Tan et al. 2010).

1.6 Environment Awareness

Once the location of a learner is known, in order to create authentic learning environment, we also need to identify what are the real life objects that are available in the learner's vicinity that can be used in the learning process. Such environments are typically outside of classroom and need to be created on-the-fly in order to support opportunistic learning, so the location of the learner is not known in advance. In such situations, there are different ways to dynamically identify real life objects. There are public databases of points of interest. For example, Google maps

Fig. 1.1 Ubiquitous learning at flower expo

allow users to upload images at certain locations and then they become accessible to everyone who searches for that location. Quick Response (QR) codes can be used to very cheaply tag different objects.

For example, Fig. 1.1 shows a photograph taken by the author at an international flower expo in Taiwan. While looking at the flowers, the nearby board provides some further details of that particular flower in three different languages. More importantly, the board contains a QR code on top right corner, which once accessed, takes the user to a website that contains more information about that particular flower. So, for a learner, the situation provides watching the real flowers, reading some basic information about those flowers on the board, and then getting further information from the Internet within the context of that real situation. Such scenario enables learners to actually experience the learning. Similar scenarios can be created within any other learning context, such as for factory processes, or any law firms. The sky is really the limit there.

So there are a number of ways to identify real life objects for learning purposes. Besides QR codes, if there are Wi-Fi access points available, certain objects can be annotated to them. In that case, as soon as the learner's mobile device approaches a Wi-Fi access point, it would be able to deduce that certain real life objects are available in nearby area. Active and passive radio frequency identification tags (RFIDs) are other technologies that can be used for the purpose of real life object identification.

1.7 The Research Framework—5R Adaptation Framework

Based on various learner, location, and environment awareness parameters, adaptive and personalized learning can be reliably provided in ubiquitous environments. An example of this approach is illustrated by the 5R Adaptation Framework, which identified these different components and then provides learning based on that. There are five different dimensions in the framework (Tan et al. 2011): timing of learning, learners' location, the device being used by the learner, learning content, and learner's individual characteristics.

The first component of the framework is *the right time*, where the date, time, and learning progress decide what kind of learning can and should happen. So for a law student, for example, who wants to learn about what happens in the Alberta legislature, then depending on the current time and the opening and closing time of the Alberta legislature, the systems built using the framework will either recommend the student to go there and provide related content, or otherwise will notify something like "No point giving you this particular content at this time because Alberta Legislature is closed at the moment". Similarly, the second component of the framework, the current geographical location of the learner, will enable the systems to show learners the content based on GPS Coordination match.

Then third component of the framework, namely the *device being used by the learner* dictates what kind of content and interactivity can be presented to the learners, based on the functionality available on different devices. For example, certain devices do not support Flash content. So, if the learners carrying those devices receive Flash content, it will not only not contribute toward the learning process but may also create serious obstacles in ubiquitous learning environments where learners rely on such content in the absence of immediate availability of teachers. The more we can find out about the technology that a learner is using, the better we can customize learning experience.

Another component of the framework is the *right content*, which indicates the kinds of objects available in the vicinity of the learner, what kind of learning activities that can be created using those objects, and what kind of learning instruction can be provided so that learner can get correct context.

The final component of the framework is the characteristics of the learners themselves. Different learners have different requirements. Different learners have different capabilities. When they are learning different things, they need different kind of content. So identification of who the learners are, and their different characteristics are then used to provide correct content.

1.8 The Vision Toward the Future

The more we know about the learners, the technologies available to them, their locations, the more there is need to understand the context of learning by analyzing all the available information. With context, we can identify, first of all, how to structure learning content, learning experience, learning activities, interaction, and so on, to suit that particular context. Then it can help in identifying what kind of learning objects, be them real life or virtual, the learners are actually interested in. This can then lead to proposing learning activities using that content, followed by leading the learner around the ubiquitous learning environment to undertake those learning activities. An early example of this approach is the context-aware mobile role playing game (Lu et al. 2014), which uses ubiquitous knowledge structure, and creates a storyline that uses that context-aware sequencing of learning objects and learning activities, based on learners' location, location of physical objects, and other parameters related to the learners.

Such ubiquitous learning environments have potential to provide effective learning to different types of learners in different situations. For example, active learning scenarios can be created for learners who have aptitude toward exploratory learning. Such environments can be created using passive technologies, such as QR codes, passive RFIDs etc., that enable learners to explore the environment and undertake various problem solving tasks. On the other hand, passive learning can be provided to those novice students who require more observational learning. Using active technologies, such as active RFIDs, Bluetooth access points, etc., the ubiquitous learning environments can guide the learners to the exact location of the learning objects and provide guided learning activities. In both types of learning scenarios, adaptive and personalized learning processes have potential to automatically assemble learning content to build the learning activities and learning path dynamically, to facilitate opportunistic learning.

In future, it is hoped that the emerging Big data analytics techniques will also play significant role in the learning process, and the lines between formal and informal learning will blur even further. Future ubiquitous learning environments will be able to use advanced data mining techniques to identify relevant patterns such as where and when the learners have difficulties and where their strengths lie. These information nuggets could then be presented to the teachers using advanced visualization techniques and smart technologies to enable them to naturally interact with the learners remotely using rich interfaces, and investigate and analyze learners' behavior, activities, and performance in truly ubiquitous learning environment. Such scenarios will enable teachers to intervene in the learning process in real time and provide learners with advice and support such as explaining the topic/tasks, pointing to particular learning material, providing learners with the activities that could help them in understanding the particular topic/task, and creating teams on-the-fly with complementary strengths. Furthermore, such environments may even help in gathering data about how different teachers respond in certain situations, which kind of support they provide to their learners, as well as how a particular teacher previously responded in certain situations. Based on this analysis, the adaptivity and personalization approach may even be able to offer suggestions and guidelines to the teachers themselves when a similar situation is identified in the future.

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Chapter 2
Learning and Teaching with Social Media

Jon Dron and Terry Anderson

Abstract This chapter is concerned with the ways that people can and do learn together, from and with one another. After discussing the benefits of dyads (pairs of people), we explain our typology of social forms, categorizing social groupings as sets, nets, and groups, along with an emergent entity, the collective, which arises from them. We describe the pedagogies, benefits, problems faced, and tools for learning using each social form and conclude with some suggestions about how social media may best be constructed to support each form and the likely future shape of social learning.

Keywords Social media · Sets · Networks · Groups · Dyads · Learning technology

2.1 Introduction

Learning is an inherently social process. We learn from and with others and, in almost all cases, that learning is mediated by technologies. Many communication technologies, especially language but also dance, painting, sculpture and more, are so deeply embedded that we seldom see them as technologies any more. The same is true of writing. For most of us, 'technology' is anything invented since we were born (Alan Kay, cited in Brand (2000)). Communication technologies are the vehicles of learning, the primary means through which we both know and create new knowledge. This chapter is concerned with the intentional design of communication technologies for learning: of social technologies.

The first generations of the digital counterparts of analog communication, many of which are still a significant part of our arsenal of tools, aimed to attempt to replicate older forms, albeit often adding incremental improvements in speed, access, cost, and management. Technologies that largely replicate what we do face-

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to-face, like telephones, videoconferencing, and screen sharing, may involve great complexity and ingenuity, but they are essentially the same thing made more accessible. The same is true of social technologies that build on other social technologies such as postal mail that is replicated in e-mail, classrooms that are replicated in learning management systems and journals that are replicated as wikis and blogs. In the process, transformations occur because, though based on earlier forms, they are never quite the same. They bring with them new adjacent possibilities (Kauffman 2000) that make new uses possible and provide the foundations for further technologies to evolve (Arthur 2009; Johnson 2012; Kelly 2010). This chapter is mostly concerned with those possibilities. It categorizes a range of social forms for learning that are facilitated through social software and describes some of the significant tools and methods that can be used with them to help people to learn.

2.2 Dyads

The simplest and perhaps the most archetypal social form for learning is that of the dyad, in which only two people are involved, typically in a teacher–student, master–apprentice, or parent–child relationship. One-to-one teaching is often held up as the gold standard for education with good reason. Bloom famously posed a 2-sigma challenge to teachers and to education systems, online and otherwise, in which he observed that students taught one-to-one show, on average, a 2-sigma improvement in their grades when compared with students taught using traditional classroom methods (Bloom 1984). Unfortunately, for mainstream teaching, the costs of dyadic learning are prohibitively expensive though personal tuition is occasionally used, especially for higher degrees and project support. There are many reasons dyads are so effective but there are three very distinctive features in this relationship that we would like to emphasize:

1. Learner control—through conversation and interaction, the learner is able to implicitly or explicitly make it very clear what he or she needs, understands, finds interesting, prefers, finds confusing or hates.
2. Because of the ease with which misunderstandings and misconceptions can be uncovered, the teacher is able to adapt the method and content of teaching to the learner's needs. There is no need to try to guess the needs of an intended audience or aim for an average of needs in a larger group.
3. The social relationship will inevitably be close: even if only as a professional requirement, the teacher is clearly interested enough in the student's needs to engage in the first place, and can be supportive and caring in a way that is hard to match when more people are involved. This remains true to an extent, even if the dyad does not get on very well, the teacher is a bully or the student is reticent. The simple fact of the relationship's existence places both parties in a reciprocal and generally well understood position of having to interact with the other.

These three distinctive features correlate directly with the cornerstones of intrinsic motivation as described by self-determination theory (SDT). SDT is a theory of motivation that has been tested and refined over some decades and is very well supported by countless research studies that show its applicability and relevance (Deci and Ryan 2008; Reeve 2002; Ryan and Deci 2000; Deci et al. 1991). SDT posits that there are three essential factors that must be present for someone to be intrinsically motivated to learn:

1. Control—the learner should feel in control of the process. This is clearly demonstrated in the first feature (above).
2. Competence—the task must be challenging but not too far beyond the learner's existing skill and knowledge. This is an outcome of the second feature.
3. Relatedness—there must be a social context to the learning in which the student feels valued by and engaged with others. This is almost inevitable thanks to the third feature.

As long as the teacher is moderately competent and caring, therefore, all the pieces are in place to enable the learner to be intrinsically motivated and to put the necessary effort into learning. Learning works effectively when learners are intrinsically motivated (Balduf 2009). They will work on skills until they have learned them, as long as nothing gets in the way of their motivation, such as extrinsic motivators such as grades (Kohn 1999), external demands (such as excessive family or work demands) or insuperable obstacles, which is where teachers can offer a lot of value. Time on task has the strongest correlation with learning effectiveness of any factor that has been measured by researchers so far (Stallings 1980). The difference between an expert and a nonexpert is almost perfectly correlated with the time spent learning and practicing (QuiŃOnes et al. 1995), although it is not clear which is the cause and which the effect, and other factors are significant too. Coupled with the knowledge of an expert who can guide them in useful directions, it is not hard to see why dyadic learning succeeds. It is not a *method* of teaching but a *condition* in which almost any method can be used, fitted to the needs of the learner.

We have many tools that support dyadic distance education, including telephones, postal mail and their newer more fully featured counterparts like e-mail, Skype, Apple FaceTime, Google Hangouts, instant messaging, etc. These newer tools allow more than just conversation: they let us work together, sharing files, screens, showing videos, and social presence, with greater convenience and less effort than older tools. Furthermore, there may often be a record of interactions that will allow the learner to reflect on and rehearse the conversations, increasing the benefit and impact, and allowing misunderstandings and confusions to be explored and examined.

Although dyadic education is inarguably social, there are some very important differences between this social form and those found in larger groups. In any larger collection of people, there can be factions and majorities. A group of three or more individuals persists when one leaves. There are social dynamics and power relationships. In a learning context, a social form of organization allows for the teaching role to be spread among learners as well as coming from the one labeled as the teacher. Learners see what other learners are doing, model how they are thinking, pick up ideas about both the content of learning and the ways that it can be achieved or refuted, and gain inspiration and motivation (or the lack of it) from those around them. In a larger group, learners are almost always teachers too, whether or not they intend to be. This can both increase the efficiency of learning and extend the breadth of what is learned. This is especially true when digital tools are used, at the very least because they enable persistence. We leave traces of our interactions in the digital space that continue to provide benefits beyond those of the immediate process of dialog. Digital tools can and usually do reify interaction so that conversations are not just a process of direct construction but also become repositories of knowledge on which we can build. Dialog and other interactions made concrete have particular benefits when many are interacting together, allowing all parties to make contributions that may be heard by others rather than be lost in the din of face-to-face interactions or, more commonly, remain unsaid due to power relationships, groupthink or simple lack of time.

2.3 Groups, Networks, Sets

The benefits of learning with others have long been known. Prior to the advent of large-scale networked technologies, most of our interactions with others were, however, confined to those in close physical proximity. This dependency led to two primary forms of social organization for learning, noted by many researchers:

1. the *group*, typically hierarchically structured, involving norms or rules and processes, with a clear focus and interests, and explicit membership, and
2. the *network*, constituted in terms of our direct connections with others, whether through friendship, relatedness, interest sharing or being in the same physical place (Rainie and Wellman 2012).

One other social form has, however, long existed: the *set*. When large numbers of people gather with no personal connection and no membership of a group with shared norms, such as at a hockey game or in a shopping mall, they may none-the-less gain benefit from (or, such as in the case of mobs, suffer from) the presence of others. Sets are simply defined as collections of people with shared attributes, which may include things like hair color, height, or religion but can also include aspects of far more relevance to learning such as interest in a subject area or topic, competence, and location. It is not uncommon to hear such collections described as ‘communities of interest’ or ‘loosely tied social networks,’ but the *set* is a preexisting and more concise term that fits these characteristics more precisely (Dron and Anderson 2014).

2.3.1 Collectives

There is one further form that must be considered to provide a full characterization of social technologies: the *collective*. It is traditional to divide communication that is enabled via digital technologies into one-to-one, one-to-many, and many-to-many variants: this is what we see in each of the social forms we have identified in greater or less degrees. Collectives, however, are concerned with *many-to-one* communication. Individuals in any combination of social forms may exhibit collective behaviors, such as when a crowd gathers around a street entertainer, a footpath emerges across a park as a result of many feet following the same trajectory, or (negatively) when a traffic jam forms emergently as a result of local behaviors. This is not a social form as such but a *consequence* of the actions of individuals that are aggregated from within other social forms, especially from sets but also, to a lesser extent, from networks and, occasionally, from groups (Dron and Anderson 2009). A collective acts as a single agent that can have a large effect on individual people, who may themselves be participants in the crowd that drive it. While collectives can occur without intentional design, simply through the decisions made by their constituents, digital technologies allow the crowd to gain more complex agency through manipulation of interface and algorithms for aggregating crowd behaviors. When we interact in a networked system, traces of our interactions may be mined and manipulated in ways that are not directly intended to communicate other things with others than the interactions themselves. For example, social navigation technologies such as tag clouds, trails, and presence indicators may be used to identify things that people find interesting or relevant. Google Search employs an archetypally collective design in its PageRank technology that uses a crowd's implicit recommendations to order the list of search results displayed to individual searchers (Page et al. 1999). Other common collective tools include rating systems, reputation management systems, and voting systems, in which the aggregated recommendations or ratings of many people are used to help individuals to make decisions.

2.3.2 Combinations

Groups, nets, and sets are overlapping categories that, more often than not, blur and blend, and all may contribute to a collective. Every group is also a set and nearly always a network. Every network is a set, the shared characteristic being connection in the network. But there are also many overlaps where one or more form is blended with another. For example, tribal groups like Goths or hockey supporters may be seen as sets, though they have shared norms and behaviors of the sort typically found in groups. Religious or political organizations are also set-like, but may involve greater group-like aspects such as hierarchies and explicit rules of behavior albeit without (necessarily) close personal ties. Communities or networks of practice (Wenger 1998; Wenger et al. 2011) share cohesiveness and common goals with groups, but have fuzzy edges and are formed of personal networked connections like networks. The social forms of sets, nets and groups are thus more like a palette of colors from which social organizations may be painted than mutually exclusive categories. The proportions of their distinctive features in any learning activity involving other people can strongly shape both interactions and the effectiveness of particular learning interventions. Figure 2.1 provides a visual diagram of these entities, indicating the blur between the categories and the fact that a collective can emerge out of any or all of them.

As the Internet has grown, different toolsets have been developed that support or encourage different social forms' emergence. Tools for groups, tools for social networks, and tools for communities of interest, or sets, not to mention support for using the wisdom of the crowd as collectives to help guide and shape our interactions. The aforementioned benefits of reification, combined with the massive interconnectivity of the Internet, have significantly increased the scope, breadth, depth and sophistication of the ways these social forms and their emergent collectives can support our learning. Every day, new ways of connecting with others are developed, often in ways that can positively or, sometimes, negatively affect our capacity to learn from and with other people. From the trivial—shared images of cats, say, or mind-numbingly stupid memes—to the profound, such as new forms of academic publishing, new scales of course delivery in MOOCs (massive open online courses) and new ways to discover knowledge, we are finding new ways to learn, engage and connect with other people. To those who question whether online social learning can work, we offer a simple challenge: to what do you first turn when you need to know something? For those with an Internet connection, the answer nearly always lies in Google Search, Wikipedia, Twitter, Facebook, or some other deeply social networked technology, some product of the read/write web.

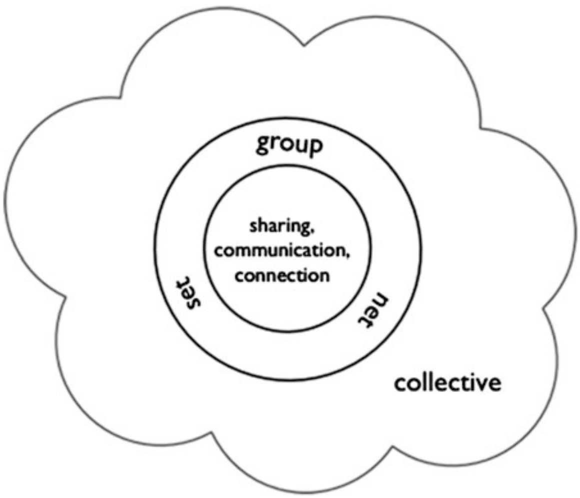

Fig. 2.1 Sets, nets, groups and collectives (after Dron and Anderson (in press))

Online social learning is perhaps the most significant broad category of deliberate learning in the world today, though language and writing still underpin these technologies and remain of greater primary importance. But, as well as magnifying our capacity to know, we are also discovering new ways to be stupid (Keen 2007), new ways to narrow rather than broaden our focus (Pariser 2011), new ways to be distracted and shallow (Brabazon 2007), new ways to become disconnected from one another (Turkle 2011). If we are to avoid the pitfalls and make the best possible use of these new technologies, learners and teachers need to understand what they are capable of, how they affect us, what are their weaknesses. At the heart of these problems lie the kinds of social form that are involved. Different social forms bring different values as well as different risks. We present here a very brief overview of issues covered fully in our forthcoming book, Teaching Crowds: learning and social media (2014) to provide a sense of the technologies and concerns with each social form and the role of collectives in supporting them. It should be noted that it is almost impossible to find a pure group, set, or net in the wild, so our brief overviews necessarily present caricatures of their behaviors. In real life, human interactions are complex, forms overlap, and people are members of many different communities that support their learning.

2.4 Groups

Groups are the stuff of formal institutional and organizational learning. They typically have labels (‘COMP266’, ‘Introduction to Philosophy’, etc.) and rites of joining and of leaving. They have rules, unwritten and/or written. They have hierarchies and roles, usually being led by a tutor of some kind. They enable collaboration, teamworking, and scheduled activities. They usually have a fairly clear purpose or focus. They are designed. In an educational context, they exist as classes, courses, cohorts, tutorial groups, seminar groups, schools, colleges, faculties, committees, and other deliberately created structures in which people work and learn.

2.4.1 Group Pedagogies

Group pedagogies typically emerge from a social constructivist tradition (Vygotsky 1978; Dewey 1916), in which learners help to construct knowledge through dialog and shared inquiry. Teachers in groups are, ideally, guides on the side, supporting and nurturing knowledge, growth, and facilitating discussion, debate and problems designed to challenge learners. Collaboration and/or competition tend to play important roles.

2.4.2 Group Benefits

When done well, group learning offers many of the benefits of one-to-one teaching, with further benefits emerging from the fact that all those in the group may play some teaching role, supporting one another's learning and helping to provide motivation. Groups are highly developed social forms that exist in many different configurations and have done so since prehistoric times. We know how to work together in groups, and there is a wealth of theories and models that explain group dynamics, group formation, processes for managing groups, and so on. Our institutions and organizations tend to be highly group-based. Groups are great for enabling collaboration, the development of trust and mutual support, for supporting planned learning journeys with clear directions and goals.

2.4.3 Group Problems

Groups are expensive to maintain: there is typically a need for administrative overhead. They often come at a cost of restricting time, place or pace of learning: as commonly used in education, they necessarily inhibit the control of at least some members. Because they are led and planned, topics may be of limited interest to at least some of their members some of the time: there is usually an averaging that makes some things boring, some too complex so, although social interactions allow negotiation of control and the potential for people to help others to understand things, their support for control and competence is a little coarse and uneven. They are subject to groupthink and are highly influenced by the quality of the group leader and the dynamics of social interaction. Group leaders may have limited knowledge when compared with all that might be known about a topic.

2.4.4 Group Tools

Digital group tools include, notably, learning management systems like Moodle or Blackboard, content management systems like Drupal or SharePoint, discussion forums, email. Such systems usually provide authorization and access control organized through roles and/or hierarchies.

2.5 Networks

Networks are concerned with the social connections between individuals, and the emergent clusters and circles that occur as a result. Joining a network consists of connecting with another person. Networks are therefore not designed, like groups, but emerge out of connections with others. They have fuzzy edges and may often only be clearly distinguished through complex analyses of social ties. Networks are built out of trust and social capital. We learn from and with people that we know who help us to discover things, solve problems.

2.5.1 Network Pedagogies

Network pedagogies typically evolve from a connectivist tradition (Siemens 2005; Downes 2008), in which knowledge is seen as an emergent network property, and connection and creation are valorized. In a network, everyone is a potential teacher but those who are most valued tend to act as role models and exemplars, sharing and connecting knowledge and people effectively, sharing cooperatively. Reflection, especially when shared with others, is vital. Many people make use of learning diaries, typically kept as blogs or portfolios to gain control of the disparate and loosely connected sources. Others use curation tools to provide a way of reifying their interactions and discoveries. Networked learning is about making sense of complex connections with the support of others, who may also help with a process of wayfinding—many people can explore multiple paths more efficiently than single individuals.

2.5.2 Network Benefits

Networks offer far greater freedom than groups for learners to discover and follow learning paths that are of interest to individuals, without following the plans or being subject to the constraints of others. Of all the social forms, networks are most firmly focused on the individual—what Rainie and Wellman (2012) describe as 'networked individualism.' With a focus on individual needs but with social ties to rely on, network-based learning is great when goals are unclear or emergent, when many heads are better than one, and to support the interests and motivations of learners. Networks provide relevance and meaning to individual learners, providing much control. The use of personal connections means that social motivation is well supported, with knowledge spreading through trusted networks.

2.5.3 Network Problems

Networks may lead to filter bubbles as people tend to connect with those they share some affinity. Furthermore, with little inherent structure beyond what emerges as ideas and memes spread around a network, learning paths may be inefficient and making choices between alternatives may be confusing. Depending on the other people in an individual's network, support for setting tasks that are appropriate to a learner's current level of competence may be patchy. There are risks of the blind leading the blind. Cultivating skill in the use of networks is important and, for less adept learners, may present a barrier to success. Networks offer many potential distractions unless methods or technologies are provided that allow the network to be segmented into relevant circles.

2.5.4 Network Tools

Digital network tools include, notably, social networking systems like Facebook, LinkedIn, Academia.edu. @mentions and following in Twitter, links between personal blogs. Such systems typically provide means to assert identity such as profiles, as well as authentication that provides trust in such identities. There is rarely much support for roles or hierarchies. Instead, many network systems allow parcellation of the network into lists or circles, allowing individuals to cluster their connections to support different learning needs. Alternatively, different tools may be used to support different subsets of one's network. For the purposes of assembly and construction, some form of personal learning environment (PLE) is useful. This can take the form of an aggregation tool like Evernote, Pocket or ReadItLater, or a purpose-built tool such as the personal dashboard provided by Elgg, which allows the user to fill a personal space with not just curated objects but also dynamic content and interactions from their network. Collectives may play an important role in networks in allowing the discovery of 'friends of friends' who may have the knowledge or competence needed to support learning needs, as well as potentially supporting the wayfinding process (Tattersall et al. 2005).

2.6 Sets

Sets mainly revolve around shared interests, with little or no explicit social connection of the sort found in networks and little or none of the design found in groups. In this way they are almost the polar opposite of networks, reducing the significance of individuals within the collection of people, and emphasizing the importance of content and subject-matter.

2.6.1 Set Pedagogies

Set pedagogies tend toward cognitivist and behaviorist models of content transmission that are concerned with how individuals learn. However, the choice of set and thus of content is entirely due to the individual learner, so they are pedagogically situated within a heutagogical tradition of self-organized and self- or peer-guided learning (Hase and Kenyon 2000; Dron 2004; Mitra 2012; Saba 1999). As for nets, individuals, supported by anonymous or barely known others, are concerned with sensemaking and wayfinding.

2.6.2 Set Benefits

Of all the social forms, sets offer the most freedom to the individual learner to guide his or her own learning. Without the filter bubbles and affinities of networks or the groupthink of groups, sets can be highly diverse, allowing many different and antagonistic viewpoints to coexist. They are thus a great source of creativity and discovery. Sets are also a useful way to gain entry into a community surrounding a particular subject area, to become familiar with norms, vocabularies and issues without having to be deeply engaged or committed to the community. They also have great value as a means of extending and developing networks. Some may evolve into or provide an entry into groups. Finally, sets can be excellent for problem solving, where diverse perspectives on problems can provide plentiful alternative solutions.

2.6.3 Set Problems

It is hard to judge the value of content and hard to trust individual people in a set. It is also sometimes difficult to find the right combination of people in a set with the right level of expertise: too little, and they are useless, too much and they are bewildering and demotivating. The relative lack of social structures or social ties mean that flaming, griefing, and trolling are commonplace. While sets are all about the subject, individual learners have the responsibility of choosing which sets to engage with and which people to pay attention to. For these reasons, the role of collectives in set-based learning is crucial and paramount. Crowd-based methods of ascertaining value such as reputation systems, collaborative filters, rating mechanisms, voting systems and crowd-based spam control are central to the effective operation of public set-based learning systems.

2.6.4 Set Tools

Digital set tools include, notably, Wikipedia pages, curated pinboards such as Pinterest and Learnist, Q&A sites like StackOverflow or Quora (though the latter has strong network elements too), shoutboxes like SlashDot, Reddit, Digg or news site discussions, #hashtags in Twitter. Like networks, PLEs and curation tools can be very valuable to the set-oriented learner, enabling sensemaking and organization of an individual learning path. It is also important that the set-based learner can make use of collective toolsets such as collaborative filters and tag clouds effectively. While, for systems like Google Search or tag clouds, this may be fairly intuitive, some set-oriented systems allow a great deal of customization and personalization of crowd recommendations, from the fine tuning of Amazon recommendations to the hundreds of different combinations of options on SlashDot.

2.7 The Future of Social Learning

As our brief overview has shown, each social form has strengths and weaknesses. There is a tension between the decentralization and individual autonomy promoted by network and set social forms and the centralization and manageability of group-oriented forms, which we see played out in the technologies used to support them. The rapid shifts in technologies that we see in the social software field are constantly moving targets. For network-oriented tools, network effects can lead to explosive growth and, as quickly, rapid shrinkage in uses of tools and systems. Similarly, and with the same network dynamics, sets come and go, existing on an evolutionary landscape with many niches within which only a few thrive and, again, the field is volatile. With a few notable exceptions (Wikipedia or YouTube, for example, both appear at the time of writing to be fairly unassailable) set-oriented systems come and go with startling rapidity. As we write this, Twitter and Pinterest are pack leaders, but this could change within a short period. The relative demise of giants like MySpace, Digg, Bebo, and Friendster amply demonstrates that tens of millions of users can become a trickle in the space of months. And the pace is accelerating. It took many years for Usenet News and Gopher to slowly decline, while Digg collapsed in a matter of weeks. This is the flipside of Metcalfe's Law (Metcalfe 1995), that the value of a network is proportional to the square of the number of connections: networks can shrink geometrically as well as grow. Within group-oriented systems like schools and universities, the opposite is true: massive investments in tools and systems to support interaction leave such deep and expensive traces that it becomes economically and practically infeasible to change platforms, especially where (following the group hierarchies) such systems are embedded from the top down. What felt like rational decisions to consolidate disparate LMSs in order to gain efficiencies and benefits of shared resources have come back to bite universities and schools hard now that they are effectively locked into single tools and systems. With every passing year and every bit of content loaded, training accomplished and systematic interdependence established, the systems become so integral to an institution's operations that the effort to move to a different platform makes a shift unthinkable. Canny publishing houses such as Pearson are rapidly moving into enhance and extend these tools in ways that, while making the lives of some teachers easier, make the lock-in worse. Meanwhile, set-based and net-based tools, often hosted in the cloud, are encroaching. This is most visible in the emergence of MOOCs and open educational resources that offer alternative and often disaggregated tools for learning. This decentralization is a two-edged sword. Though there are many options for those seeking to learn, such systems are again centralized at an individual system level and, in many cases, lock content and processes into specific systems from which it becomes hard to extricate oneself. On the other hand, they are distributed and have a rapidly expanding number of competitors. When the cost of engaging in a MOOC as a teacher or as a learner is low, it takes very little effort to shift from one to another.

We believe that, to take full advantage of the opportunities afforded by tools that support network and set social forms, it is crucial to build distributed systems without single points of control. Connectivist models of learning work on an assumption of open and unfettered connection, communication, and sharing. This makes them scalable and resilient, as well as highly adaptable to fast-changing needs and technologies. Systems built from small pieces are inherently more flexible and, ultimately, more reliable than carefully managed centralized systems.

To support such distribution, we need to look at different models of control and accreditation than those based around groups and hierarchies. The Open Badges project (http://openbadges.org), an open set of standards and technologies supported mainly by the Mozilla foundation, suggests an accreditation framework that has the flexibility and authority to compete with centralized models and allow evidence of lifelong learning outside closed group-oriented institutions to be counted. Anyone may award a badge to anyone for anything, each badge certified by the signature of its issuer and, through the same technologies, untransferable to another recipient. The system is very flexible and allows for an incremental shift in authority. Badges may be awarded, for example, for courses and degrees by institutions that are already known to be reliable. However, they can equally be awarded by individuals, whose reputations may equal or exceed those of institutions. We are already seeing effective use of a similar approach, albeit within a closed system, in the form of LinkedIn endorsements, that allow people to endorse the skills of others within their network. A network of people that you trust thus in enabled to provide a fairly reliable indicator of the skills and abilities of others in the network.

2.8 Conclusion

Social technologies are soft tools that can and must be seen as consisting of both tangible digital software and devices and less tangible social behaviors, norms, rules and methods of the people that use them. There is an intimate relationship between the constraints and propensities of those tools and the behaviors that occur within them. The tools both embody and facilitate the use of pedagogies that are entwined in a dynamic dance. Different tools lead to different behaviors but, equally, the same tools can lead to very different behaviors when applied to different social forms. As our tools become more sophisticated, they open up new possibilities and lead to the development of yet more sophisticated tools and methods, so we are in the midst of an explosion of invention in which the goalposts move on an almost daily basis. In this chapter we have provided a framework for looking at and understanding this evolving landscape from the perspective of how social learning can be supported. As our education comes to be seen not as (just) the outcome of institutional and commercial courses, but something that is ongoing and lifelong, the traditional group-based approaches to teaching are beginning to look clunky, inflexible and expensive. The ability of net-based tools to support and enhance the old social patterns of sets and nets, especially when combined with analytics that enable the collective to gain greater power and agency, makes them of huge importance for learning not just in the future but for today. We are just beginning to learn ways to take advantage of this enormous power and there is much research and invention still needed before they can release the strong hold that group-oriented learning methods have on our society, and some large problems to be overcome. We have evolved as a species in groups, and the forms that have evolved are highly sophisticated and well developed. There will probably always be a place for group-based methods, albeit greatly enhanced by the power of social forms that extend beyond them but, if we are to move forward and allow rich, lifelong learning for all, we must find ways to take better advantage of the large and richer networks, sets and collectives that the Internet makes possible.

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Chapter 3
Causal Models and Big Data Learning Analytics

Evolution of Causal Relation Between Learning Efficiency and Instructional Effectiveness

Vivekanandan Suresh Kumar, Kinshuk, Clayton Clemens and Steven Harris

Abstract New statistical methods allow discovery of causal models purely from observational data in some circumstances. Educational research that does not easily lend itself to experimental investigation can benefit from such discovery, particularly when the process of inquiry potentially affects measurement. Whether controlled or authentic, educational inquiry is sprinkled with hidden variables that only change over the long term, making them challenging and expensive to investigate experimentally. Big data learning analytics offers methods and techniques to observe such changes over longer terms at various levels of granularity. Learning analytics also allows construction of candidate models that expound hidden variables as well as their relationships with other variables of interest in the research. This article discusses the core ideas of causality and modeling of causality in the context of educational research with big data analytics as the underlying data supply mechanism. It provides results from studies that illustrate the need for causal modeling and how learning analytics could enhance the accuracy of causal models.

Keywords Big data learning analytics · Artificial intelligence in education · Bayesian networks · Causal models

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3.1 Introduction

People make constant use of causal relationships in our everyday lives. We recognize many different types of causes, be they mechanical, psychological, or historical. In many instances, people are wrong about the causal relationships we assume in life solely because the everyday behavior of individuals lacks formal methods of evaluating the likelihood that people are right or wrong. At the same time, the data people typically rely on to establish causality tends to be static. That is, the changing nature of the data is something people overlook, particularly when the change is continuous. Recent advances in causal modeling address these problems and have offered solutions that are significantly advanced compared to contemporary research methods in educational research. This article squarely addresses these advances and offers a perspective on significance of the differences between causal approaches and the rest in educational research.

This section offers a brief introduction to causality and causal modeling, followed by an introduction to learning analytics. The section concludes with a remark on the need to marry these two areas toward futuristic learning environments.

3.1.1 Causality and Causal Models

Over the last two decades several groups of researchers, in particular Judea Pearl and colleagues at UCLA and Peter Spirtes group at CMU, as well as David Heckerman at Microsoft Research have begun to make major advances in formally representing the notion of causality, providing mathematical manipulations of it, and algorithms for discovering causal relationships from data. These advances now allow us to discover some causal relationships formally, given certain assumptions, from purely observational data. We can also characterize what relationships can be learned in this way, and what assumptions are necessary. They also allow us to evaluate when, how many, and which experiments are necessary to discover causal relationships we cannot derive from observational data alone.

Causal relationships could be embedded among multiple, related variables of interest, yielding causal models. In addition to their formal properties, these causal models are graphical, and are reasonably easy for people to understand. They allow the compact representation of the causal claims made in a field for easier understanding by researchers in that field.

Descriptive statistics and correlations make no claims about causation, only statistical conclusions. That is, correlations and conditional probabilities can be drawn from descriptive statistics and correlation without additional assumptions or experimental results. Meta-analysis combines data and statistics from multiple studies to increases the effective sample size, but it does not allow one to draw causal conclusions unless experimental studies are being meta-analyzed.

Regression testing is sometimes used to attempt to identify causal relationships by analyzing how much variance variables "explain" about each other. However, in general, regression analysis per se makes no supportable claims about causation. Spirtes et al. (2000) argue strongly that regression, as used, is in fact poorly suited to causal analysis in most cases.

Structural Equation Model (SEM) is a graphical representation of relationships between variables which have been in use in the social sciences for decades. Linear SEM represents linear relationships between variables generally assuming a normal (Gaussian) distribution. The relationship between variables is represented as a linear equation of the form $y = x + u$, where y is the effect, x the cause, u the error term represents the effect of all other variables, and is the path coefficient which quantifies the strength of the relationship between the variables (Pearl 2003). They can be used to represent both measured variables and latent variables. The measured variables are often the results of surveys or other instruments where multiple measures are intended to estimate an unmeasured (latent) variable. In this case, the measured variables are called the measurement model and the latent variables are called the structural model. In SEM, an undirected edge represents a correlation relationship, and a directed edge represents a "directed relationship" (MacCallum and Austin 2000). Structural Equation Models' original interpretation did include causation. However, that interpretation has fallen out of favor over time (Pearl 2000).

Path diagrams, also called path analysis, are a special case of SEM which excludes latent variables. In the terminology of Spirtes et al. (2000), this is known as a pure measurement model. Pearl notes that the causal assumptions in path diagrams are represented by the absence of links representing a definite absence of a relationship and the presence of a link only represents the possibility of a cause (2003).

In psychology, SEM is often employed to analyze the results of observational studies, though they can represent experimental studies as well (MacCallum and Austin 2000). Social scientists generally use SEM in a confirmatory approach. The researcher proposes a model based on a theory or other considerations and then either tests the fit of the model to the data, or compares the fit of the proposed model against another baseline model. The a priori proposal of models presents a serious difficulty as model fit to data does not imply correctness of the model, and large sets of models which are statistically equivalent may exist. It appears that researchers are often unaware of or discount the existence of equivalent models, and are likely to overestimate the likelihood of the proposed model being correct (MacCallum and Austin 2000). Formal causal modeling approaches address such difficulties.

Causation can be defined in terms of counterfactual relationships. A counterfactual is a statement that is literally counter to fact, that is, something which did not happen. Counterfactual questions are about what would have happened had some factor been different from what in fact occurred. From the counterfactual perspective, a causal relationship exists between two variables if the "cause" occurred differently would have resulted in the "effect" occurring differently. An example of counterfactual question is about asking whether a poorly achieving student would be a good student if he had been in a smaller class. In causal language, is class size a cause of performance gains in students?

Causality can also be defined in terms of intervention, also called manipulation. Essentially, a variable A is considered a cause of variable B if changing (manipulating) A results in a change in B. For example, we say that impending rain, and the accompanying increase in air pressure causes a barometer to rise, but the rising barometer does not cause the rain, or the air pressure. From the manipulation perspective this means that manipulating air pressure changes the barometer level but manipulating the barometer level does not change the air pressure or the rain. This practical definition is essentially what is used in randomized controlled experiments throughout the sciences to detect causation. An experiment attempts to manipulate one or more variables while ensuring through randomization that the other variables have the same characteristics they would normally have. If an unmanipulated variable changes with our manipulation we ascribe a causal relationship between the manipulated and unmanipulated variable.

Spirtes et al. (2000) define causation as: "We understand causation to be a relation between particular events: something happens and causes something else to happen. Each cause is a particular event and each effect is a particular event. An event A can have more than one cause, none of which alone suffice to produce A. An event A can also be overdetermined: it can have more than one set of causes that suffice for A to occur. We assume that causation is (usually) transitive, irreflexive, and antisymmetric. That is, (i) if A is a cause of B and B is a cause of C, then A is also a cause of C, (ii) an event A cannot cause itself, and (iii) if A is a cause of B then B is not a cause of A."

Causal representations allow us to answer a broader set of questions than stochastic representations. In a purely probabilistic model, represented by the joint probability distribution, we can answer questions about the correlation between any sets of variables. Probabilistic representations such as Bayesian networks can answer questions about the likelihood of one set of variables taking particular values, given that we have observed another set, and about which set of variables we should observe to obtain the most information about the likelihood of another set of variables taking particular values.

Causal models add the ability to answer questions about the likelihood of a set of variables taking particular values if we intervene to change the value of another set of variables. The distinction may not seem large, but it has major implications. This type of question is asked often, for example, in trying to improve education, we are interested in how various factors relate to learning achievement because we want to take some action to improve achievement. Knowing the correlation of achievement with high self-efficacy beliefs is interesting, but what we want to know is if intervening to increase self-efficacy beliefs will cause an increase in achievement. These questions cannot be answered by purely stochastic models.

The most important differences between probabilistic models and causal models are the type of information they can represent and hence the type of questions they can answer. Probabilistic models can be used to perform probabilistic inference, answering questions such as "What is the likelihood of X if I observe Y?", "What is the prior probability of X", and "Which variable should I observe to gain the most information about X (other than X)?" These questions can either be answered directly from a joint probability distribution, or by using a probabilistic model which represents the joint probability distribution more efficiently, such as Bayesian Networks.

Perhaps less obvious is what questions cannot be answered by stochastic models, but are answerable by causal models. Causal models allow for causal inference, answering questions such as "What is the likelihood of X if I do Y?", equivalently, "What is the likelihood of X if I force Y to take on a particular value?". The difference between doing and seeing, elucidated by Pearl (2000), is essential to the manipulative account of causation.

Causal models allow us to answer questions about what will happen if we take action to change the world, instead of what will happen if we simply observe it. If we know that drinking and driving causes increased likelihood of car collisions, and car collisions cause increased likelihood of death, and we observe two cars get in a head on collision we have reason to increase our belief that the driver is both drunk and dead, but if we take control of the car remotely and cause the head on collision, we still expect the unsuspecting driver to die, but we would have no reason to suppose him to be drunk. Our, rather immoral, intervention has broken the regular causal connection between drunk driving and traffic collisions, and trying to draw a conclusion solely from the correlation and drunk driving is erroneous. The change in circumstances invalidates our existing correlation and we have no way of recording the difference using probability alone. There is no way to write "The barometer does not cause the rain" using the language of probability. We can only denote the dependency and only under static conditions.

Causal models can also answer questions about counterfactuals such as "What is the likelihood that X would have been x if Y was y given that X was not x and Y was not y?" or more clearly "What would have happened if X had been different?" A wide variety of policy issues require answering causal questions. To take an example in education, a probabilistic question might be "If we observe that a student has high self-efficacy beliefs, what is the likelihood he will be a high achiever?" a causal question "If we intervene to increase a student's self-efficacy beliefs, what is the likelihood he will be a high achiever?" or "Will intervening to increase a student's self-efficacy beliefs cause an increase in his achievement?" or the counterfactual "Would a student's achievement have been greater if his self-efficacy beliefs had been higher?" The causal questions are clearly what we want an answer to, and those answers are not available from purely probabilistic models. Knowing that self-efficacy beliefs are correlated with performance does not tell us whether acting to increase an individual's self-efficacy beliefs would have an effect on their performance, and this is precisely what we want to know.

There are several varieties of graphical causal models. All of these models have in common the ability to represent causal relationships between a set of measured variables. The representations differ in their ability to represent latent variables and cyclic relationships. They also differ in their amenability to algorithms which discover causal relationships from observational data and efficiently perform both causal and probabilistic inference. The different models rest on different assumptions about the structure of the domain being modeled.

By using a combination of techniques from the graphical causal model literature, we are able to discover some causal relationships from observational data, even allowing latent variables, and improve the model using both background knowledge and experimental results. We may also learn parameterisations of the models from data, and conduct causal and probabilistic inference over the models to answer questions of interest.

While graphical causal models can be proposed a priori by researchers as with SEM, the ability they provide to discover an equivalence class of models directly from data provides additional power to the researcher. The equivalence class indicates which potential relationships between variables require background knowledge or experimental results to determine. This knowledge allows a researcher to guide their investigation into productive areas, collecting observational data only where useful and experimental data only where necessary.

Researchers have designed algorithms for performing causal inference over graphical causal models, allowing computational answers to questions about the likelihood of world states given an intervention, and counterfactual questions about alternative states of the world. These algorithms extend the capabilities of both SEM and existing probabilistic representations, and should prove useful in educational research. The two greatest limitations faced by these methods are the assumptions they require in order to connect statistical relationships with causal relationships, and the amount of data necessary for reliability. The issue of the amount of data is addressed by the emerging field of big data analytics.

3.1.2 Learning Analytics

The analysis and discovery of relations between human learning and contextual factors that influence these relations have been one of the contemporary and critical global challenges facing researchers in a number of areas, particularly in Education, Psychology, Sociology, Information Systems, and Computing. Traditionally, these relations concern learner performance and the effectiveness of the learning context from a summative point of view. Be it the assessment marks distribution in a classroom context or the mined pattern of best practices in an apprenticeship context, analysis and discovery have always addressed the elusive causal question about the need to best serve learners' learning efficiency and the need to make informed choices on a learning context's instructional effectiveness.

Learning efficiency encompasses any and all aspects that concern "learning" of individual learners or groups of learners. Examples of learning efficiency aspects include learning style, metacognitive scaffolds, peer interactions, self-regulation, coregulation, social networking, and other learning-oriented activities and characteristics associated with learners.

Instructional effectiveness encompasses any and all aspects that concern enhancement of targeted as well as inadvertent “support for learning”. Examples of instructional effectiveness include pedagogy, andragogy, peer evaluation, software agent-oriented guidance, lectures, content, presentation of content, instructional design, learning objects and other resources, assessment structures, open learning, and so on.

Significant advances have been made in a number of areas from educational psychology to artificial intelligence in education, which explored factors contributing to learning efficiency and instructional effectiveness. A number of these factors have been combined to yield improvement in learning efficiency or in instructional effectiveness or both. Again, most of these advances are situated in a summative approach.

With the advent of new technologies such as eye tracking, activities monitoring, video analysis, content analysis, sentiment analysis and interaction analysis, one could potentially engage in repeating portions of experimentation performed under the summative approach but with the inclusion of formative data. This would not only enable one to understand the relationship between process-centric formative data related to learning and the product-centric summative data related to learning, but would also allow only to address learning efficiency and instructional effectiveness at an optimal granular scale. This very notion is what is currently being explored under the aegis of big data learning analytics, which includes sub areas such as learning process analytics, institutional effectiveness, and academic analytics.

Big data analytics, as opposed to smaller data analytics that can be equated to approaches that use data mining or simpler artificial intelligence in education techniques, targets large volumes of data as well as large number of voluminous, yet likely distributed, computational models concerning learning efficiency and instructional effectiveness. Big data learning analytics is all about analysis of learning patterns in various yet related levels of granularity from the large volumes of data and the large number of voluminous models.

Technologies now exist to track the study processes learners undertake to achieve their learning goals and outcomes, particularly in online learning environments. Tracking of study processes lead to what we term as “learning traces”. A learning trace comprises of a network of study activities that lead to a measurable chunk of learning. For example, a learning trace in the context of writing could be on “the types of sentence openers used by a group of learners”. By observing how this particular group of learners developed their writing assignment, within a specified time frame, at the word level, one can expect to collect raw data such as preparatory work prior to writing (if any), speed with which words and phrases were added to a sentence opener, lexical/grammatical errors made and corrected as part of sentence construction, and topic flow in a paragraph. One can then analytically extract types, quality, and distribution of sentence openers developed by this group of learners. Further, the tracing system can provide just-in-time feedback to individual students (and inform instructors, if required) as and when pedagogically valid issues are recognized about their sentence opener patterns.

Learning analytics in the domain of human learning and machine learning can be defined as a field that concerns analysis and discovery of learning traces from raw learning related data, gaining new relationships among learning traces, evolving new knowledge about networks of learning traces, promoting learning activities and instructional activities that lead learner(s) and instructional resources (including teachers) toward targeted learning traces and study skills, and measuring the impact of analytics techniques with big data as the premise. The big refers to the combination of volumes of data as well as the volumes of models that contribute to the analytics.

Big data is characterized using the following five factors—volume, speed, variety, veracity, and value. Volume addresses the sheer quantity of data that is expected to be in orders of magnitude much higher than Gigabytes. Speed refers to the arrival and processing of learning related data; while it is discrete in nature, it could be sufficiently dense to be treated as a continuum. Variety implies that learning related data could be structured, semistructured, unstructured, interconnected, and discoverable. Veracity advocates the need for information extraction, model development, and machine-oriented learning to adhere to quantifiable truth in BIG data, which requires multiple levels of validation of the underlying data and its transformation. Finally, Value dictates that the utility of recognizing, discovering, and promoting learning related patterns, aka learning traces, be explicitly associated with performances of individuals, instructors, institutions, and software agents.

Learning Analytics can be distinguished from Artificial Intelligence in Education in terms of the focus on learning evolution using BIG data as the basis. Learning Analytics can be distinguished from Educational Data Mining in that it does not expect well-defined data to be available in a repository. Learning Analytics can be readily applied in the domains of reading, writing, free-hand writing, coding, mathematical problem solving, understanding learning styles, gaming, chats (e.g., video, audio, text), in-class performances, metacognitive activities (e.g., self-regulation, coregulation), social network contributions (e.g., social network analysis), and usage of learning resources/tools such as Matlab, SPSS, Eclipse, and Moodle.

Learning Analytics would yield data about learners that are typically not available. For instance, in the domain of writing, in addition to analytics on sentence openers that we discussed earlier, analytics results such as chronic difficulties students face while writing, flow of topic, speed of writing, writing density, distribution of lexicon, grammatical error creation and correction patterns, conceptual buildup prior to writing, and content review pre/during/post writing can be tightly integrated with contemporary assessments of student writing. As a result, along with marks/grades, students can explicitly associate skills they evolved and exhibited in achieving these marks/grades.

Learning analytics allows continuous monitoring of learner progress and traces of skills development among individual learners across programs and institutions will serve as a comparative measure. It tackles issues concerning continuous mapping of institutional learning related achievements to gage alignment with strategic plans and alignment of governmental strategies. It develops assessment frameworks of academic productivity to continuously measure impact of teaching. It discusses concerns such as quality of instruction, attrition, and measurement of curricular outcomes could be measured and visualized based on evidences of learning traces. Additional details on big data learning analytics can be pursued in Chap. 10 in the same volume.

3.1.3 The Need to Infuse Causal Modeling with Learning Analytics

By definition, BIG data analytics involves large volumes of data as well as large number of voluminous models. One of the key characteristics is the continuous flow of data. That is, we expect data being recorded, mined, and analyzed on a continual basis throughout the episode of each learning activity. Also, there could be multiple sensors observing the same learning activity from different perspectives offering multiple avenues of analyses.

It is quite possible to engineer causal models based on the literature by observing variables and relationships between those variables that have been established via experiment or observation. These causal models could also include theoretical, unexperimented relationships expected by researchers. Such engineered models have several uses. They clarify the state of the theory in a clear and formal manner, thus explicating narrative form claims from the literature, where variables can be implicit, explicit, covert, and measurement variables. Modeling observations from the literature in this way allows us to attempt to draw conclusions about appropriate interventions to take based on what the model claims. For example, if having goals (self-set or otherwise) causes a student to perform better, we can intervene to set goals for the student. However, if having goals is only correlated with performance as a result of a common cause like goal orientation, then we should attempt to intervene to cause goal orientation. Having such a common model also allows one to improve upon it over time as many researchers work on different and possibly overlapping subsets of the same common model. Having a set of engineered models allows one to fit the incoming data onto the model and determine the validity of various claims portrayed by the model.

Causal models also allow one to discover such models from observational data using structure learning algorithms such as Fast Causal Algorithm (FCI). That is, without explicitly making assumptions about relationships that might exist among various components of the incoming data, structure learning algorithms could potentially derive a set of plausible models that represent perceived relationships among components of the incoming data. It is important to note that the point of statistical indistinguishability can only be attained once a certain threshold of volume of observational data is reached. This also indicates which relationships would require additional background information or experimental results to fully determine causal relationships.

Knowledge of how much of the causal relationships we can learn from observational data is useful because it is generally easier to collect observational data than experimental data. In attempting to learn as much as possible from the observational data, one would also like to know the assertions about causal relationships that can and cannot be established with observational data. Importantly, one can also know approximately how much data is required because it governs the confidence in causal conclusions.

The FCI algorithm is one of a class of algorithms that can discover causal models from conditional independence relationships among variables, which can be determined from statistical data. When the statistical data is perfectly accurate, it represents the true dependencies and independencies which exist in the real population represented by the variables. When supplied with the conditional independence relationships, either directly or through accurate statistical data, the FCI algorithm produces a representation of the equivalence class. Causal models represent the conditional independence relationships between the variables. Using the TETRAD IV software package, one could employ the FCI algorithm on the conditional independence relationships represented by the engineered theoretical model to discover the model up to the point of statistical indistinguishability. By doing this from the conditional independence relationships represented by the graph, we avoid any artifacts due to sampling variation. One can then incorporate temporal background information to determine what if any additional links can be established.

The equivalence class of the theoretical model establishes the upper limit of our ability to discover causal relationships from observational data alone, assuming that data is perfect. Unfortunately infinite perfect data is not available. In order to determine the amount of observational data required to accurately discover the equivalence class, one could conduct a simulation study repeatedly using the engineered models to generate statistical data samples and then applying the causal discovery algorithms to that data, increasing the amount of data generated and evaluating the match of the discovered model against the model discovered directly from the conditional independence relationships, thus establishing the viability and limitations of discovering causal relationships from observational studies.

One can also use theoretical results about the number of experiments necessary to evaluate which and how many experiments would be required to fully orient the causal network, thus comparing this number to the number of experiments required if such methods are not possible.

Causality is an essential concept to people in everyday lives attempting to understand the world. The world of learning is quite complex and causal models can be handy in clarifying such complexity. Causal models require large volumes of data, which can be provided by learning analytics. In turn, learning analytics require clear and concise relationships to be established between learning efficiency and instructional effectiveness, which can be provided by causal models. The rest of the chapter will demonstrate this idea with two case studies.

3.2 Case Studies

The following case studies illustrate the power of use of causal modeling in educational research. The first study explores writing analytics infused with causal modeling. The second study presents metacognitive analytics infused with causal modeling.

3.2.1 Writing Analytics

Writing competence comprises factors that relate to the knowledge of sentence structure, spelling, readability, grammar, the context of writing, and measurable proficiency levels of the individual. The goal here is to generate the underlying causal structure that exists among a set of factors associated with writing.

The test data that was analyzed to extract the underlying causal structure is taken from the University of Michigan's freely available Michigan Corpus of Upper-Level Student Papers (Römer and Wulff 2010). This corpus contains data across several disciplines at various levels of university studies. Many different nationalities and levels of proficiency are represented. A total of 1,323 sentences were chosen as the raw data for this study. Five different factors were chosen for study in the raw data (see Figs. 3.1 and 3.2).

Tetrad IV,[1] a statistical analysis program designed to explore trends in datasets was used to look for causal relationships among a number of factors related to writing. Tetrad IV offers four major categories of algorithms to extract causality and causal relations from raw data.

First, the PC family of algorithms assume that the variables represent a complete set of data, in which there are no hidden or latent variables that relate them. The PC algorithms assume that the relations between the data variables are acyclic in nature, and they do not form a causal loop. They work by making judgments about the independence of pairs of variables.

Second, the FCI family of algorithms allows for error within the data sets, and will attempt to discover hidden and latent variables. The other assumptions are the same as the PC family of algorithms such as discrete or continuous input, nondeterministic variables, and true acyclic graph. The primary difference between PC and FCI is that FCI produces a Partial Ancestral Graph (PAG) rather than a Directed Acyclic Graph (DAG). This means primarily that an edge in the PAG does not necessarily indicate a true direct causal relationship; only that an indication of causality is present.

Third, the Bayesian algorithms that include Greedy Equivalence Search (GES) and the Markov Blanket Fan (MBF) search. The former uses Markov equivalence classes represented by patterns to interpret the data. A pattern is essentially an

[1] http://www.phil.cmu.edu/projects/tetrad/current.html.

Fig. 3.1 Graph generated for writing analytics by the PC algorithm

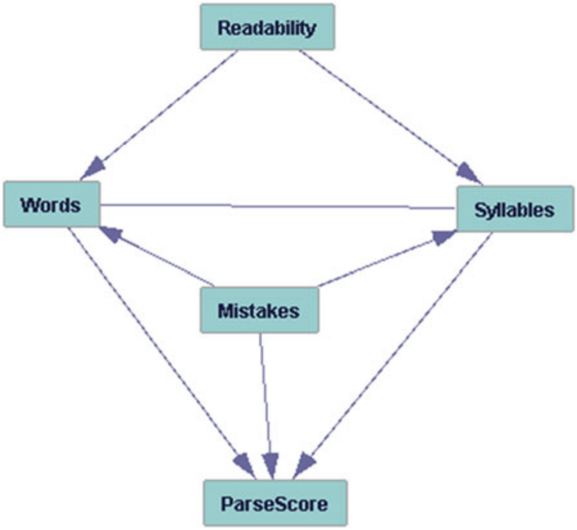
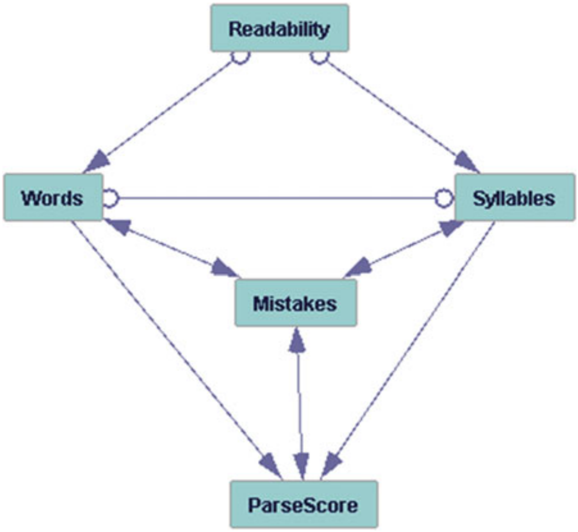


Fig. 3.2 Graph generated by the FCI algorithm



acyclic graph that represents the edges that can be determined by the search. Patterns are scored using a forward-backward method. In a forward sweep, the algorithm determines which edge should be added to increase the score the most. In the backward sweep, the algorithm determines which existing edge should be removed to increase the score the most. This is why the algorithm is called"“greedy”. When there are no more possible increases, a PC-like orientation phase begins. The highest scoring pattern is returned (Chickering 2003; Zhang and Spirtes 2005). Markov Blanket Fan search is a mix between PC and GES. Like both of these algorithms, it makes the assumption that the underlying relationships are acyclic containing no hidden variables and no determinism. It also returns a pattern. The difference from the other two algorithms is the nature of the pattern it returns. As per its namesake, the pattern is based on the Markov blanket of the graph.

The final class of algorithms build pure measurement/structural models. These algorithms assume that every observed variable is indicative of a number of latent variables. The measurement model describes which latent variables case which observed variables, and the structural model determines causality between latent variables. Such models are considered to be pure if every observed variable has one latent variable as a parent, and if every observed variable is connected with another through a path that doesn't include a latent variable.

The same basic graph structure (see below) was obtained when the raw data was supplied into Tetrad IV and when all four classes of algorithms were run. The relations between these variables are all consistent across each different type of algorithm. The differences between what the results tell us is in the exact type of relations that are asserted to exist in each graph.

The most basic of our search algorithms, PC (Fig. 3.1), indicates a number of causal relations between the variables.

Readability, according to the diagram, influences the number of words and the number of syllables. In fact, the opposite is true from a conceptual standpoint. The number of words and the number of syllables in a sentence are used to functionally compute the readability score.

The number of words, according to the graph, is influenced by the readability of the sentence, and the number of mistakes that are in it. Like readability, we would expect these causal influences to be reversed. The number of words should affect the number of mistakes, and the readability, rather than vice versa.

The words variable is also shown in the graph to have a relation to the number of syllables in the sentence, and is considered to be a cause of the parsing score. This is correct, though we would expect the number of words to be a direct cause of the number of syllables. However, one could also state the same for the syllable count itself. And in fact, the syllable count has exactly the same causes and effects as the word count for a sentence.

The number of mistakes influences the number of words, syllables, and the parse score, according to the graph. Again, we would expect the opposite for the former two assertions; the words and syllables are more likely to be a cause of the number of mistakes.

Finally, the parse score is influenced by the number of words, the number of mistakes, and the number of syllables, which makes logical sense.

Given the nature of the produced graph for PC, the relationships are all in correct places; the causal directions are simply reversed in certain key places. It is likely that this is simply a matter of confusion as to the point of reference: which data series was analyzed first by the algorithm. If the readability was analyzed first, the correlation between itself, the number of words, and the number of syllables would cause it to be interpreted as causing its constituents Fig. 3.2.

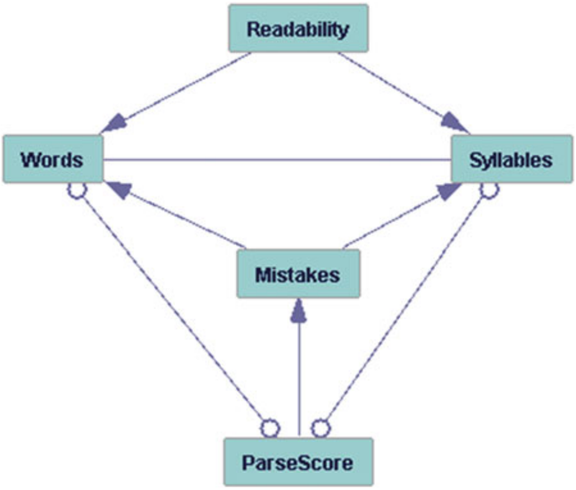


Fig. 3.3 Graph generated by the CCD algorithm

The FCI algorithm provides some further insights by indicating where it cannot determine where a causal relationship exists. This lends further credence to the idea the word-syllable-readability relationship is opposite of what's suggested in the PC graph. The "o" shapes at the ends of the word-syllable, readability-word, and readability-syllable relations mean that there may be causal relationships at those variables. Thus, there would be a two-way causation between each pair of the readability, word count, and syllable count variables (Fig. 3.3).

CCD also indicates some uncertainty, but in different pairs of variables; preferring instead the relations between words, syllables, and the parser score. In this case, it is uncertain where the direction of causality lies.

The remaining algorithms (CPC, CFCI, GES, and MBF) give the exact same relations as the more specific algorithms do, simply without asserting exact causality between them.

While the causal models discovered from the raw data for these 5 factors have originated from sentences written by a number of students, it is quite conceivable to generate similar models for an individual student.

3.2.2 Metacognitive Analytics

Self-regulation of behavior is a general concept in psychology and is studied in many different domains. SRL research focuses on self-regulation of learning, primarily in academic or classroom environments. SRL theory places the learner at the center of the learning process as an engaged, proactive agent (Zimmerman 2001; Boekaerts and Corno 2005; Pintrich 2000). Students are considered self-regulated if they actively manage their own learning behavior, setting and evaluating goals, monitoring the progress, using strategies and tactics for learning and accomplishing their goals, and conducting self-evaluation in order to improve their goals and strategies. This is in contrast to theories which have influenced American educational reform over the past 50 years, which regard the learner as reactive instead of proactive, as a recipient of taught information (Zimmerman and Bandura 1994).

SRL is a complex concept with multiple theories which differ in inspiration and emphasis on different learning elements. Boekaerts and Corno (2005) suggest several assumptions common to most if not all SRL theoreticians:

> …students who self-regulate their learning are engaged actively and constructively in a process of meaning generation and that they adapt their thoughts, feelings, and actions as needed to affect their learning and motivation.
> …biological, developmental, contextual, and individual difference constraints may all interfere with or support efforts at regulation.
> …students have the capability to make use of standards to direct their learning, to set their own goals and subgoals.
> …there are no direct linkages between achievement and personal or contextual characteristics; achievement effects are mediated by the self-regulatory activities that students engage to reach learning and performance goals.

In essence, the researchers believe that actively engaged students take a proactive role in their learning employing learnable skills, strategies, and tactics in all their different domains of action, and that while their personal or environmental characteristics may affect their performance, those effects take place in the context of a student's SRL skills. In particular, SRL researchers consider self-awareness of cognitive control strategies and learning strategies.

Metacognition, the process of thinking about thinking, is a key aspect in the ability of learners to regulate their own behavior. The process of learning in a self-regulated fashion is conceived of as a cycle. The student repeatedly passes through a series of phases as they learn, taking relevant actions and using appropriate cognitive and metacognitive strategies and tactics as they progress through the cycles.

SRL researchers have proposed, used, and evaluated multiple models of the SRL. The differing models emerge from different theoretical orientations, differentiate and organize the phases differently, and focus on different actions and behaviors within each (Puustinen and Pulkkinen 2001). Some focus more on overtly visible behavior, others on more covert behavior. Zimmerman identifies seven major theoretical traditions in SRL: operant, phenomenological, social cognitive, information processing, volitional, Vygotskian, and constructivist (Zimmerman 2001). While the major traditions generally agree on the few assumptions noted above, their stance on what is significant and included in SRL research varies with their source of inspiration. Two major models of SRL are the social cognitive model of Zimmerman (2001, 2002) and the model of Winne and Hadwin based on information processing (1998).

Boekaerts and Corno describe eight major categories of measurement methods used in SRL research (2005). Self-Report Questionnaires attempt to measure learners' SRL behavior via a series of questions which ask the learner to describe self-regulatory responses to various learning situations. Observations of Overt Behavior record ongoing behavior and "score" it according to predefined coding system which determines what variables will be included for consideration. Counts of scores can be subjected to statistical analysis. Qualitative data (e.g., recordings of actions) can also be interpreted, but not statistically. Interviews generally seek to obtain qualitative information about experiences during SRL. Interviews take several common forms, including unstructured interviews where learners tell stories of their behavior, structured interviews where the interviewer asks questions which build upon each other, guiding the respondent, semistructured interviews which allows researchers to adaptively select from a predefined list of questions as the interview progresses, and stimulated recall, in which students comment while watching a recording of themselves working. In Think Aloud Protocols students verbally report their thoughts/strategies etc. while they work. This process is limited by the need to train learners beforehand, and it may impact the tasks due to the increased cognitive load experienced. It may also force the students to be more cognitively aware than they might otherwise be. With Traces of Mental Events and Processes the research attempts to identify observable traces (evidence) of student learning processes and code them for what each trace indicates. Situational Manipulations are experimental studies where students' actions in the learning phase are connected with their performance. In Recording Student Strategies During Work students report their mental state with regard to particular variables at regular intervals. Finally, with Keeping Diaries students keep a diary where they report their SRL behavior, knowledge, and skills. Some students are more capable writers, which can affect the data. Like interviews, this method produces qualitative data. While difficult to conduct, experimental investigations in SRL research are certainly possible.

Bandura describes methods of experimental control and manipulation in investigations of self-efficacy beliefs (Bandura and Locke 2003). Experimental investigations which attempt to investigate impacts while in an authentic educational environment are made more difficult by the complexity of the environment and the possibility for interactions between the groups.

As Green and Azevedo put it "Self-regulated learning (SRL) theories attempt to model how each of these cognitive, motivational, and contextual factors influences the learning process" (Green and Azevedo 2007). The question is not if various factors influence learning, it is how they influence learning, and that is a causal question.

Compared to existing methods used in the social sciences this methodology is most closely related to an exploratory use of structural equation modeling. The very important difference is that as conventionally used SEM provides only a single model, which in some sense "fits" the collected data. The FCI algorithm provides a representation of the equivalence class of causal models which can produce the given statistical data.

An exploratory approach with SEM is difficult to justify for two reasons. Firstly, only a single model out of the many models which are indistinguishable given the evidence is considered. Assuming the justification for the model is observational data or statistics, there is no reason to prefer one model from the equivalence class to another. Thus the "fit" of the model to the data does not provide a strong reason to believe that the relationships represented are true, that is, that they exist in the world.

The class of indistinguishable models provided by the FCI algorithm indicates which relationships are common in all models which can produce the data under the given assumptions. Given the accuracy of the data, and the validity of the assumptions, this does give us a strong reason to believe that those relationships are true, and hold in the world.

The second reason the existing exploratory approach is difficult to justify is the possibility of overfitting, as it is called in machine learning. A model is over fitted if it assumes that either random variance in the sample data or peculiar characteristics of the sample apply to the wider population where they do not. In the exploratory approach, we are attempting to generalize from sample data to population characteristics and risk assuming that relationships which appear to exist in the sample do no exist in the population. Attempts to specify a completely oriented causal model from statistical data when there are many models which can produce the same statistics is one form of overfitting which results from the exploratory approach where a single model is proposed to fit the data. The FCI algorithm avoids this problem by only specifying the equivalence class.

Several approaches are used in scientific work to avoid or overcome overfitting. The first is the use of Occam's Razor which, to paraphrase, states that all things being equal we should prefer explanations which make less assumptions. This is embodied in the assumptions made by the FCI algorithm, that the model be minimal (Pearl 2000).

Another essential step is attempting to falsify models by testing their predictions. A model which is over fitted to the sample data will fail when applied to data gathered from another sample, or a somewhat broader population. This confirmatory or, more appropriately, disconfirmatory approach is used in SEM when a proposed model or theory is tested against data. The same approach can and should be applied to models which are discovered using this approach.

Not only does an equivalence class indicate which relationships are supported by the data, it also indicates which relationships cannot be determined from statistics alone. Statistically indistinguishable models may be distinguished by incorporating background information, temporal information, or experimental results to determine the nature and orientation of the remaining relationships. By indicating which relationships require experimentation to determine the equivalence class acts as a guide to which relationships to test experimentally. The clear implications of the model also allow a researcher to see what relationships are being asserted, and devise tests for those relationships if they seem suspect.

By clarifying exactly what relationships are claimed, this formal representation allows the claims to be more easily understood and argued for or against than comparatively vague natural language specifications or informal diagrams. Describing relationships in such formal detail leads directly to testable predictions. Fully parameterised causal models can be used to make testable predictions about the values of variables in different circumstances. A causal model which is fully oriented and parameterised can be used to infer the outcomes of different circumstances and interventions. If the predictions are being made about measurable variables then these predictions are testable against real world data.

Education researchers can apply the models to different sets of circumstances and compare the results to their intuition, experience, theories, and evidence. If the results appear to be questionable, or if we simply wish to verify the results, observational or experimental studies can be undertaken to falsify or augment the model. The results of any such studies, data, or additional constraints on the structure of the model, can be supplied to the causal discovery algorithm to refine or falsify portions of the existing model.

Presuming the model is valid it can be used to guide educational practice and policy by computing the expected results of educational policies. For example, a causal model which correctly identifies the relationships between study skills and learning could guide policies toward teaching such skills in the classroom.

Structure discovery algorithms are used to discover the causal structure between variables from data about the variables. The FCI algorithm and other constraint based algorithm need as their input a set of conditional independence relationships. These relationships can be determined from raw data using any standard statistical test for conditional independence or vanishing partial correlation or a correlation or covariance matrix can be supplied if known.

Existing observational studies can provide the necessary information about covariance or correlation, though the raw data is not typically available. We can also attempt to collect the results of multiple individual studies, conducting a meta-analysis of many studies to determine the conditional independence relationships more accurately by increasing the number of studies included, subject to the usual limitations of meta-analysis. The ability to combine multiple studies is especially important when considering large networks or highly improbable events both of which require larger samples to deal with effectively.

Robbins et al. present the results of a meta-analysis of 108 papers relating psychosocial and study skill factors to college outcomes (Robbins et al. 2004). From the correlation matrix they present it is possible to directly run the FCI algorithm and investigate the results. Figure 3.3 presents the results from running the algorithm on a subset of the variables they present, excluding two variables due to insufficient sample size, and one due to irrelevance to SRL. The aggregate sample sizes for the correlations vary from as low as 110 up to approximately 17,000. The correlations for variables are low enough that we do not expect the inferences to be extremely reliable. In particular, this is the case for relationships between AcademicRelatedSkills and AcademicSelfEfficacy and between AcademicRelatedSkills and GeneralSelfConcept.

As can be seen from the double headed arrows in Fig. 3.4, multiple variables are identified as having latent common causes. From the provided data the algorithm is unable to completely orient any edges other than those which represent the presence of confounding variables. For many of the variables it is reasonable to expect confounding in this example, given the presence of several indicators of performance or ability such as GPA, ACT/SATScores and HighSchoolGPA. Overall, it is difficult to draw conclusions from such a study network due to insufficient data. Given the known convergence of the algorithms at large sample sizes and the demonstrations of the results from the simulation study, we suggest that given

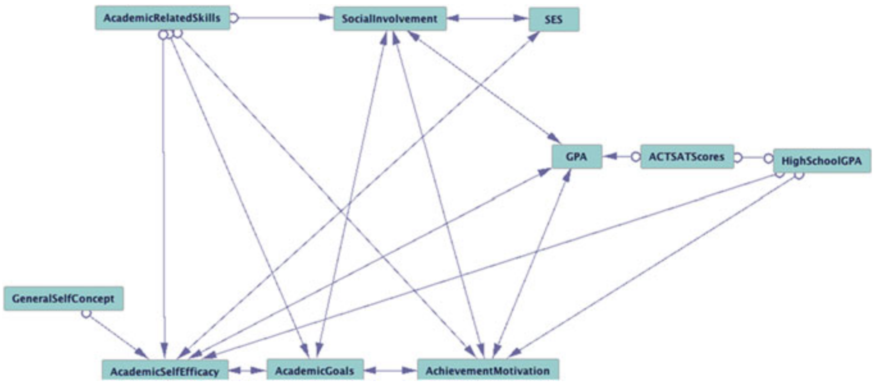


Fig. 3.4 Equivalence class (PAG) derived from Robbins et al.

increased data the results would be more informative. Sample sizes of 17,000 as available for some correlations are sufficient to be reliable for the adjacencies, and becoming reliable for the presence and absence of orientation information, unfortunately the low sample sizes for the other correlations can produce errors which propagate throughout the network. This is where learning analytics come into play where finer level observations of study activities and performance estimates can be used to improve sample sizes.

FCI algorithm has been used to discover a causal model for self-regulated learning (see Fig. 3.5). There are several limitations to applying FCI to discover causal models from observed data. When using causal discovery algorithms, we are limited by the size of the sample, the statistical power of the simple correlations, the accuracy of the measurements, and the difficulty of evaluating high order conditional independence relationships from a reasonable amount of data. The solution to these problems is the same as in any observational study: collect more data, and collect better data. The FCI algorithm is constrained by a number of assumptions including Causal Markov Condition and Causal Faithfulness Condition (Zhang and Spirtes 2008). For a model with a large number of variables, running the tests for conditional independence at conventional significance levels may result in multiple incorrect results given the large number of such tests required. Increasing the thresholds for significance of the statistical decisions changes the type of mistake likely to be made, as correct results may not meet significance thresholds. Given the reliance of the algorithms on patterns of such results, changing the significance of the decisions can produce very different results from the algorithms. There is still a need for exact characterization of the reliability of the FCI algorithm or related algorithms in the face of inaccurate data or violation of the assumptions. The FCI algorithm is exponential in the in-degree (number of parents) that nodes have in the graph. For a sparse graph the algorithm runs in a reasonable amount of time, however the algorithm quickly becomes infeasible for graphs with many parents. This is directly related to the issue Bayesian networks face with large conditional probability tables with graphs have high average in-degree.

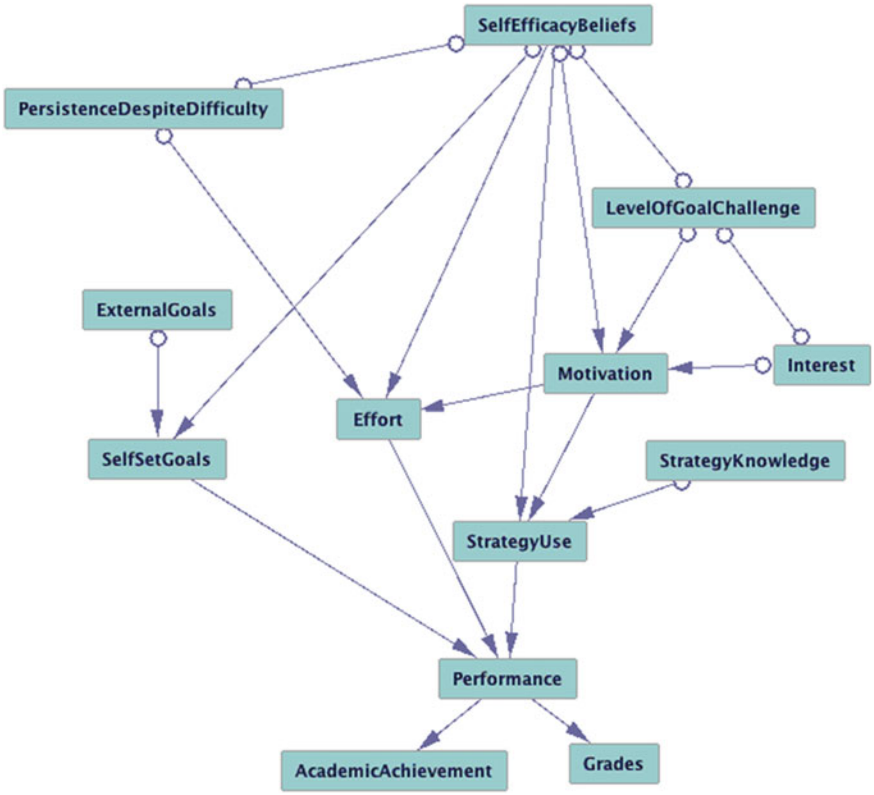


Fig. 3.5 Equivalence class (PAG) for self-regulated learning

In spite of these difficulties, FCI and similar causal discovery algorithms do offer us the power the see research results in a connected fashion, as an ever-growing tapestry that causally relates new research findings in the context of existing ocean of research results. Further, with longitudinal data, continuous causal discovery implies variations in observed skills of learners, which is a powerful self- and coregulatory tool for the instructors and the learners. Additional details regarding the study on metacognitive analysis and causality are reported in Brokenshire and Kumar (2009).

3.3 Conclusions

Graphical causal models and structure learning provide a useful means of representing the causal claims in a formal and computable form, but they are limited by the availability of sufficient quantities of accurate data. Using a theoretical model, one can produce the equivalence class of relationships discoverable from ideal statistical data and simulated statistical data of varying sample sizes. FCI class of algorithms can discover the models back from the data. One can then compare the equivalence class of the theoretical model to the models discovered by the algorithms at different sample sizes. Such a comparison would yield accuracy of adjacency inclusion and orientation. Given the complexity of the theoretical model, one can estimate a sample size that is appropriate for the domain that is to be causally represented. Large sample sizes could imply less false negatives and yet producing a significant number of false positive arrow points. The application of more conservative algorithms may alleviate the errors of commission, but at the cost of increases in false negatives.

The exploratory approach taken by the causal discovery algorithms stands in contrast to the confirmatory approach to SEM. The use of a confirmatory approach in which a model is proposed a priori has the considerable limitation of ignoring the equivalence class of models which can equally account for data. The confirmatory approach is appropriate for disconfirming proposed models, but cannot confirm one model over another equivalent model.

The exploratory structure discovery approach has the benefit of discovering the complete equivalence class for the available data. A standard challenge of data based methods in machine learning and in science is overfitting of a model to idiosyncrasies of the data. The FCI algorithm and related algorithms partially overcome this difficulty by incorporating the faithfulness assumption, but may fail to correctly evaluate relationships when this assumption is violated.

The models must of course be tested repeatedly in the same fashion as any proposed theory in order to be considered valid.

The creation of graphical causal models representing educational theories offers multiple benefits. They require a clear and precise specification of the claims of a theory and the definitions of the variables, and represent those claims in an understandable form. This formal, understandable representation should allow for clearer specifications of causal claims in the theoretical literature.

The biggest constraint facing a causal approach is the sample size. This issue can be addressed by finer level observations advocated by learning analytics. That is, new sets of data at various levels of granularity could be employed to confirm edges and to substantiate causal directions in the PAG. More importantly, the changes that the PAG undergoes can be observed as the new datasets stream data into the algorithm in a continuous fashion. This observation directly corresponds with changes in skillsets of learners, since the new datasets are generated solely from observed study activities of learners.

It is possible to use causal structure learning to process the results of a meta-analysis of empirical results and create a causal structure directly from existing observational results. Such a representation has the benefits of indicating what experiments are necessary in order to evaluate unoriented edges and clearly showing the relationships which cannot be derived solely from observational data. Additionally, any new results can be incorporated into the model, producing a integrated, continuously improving model.

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Chapter 4
The Effect of Story in Mobile Educational Game

Chris Lu, Maiga Chang, Kinshuk, Echo Huang and Ching-Wen Chen

Abstract The trend of designing and developing mobile apps attracts many researchers' attention on using mobile devices to make users have feelings that they are living in the era or the place in which they can learn knowledge of particular domain, e.g., the users can learn rainforest plants and ecology in the Amazon River zone of a botanic garden (Chang and Chang 2006; Chen et al. 2004; Kurti et al. 2007; Wu et al. 2008). Some other researchers further develop mobile games for educational purpose; these games not only make users do learning activities in authentic environments such as museums and historical sites, but also make them get motivated if compared with the abovementioned mobile learning systems (Chang et al. 2008; Wu et al. 2010).

4.1 Introduction

The trend of designing and developing mobile apps attracts many researchers' attention on using mobile devices to make users have feelings that they are living in the era or the place in which they can learn knowledge of particular domain, e.g., the users can learn rainforest plants and ecology in the Amazon River zone of a botanic garden (Chang and Chang 2006; Chen et al. 2004; Kurti et al. 2007; Wu et al. 2008). Some other researchers further develop mobile games for educational purpose; these games not only make users do learning activities in authentic environments such as museums and historical sites, but also make them get motivated if compared with the abovementioned mobile learning systems (Chang et al. 2008; Wu et al. 2010).

A context-aware educational game-based mobile application can generate inquiry-based learning activities for the users according to their needs (under

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informal learning situation) and the courses they are taking (under formal learning situation). Such context-aware educational game allows users learning through role playing in a game world that integrates physical environment with the challenges and excitement of game play. The research team develops one, namely CAMEG (Lu et al. 2010a, b), and its usability has been confirmed (Lu et al. 2011).

To make the generated learning activities more attractive to the users and make the mobile game become an immersive learning environment for the users, a new version of the game, namely CAMRPG, then is designed developed. In order to make the CAMRPG interesting and engaging to users, the research team applies the story generation engine which is based on narrative theory to an educational mobile game for generating decorative stories of learning activities and for making students feel that they are living in the game world and role play an actor, explore the game world, complete the quests, and learn something.

The elements in narrative theory include storyline, character, and interaction have been analyzed and used in the design of game-based learning system (Ying et al. 2009). Conle 2003 summarizes that a story should have temporal sequences, plots, characters, context, and the sense of an ending (Conle 2003). Some researchers have done the research in terms of finding the relationships between narrative elements and games (Mallon and Webb 2005). They argue that some narrative features such as causality, temporality, and linearity, should be also considered so an interactive and engaging game can be well-designed and developed.

This research has four research questions needed to be examined for getting better idea of the effects that the stories in the mobile educational game have: (1) Do the stories have positive influence user acceptances toward the use of CAMRPG? (2) Do the stories make users feel the game is useful? (3) Is there any gender difference existed in terms of the perceived effectiveness and satisfaction toward CAMRPG? (4) Do gaming experience influence user acceptances toward the use of CAMRPG?

Two pilots have been conducted. In the pilots, a questionnaire is designed and used to gather learners' attitude (through a revised technology acceptance questions), perceived effectiveness, efficiency, and satisfaction toward the CAMRPG. The data have been collected and analyzed with quantitative analysis approach (e.g., independent t-test) for assessing users' perceptions toward both games (i.e., CAMRPG and CAMEG). With the analysis results, this research can evaluate the effects that the generated stories in the mobile educational game has by seeing if there is any significant difference of user perceptions toward the two games.

4.2 Context-Aware Mobile Learning Activity and Story Generation

4.2.1 Knowledge Structures

In order to provide users' with personalized/customized learning services, first, we need to know what the users want to learn and what they already know. Quillian

1967 proposes a very first structure which is a kind of memory model (Quillian 1967). After that, many different knowledge structured are designed and proposed. Novak and colleagues propose Concept Maps which can be used for storing and presenting the concept relations that learning materials have (Novak and Cañas 2006; Novak and Gowin 1984). Ogata and Yano propose a knowledge awareness map, which can visualize the relations between the sharing knowledge and the learner interactions (Ogata and Yano 2005). Another well-known structure—semantic network—was proposed by Sowa. A semantic network is a systematic means for researchers to model an individual's mental schema of declarative knowledge (Sowa 1984).

Ontology in the computer science and artificial intelligence fields which is evolved from the philosophy domain has been applied in the text analysis area and has been used widely to analyze the semantic lexicon of words (Mathieu 2005). Researchers use ontology to define vocabulary that presents the knowledge of a particular domain in order to provide a platform for effective communication and knowledge sharing among users and systems.

Olawande et al. (2009) present an ontology-based architecture framework that constructs tourism-related web ontology language for tourism recommendation system development (Olawande et al. 2009). In their research, they define two ontologies—destination context ontology (DCO) and accommodation ontology (AO)—with respective social attributes (i.e., weather temperature, scenery, volume of traffic, crime rate, and city type). The tourism recommendation system first takes user preferences as input and retrieves and sorts the correlated destinations as initial recommendations. The system then uses DCO to filter and revise the initial recommendations based on the user's preferred social attributes. Finally, the system uses AO to filter and generate a list of accommodation suggestions.

Wu et al. 2008 propose an ubiquitous knowledge structure for museum learning and elementary-level botanic learning (Wu et al. 2008). It has been proven to be a good way to store the knowledge that learning objects (in the real world) and materials (in the textbook) in one single knowledge structure. Its hierarchical structure is easy to understand and manage for general administrators (e.g., school teachers and system managers) and there is no specific rule for building a knowledge structure. In addition, a single structure can store knowledge associated with multiple domains/disciplines.

Three layers of the ubiquitous knowledge structure are adopted in this research to build the context-awareness knowledge structure of the authentic learning environment in which the mobile game takes place. Figure 4.1 shows the altered context-awareness knowledge structure. The domain layer represents learning topics and domains that users are learning as well as the game themes that users can choose to play. The characteristic layer is a hierarchical structure in which the root nodes are associated with one or more nodes in the domain layer. The object layer stores all learning objects in the real world (e.g., rooms, equipment, pine trees, etc.) and in the virtual world (e.g., payroll system, business policy, electronic forms, etc.).

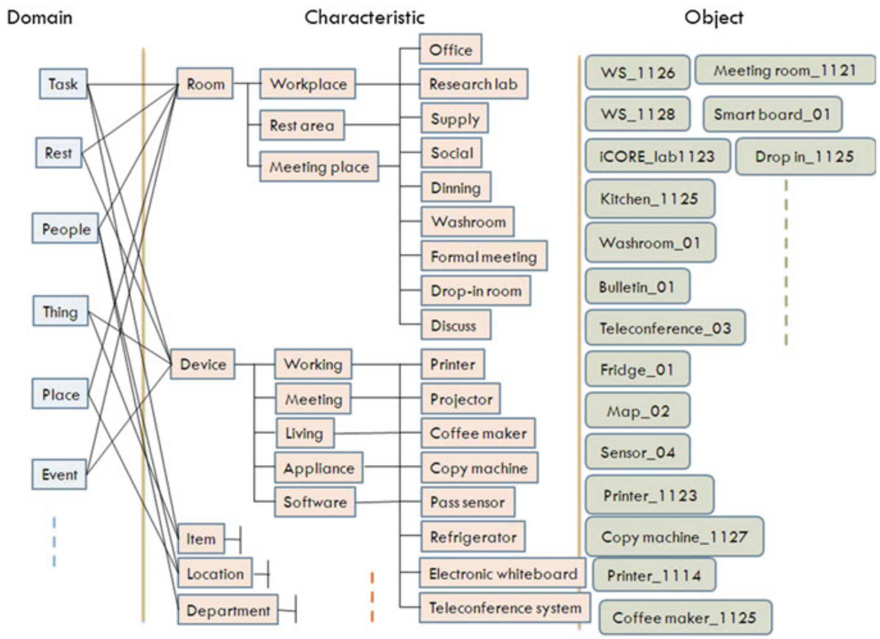

Fig. 4.1 Partial ubiquitous knowledge structure of an authentic learning environment

In summary, a variety of knowledge structures have been designed and used by researchers. By analyzing and modifying the existing knowledge structures, this research chooses to adopt the ubiquitous knowledge structure as a solution to store and present the knowledge for the CAMRPG.

4.2.2 Learning Activity Generation

The use of location-based service can offer users more attractive and context-aware game-play experiences. However, the learning activities that games have usually are predefined and designed activities. This research designs a mechanism which can automatically generate learning activities according to user needs and the surrounding context to provide users personalized context-awareness learning activities.

Since, the knowledge structure stores all learning objects and their attributes and embedded concepts, as well as the relationships among objects, an approach of retrieving relevant learning objects according to the user context, e.g., the chosen theme, location, learning experiences, is developed. The learning objects retrieved via the approach can make users feel that the objects are what they want to see/know.

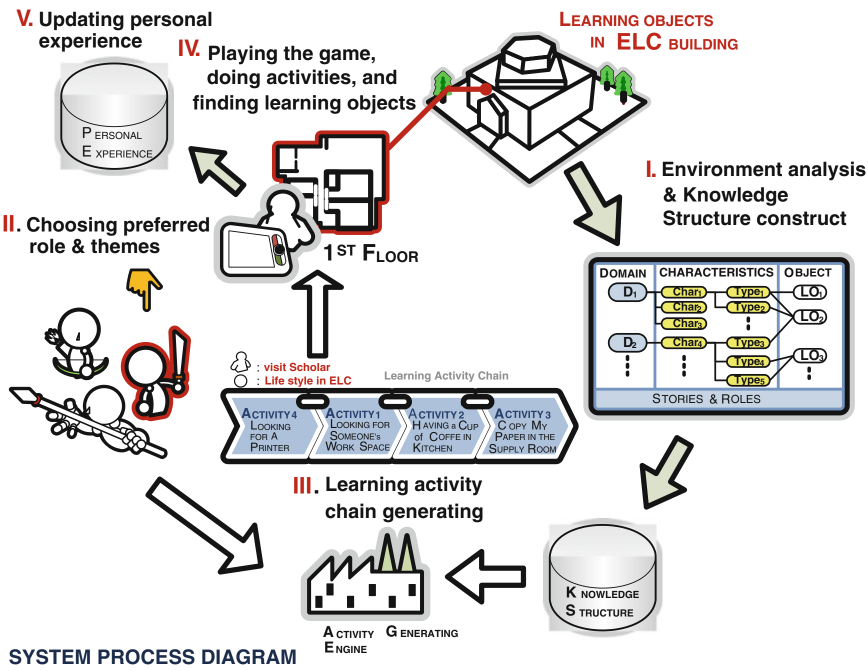

Fig. 4.2 Learning activity generation flow

A learning activity may involve more than one learning object, so a user may need to spend more time to find all of the required learning objects that the learning activity asks for. Even if two learning activities have same amount of learning objects, some learning objects might not be so easy to find (or to access). Since, the order of learning activities may be an important factor from both learning and playing viewpoints, the research team designs a mechanism to sort the learning activities by the amount of associated objects and their complexity. Users may solve their first learning activity with less difficulty and then, in the later stage, seek for multiple learning objects which some of them may not common to see. The activities associated with common learning objects can be seen as training quests and the activities associated with many or uncommon learning objects can be seen as challenges. Figure 4.2 shows the learning activity generation flow. This flow has five steps.

Analysis: The first step is to list the learning domains and corresponding objects which can be used for learning by users in the authentic environment; then to identify all characteristics that the objects have and to figure the relationships among characteristics and objects out. The analysis results are stored into the ubiquitous knowledge structure. After that, roles and corresponding themes covering one or more learning domains in the game are designed for users choosing to play.

Role and theme: At this step, users can choose one of the roles that teachers and course authors designed at Step 1 and choose the theme s/he wants to play.

Learning activity chain generation: The game puts the chosen role and theme into the activity generation engine to generate activities. The activity generation engine retrieves suitable learning objects from the ubiquitous knowledge structure accordingly and then generates a list of learning activities which users may do in the authentic learning environment. At the end, the engine sorts the learning activities into a chain by comparing their complexity (as well as the rarity of required learning objects) and offers users learning activities in the chain one by one.

Learn by playing: Users can follow the instructions and look for the designated learning objects to solve the learning activities one by one, at meanwhile, s/he can get familiar with the environment and learn the associated knowledge.

Personal experience update: The learning objects and related knowledge users have seen and learnt will be recorded in the database, so the game is aware of users' learning progresses (e.g., what learning activities they have solved and what concepts they have learnt) and performances (e.g., how well and how fast they did in solving the learning activities and how many learning activities they have done so far).

More details of the learning activity generation mechanism can be found in (Lu et al. 2011).

4.2.3 Transition Story Generation

Even the game can generate a series of learning activities for users, users may still be bored if they are just asked to do activities one by one. Few research talks about how to design the contents of mobile educational games and how to make users feel interested and want to play the game continuously. Story is important for designing an interesting and engaging game. Most of popular games have its background story no matter the story is a simple linear story (i.e., saving the princess) or a complex drama (i.e., the war happened between Alliance and Horde in World of Warcraft). Good story in the game design makes the game realistic and immersive as well as users involve constantly.

Therefore, it is important for designers to understand classic story structure. Generally, a story usually begins with a basic concept or an idea. The basic is to put one or more characters, in a kind of situations, in one of the settings in the game (Rabin 2010). The research designs an educational role-playing game by applying narrative theory to decorate the generated learning activities, so the game can make users feel that they are living in the game world. Users play an actor, explore the game world, complete the quests, and learn something.

According to the literature review, the core narrative elements are identified and a structure is designed to store all necessary narrative element data for creating a story. A simple method is developed to pick up narrative data from the structure. The method is simple but it still maintains the consistency and sequence of story fragments among the learning activities of a chain, for instance, users won't see the car in the story of later activities if they sell it in the story of the activity they are solving at this moment.

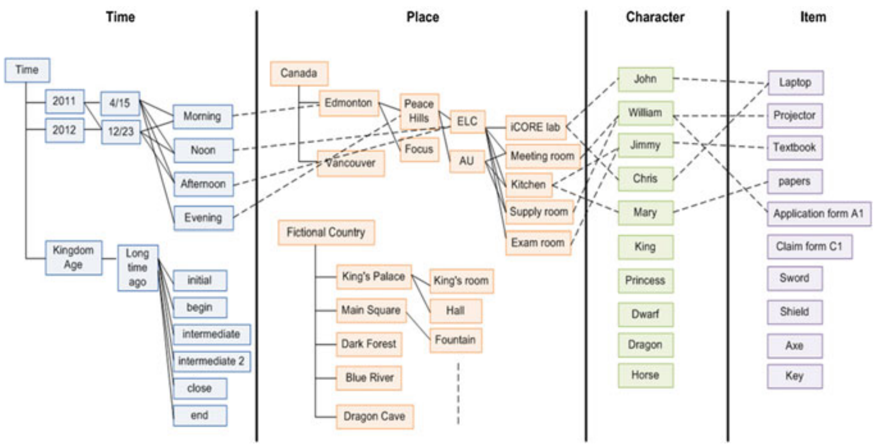

Fig. 4.3 Narrative knowledge

By combining the idea of ubiquitous knowledge structure and the four narrative elements defined by other researchers, a four-layer narrative knowledge structure as Fig. 4.3 shows, is designed to help the game generate stories based on the chosen theme and generated learning activity chain's length.

In the narrative knowledge structure, each layer can have more than one level. The relations among elements are optional. The elements built in the narrative knowledge structure can be mixed of truth and fiction. Different schema is designed to store the properties of narrative elements. The schema of narrative elements can be seen as the settings of the storyline and used for generating story. Figure 4.4 presents the schema of "Noon" element in time layer and "William" element in character layer.

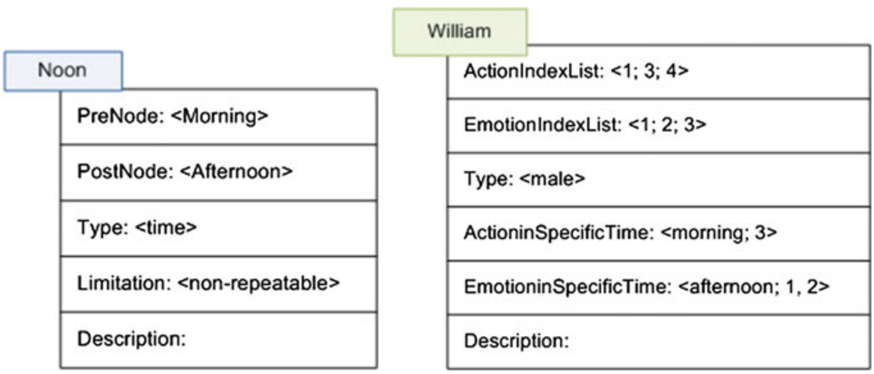

Fig. 4.4 Narrative element schema examples

The above-mentioned narrative knowledge structure and narrative element schema are simple and clear, so teachers and course authors are capable of building their own for various learning domains and authentic learning environments. The story generation engine then can generate a series of stories (i.e., a storyline) to decorate the generated learning activities. More details of the story generation engine can be found in (Lu et al. 2011c).

4.3 Context-Aware Mobile Role-Playing Game

To develop a lightweight, flexible, and scalable mobile educational game so the game can be played at any platform as well as additional components can be added to make the game better, this research takes multi-agent architecture into consideration for the game design. Multiagent architecture not only allows different agents to have different responsibilities, but also provides an expandable way to develop further functions. For instance, new agents can be put into the game for special purpose and old agents can be replaced with new and more functional ones. Figure 4.5 shows the multi-agent architecture that this research uses in designing and developing the mobile educational game.

Two groups of agents reside on the user's mobile phone: three agents, namely Player Agent, Translator, and Learning Activity Item Collector, form a group to serve and interact with the user; and six agents, namely Learning Activity Generator,

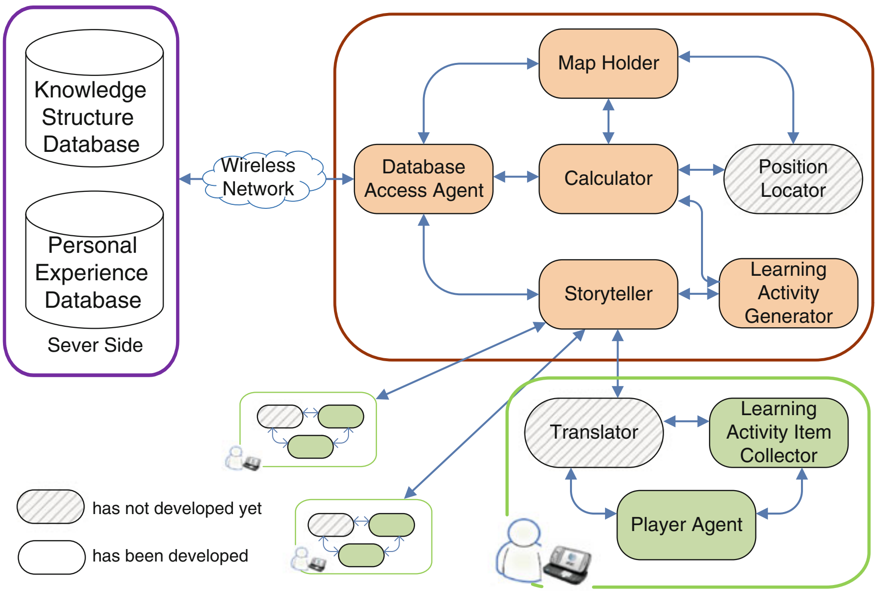

Fig. 4.5 Multi-agent architecture of the proposed mobile educational game

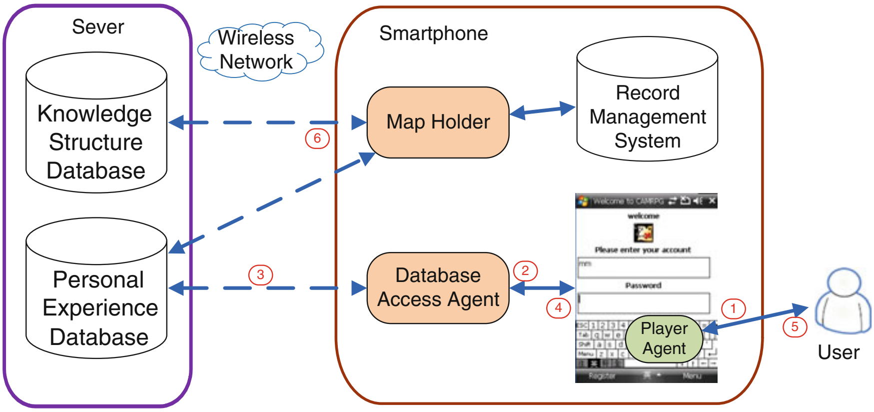

Fig. 4.6 Interactions among the user and agents in teleport phase

Calculator, Map Holder, Database (DB) Access Agent, Storyteller, and Position Locator, form a group to work out context-awareness and the location-based learning activity chain. Each agent has its goal, task, demands, and communicated targets. More details for the responsibilities of each agent and the collaboration among agents can be found in (Lu et al. 2011a).

During the game-play, Player Agent is the only agent that interacts with the user and enables data exchange between the user and other agents. The following subsections describe five phases of the game-play, during which a variety of agents participate in different phases to help, train, and challenge the user to complete the required activities.

4.3.1 *Teleport Phase*

In this phase, the user enters the game world. Player Agent, Map Holder, and DB Access Agent are awakened to handle the user's log in/register request (Fig. 4.6). The teleport process is necessary in order to give the user a feeling that she/he is entering a virtual, imagined, and fantasy world.

4.3.2 *Transfer Phase*

In this phase, the user is asked to choose a role and the theme she/he wants to play. Player Agent and Learning Activity Generator are awakened to deal with the user's choices. The transfer phase is used to give the user an idea of the roles and the themes in the game. Correspondingly, the user can gain a better understanding of what the game offers via his/her chosen role and theme (Fig. 4.7).

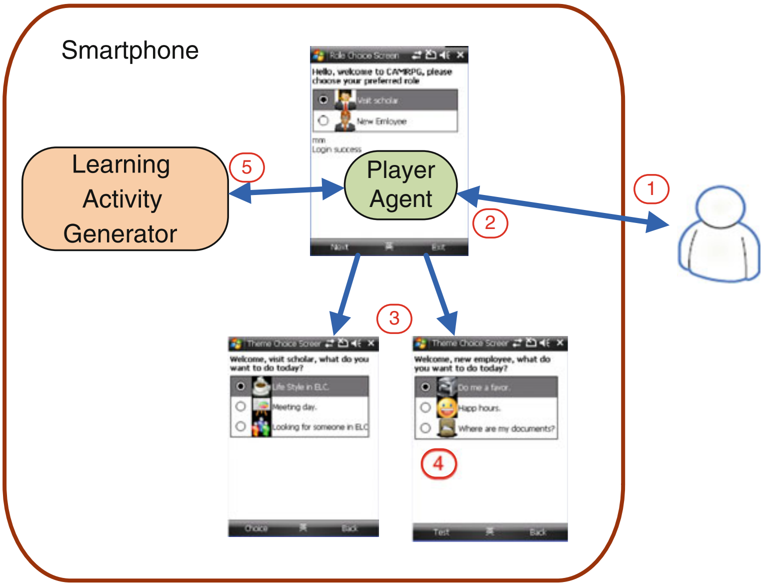

Fig. 4.7 Interactions among the user and agents in transfer phase

4.3.3 Training Phase

In this phase, Player Agent displays a progress bar and asks the user to wait for a few seconds. In the background, Learning Activity Generator, Calculator, Storyteller, DB Access Agent, and Map Holder start collaborating to generate a series of story decorated quests for the user (Fig. 4.8). The training phase focuses on agent collaborations involving retrieving, weighting, and sorting the learning objects and learning activities based on the user's chosen theme, location, and learning objects nearby. Player Agent then receives several story decorated quests.

4.3.4 Challenge Phase

In this phase, Player Agent receives a series of learning activities from Learning Activity Generator (Fig. 4.9). The challenge phase provides the user learning activities as quests in the game. The user is then asked to solve the quests one by one.

4.3.5 Adventure Phase

In this phase, the user starts solving the activities one by one. S/he looks for the activity-relevant items (activity items for short), for example, the Decision Support

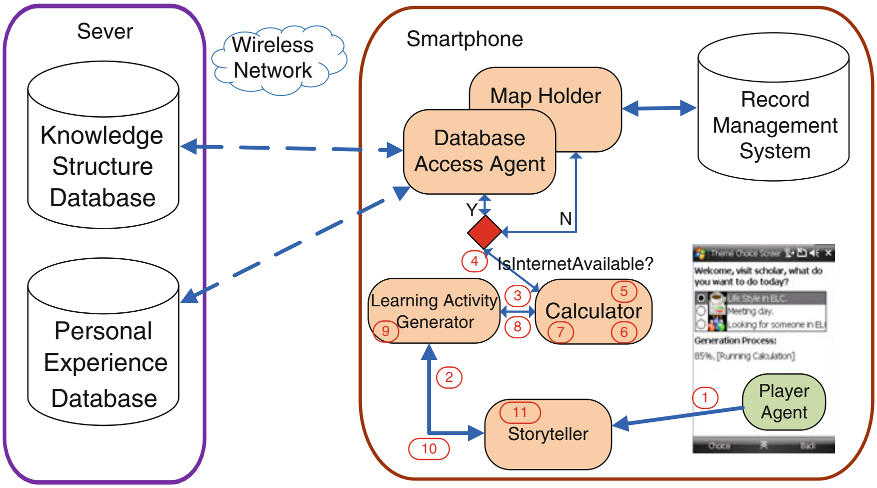

Fig. 4.8 Interactions among the user and agents in training phase

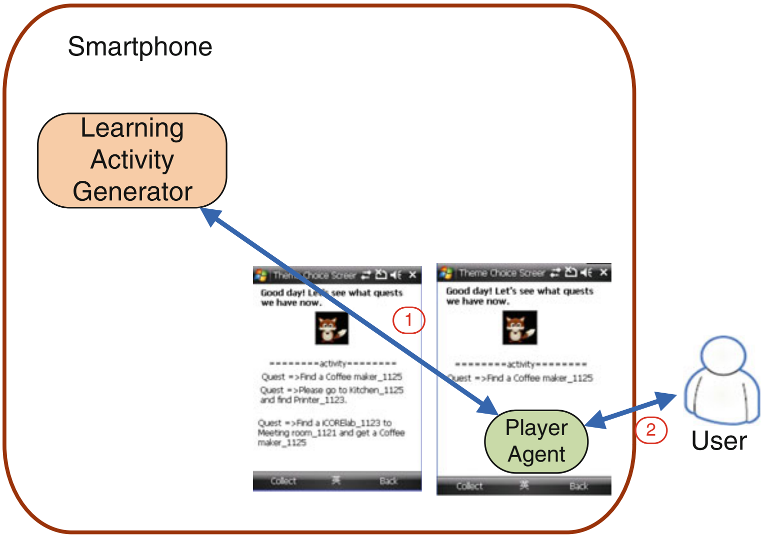

Fig. 4.9 Interactions among the user and agents in challenge phase

System, “Oracle Decision Support Systems (DSS),” and the company, “Oracle”. Player Agent, Learning Activity Item Collector, Map Holder, and DB Access Agent are awakened to support the user. The activity items are learning objects in the real environment and have two-dimensional barcodes attached. The user needs to explore the environment and look for the activity items required for his/her quest.

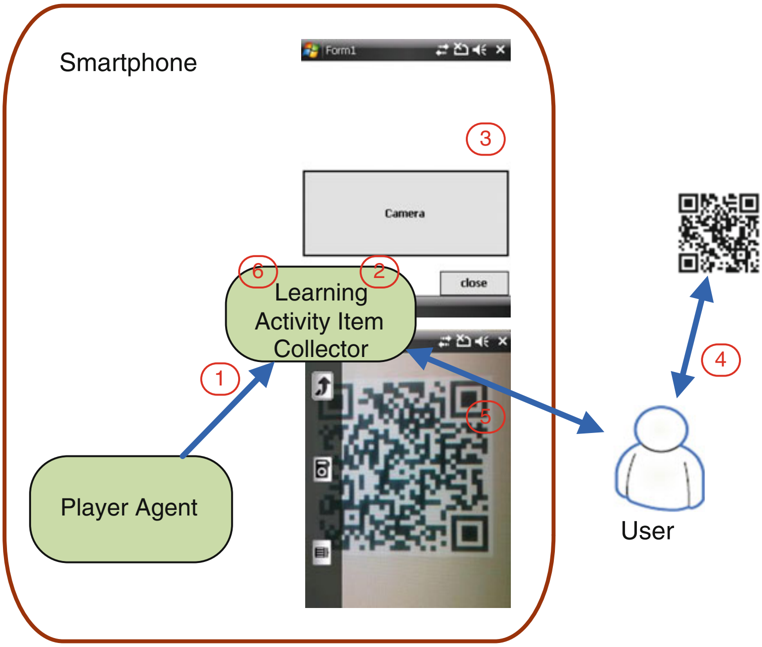

Fig. 4.10 Interactions among the user and agents in adventure phase—item collecting

The adventure phase enables the user to walk around in the real world, look for specific activity items, take pictures on the two-dimensional barcodes, and receive the relevant instructions/tutorial for the learning objects (Fig. 4.10).

4.4 Evaluation and Discussion

4.4.1 Hypotheses

This subsection describes the hypotheses we have in minds and want to verify, furthermore, this section also talks the pilot design and the data we are going to collect. As this research wants to know the effect of story in the mobile educational game, six hypotheses based on the four research questions are made:

H1: The generated stories in the game have a positive effect on user's acceptance toward using CAMRPG.
H2: The generated stories in the game have positive effect on user's perceived usability of CAMRPG.
H3: The generated stories in the game makes users more appreciate the game.
H4: There is gender difference on user's acceptance toward using CAMRPG.

H5: There is gender difference on user's perceived usability of CAMRPG.
H6: Gaming experience has positive effect on user's acceptance toward using the CAMRPG.

To verify these hypotheses, a questionnaire consists of demographic questions, technology acceptance-related questions, and usability related questions are needed. Usability is a general term used in human computer interaction (HCI) research and can be widely explained rather than the traditional term, "user friendliness". The Specifications of International Standard Organization for HCI and Usability, ISO 9241-11 document (ISO/IEC 1998), is a guidance of usability. This standard provides developers the definition of usability and tells research how to identify the necessary items such as user's performance and satisfaction while evaluating system's usability. The definition of usability described in ISO 9241-11 is:

> Usability extents to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use.

A revised usability questionnaire has been made based on the usability analysis results we had for discovering the usability of the game without stories (i.e., CAMEG) (Lu et al. 2011). The revised questionnaire contains eleven five-point Likert-scale items (5 for "strongly agree" to 1 for "strongly disagree") which may affect a system's usability in the three dimensions described in ISO 9241-11, i.e., effectiveness, efficiency, and satisfaction. All items exist in the original questionnaire. The validity of these items was established by a review of three experts in educational technology field.

To gather CAMRPG users' acceptance and perceived usability toward CAMRPG, the researchers introduced CAMRPG to an undergraduate Management Information System (MIS) class of the department of Information Management (IM), National Kaohsiung First University of Science and Technology (NKFUST), Taiwan. The researchers explicitly told the students that the pilot is a voluntary activity and there is no compensation, reward, or recognition for anyone who participate the pilot and nothing will happen to the students who do not want to take place in the pilot. At the end, 55 undergraduate students (ages range 21–22 years old) were recruited, including 31 males and 24 females.

The experiment environment of the pilot took place in teaching building E of the university. The MIS course contents and concepts were taken into the game. The teaching building was considered as a virtual science park where many famous IT business and company reside in for participants learning MIS concepts while playing CAMRPG.

All participants had 20 m to play the game with the smartphones the researchers prepared at the authentic learning environment, as not all participants have smartphones and to avoid the influences that different devices may have in terms of affecting user's experiences in playing the game and perceptions toward the game. After they played the game, they were asked to fill up the questionnaire in order to gather necessary data for analyzing and verifying the proposed research questions.

The Cronbach's alpha value of the questionnaire is 0.840 with CAMEG's data set indicating that the questionnaire (and its items) can be seen as reliable due to its internal consistency is good enough (i.e., exceeds 0.75) (Hair et al. 1995). In order to make sure that the questionnaire maintains good reliability for further quantitative data analysis, we also test its reliability with both CAMRPG's data set and the mixed-up of the two datasets (i.e., the data set of CAMEG and CAMRPG). The Cronbach's alpha values are 0.873 (for CAMRPG's data set) and 0.853 (for the mixed-up data set) showing that we can use the collected data to do follow-up analysis to find out the answers of the research questions.

4.4.2 Data Analysis

The demographic information includes CAMRPG user's gender information, experience in playing games, and time spent on playing games. Table 4.1 lists the descriptive statistics for 55 CAMRPG users.

The results of Table 4.1 show that most of CAMRPG users had rich experiences in playing games, especially computer games. Video and computer games are both found to be major entertainment activities for them. Table 4.2 further summarizes how much time they usually spent (hours per week) on playing video games, handheld video games, and computer games. The data listed in Table 4.2 show that there is significant difference between male and female CAMRPG users in terms of playing computer games.

Table 4.1 Descriptive statistics of CAMRPG users

Gender	N	Playing video games (%)	Playing handheld video games (%)	Playing computer games (%)
Male	31	26 (83.9)	26 (83.9)	30 (96.8)
Female	24	17 (70.8)	19 (79.2)	22 (91.7)
Total	55	43 (78.2)	45 (81.8)	52 (94.5)

Table 4.2 Comparison table of game playing time

Time for playing	Gender	N	Mean (hours per week)	Standard deviation	*t*-value
Video game	Male	31	4.5161	7.43806	−0.137
	Female	24	4.8542	10.90819	
Handheld video Game	Male	31	4.2742	7.29365	1.087
	Female	24	2.4583	4.20123	
Computer game	Male	31	21.7097	16.58954	2.314[a]
	Female	24	12.7500	10.40171	

[a] $p < 0.01$

Table 4.3 Sample sizes of different groups

Time for playing	Gender	N	Mean
Gender	Male	31	–
	Female	24	–
Time spend on playing computer games	Hard-core player	14	40.21 (hrs/week)
	Regular player	26	17.19 (hrs/week)
	Casual player	15	3.67 (hrs/week)

The groups were further observed and distinguished by comparing the time they spent on playing games. Students who were among top 25 % in terms of the time spent playing computer games were defined as hard-core players. On the other hand, students who were among bottom 25 % in terms of the time spent playing computer games were defined as casual players. The rest of students were defined as regular players.

It is possible that the students who spend a lot of time playing computer games may have higher expectation with the proposed game and may not recognize the proposed game as a good game. If this assumption is true, it would mean that the students in hard-core player and casual player groups will perceive the usability of CAMRPG and appreciate the stories in CAMRPG significantly differently. Table 4.3 lists the new sample sizes of the comparable variables to be used for the quantitative analysis (i.e., independent *t*-test).

Before we test if there is any difference of the user perceptions between hard-core and casual players, we can see, from Tables 4.4 and 4.5, that although both groups' mean values are quite high (i.e., positive perceptions) for the generated stories and the game, male users have relatively higher standard deviation but there is no gender difference between male and female users. This circumstance shows that male users may perceive extreme high or low responses for the stories and the game. Therefore, hypothesis H1 is *supported* but hypothesis H4 is *rejected*.

Table 4.6 lists the results of independent *t*-test on the two groups (hard-core and casual players) of CAMRPG users' acceptance toward the use of CAMRPG. The results show that there are significant differences between hard-core and casual players in terms of their acceptance toward CAMRPG ($p = 0.018$). Therefore, hypothesis H6 is *supported*.

In order to verify the hypotheses H2 and H3, we need to test if there is perception difference between CAMEG users and CAMRPG users toward the usability of the games they played as CAMEG has no story. All data from 92 participants

Table 4.4 Descriptive statistics of CAMRPG users' perceptions toward the stories and acceptance toward the game

	N	Mean	Std. error	Standard deviation
Perception toward the generated stories	55	4.0364	0.07823	0.58019
Acceptance toward using CAMRPG	55	4.1500	0.08646	0.64118

Table 4.5 Independent t-test on gander difference

	Gender	N	Mean	Standard deviation	t-value
Perception toward the generated stories	Female	24	4.1458	0.48295	1.237
	Male	31	3.9516	0.64038	
Acceptance toward using CAMRPG	Female	24	4.2813	0.37816	1.458
	Male	31	4.0484	0.77840	

Table 4.6 Independent t-test on the time-spent groups

	Time-spent	N	Mean	Standard deviation	t-value
Acceptance toward using CAMRPG	Hard-core	14	4.3750	0.35014	−1.994[a]
	Casual	15	3.9667	0.68704	

[a] $p < 0.05$

Table 4.7 Descriptive statistics of the perceived usability for CAMEG and CAMRPG group

	Group	N	Mean	Standard deviation	Std. Error Mean
Effectiveness	CAMEG	37	3.8784	0.66044	0.10858
	CAMRPG	55	4.2364	0.56809	0.07660
Efficiency	CAMEG	37	4.2230	0.53289	0.08761
	CAMRPG	55	4.0591	0.53568	0.07223
Satisfaction	CAMEG	37	3.8811	0.61003	0.10029
	CAMRPG	55	3.9818	0.50077	0.06752

Table 4.8 Independent t-test to examine the different perceptions toward the two games

Usability factors		Levene's test for equality of variances		t-test for equality of means			
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference
Effectiveness	Equal variances assumed	0.944	0.334	−2.775	90	0.007[a]	−0.35799
Efficiency	Equal variances assumed	0.732	0.394	1.442	90	0.153	0.16388
Satisfaction	Equal variances assumed	1.503	0.223	−0.866	90	0.389	−0.10074

[a] $p < 0.01$

Table 4.9 Descriptive statistics of the perceived usability of CAMRPG for male and female students

CAMRPG	Gender	N	Mean	Standard deviation	Std. Error Mean
Effectiveness	Female	24	4.4167	0.54507	0.11126
	Male	31	4.0968	0.55407	0.09951
Efficiency	Female	24	4.1042	0.53627	0.10947
	Male	31	4.0242	0.54143	0.09724
Satisfaction	Female	24	3.9667	0.43606	0.08901
	Male	31	3.9935	0.55253	0.09924

(include 37 CAMEG users and 55 CAMRPG users) are used for doing statistical analysis and independent *t*-test.

Table 4.7 lists the descriptive statistics of the perceived usability that the users have for the games they played. Apparently CAMRPG users have perceived the effectiveness of the game they played more positively as well as more satisfy with it than CAMEG users. Therefore, hypothesis H2 is *supported*.

We further use the independent *t*-test to check whether or not there is significantly difference on the perceived usability between CAMEG and CAMRPG users. The results listed in Table 4.8 show that there is significant difference found for the perceived effectiveness toward the games the users played, but no significant difference has found on the perceived efficiency and satisfaction factors. This finding further shows us that having stories in the mobile educational game not only make the users have higher satisfaction toward the game, but also increase their perceived effectiveness of the game. The results lead us to a positive answer for our research question—does having story in the mobile educational game make the game more appreciated by learners? Therefore, hypothesis H3 is *partially supported*.

Table 4.10 Independent *t*-test to examine the perceptions that different gender has toward CAMRPG

CAMRPG (using story in mobile educational game)		Levene's test for equality of variances		*t*-test for equality of means			
		F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean difference
Effectiveness	Equal variances assumed	0.012	0.913	2.138	53	0.037[a]	0.31989
Efficiency	Equal variances assumed	0.115	0.736	0.546	53	0.588	0.07997
Satisfaction	Equal variances assumed	1.230	0.273	−0.196	53	0.846	−0.02688

[a] $p < 0.05$

For verifying if there is any gender difference on the perceptions toward the usability of CAMRPG, we check the descriptive statistics and do an independent *t*-test on CAMRPG users' perceptions based on their genders. Table 4.9 lists the descriptive statistics, all CAMRPG users perceive positive usability of CAMRPG. It seems that the female users have perceived the effectiveness and the efficiency of the CAMRPG a little bit more positively than the male users.

Also, according the *t*-test results listed in Table 4.10, there is significantly different perceived effectiveness toward the CAMRPG between male and female participants. These results lead us to a partial positive answer for the research question—is there any gender difference existed in the perceived usability of CAMRPG? Therefore, hypothesis H5 is supported.

4.4.3 Findings and Discussions

Based on the collected data and the quantitative analysis, we then have answers for the proposed four research questions and get better idea of the effects of stories in the educational games, at least in the mobile education games.

(1) *Do the stories have positive influence user acceptances toward the use of CAMRPG?*
Yes, as the descriptive statistics of CAMRPG users' acceptance toward the game (listed in Table 4.4) and the results of independent *t*-test on the difference of acceptance among genders (listed in Table 4.5) show, CAMRPG users do have very positive responses toward the acceptance of the game and there is no gender difference found.

(2) *Do the stories make users feel the game is useful?*
Yes, except the perceived efficiency of the game may be dropping. The descriptive statistics listed in Table 4.7 shows that CAMRPG users perceive higher effectiveness and are more satisfying with the game than their counterpart—CAMEG users. The descriptive statistics also shows that the perceived efficiency of the game that CAMRPG users have is lower than CAMEG users. One possible reason for that is because CAMRPG does not allow users to start a learning activity until they read the story. In such case, the users are always encountering extra step (i.e., transition story) in-between two learning activities, which is, highly possible to make the users feel not so efficient in playing the game.

Fortunately, from the results of the correspondent independent *t*-test listed in Table 4.8, we can find that there is no significant difference on the perceived efficiency toward the games among the two groups, which means, the stories in the mobile educational game does not have too much negative impact on the perceived efficiency that the users may have while playing the game.

Table 4.11 Independent *t*-test to examine the perceptions that different gender has toward CAMEG

CAMEG (mobile educational game without story)		Levene's test for equality of variances		*t*-test for equality of means			
		F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean difference
Effectiveness	Equal variances assumed	3.179	0.830	2.185	35	0.036[a]	0.36889
Efficiency	Equal variances assumed	1.273	0.267	1.470	35	0.150	0.27497
Satisfaction	Equal variances assumed	1.778	0.191	2.339	35	0.025[a]	0.51143

[a] $p < 0.05$

(3) *Is there any gender difference existed in terms of the perceived effectiveness and satisfaction toward CAMRPG?*
First of all, the descriptive statistical data (i.e., Table 4.9) shows that the responses from both males and females were positive in terms of perceived effectiveness and satisfaction toward CAMRPG. In addition, responses of female participants to the perceived effectiveness are higher than those of male participants in the pilot. This finding align with other researchers' findings, which are males tend to feel educational games are boring but females have more positive perceptions toward educational games (Gwee et al. 2010; Law 2010).

One interesting finding comes from the usability assessment of the proposed game. Female users have more positive perceived effectiveness and efficiency toward CAMRPG than male users. For the effectiveness factor, in particular, a significant difference exists between female and male users. Female users believe that they can learn object relevant knowledge effectively in the authentic learning environment.

One thing needs to be noted is, the results of independent *t*-test for examining the differences between male and female users who played CAMEG listed in Table 4.11 shows—the male and female CAMEG users have significant differences in terms of satisfying with the game they played. However, there is no significant difference on the perceived satisfaction toward the game among CAMRPG users. This finding implies that the user of stories in the mobile game may make male users feel the game more like a real game and make them have higher satisfaction toward the game.

(4) *Do gaming experience influence user acceptances toward the use of CAMRPG?*
According to the demographic information of the participants listed in Table 4.3, the results show that hard-core game players spend average almost ten times of the hours on playing computer games than casual game players.

Since, hard-core game players play more games, it may lead us to have an assumption that they have a higher standard while evaluating the proposed game than casual game players. Surprisingly, hard-core game players, on the contrary, do have significantly more positive response in terms of the acceptance toward using the game than casual game players as the results show in Table 4.6. One possible reason that leads us to this finding—hard-core players like game and would like to give any game a shot. However, as the data is collected after the users played the game, such reason may imply that even hard-core players treat CAMRPG a real game instead of "learning application".

4.5 Conclusion

This chapter first reveals the design of a story generation engine for mobile educational role-playing game and the use of decorating mobile learning activities with the generated story fragments. An experiment has been done for assessing the effect of stories. The results show that the stories play an important role in terms of increasing student perceptions toward the mobile educational game's effectiveness and making students more satisfied with the game.

Many interesting and important findings have been found. For instance, male students perceived lower effectiveness of using a mobile educational game for learning and not satisfy with the game as their counterparts do when the game has no story. However, male students are more satisfied with the game when the game has stories to decorate its learning activities and become no significant different from female students. With such finding, mobile learning activity designer and mobile learning systems (apps) developers should consider the integration of stories into their designs and apps so both male and female students may perceive effectiveness and get more satisfy with the mobile learning systems/apps.

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Chapter 5
Adaptive and Personalized Learning Based on Students' Cognitive Characteristics

Ting-Wen Chang, Jeffrey Kurcz, Moushir M. El-Bishouty, Kinshuk and Sabine Graf

Abstract Working memory capacity (WMC) is a cognitive characteristic that affects students' learning behaviors to perform complex cognitive tasks. However, WMC is very limited and can be easily overloaded in learning activities. Considering students' WMC through personalized learning materials and activities helps in avoiding cognitive overload and therefore positively affects students' learning. However, in order to consider students' WMC in the learning process, an approach is needed to identify students' WMC without any additional efforts from students. To address this problem, we introduce a general approach to automatically identify WMC from students' behavior in a learning system. Our approach is generic and designed to work with different learning systems. Furthermore, by knowing students' WMC, a learning system can provide teachers meaningful recommendations to support students with low and high WMC. Accordingly, we created a recommendation mechanism that provides recommendations based on the guidelines of cognitive load theory. These recommendations are intended to assist in presentation

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of information in order to reduce working memory overload. Information about WMC is also the basis for designing adaptive systems that can automatically provide students with individualized support based on their WMC.

Keywords Adaptive and personalized learning · Cognitive characteristics · Working memory capacity

5.1 Introduction

Working memory capacity (WMC), one of students' cognitive characteristics, is to keep active a limited amount of information for a very brief period of time (Miller 1956; Driscoll 2005). Results of several studies have shown that students with low or high levels of WMC have very different performances on the different attention levels during performing cognitive tasks (Broadway and Engle 2011; Engle 2010; Gathercole and Alloway 2008). Knowing the levels of students' WMC can help in many ways to enhance learning and teaching in learning systems. First, teachers can use this information to provide meaningful recommendations to their students. Furthermore, information about students' WMC can be used as input for adaptive systems to provide students with customized learning content and activities to suit their individual WMC. This chapter focuses on two main questions: how to identify students' WMC from their learning behaviors in learning systems and how to provide teachers with recommendations to support students based on their individual WMC.

Deficiencies in student's WMC result in varying performances on a variety of tasks. Traditionally, WMC can be measured by a variety of memory span tasks including counting span, operation span, and reading span tasks which are related to the complex cognitive tasks (Broadway and Engle 2011; Carretti et al. 2009; Unsworth et al. 2012). However, the main disadvantage of these measured tasks is that students have to do them in addition to their learning. Therefore, our research aims at enabling typical learning systems to automatically identify different levels (high/low) of students' WMC without any distractions while students learn. An approach is proposed to profile student behaviors from the log data available in a learning system's database. These behaviors are then analyzed and used as basis to calculate and identify students' WMC.

WMC is very limited and can be easily overloaded in learning activities that require complex cognitive tasks. Other related studies have also indicated that cognitive load can affect students' performance of cognitive tasks in online learning (Gathercole and Alloway 2008; Sweller et al. 1998). These studies argued that if the sum of the cognitive loads exceeds the students' WMC, learning will be impaired. In other words, if the students' cognitive load is too high, it will affect them in learning effectively in learning environment. According to the cognitive load theory, the load of working memory may be affected by the intrinsic nature of the learning materials, by the presentation of those materials and by the learning activities students should do (Sweller et al. 1998). The second aim of our research is, therefore, to present meaningful recommendations and suggestions for teachers in order to avoid overload of students' WMC and to enhance the instructional design in learning systems. The recommendations aim at assisting teachers to provide individual support for students based on their WMC.

The next two sections present an overview of students' cognitive characteristics, in particular WMC, and related works on adaptive and personalized technologies. In the fourth section, an approach for identifying WMC in learning systems is introduced, including explanations on the preprocessing steps, the relevant behavior patterns for WMC detection, and the calculation of individual WMC from these patterns. In the fifth section, a recommendation mechanism to provide recommendations to teachers based on students' different levels of WMC is introduced. The final section concludes the chapter and discusses future works.

5.2 Cognitive Characteristics—Working Memory Capacity

Humans have a limited working memory in both capacity and duration to deal with cognitive activities. From the aspect of capacity, working memory is capable of holding only about seven (minus/plus two) elements (or chunks) of information for a brief period of time (Miller 1956). From the aspect of duration, Driscoll (2005) found that new information retained in working memory without rehearsal is forgotten after a very short time. Several studies have highlighted the importance of WMC for learning and investigated the relations between WMC and different aspects, such as reading comprehension, academic achievement, and attention control (Carretti et al. 2009; Woehrle and Magliano 2012). Carretti et al. (2009) concluded that individuals with poor reading comprehension seem to be impaired in their WMC to actively maintain relevant information, inhibiting off-goal information or to update their memory content. In terms of attention control, individuals with high WMC are better in maintaining attentional focus on a cognitive task, especially when faced with distractions (Woehrle and Magliano 2012). The findings of Alloway and Alloway (2010) showed that a five-year-old child's working memory is a better predicator of academic achievement than IQ. These studies suggest that working memory may be a core cognitive ability that underlies and constrains our ability to process information across cognitive domains. WMC is also crucial to many learning activities in online learning because students have to hold information in their minds while engaging in an online learning activity. Traditionally, WMC can be measured by a variety of memory span tasks. Such tasks are used to measure the amount of information that can be held accessible in the working memory. For example, such tasks look at how many words or digits a person can retain and recall in a brief period of time. However, an obvious disadvantage is that students have to take this kind of task additionally to their learning activities. Another disadvantage is that students' WMC is detected at one point of time and any distractions or lack of motivation to conduct this task would seriously and permanently affect the result.

5.3 Adaptive and Personalized Learning Technology

An adaptive learning system offers students with personalized content, presentation, and navigation supports in a learning environment (Park and Lee 2003). Such systems are able to consider relevant students' characteristics (Park and Lee 2003). The student model is the basis for personalization in such adaptive learning systems (Chrysafiadi and Virvou 2012) and is responsible for storing students' characteristics such as intellectual ability, cognitive abilities, learning styles, prior knowledge, achievement motivation, self-efficacy, and abilities to solve problems and making decisions (Park and Lee 2003; Chrysafiadi and Virvou 2012). By knowing the characteristics of students, an adaptive learning system can offer personalized learning spaces (adaptive courses and materials) and support (such as adaptive annotations, navigation, and recommendations).

Building and updating a student model is called student modeling. Two different student modeling approaches exist for identifying students' characteristics, preferences, and needs in learning systems: collaborative and automatic (Brusilovsky 1996). In the collaborative approach, the student provides explicit information (e.g., learning goals, preferences, etc.) for the student modeling mechanism (Brusilovsky 1996). In this approach, the adaptive learning system gets the required information about students by collaborating with the students in collecting the information. An example of such collaborative student modeling approach is WebOSPAN (Lin 2007), where students perform a sequence of memory and calculation tasks based on which their WMC is identified. The automatic student modeling approach refers to building and updating the student model automatically based on the behaviors and actions of students in learning systems. Conati and Maclaren (2009) used an automatic approach to analyze students' browsing data recorded in the log file of a web-based learning system and concluded that students' cognitive style (field dependence and independence) and learning behaviors are related. Cognitive trait model (CTM) is another example for an automatic student modeling approach that profiles students according to their three cognitive traits: WMC, inductive reasoning ability, and associative learning skills (Lin 2003). In CTM, the students' behaviors in a course are used to infer those three cognitive traits. The results of an evaluation of the CTM (Lin 2007) showed a significant correlation between the results of WMC obtained from CTM and the scores from WebOSPAN task. Lin's study (Lin 2007) provides a practical validation to CTM as well as proves the effectiveness of the selected behaviors to determine WMC. The CTM is very much related to our work. While the concept of CTM could be generalized, its implementation has not been that way. In our work, we particularly focus on using behavior patterns that can be identified in any learning system and course, and integrate this concept into a detection tool that can be applicable for learning systems in general. In the following section, we will introduce an approach for automatically detecting students' WMC based on their continuous behavior in learning systems.

5.4 Approach of Detecting WMC in Learning Systems

This section focuses on how to enable typical learning systems to automatically identify different levels (high/low) of students' WMC from their learning behavior and actions in learning systems. A student modeling approach is introduced and a detection tool, DeLeS (Graf et al. 2009a, b), is extended to identify students' WMC from their activity log data of learning systems. In the following subsections, a detailed explanation is provided about each step of this approach.

5.4.1 Preprocessing of Data

In order to analyze students' behavior and detect relevant behavior patterns, some preprocessing of behavior data and course data in learning systems is required. The preprocessing includes (1) the identification of learning sessions, (2) filtering out activities that are not dedicated to learning as well as activities where students visit a learning activity only for very short time, and (3) building a Learning Sequence Table called LSEQ table that includes the structure of the course in terms of the predefined sequence of learning activities/objects in a course.

5.4.2 Relevant Behavior for WMC Detection

In learning situations, there are several behavior patterns known in the literature that give indications for a student's WMC. Six patterns are considered and explained subsequently. Since most of these patterns are based on students' navigational behavior, types of navigational behavior are described by a relation function, *R (preLO, currLO)*. This function relates two learning objects (LOs): the source (*preLO*) and the destination (*currLO*).

1. **Linear navigation pattern**: Linear navigation means that students learn the materials linearly and follow the learning sequence of the course defined by teachers. Huai (2000) performed an experiment to investigate the relationship between WMC, long-term memory, and a serial/holistic learning style. To draw conclusions about the relationship between WMC and a serial/holistic learning style, linear and nonlinear navigational behavior of students was investigated. As a result, Huai also found that students with high WMC tend to focus on linear navigation and students with low WMC tend to use nonlinear navigation.

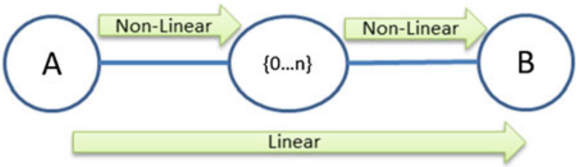

Fig. 5.1 A sample of linear navigational behavior

A sample of linear navigational behavior is shown in Fig. 5.1. When LO B is learned, and the previous LO of LO B (defined in the LSEQ table), LO A, has been learned before, linear navigation is found, no matter whether other LOs are visited between LOs A and B. If this linear navigation is found, it gives an indication for high WMC. Otherwise, nonlinear navigation is found, which gives an indication for low WMC.

2. **Constant reverse navigation pattern**: Reverse navigation means that a student revisits an already visited LO. Constant reverse navigation indicates that a student frequently goes back to an already visited LO. This behavior can be explained by the limited capacity of working memory for students with low WMC (Graf et al. 2009a, b). The process of constant reverse navigation is caused by an insufficient WMC to hold on the materials that have just been visited (Lin et al. 2003). When the learning materials that a student just read on the previous page should be still fresh in his/her working memory, the constant need to navigate backward is a sign of working memory deficiency. The definition of constant reverse navigational behavior is that there are more than two LOs revisited in the same learning session and the navigational relations of these LOs are not defined in the LSEQ table (and therefore not in line with the sequence of LOs in the course structure). Figure 5.2 shows a sample of constant reverse navigational behavior including the following relations of navigation: *R(A, B), R(B, C), R(C, A),* and *R(A, C)*. In these navigational relations, two relations, *R(C, A)* and *R(A, C),* are not defined in the LSEQ table and the two destination LOs, *A* and *C*, are revisited. Thus, the constant reverse navigational behavior is found, which gives an indication for low WMC.
3. **Simultaneous tasks pattern**: The simultaneous tasks pattern is transferred from the ability of attentional control on performing two tasks simultaneously. Previous studies have shown that when performing two tasks simultaneously, low-WMC participants were less accurate than participants with high WMC (Engle 2010; Woehrle and Magliano 2012). For identifying this pattern, overlapping navigational behavior is investigated which indicates that a student tries to

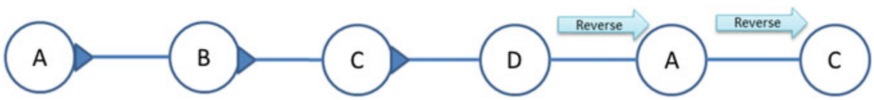

Fig. 5.2 A sample of constant reverse navigational behavior

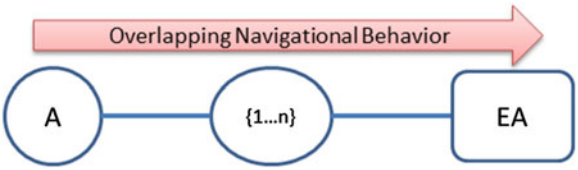

Fig. 5.3 A sample of overlapping navigational behavior

perform two tasks simultaneously. As shown in Fig. 5.3, if a student visits at least one other LO in between LO A and its evaluation, *EA*, overlapping navigational behavior is found. In such situation, the student learns LO A first and then learns other LOs before taking the evaluation of LO A. Therefore, she/he needs to remember the concept of LO A in her/his working memory while learning other LOs. If the student then passes the evaluation of LO A, the simultaneous tasks pattern is found, which gives an indication for high WMC. If she/he fails, the nonsimultaneous tasks pattern is identified, which gives an indication for low WMC.

4. **Recalling learned material pattern**: The recalling learned material pattern is transferred from the relationship between WMC and long-term memory. This pattern is similar to the simultaneous tasks pattern but it is identified within two different learning sessions. Prior works have argued that the individual's ability to retrieve information from long-term memory is determined by their WMC (Unsworth et al. 2012; Engle 2010). As a result, they found that low-WMC participants cannot recall as much information from long-term memory as high-WMC participants since low-WMC individuals do not search the remembered information in their long-term memory as effectively as high-WMC individuals. Figure 5.4 shows a sample of this pattern. This pattern is found if a student visits LO A in one session but does not perform an evaluation of his/her knowledge on LO A in that session. In a different learning session, the student then does not visit LO A but goes directly to the evaluation of LO *A (EA).* If the student then passes the evaluation, it means that she/he could recall the previously visited

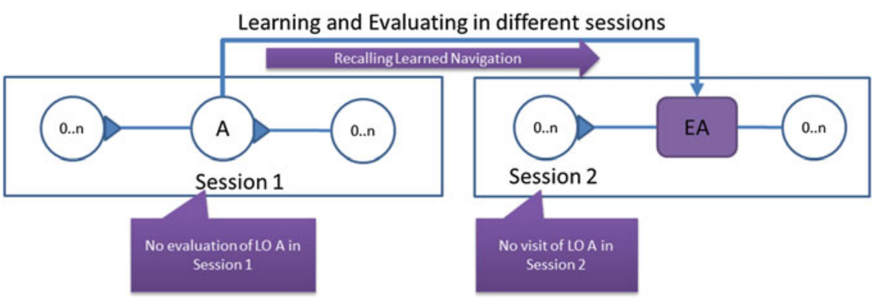

Fig. 5.4 A sample of recalling navigational behavior

information from LO A from her/his long-term memory and the recalling learned material pattern is found, which gives an indication for high WMC. If she/he fails the evaluation, the non-recalling learned material pattern is identified which gives an indication for low WMC.

5. **Revisiting passed learning object pattern**: Similar to the previous pattern, the revisiting passed learning object pattern is transferred from the ability of using WMC to retrieve information from long-term memory. As mentioned in the previous sections, several studies have argued that individuals with low WMC cannot recall as much information from long-term memory as individuals with high WMC (Engle 2010; Unsworth et al. 2012). This pattern considers a situation where a student visited LO A and successfully completed its evaluation (EA) in the same session but then revisits LO A afterward in a different learning session, as shown as a sample in Fig. 5.5. In such case, the student seems to have problems recalling information from his/her long-term memory and wants to reread some of the already learned information. The more time the student spends on LO A during such revisit, the more problems the student seems to have in recalling the respective information from the long-term memory and therefore, the stronger the indication for low WMC is. In order to calculate this pattern, we consider the time the student i spent on LO A in order to pass the evaluation as base value b_i, and the time that the student spent when he/she revisits LO A as value v_i. Furthermore, let r_i be the ratio v_i/b_i, representing how much time a student spent on revisiting LO A in relation to how much time he/she spent to learn this LO. Let r_{avg} be the average ratio of all students, calculated based on formula 1 and representing how much time on average each student spent on revisiting LO A in relation to how much time he/she spent to learn this LO.

$$r_{\text{avg}} = \frac{\sum_{i=1}^{n} r_i}{n}, \tag{5.1}$$

where n is the overall number of students. This average ratio r_{avg} is then used as threshold and compared to a student's r_i value. If r_i is greater than r_{avg}, the time the student took for reading and recalling already learned information is above average and therefore indicates low WMC. On the other hand, if r_i is smaller

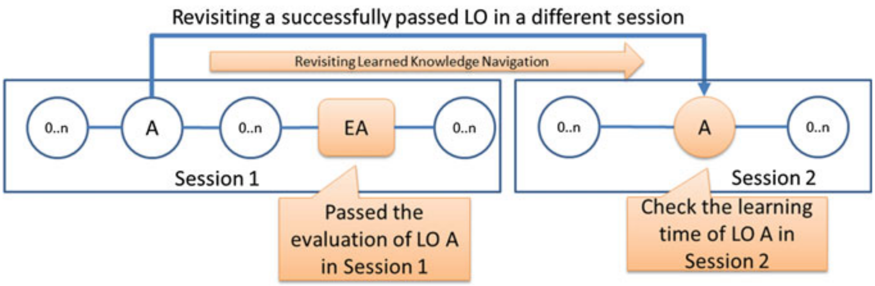

Fig. 5.5 A sample of revisiting navigational behavior

than r_{avg} the time the student took for reading and recalling already learned information is below average and therefore indicates high WMC. If r_i is equal to r_{avg}, an indication for average WMC is given.

6. Learning style pattern: The learning style pattern is based on the relationship between learning styles and WMC. Graf et al. (2009) investigated the direct relationship between WMC and the four learning style dimensions of the Felder-Silverman learning style model (FSLSM) (Felder and Silverman 1988), namely the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimensions. The results of the study showed that students with a reflective or intuitive learning style tend to have high WMC and students with an active or sensing learning style tend to have low WMC. For the visual/verbal dimension, the study found only a one-directional relationship, namely that learners with a verbal learning style tend to have high WMC, whereas visual learners have either high or low WMC. No relationship for the sequential/global dimension was found. The learning style pattern considers these relationships. Accordingly, if a student has an active or sensing learning style, this gives an indication for a low WMC. On the other hand, a reflective, intuitive, or verbal learning style gives an indication for a high WMC. An average value of all indications from a student's learning styles is calculated and this value represents the overall indication of WMC for this learning style pattern.

5.5 From Learning Patterns to WMC

After preprocessing the data, these data are used to calculate the students' WMC based on the five navigational behavior patterns and the learning style pattern. If a navigational behavior pattern is detected in a relation between two LOs, this relation is considered as an activated relation for the particular pattern. In each learning session, a value p is calculated for each of the five navigational behavior patterns based on the number of activated and non-activated relations in this session. This value p shows how strongly the student's behavior represents the respective pattern. Subsequently, the value p for each pattern is transferred to its indication for WMC (e.g., a high p value for linear navigation provides an indication for high WMC). Then, the indications from the five navigational behavior patterns and the indication based on the learning style pattern are summed up and divided by the number of activated patterns (where the learning style pattern is considered as activated as soon as the learning styles of the student are known). The result of this calculation represents the indication for WMC of the respective learning session. Although the learning style pattern is not dependent on learning sessions, we decided to add the indication from this pattern in each session in order to ensure that this pattern has the same impact in the detection process as all other navigational behavior patterns. Each learning session also contains a weight, which determines the influence of each session on the overall value of WMC and is calculated based on the number of activated relations in a session for all patterns. In order to calculate the student's WMC, the WMC indication of each session is multiplied by the weight of the respective session. Subsequently, the results for all sessions are summed up and divided by the number of sessions. The resulting value is the identified WMC for the respective student.

5.6 Recommendation Mechanism for Teachers to Support Learners with Different WMC

While the previous section presented an approach to automatically identify students' WMC, in this section, a recommendation mechanism is introduced that uses the information about students' WMC to present meaningful and personalized recommendations for teachers in order to avoid overloading particular students' WMC as well as to enhance the instructional design in their courses. Students in an online course exhibit different performance in different learning sessions and one reason can be different levels of WMC. The recommendations provided by this mechanism are therefore considering the level of WMC at which a student performs in the learning sessions and provide teachers with suggestions on how to support a particular student according to cognitive load theory (Sweller 2005; Watson and Gable 2013) and the features of working memory (Miller 1956; Driscoll 2005). For example, if a student with high WMC exhibits signs of low WMC in a particular learning session, the teacher is made aware of this mismatch and provided with recommendations on how to support the student to successfully learn in the respective learning session.

Two types of WMC results of a student are considered in the recommendation mechanism: the WMC identified in one session (called session WMC) and the total WMC from all sessions. Both of these types of WMC results can be automatically detected as described in the previous section. If the session WMC and the total WMC match, it means that the student is acting with the same performance in that session as the overall performance from all sessions. The recommendation mechanism does not take any action in that situation and does not present any information to the teacher. On the other hand, if the results do not match, it means that the student has probably faced some problems or distractions in that session. When a mismatch is found, further information and recommendations based on the student's WMC are displayed to the teacher. If a student has high total WMC but her/his session WMC is low, the recommended information for high WMC will be displayed. On the contrary, if a student has low total WMC but her/his session WMC is high, the recommended information for low WMC will be presented to the teacher. Figure 5.6 shows a screenshot of a student who has low WMC but exhibits high WMC in a session.

The recommendations based on WMC consist of general and recommended information. The general information provides further details on those sessions in which the WMC results are mismatched. The recommended information presents guidelines and suggestions for supporting the respective student based on her/his WMC.

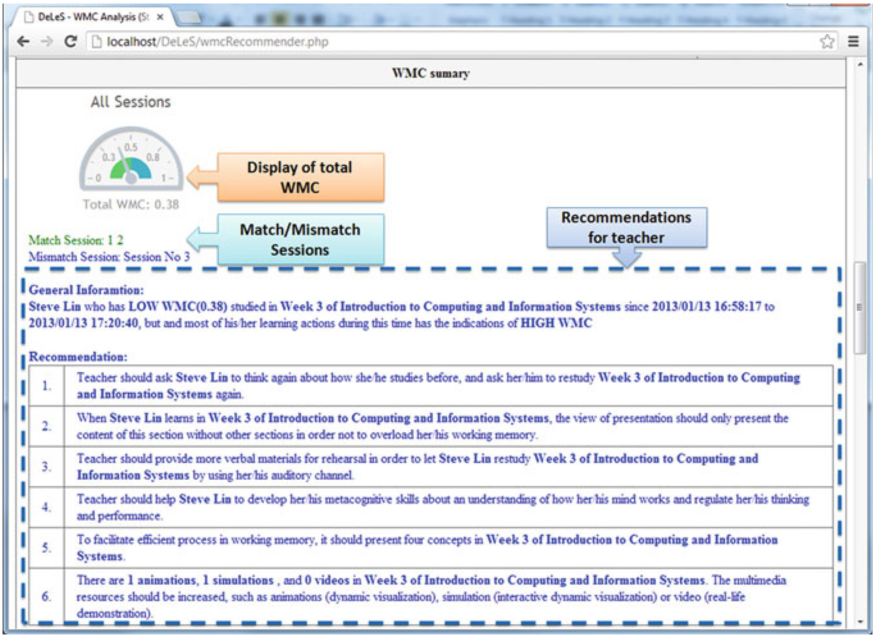

Fig. 5.6 Information and recommendations for a learner with low WMC

General Information: General information presented to the teachers consists of student, course, and session information. This information enables teachers to know who, where, and when a student might have problems. The teachers can then conduct investigations for improving their instruction materials. The mechanism presents overviews of student and course information to teachers, showing them a list of students who have a mismatch in their session WMC and total WMC, as well as the number of mismatches that each student and each session/course has. For a single student, the format of general information is as follows:

> {StudentName} who has {TotalWMC} studied in {SectionTitle} of {CourseTitle} since {BeginTime} to {EndTime}, but most of his/her learning actions during this time indicate {SessionWMC}.

Recommended Information: The following paragraphs describe the recommendations based on different levels of WMC, including a brief discussion on the features of recommendations, the relationship with cognitive load as well as concrete suggestions for each feature.

- **Recommendations for high WMC**: Students with high WMC have high capacity in their working memory to process information. Accordingly, the recommendations for high-WMC individuals (described in the following paragraphs in more detail) focus on how to guide them effectively to use their working memory.

1. **Increasing learning space**
   Unsworth and Engle (2007) suggested that individuals with high WMC are better at discriminating relevant and irrelevant information in their search set. They also mentioned that high-WMC individuals have poorer performance than low-WMC individuals if they use constrained search set. Increasing the learning space can lead to extending the search set and therefore, can be helpful for high-WMC students. The view of presented information will then be increased to allow the students to get the most out of the domain (Kinshuk and Lin 2003). The recommendation for this feature is:

When {StudentName} learns {SectionTitle}, the other sections of {CourseTitle} should also be presented to her/him in order to extend her/his available learning space.

2. **Promoting deep processes**
   Anderson (2008) suggested that real-life applications should be used in online learning to help transfer information to students' long-term memory by promoting their deep processes. High-WMC individuals have a better ability of using different strategies to transfer the knowledge into their long-term memory effectively (Unsworth et al. 2012). In cognitive load theory, the variability effect also encourages students to develop knowledge structure that aids in transfer of training to similar situations in the real world (Sweller 2005). Therefore, teachers should encourage high-WMC students to engage in deeper thinking by transferring their knowledge to real-life applications. The recommendation for this feature is:

{StudentName} should think about how to apply the learned knowledge of {SectionTitle} of {CourseTitle} in real life. This activity can help her/him in processing information to her/his long-term memory and encourages deeper thinking.

3. **Attending learning activity**
   Anderson (2008) also suggested that students should use the strategies or tools to construct a memory connection between the novel information and learned knowledge already stored in long-term memory. Unsworth and Engle (2007) pointed out that high-WMC individuals could maintain the task goal better compared to low-WMC individuals when they are learning new information. Therefore, in a situation where students with high WMC have shown signs of low-WMC behavior, they could be suggested to use additional tools such as mind maps or concept tools to help them connect their new and already learned information. Also, the hierarchical organization of information presented as mind map or concept map provides a high degree of structure, which would facilitate connection of new knowledge with already learned knowledge and reduce the cognitive load for learning new information (Watson and Gable 2013). The recommendation for this feature is:

{StudentName} should be encouraged to attend a summary activity (such as creation of mind map or concept map) after learning {SectionTitle} of {CourseTitle}. This hierarchical map will help her/him to connect the main concepts (ideas) of this section to already learned knowledge.

4. **Using metacognitive skills**
   Students should be given more opportunities to use their metacognitive skills and should be encouraged to participate in activities that use their metacognitive skills actively (Anderson 2008). Whitebread (1999) argued that high-WMC individuals have better metacognitive skills about how to learn new knowledge than low-WMC individuals. Therefore, teachers should encourage high-WMC students to use their metacognitive skills when they have difficulties. The recommendation for this feature is:

{StudentName} should be encouraged to rethink how she/he studied before and compare the differences between her/his learning in {SectionTitle} of {CourseTitle} and previous sections. This will help {StudentName} to use her/his own metacognitive skills to find out what difficulties she/he encountered in {SectionTitle} of {CourseTitle}.

- **Recommendations for low WMC**: For students with low WMC, their capacity of working memory can be exceeded easily. Accordingly, recommendations for students with low WMC (described in the following paragraphs in more detail) focus on how to reduce their cognitive load.

1. **Decreasing learning space**
   Previous studies have argued that low-WMC individuals are poorer than high-WMC individuals at searching information in a larger search set (Unsworth et al. 2012; Unsworth and Engle 2007). In order to protect the students from overloading the working memory with complex hyperspace structure, the number of navigational path should be decreased (Gathercole and Alloway 2008; Kinshuk and Liu 2003). Thus, decreasing the learning space into particular parts would reduce the intrinsic load by presenting less information at a time. The recommendation for this feature is:

When {StudentName} learns {SectionTitle} of {CourseTitle}, the view of presentation should only present the content of this section and no other sections in order to avoid overloading her/his working memory.

2. **Rehearsing learned information**
   Low-WMC individuals are not able to keep information in their working memory as long as high-WMC individuals can (Unsworth and Engle 2007). Rehearsal would be an effective way to help students remember and transfer the learned information from her/his working memory to the long-term memory (Gathercole and Alloway 2008). Driscoll (2005) argued that novel information in human cognitive system is lost within a very short time without rehearsal. The recommendation for this feature is:

{StudentName} should be encouraged to rehearse {SectionTitle} of {CourseTitle} in order to help her/him to retain important information.

3. **Training metacognitive skills**
   As mentioned in Anderson's article (Anderson 2008), teachers should provide students more opportunities to use their metacognitive skills. However, students with low WMC may have difficulty concentrating and may frequently lose their task goal when learning information (Unsworth and Engle 2007). Previous studies have suggested that training of metacognitive skills may help students with low WMC in developing an understanding of how to learn and how to think when learning new information (Watson and Gable 2013). The recommendation for this feature is:

{StudentName} needs some help in developing her/his metacognitive skills about how her/his mind works and regulate her/his thinking and performance. {StudentName} should be encouraged to rethink how she/he learns in general and how she/he thinks when she/he learned in previous Sects.

4. **Preventing overload**
   Miller proposed a "magical number seven" to give the earliest quantification of the capacity limit associated with working memory (Miller 1956). Watson and Gable suggested that up to four facts about a learning object are more easily handled in working memory (Watson and Gable 2013). If the number of facts (such as concepts or ideas) increases, the natural complexity of information increases and the intrinsic cognitive load thus is high. The recommendation for this feature is:

To facilitate efficient processing in working memory, {SectionTitle} of {CourseTitle} should present maximum four concepts/ideas.

5. **Using multimedia resources**
   Previous studies have suggested that the number of multimedia resources should increase for low-WMC students so that they could be provided with multimedia resources that work best for their WMC (Broadway and Engle 2011). In cognitive load theory, the modality effect suggests that multiple recourses of information are essential for understanding and learning (Sweller 2005). The recommendation for this feature is:

There are {NumofAnimation} animations and {NumofSimulation} simulations in {SectionTitle} of {CourseTitle}. More animations (dynamic visualization or video demonstration) and more simulations (interactive dynamic visualization) could help {StudentName} to better understand and learn this Sect.

6. **Attracting attention**
   Low-WMC individuals are more likely to have their attention captured by distractions compared to high-WMC individuals and thus are also more susceptible to losing access to the task goal (Unsworth et al. 2012). Therefore, in order to attract student attention, the important and critical information should be highlighted and be explained with additional explanations. In cognitive load theory (Sweller 2005) the split attention effect occurs when attention is split between multiple sources of visual information that are all essential for understanding. Thus, the extraneous cognitive load is reduced

by integrating multiple sources of information (Sweller 2005). The recommendation for this feature is:

> {StudentName} would benefit from having pointed out the important information in {SectionTitle} of {CourseTitle} again or using different explanations in order to gain her/his attention and help in remembering the information.

In conclusion, this section introduced a mechanism that provides teachers with various recommendations and suggestions based on different levels of students' WMC. The mechanism presents general and recommended information about students' performance to the teachers once it identifies that a student's behavior in a particular session does not correspond with her/his WMC. Teachers can then use this information to provide appropriate materials and personalized suggestions for students based on their WMC levels.

5.7 Integration and Visualization of WMC Information and Recommendations in Learning Systems

Both, the detection tool for identifying students' WMC based on their behavior as well as the recommendation mechanism to provide teachers with recommendations on how to support students with different WMC, are designed to be integrated into

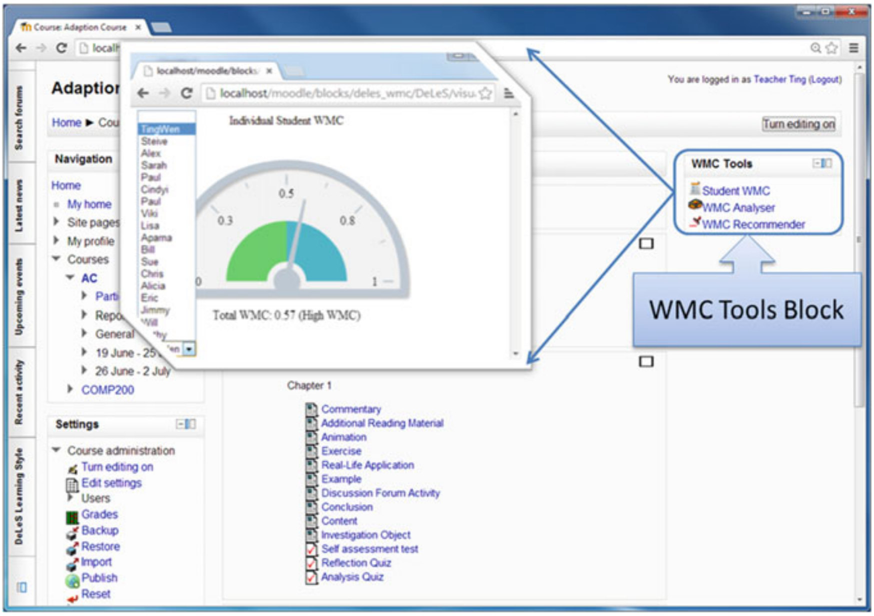

Fig. 5.7 Detection Tool Block in Moodle and Individual Student WMC

existing learning systems. To validate the detection tool and the recommendation mechanism, both have been implemented as plugins for the learning management system Moodle (Moodle 2013) in the form of a block. This block is easily accessible for teachers in a dedicated area at the right side of the learning systems' display (see Fig. 5.7).

The block consists of three links: "Student WMC," "WMC Analyser," and "WMC Recommender." The "Student WMC" link leads to a page that provides teachers with information on their students' WMC. As can be seen in Fig. 5.7, a teacher can select a particular student and can see her/his WMC, which is presented on a scale from 0 to 1, where 0 indicates a very low WMC and 1 indicated a very-high WMC.

The second link ("WMC Analyser") provides more detailed information about students' WMC with respect to each learning session. A teacher can see the students' behavior of each learning session based on the six patterns (LN: Linear Navigation; CR Constant Reverse navigation, ST: Simultaneous Tasks, RC: ReCalling learned materials, RV: ReVisiting passed learning object, and LS: Learning Style), what indication this behavior gives with respect to a student's

Fig. 5.8 WMC Analyzer Interface—LN, CR, ST, RC, RV represents the activated behaviors of respective patterns; nonLN, nonCR, nonST, nonRC, nonRV represents the nonactivated behaviors of those patterns; LS(ref/ins/ver) represents reflective, intuitive, and verbal learning styles; LS(act/sen) represents active and sensing learning styles

WMC as well as the WMC of each session. As shown in Fig. 5.8, the blue bars represent indications for high WMC and the green bars represent indications for low WMC. The WMC of each session is calculated based on the indications from all patterns. For example, Fig. 5.8 shows that the respective student performed more linear navigation behavior than nonlinear in session 6 and therefore, the LN pattern gives an indication value of 0.9 on a scale from 0 to 1 where 0 represents a strong indication for low WMC and 1 represents a strong indication for high WMC. Accordingly, the indication value of 0.9 suggests that the student has high WMC.

The third link ("WMC Recommender") provides teachers with recommendations on how to best support individual student based on their WMC. Once a teacher clicks on this link, the teacher can select for which student she/she wants to get recommendations and subsequently, recommendations are presented as shown in Fig. 5.6.

5.8 Conclusions and Future Works

This chapter proposed an approach for identifying students' WMC from their activity log information in learning systems as well as introduced a mechanism that provides teachers with various recommendations and suggestions based on different levels of students' WMC in learning systems. For detecting students' WMC, six behavior patterns have been identified to be, on one hand, relevant for the identification of WMC as concluded by the literature, and on the other hand, to be domain and learning system independent so that our proposed approach is generic and can be used in different learning systems. As identified in several studies, students' different levels of WMC can affect students' learning performances (Alloway and Alloway 2010; Marengo et al. 2012). The information about students' WMC can be helpful to support students in many ways. For example, by making students and teachers aware of the different WMC levels, teachers can individually support students and provide them with personalized recommendations, while students can better understand their weaknesses and strengths, and use this information to improve their learning.

Accordingly, we proposed a recommendation mechanism to provide teachers with suggestions in order to better support individual students based on their WMC. The proposed recommendation mechanism considers cognitive load theory and the features of working memory to understand students' performances during their learning processes. The mechanism presents general and recommended information about students' learning processes to the teachers once it identifies that a student's behavior in a particular session does not correspond with her/his WMC. Teachers can then use this information to provide appropriate materials and personalized suggestions for students based on their WMC levels.

In addition, information about students' WMC can be used as input for an adaptive learning system to automatically provide students with individualized materials and activities as well as personalized recommendations, considering their level of WMC. Furthermore, since there are other cognitive abilities that affect the learning process, our future work will focus on extending the proposed mechanism to additionally consider those other cognitive abilities, such as inductive reasoning skill, associative skill, and information processing speed.

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Chapter 6
Augmentation Strategies for Paper-Based Content Integrated with Digital Learning Supports Using Smartphones

Nian-Shing Chen, I-Chun Hung and Wei-Chieh Fang

Abstract Up to the twenty-first century, paper is still widely adopted for recording and reading. However, paper-based materials are fully capable of presenting abstract concepts and complicated knowledge with static text and figures. Learners usually need timely and adequate supports when encountering difficulties during learning. With a consideration of applying technologies, the learning tool must have a certain mobility and accessibility for acquiring facilitative resources. Using the networking capability of smartphone to access digital content from the Internet to enrich conventional paper-based learning activities is worth investigating. This chapter introduces an augmentation-enhanced learning context with an integration of digital content into paper-based materials in order to facilitate learning. Constructive feedback, scaffolding questioning, and procedural scaffolding are three strategies applied into the instructional designs and learning system. Quasi-experiments for personal learning and collaborative learning were also conducted to evaluate the effects on learning performance. The results suggest that the three instructional designs had significantly positive effects on individual's learning performance. Team's learning performance and team's discourse levels were promoted as well. This chapter lays out a strong foundation for researchers to further explore how to better design different learning strategies for different learning subjects in the augmentation-enhanced learning context using smartphones. It is hoped that educational practitioners are able to obtain concrete ideas and solutions on how to better leverage the benefits of both paper-based content and digital learning materials in a real blended learning environment.

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6.1 Introduction

Paper-based materials have been prevalent for delivering knowledge over the past centuries (Macedo-Rouet et al. 2009). Many convenient features of paper-based materials have been widely used such as ease of reading, writing, note-taking, and carrying around. However, paper-based materials provide very limited assistance in one's reading comprehension due to static representations or lack of timely supports. Integrating digital learning supports with a pre-designed strategy into paper-based content may enhance comprehension.

Recently, smartphone is considered an educational tool and its technological features have potentials for providing additional learning supports for traditional paper-based learning context. Comprehension is the ultimate goal of reading. Reading, the foundation of learning (Berninger and Richards 2002; Cunningham and Stanovich 2001), is an active and purposeful process of understanding content and blending self-experience to construct new knowledge (Armbruster et al. 2001; Oakhill et al. 1998; Smagorinsky 2001). Reading failure may lead to long-term learning difficulties and further engender a possibility of losing their confidence and learning motivation (Armbruster et al. 2001; Nation et al. 2002). Digital content (e.g., multimedia) can help learners understand complex concepts, elicit higher self-motivation, and foster individual engagement in learning activities (de Jong et al. 2010; Lowe et al. 2010). By applying technologies into a learning activity, the digital content can be presented to learners during learning. One candidate is the smartphone because its popularity and mobility can construct such a learning environment. The cost of smartphones has been affordable and accessible to people (Chen et al. 2008). Therefore, using smartphones as educational tools for supporting instructional activities with adequate pedagogical theories and strategies is conceivable (Lan and Sie 2010; Özdemir 2010). Although paper-based materials had been used for a long time, they still suffer from some major drawbacks, such as not being able to present audio/video or animation content.

Feedback is considered essential to learning not only for cultivating learners' profession but also improving their self-efficacy, self-awareness, and enthusiasm (Bain and Swan 2011; Timmers and Veldkamp 2011; Wang and Wu 2008). Effective feedback should include constructive information (i.e., constructive feedback) which can contribute to learners' actual performance and raise it to the expected performance (Timmers and Veldkamp 2011). Instructors nowadays have to provide learners adequate and timely feedback for aligning learners with needs and expectations (Rolfe 2011; Whitelock et al. 2010). For example, feedback can be utilized as a learning facilitator for learners based on learners' assessment results (Whitelock and Watt 2008). Constructive feedback is defined in this chapter as the act of providing timely personalized learning suggestions with meaningful direction for learners according to the results of assessment, which are analyzed and measured by the learning system through smartphones.

Furthermore, scaffolding strategies, closely related to the notion of zone of proximal development (Vygotsky 1978), can be applied to the instructional designs to provide more support to learners than the constructive feedback. Hannafin et al. (1999) suggested that scaffolding can be used during learning to guide learners what to consider, how to think, how to utilize available resources, or how to approach the learning goal. Scaffolding has two types, namely hard and soft (Saye and Brush 2002). Hard scaffolding is static supports pre-designed based on common learners' difficulties in a learning activity, whereas soft scaffolding is dynamic and situational requires to provide timely supports in response to each individual learner's needs during learning (Wood and Wood 1996). Scaffolding is provided to students with necessary learning supports for facilitating what they are not fully capable of when achieving a learning goal alone (Wood et al. 1976). The learning supports in one's individual learning process enable the learner to move from the current developmental level to the level of potential development. Assisting learners with performing high-level cognitive activities, such as reading, inquiry, and problem solving, requires effective strategies (Kim and Hannafin 2011; Li and Lim 2008; Pearson and Fielding 1991). Scaffolding questioning is one of the most conventional classroom instructional activities for instructors to facilitate knowledge construction during learning (Ge and Land 2003). Providing proper scaffolding questions to learners can promote knowledge constructions, reasoning, problem solving, and metacognition (Ge and Land 2004; King 1994; McDaniel and Donnelly 1996). When learners participate in a reading activities, questions are usually applied into the pre- and post-reading phases to facilitate understanding of the whole reading materials and memorization of important concepts (King 1994).

On the other hand, collaborative learning allows learners to interact with peers and facilitate their development of thinking skills in face-to-face settings (Davidson 1985; Dillenbourg 1999; McCarthey and McMahon 1992). Constructive feedback and scaffolding questioning can benefit personal learning well. However, additional requirements have to be considered for collaborative learning such as group discourse level. In such collaborative learning context, guiding and facilitating group members to discuss and learn are also essential. Applying procedural scaffolding into a learning activity is able to improve learners' performance and create a context helpful for accomplishing a learning task (Pea 2004). Procedural scaffolding strategy for supporting group collaborative learning can be utilized to make learners think first and then discuss with other group members (Chen et al. 2011). The purpose of applying procedural scaffoldings in learning activities is to reduce social loafing and free rider effect (Janssen et al. 2007; Johnson and Johnson 1989). In a social loafing situation, group members would invest less effort in a group than they are assigned to complete tasks individually. Besides, when a learner does nothing and leave the work to other group members, the free rider effect can take place. Through procedural scaffoldings, the social loafing and free rider effect can be reduced for better knowledge construction and cognitive development (Veerman et al. 2000).

In the following sections, this chapter will explain how to utilize the three strategies (i.e., constructive feedback, scaffolding questioning, and procedural scaffolding) into real instructional activities with learning systems using smartphones. The learning performance is a key measure of goodness which shows how well learners can benefit from the augmented strategies for paper-based content enabled by smartphones. Team's learning performance and team's discourse levels were also regarded as two indexes of learning outcomes for collaborative learning.

6.2 Paper-Based Learning with Mobile Technologies

Reading activities can be enriched by using information and communication technologies (ICTs) such as electronic reader devices (Daniel and Woody 2013; Embong et al. 2012; Koike et al. 2001; Rockinson-Szapkiw et al. 2013; Woody et al. 2010). However, learners have to read on or with a specific mobile device apart from the printed materials during the whole learning process. Reading comprehension is a result of the interaction between the learners and paper-based materials in conventional reading activities. If reading assistances can be brought into the undergoing reading process on each reader's demand, the conventional reading activities can be enriched with both advantages of paper-based materials and digital content, and learners' reading experience and performance will lead to positive outcomes (Chen et al. 2011). With the support of ICTs, learners' comprehension can be maximized even in the traditional paper-based reading activities (Chen et al. 2008; Koike et al. 2001).

To efficiently facilitate learners' reading, ideal reading assistances, which are paper-based materials augmented with digital support content, enable readers to immerse in a reading process (Chen et al. 2011). Now, the question is how to leverage the benefits of both paper-based content and digital content. Weiser (1991) proposed the vision of embedded virtuality, which means a seamless integration of ICTs into real world to power human on different kinds of tasks. From the technical perceptive, learners can acquire knowledge through seamlessly integrating digital support content into paper-based learning materials through a mobile device because of its popularity and mobility. A mobile device could integrate QR code technique which features fast readability and easy reproduction. The storage capacity of QR code is larger than the conventional one-dimensional bar code. Learners can easily access digital content such as animations or other multimedia information on a smartphone right after reading the QR code on a smartphone. On the other hand, instructional designs also have to apply appropriate learning strategies to improve learners' performance. With adequate learning strategies, the educational potential of using QR codes has been examined and positive learning results have been observed (Chen et al. 2011, 2013; Huang et al. 2012; Law 2010; Ozcelik and Acarturk 2011).

6.3 The Augmentation Design and Three Applications

This chapter proposes an augmentation design for paper-based content integrated with digital learning supports using smartphones. The composition of the augmentation-enhanced learning context includes four layers, namely hardware, strategy, knowledge, and application (Fig. 6.1).

Educational practitioners can refer to the four layers for preparing and setting up an augmentation-enhanced learning context. In first layer, a digital content distribution server, a smartphone with a QR code reader app, and a wireless network infrastructure are the hardware as the foundation. The digital content distribution server can be a self-owned computer with networking capability or a cloud service over the Internet. The smartphone is used to decode a QR code with a reader app (i.e., a software tool for the smartphone). The learning environment has to be equipped with a wireless Internet infrastructure. The second layer is about the strategies for facilitating learning activities. The third layer consists of paper-based materials and digital content as the source of knowledge. Paper-based material is the main learning media such as a textbook or a lecture, while the digital content is the learning support on demand for further elaboration. Besides, the digital content can be provided as personalized assistance depending on what strategy is adopted for the learning activity. The upper, last layer is the application which forms a learning activity by combining the previous three layers. Different combinations of layer components create different learning activities. In the following sections, three applications will be provided for the augmentation-enhanced learning context, including self-learning with constructive feedback, self-learning with scaffolding questioning, and collaborative learning with procedural scaffolding.

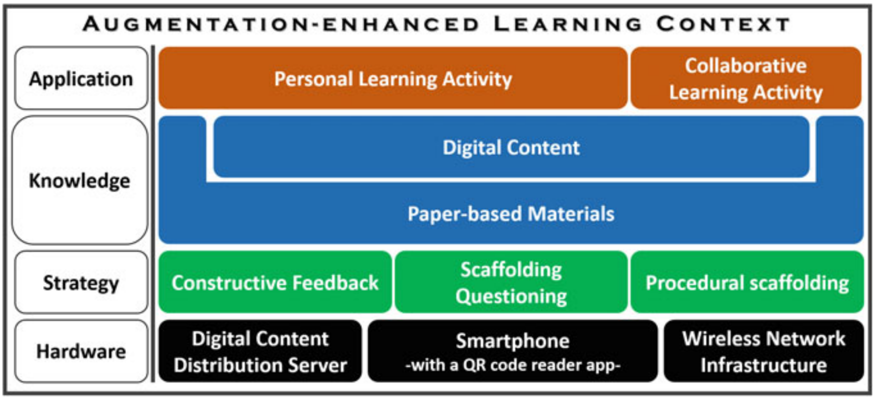

Fig. 6.1 The components of the augmentation-enhanced learning context

6.3.1 Application 1: Self-learning with Constructive Feedback

The first application was designed for self-learning with the support strategy of constructive feedback (Chen et al. 2013). An instructional experiment was conducted in a university course entitled Computer Networks regarding Internet protocol (IP) to evaluate the effectiveness of the scaffolding questioning strategy on learning performance in the augmentation-enhanced learning context. A learning unit of IP addresses was chosen as the topic.

6.3.1.1 Participants

A total of 80 students were recruited to participate in this instructional experiment. The participants were randomly assigned to two groups with or without constructive feedback strategy respectively. A pre-test as well as a post-test included 20 question items, which were used for assessing students' prior knowledge and learning performance, respectively.

6.3.1.2 System Design

In application 1, a self-owned digital content distribution server was deployed to manage updates of supplemental materials, video lectures, and self-evaluation quizzes (Fig. 6.2). The digital content can be accessed through a smartphone by decoding a QR code printed on paper-based materials (Fig. 6.3). Supplemental materials were additional/up-to-date information not included in the paper-based materials. Video lectures consisted of instructional recordings made by instructors

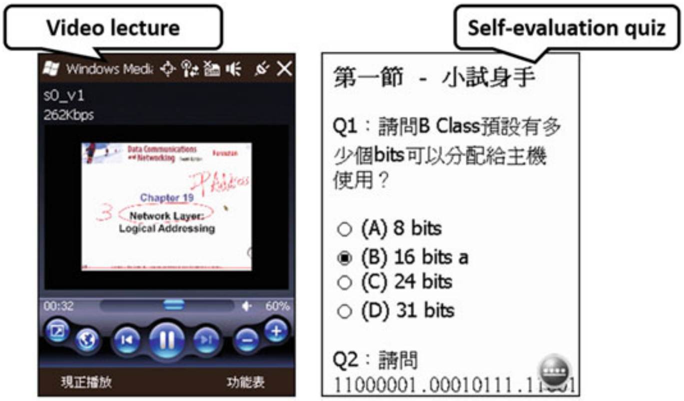

Fig. 6.2 The smartphone accessible digital content

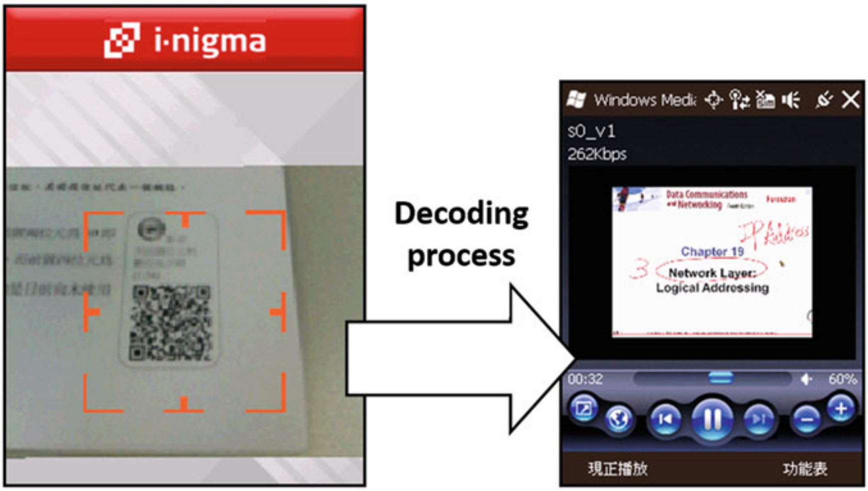

Fig. 6.3 A decoding process to play a video lecture

for further elaborations of the learning topic. Self-evaluation quizzes provided by a computer-supported learning system are capable of facilitating learners' reflection (Whitelock 2009; Whitelock and Watt 2008).

Application 1 used the self-evaluation quizzes to assess how well each learner learned with the strategy of constructive feedback. Two types of constructive feedback (Fig. 6.4) was automatically generated and provided timely to each learner based on the learning activity and the result of self-evaluation quizzes. Such fast delivered learning assistances benefit learners when learning a new concept (Timmers and Veldkamp 2011; Whitelock et al. 2010). One is to suggest unread

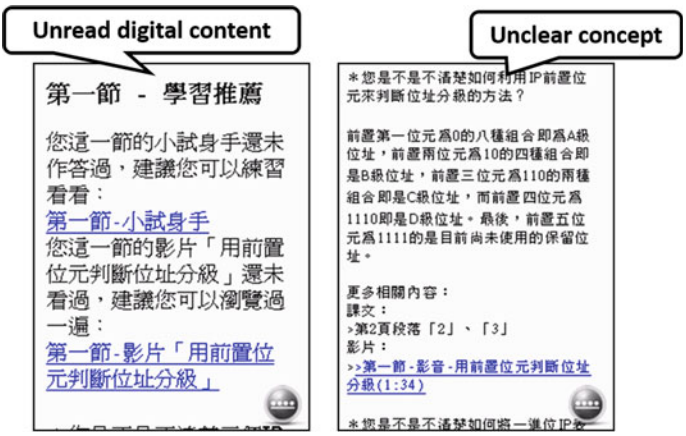

Fig. 6.4 Examples of the constructive feedback to a learner

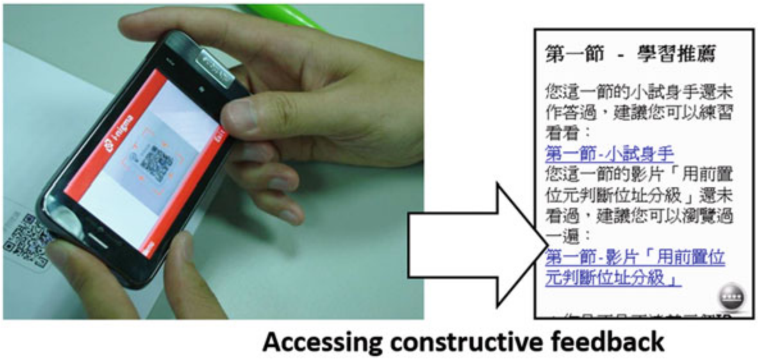

Fig. 6.5 Accessing constructive feedback through a smartphone

digital content which may be visited. The other is to make a recommendation according to the result of self-evaluation quizzes for further understanding the unclear concepts. Learners can easily and quickly access the constructive feedback provided by the learning system (Fig. 6.5).

6.3.1.3 Experimental Procedure

The chosen learning topic requires certain prior knowledge to comprehend the advanced materials. Therefore, a total of 80 students were recruited from two computer networking courses for this instructional experiment. They were 47 male (58.75 %) and 33 female (41.25 %); 45 % was undergraduate students and the rest were graduate students. The experimental procedure included five steps. Firstly, participants were given orientation and briefed about the experiment. Secondly, participants took a pre-test. Thirdly, participants hold a smartphone and received paper-based materials. Fourthly, participants studied the learning unit regarding IP address. One group was with constructive feedback; the other was not. Finally, participants took a post-test. The entire experiment took 110 min.

6.3.1.4 Result

A statistical test was conducted to examine the main effect of constructive feedback on learning performance. The findings revealed that the strategy of constructive feedback had a significant influence on learning performance ($F = 5.647$, $p = 0.02$). The strategy of constructive feedback can help learners improve their learning outcomes in the augmentation-enhanced learning context.

6.3.2 Application 2: Self-learning with Scaffolding Questioning

The second application was designed for self-learning with the support strategy of scaffolding questioning (Chen et al. 2011). An instructional experiment was conducted in a university course entitled Advanced Business English and Communications to evaluate the effectiveness of the scaffolding questioning strategy on learners' English reading comprehension in the augmentation learning context.

6.3.2.1 Participants

A total of 77 students (8 sophomores, 14 juniors, 9 seniors, and 46 graduate students) were recruited to participate in this instructional experiment. The participants were randomly assigned to two groups with or without scaffolding questioning strategy respectively. A pre-test and a post-test were used to evaluate the change of students' reading comprehension. The pre-test had a total of 12 comprehension questions for two articles before the instructional experiment. The post-test had 18 comprehension questions for the other two articles after the instructional experiment.

6.3.2.2 System Design

In application 2, a self-owned digital content distribution server was deployed to deliver the pre-designed digital content, including additional learning materials and scaffolding questions. QR codes printed on paper-based materials were used to help learners quickly access digital content. Articles, selected from textbooks as the reading materials, were further rearranged along with QR codes for this instructional experiment (Fig. 6.6). The main text was represented on the left side of a page. The QR codes were printed on the right side of the page according to the availability of the supplementary digital content related to the main text. If the digital content was available, related words of the main text were highlighted in yellow color with different colors of QR codes and different types of icons.

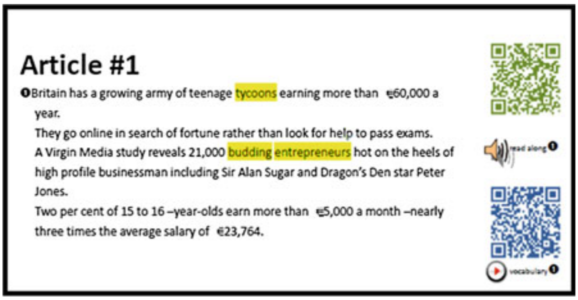

Fig. 6.6 The QR codes printed on the paper-based materials

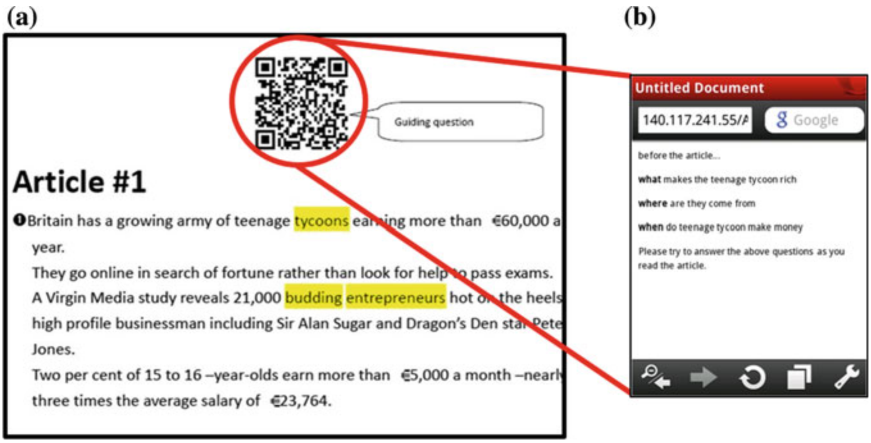

Fig. 6.7 **a** A QR code for a pre-reading questions. **b** A pre-reading question shown in the smartphone

The strategy of scaffolding questioning provided learners with question-based digital content along with QR codes, printed at the center of the page. The locations of the QR codes were before the first paragraph, in-between paragraphs, and after the last paragraph for pre-reading, during-reading, and post-reading questions, respectively. These scaffolding questions were designed to facilitate students' understanding of the learning materials. Figure 6.7a shows the QR code for pre-reading questions. Pre-reading questions were used for briefing the key points to students before reading the article, and students can receive the pre-reading questions using a smartphone to quickly finish the decoding process (Fig. 6.7b).

After students read a certain part of the main text (e.g., a paragraph), the during-reading questions were given to students for helping them reflect on what had been read and evaluate how well they comprehend the content they read (Fig. 6.8a). A few multiple-choice questions were showed on the smartphone one by one after the

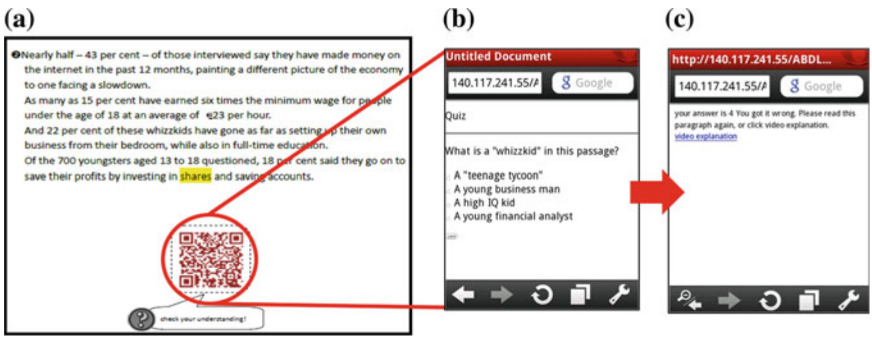

Fig. 6.8 **a** A QR code for a during-reading question. **b** A during-reading question shown in the smartphone. **c** System feedback after students gave their answer

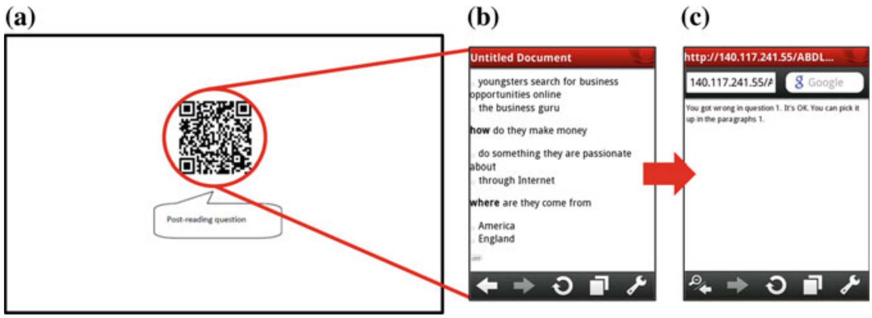

Fig. 6.9 **a** A QR code for an post-reading question. **b** An post-reading question shown in the smartphone. **c** System feedback after students gave their answer

decoding process of the QR code (Fig. 6.8b). Students could continue to read the next paragraph when they answered the question correctly. If they had a wrong answer, the learning system would prompt them to read the related paragraph(s) again or provide them associated digital content for further clarification (Fig. 6.8c).

After students finished the whole main text, the last page of the paper-based materials only printed a QR code of the post-reading questions (Fig. 6.9a). These post-reading questions, which were accessed through scanning the QR code, helped students review what they have learned (Fig. 6.9b), and then the learning system would give them corresponding suggestions based on their answers (Fig. 6.9c).

6.3.2.3 Experimental Procedure

Participants took a 15-minute pre-test at the beginning of the instructional experiment. Then, a 10-minute briefing and instruction on the experimental procedure and learning system operation were given. All participants were then randomly assigned to the two groups with or without scaffolding questioning strategy respectively. Each participant received paper-based materials and a smartphone. The reading activity lasted 50 min and then participants took a comprehension test (i.e., post-test). The total length of the instructional experiment was 90 min.

6.3.2.4 Result

A statistical test was conducted to examine the main effect of scaffolding questioning on learning performance of English article reading. The results suggested that the reading strategy of scaffolding questioning significantly improves students' understanding of the English reading materials ($F = 4.15$, $p = 0.04$). The strategy of scaffolding questioning can help learners improve their English reading performance in the augmentation-enhanced learning context.

6.3.3 *Application 3: Collaborative Learning with Procedural Scaffolding*

The third application was designed for collaborative learning with the support strategy of procedural scaffolding (Huang et al. 2012). An instructional experiment was to evaluate the effectiveness of using procedural scaffoldings in fostering students' team's discourse levels and individual learning performance in the augmentation-enhanced learning context.

6.3.3.1 Participants

A total of 60 students, 27 males and 33 female, were recruited from a university to participate in this instructional experiment. The participants (11 undergraduates and 49 graduate students) were randomly assigned to two groups with or without procedural scaffolding strategy respectively. The participants self-selected their teams. Two groups of 10 teams were formed to proceed with the collaborative learning activity in this instructional experiment.

6.3.3.2 System Design

In application 3, a self-owned digital content distribution server was deployed to deliver the predesigned digital content and to record the responses of individual learners and teams. QR codes printed on paper-based materials were used to help learners quickly login to the learning system (Fig. 6.10), access digital content

Fig. 6.10 The cover page of the paper-based materials with a login QR code for the collaborative learning activity

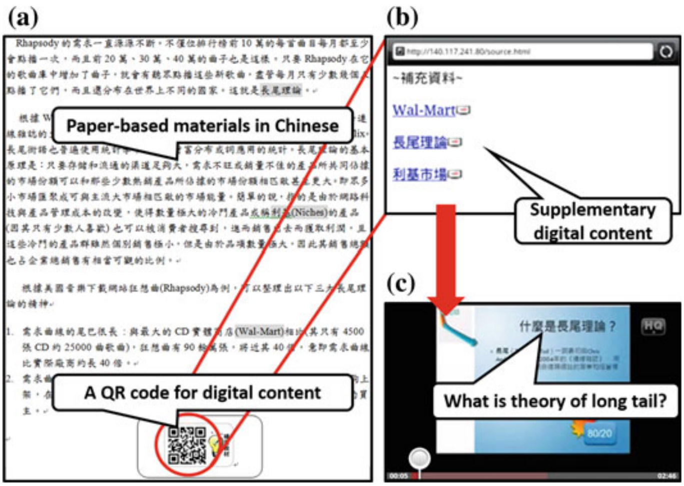

Fig. 6.11 **a** A QR code printed on the paper-based materials for accessing the digital content. **b** A list of available options of digital content. **c** A screenshot of playing a supplementary video for elaborating theory of long tail

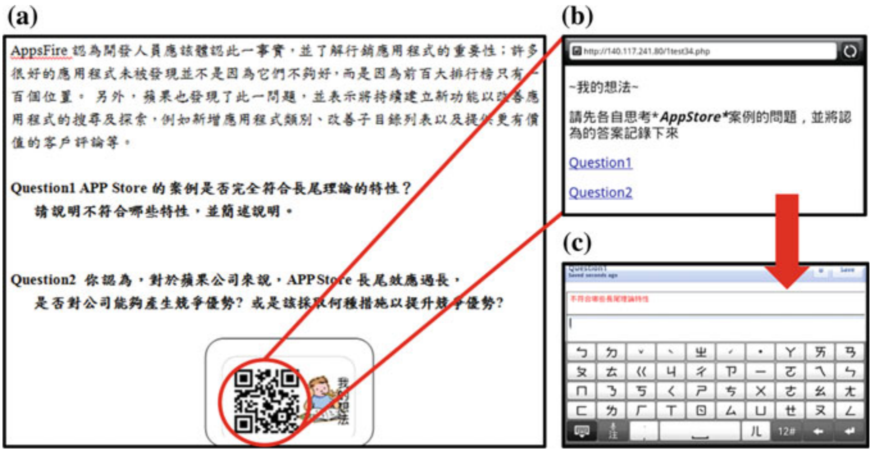

Fig. 6.12 **a** Two questions for learners with a QR code to enter individual responses. **b** A screenshot after decoding process. **c** A smartphone interface for entering responses in Chinese

(Fig. 6.11), and enter the responses of individual learners and teams (Figs. 6.12 and 6.13). The learning unit in this instructional experiment was theory of long tail for collaborative learning.

One type of the QR codes printed on the paper-based materials was to provide supplementary digital content (Fig. 6.11a). After the decoding process, options of

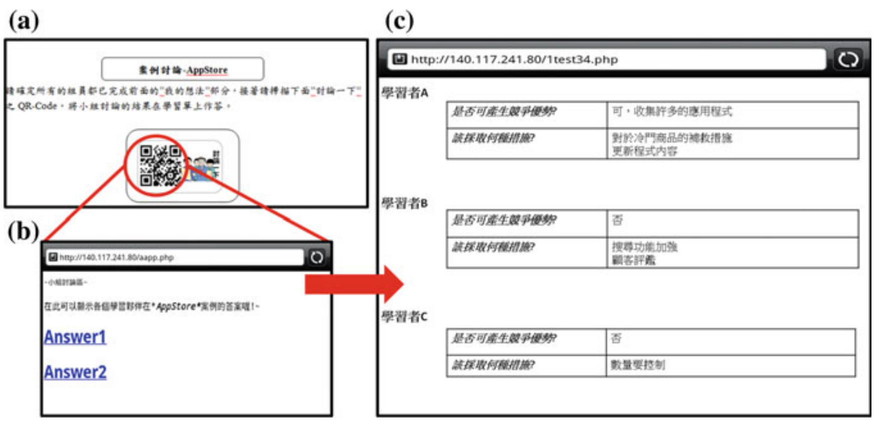

Fig. 6.13 **a** A QR code for starting a collaborative discussion in a team. **b** A screenshot after decoding process. **c** Team members' responses to the question

the supplementary digital content related to the learning materials of the scanned page were available (Fig. 6.11b). Figure 6.11c shows an example that a learner decided to play a supplementary video for further elaborating the theory of long tail.

The strategy of procedural scaffolding includes three steps, problem statement, individual response, and group discussion. In the problem statement step, questions regarding the read learning materials were given to help learners reflect what they have learned and stimulate their deep thinking (Fig. 6.12a). In the individual response step, participants in the group with procedural scaffolding were asked to answer the questions (Fig. 6.12b) and to enter the individual responses to the questions after scanning the QR code (Fig. 6.12c). All the individual responses were stored in the learning system simultaneously. Participants in the group without procedural scaffolding did not enter or receive any information about other team member's answers on their smartphone screen. In the group discussion step, every team member scanned the QR code to initiate a group discussion (Fig. 6.13a). Every team started discussing (Fig. 6.13b) and negotiating (Fig. 6.13c) each team member's responses. All team members' answers were showed on the each team member's smartphone screen. Participants in the group without procedural scaffolding only had verbal discussions in this step. All teams' responses were recorded on a paper-based team learning sheet.

6.3.3.3 Experimental Procedure

A pre-test was conducted to evaluate the participants' entry-level performance on the concept of long tail theory. Then, all participants at-tended a 15-minute training session to learn how to use a smartphone to scan a QR code printed on the paper-based materials. No additional instruction or support was provided at the beginning of the instructional experiment. After participants completed the pre-test, they were randomly assigned to two groups with and without procedural scaffolding strategy respectively. All participants then read a four-page paper-based materials on the long tail effect for 15 min. After reading, participants in the group with procedural scaffolding strategy were asked to enter individual and team responses for 30 min. Participants in the other group had 15 min because they only had to enter team's responses. Before ending the instructional experiment, all teams were required to hand in their paper-based team learning sheets and then completed a 20-minute post-test.

6.3.3.4 Result

Statistical tests were conducted to examine the main effect of procedural scaffolding on collaborative learning. The findings suggest that participants in the group with procedural scaffolding strategy achieved better team's discourse levels (test 1: χ^2 (3, 192) = 9.15, p = 0.027; test 2: χ^2 (3, 234) = 15.09, p = 0.002), team's learning performance (t = 2.68, p = 0.015), and individual learning performance (F = 9.68, p = 0.003).

6.4 Implications for Educational Practices

The augmentation-enhanced learning context with three strategies (i.e., constructive feedback, scaffolding questioning, and procedural scaffolding) can positively contribute to personal learning and collaborative learning. A seamless integration of supplementary digital content into paper-based materials was proven to improve learning performance on personal and collaborative reading activities.

For personal learning, the augmentation learning context with constructive feedback and scaffolding questioning strategies is suitable for helping learners in reviewing a lesson. The advancement of mobile technologies makes a smartphone affordable for daily communication with family, friends, and so on. By well-utilizing the functionalities of a handy smartphone, educational practitioners can further add values to extracurricular learning activities. No additional hardware is required for learners to buy in. A smartphone, the Internet access device, can help learners retrieve a lot of supplementary digital content. Although the mobile devices are already there, learners still need a well-design instructional activity to form an authentic augmentation-enhanced learning context. Thus, instructors have to provide learners adequate paper-based materials with effective supplementary digital content using right strategies for delivering knowledge and improving learning performance. The QR code printed on the paper-based materials can be regarded as a portal to access the digital content. Instructors can keep updating the latest digital content to the Internet without reprinting a new QR code to each individual learner. Learners, who already have the paper-based materials, can learn with the latest supplementary digital content easily.

For collaborative learning, this chapter suggests that educational practitioners can apply procedural scaffolding strategy to facilitate a team's discourse levels and learning performance (i.e., individual and group). Literature suggests that effective group discussion require appropriate guidance, instruction, and training (Blatchford et al. 2003; Chen et al. 2011; Nussbaum et al. 2009; Pea 2004). The result of application 3 shows that a team's collaborative discussion was not satisfactory because the team members did not have a chance to reflect on the reading materials before the discussion. Obviously, procedural scaffolding strategy (i.e., thinking before talking) can facilitate collaborative discussion and learning in a well-prepared condition.

Instructors can refer to the applications to design different representations of the paper-based materials and the digital content. Applying the strategies of constructive feedback, scaffolding questioning, and procedural scaffolding in authentic learning environments is also worth investigating, such as nature science observation activities. Instructors can pre-design paper-based materials with supplementary digital content for indoor or outdoor observational activities. Then, learners can situate themselves in a real environment and learn in such an augmentation-enhanced learning context. More personalized feedback and questions can be applied for instructors to utilize the augmentation-enhanced learning context in the future instructional designs. Learners' characteristics, such as longitudinal learning portfolio, learning style and cognitive style, can also be the basis of the provision of the personalized feedback and questions.

6.5 Conclusion

This chapter proposes an augmentation-enhanced learning context for paper-based content integrated with digital learning supports using smartphones. Three strategies are designed and implemented for real educational practices that have been observed to enhance individual learner's reading comprehension and a team's discourse levels for specific subjects. The way of integrating paper-based content with digital learning supports using smartphones has been demonstrated to be a well-structured design and effective for enhancing learning performance.

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Chapter 7
Semantic Analysis-Enhanced Natural Language Interaction in Ubiquitous Learning

Dunwei Wen, Yan Gao and Guangbing Yang

Abstract Natural language interaction (NLI) is vital and ubiquitous by nature in education environments. It will keep playing key roles in ubiquitous learning and even show stronger presence there. NLI may happen ubiquitously, with many varied forms of texts, bigger textual data, and different learning situations on all kinds of devices, to meet new user needs, thus pose challenges on its design and development. This chapter introduces how natural language processing (NLP) technologies can be employed to help build and improve NLI that can support ubiquitous learning. We emphasize semantic analysis such as semantic role labeling and semantic similarity, and develop and use them to enhance question and answer processing, automated question answering, and automatic text summarization that are involved in our educational systems. Our proposed approaches can improve the technology of natural language processing and help develop different NLI systems in the ubiquitous learning environments and eventually benefit learners.

Keywords Natural language processing · Question answering · Semantic analysis · Automatic text summarization · Topic modeling · Ubiquitous learning

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7.1 Introduction

In a ubiquitous learning environment, learning can happen wherever and whenever the learners need with the support of various computing devices (Kidd and Chen 2011). As the main medium of knowledge communication, interaction, and representation in education, natural language will only be involved more broadly and deeply in ubiquitous learning by its very nature. For instance, how learners can query learning questions and obtain responsive answers whenever and wherever they need is a defining problem for ubiquitous learning environment. Also, how vast and variant textual information and knowledge in ubiquitous learning environments can be effectively summarized and contextually delivered to the learners to improve their efficiency and achievement and learning.

Thanks to recent advances in computer linguistics and machine learning, natural language processing (NLP) technologies have been made substantial progress in the last decade (Jurafsky and Martin 2009). More and more attention of the NLP community has been given to deeper analysis/understanding of natural language, e.g., semantic analysis, from previous focuses on lexical and syntactic processing. Applying state-of-the-art NLP to ubiquitous learning environment for providing automated services in natural language can significantly improve the satisfaction and responsiveness of learning activities involving knowledge interaction and retrieval.

This chapter will mainly present a few advanced NLP applications that will enhance ubiquitous learning. We first provide some key techniques/components of NLP in Sect. 7.2, and then introduce three semantic analysis enhanced example applications, i.e., instant guidance, automated question answering (QA), and automatic text summarization in Sects. 7.3, 7.4, and 7.5, respectively, to demonstrate NLP's usefulness and the benefits that the learners can receive in the ubiquitous learning environment.

7.2 Core NLP Technologies and Resources

Generally speaking, natural language processing involves different levels of processing that relate to different linguistic knowledge from shallow to in-depth, e.g., lexical analysis, syntactical parsing, semantic analysis, and pragmatics and discourse analysis. We briefly introduce a few of them in this section and discuss their roles in NLI systems in the following sections.

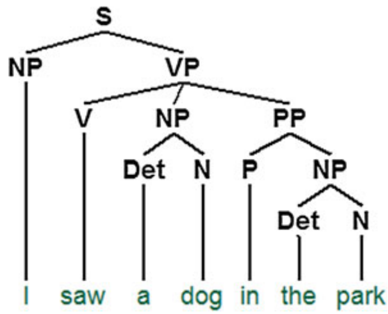

Fig. 7.1 The sentence's syntactical tree structure generated by NLTK (Bird et al. 2009)

7.2.1 Lexical and Syntactical Parsing

Lexical parsing is a process of converting a sequence of characters into a sequence of tokens which roughly correspond to "words," identifying the word based on the root, and assigning the part of speech (POS) tags of words according to its position and function in the sentence. The tagging of words is the grammatical categories–noun, verb, adverb etc. We give the lexical analysis of the example sentence:

> [('This', 'DT'), ('page', 'NN'), ('list', 'VBZ'), ('article', 'NNS'), ('associate', 'VBN'), ('with', 'IN'), ('the', 'DT'), ('same', 'JJ'), and ('title', 'NN')]

Syntactical parsing provides an order and structure of each sentence in the text according to the rules of a formal grammar which is the rule to put together words to form components of sentence and to put together these components to form sentences. Syntactical parsing analyzes three kinds of linguistic structure: constituency, grammatical relations, and dependency. Constituency means that a group of words may behave as a single unit or phrase which we always use context-free grammar to model. Grammatical relations are a formalization of ideas from traditional grammar such as SUBJECTs and OBJECTS and other related notions. Dependency relations refer to certain kinds of relations between words and phrases. An example of syntactical parsing is shown in Fig. 7.1, which is a full parsing of grammatical relations.

There are many off-the-shelf syntactic parsing tools that can be used in developing NLP applications in ubiquitous learning, e.g., Stanford Parser (Socher et al. 2013).

7.2.2 Semantic Analysis

Semantic analysis is to find the literal meaning, and pragmatic analysis is to determine the meaning of the text in context. Mainstream Semantic analysis mostly includes named entity recognition, word sense disambiguation, and semantic role labeling (SRL), and semantic parsing. The task of name entity recognition is to recognize information units such as the names of persons, organizations, locations, expressions of times, quantities, monetary values, percentages, etc. The task of word sense disambiguation is to determine which sense of each word is used according to its context. The task of semantic role labeling is to indicate exactly what semantic relations hold among a predicate and its associated participants and properties, with these relations drawn from a prespecified list of possible semantic roles for that predicate (or class of predicates). Semantic parsing is consequential step that further provides logical or formal representation of the meaning understandable to computers with logical processing capability. The output from lexical analysis and syntactic analysis is input to semantic analysis.

Name entity recognition (NER) plays an import role on many NLP applications, especially in QA (Mcnamee et al. 2008). The name entity recognition task includes two sub-tasks: (1) recognizing the boundary of entity and (2) identifying the category of entity (such as person name, location name, organization name etc.). The grammar-based rules and statistical models are widely used in NER systems. Recently, researchers focused on using statistical models (such as CRF, HMM) and web-based resources (such as Wikipedia) to improve the accuracy of NER.

Semantic role labeling is a rapidly growing researching area in semantic analysis. Many significant computational lexicon capturing the foundational properties of predicate-argument relation have been created, such as FrameNet (Fillmore et al. 2004), VerbNet (Kipper et al. 2000), Proposition Bank (PropBank) (Palmer et al. 2005), and NormBank (Meyers et al. 2004). And many algorithms are designed to the task of SRL based on the machine learning methods and supporting lexical resources. Figure 7.2 is an example of SRL based on FrameNet.

Many systems divide the semantic role labeling task into two steps, i.e., identification, in which a binary decision is made to whether a constituent carries a semantic role for a given predicate, and classification, in which the specific semantic role is chosen. Separate or joint classifiers are trained for these two tasks (O'Hara and Wiebe 2003; Pradhan et al. 2008; Toutanova et al. 2008). In order to solve the problem of scarcity of annotated data, semi-supervised and unsupervised algorithms are used to automatically annotate the semantic roles recently, such as

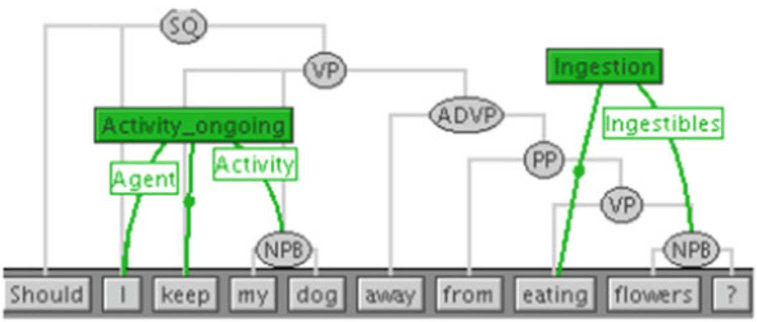

Fig. 7.2 An example of SRL based on FrameNet (Wen et al. 2012)

co-training algorithm, bootstrapping algorithm, and unsupervised Bayesian model (Titov and Klementiev 2012; Swier and Stevenson 2004; He and Gildea 2006).

The features used in these algorithms affect the correctness of SRL systems. Gildea and Jurafsky (2002) presented a compact set of feature across these three types, which has used as the core of most of the subsequent SRL work: (1) the phrase type, headword, and governing category of the constituent; (2) the lemma, voice, and sub-categorization pattern of the verb; and (3) the left/right position of the constituent with respect to the verb, and the category path between them. Extensions to these features have been proposed in various directions. Wen and Dou (2010) proposed a new Frame-based feature. In the Support Vector Machines (SVM) classifier, they also combined argument structure features and new frame-based features to label the semantic role of prepositional phrase. This new feature set improved the performance of classification.

Semantic parsing plays an important role in any natural language processing (NLP) application that deep understanding can help improve the process and performance, such as information extraction (Surdeanu et al. 2003), question answering (QA) (Shen and Lapata 2007; Surdeanu et al. 2011; Wen et al. 2012), text summarization (Melli 2005), and machine translation (Wu and Palmer 2011), most of which can find good fit in ubiquitous learning for improving natural language interactions. By introducing SRL to parse questions and the related answers in a QA system, the semantic similarity matching between a question and its candidate answers can be improved.

7.2.3 Corpus Useful for Ubiquitous Learning

In ubiquitous learning environment, people can access the learning resources by mobile device at anyplace at anytime. The traditional learning resources should be place on the Web, such as e-book, course outline, course exercises etc. Besides these, many corpora provide by the application of Web 2.0 are also the important learning resources.

Based on the core of Web 2.0, collective intelligent (Ginger 2009), the technology of Web 2.0 provides us with collaborative learning. Everyone is permitted in participating in the creation and modification of the teaching corpus. Wikipedia, which is a free encyclopedia maintained by every people in the world, can give students the concept definition and concept semantics. And everyone can also publish their understanding of the course and their collected learning resources on their blog sites. The forums and mailing lists embedded in the online learning system are provided to students and teachers to discuss the problems in the courses.

Microblogs are also import services for students and teachers to communicate and stay connected through the exchange of quick and frequent answer. The most important microblog is Twitter. People can use linked tweets and hashtag to create course-community and use Twitter to share inspiration, readings, thoughts, ideas etc. Through tweets, teachers can open discussion in time-stabled seminar/class, and continue it outside. The community organized by Twitter is open, where not only the students and teacher in a course are linked, but also their friends can take part in the discussion in tweet.

All these resources mentioned above give more convenient ways of learning in ubiquitous learning environment. While they also bring the problem of overhead information, NLP technology can provide focused and/or condensed information of them for students and thus help them find the appropriate knowledge in ubiquitous learning environment. This can be demonstrated through the example NLP applications described in the following sections.

7.3 Language Understanding and Generation for Instant Guidance

7.3.1 Understanding of User Queries

In ubiquitous learning environment, QA system can help students find concise answers from many digit contents. The user queries are always organized in natural language form. Many NLP technologies are used to help computer understand these questions. The two tasks in question processing phase are question formulation and question classification.

Question formulation is to create a keyword list from a query. During this processing, a query is tokenized, its stop words are removed, and each word in the query is assigned a POS tag, and the name entities in the query are then recognized. This list can be further expanded by using lexical information to improve QA system's recall and precision, such as morphological information (Bilotti et al. 2004).

Question Classification is to classify a question by its expected answer type. If the answer type is decided for specified query, we can narrow the search scope of the documents. For example, the question "what is computer?" may have an answer using the template like "The computer is…." The answer types are different according to the domain. Most commonly used types are from a set of named entities such as PERSON, LOCATION, and ORGANIZATION. The answer type taxonomy can be built semi-automatically or by hand, for example, from WordNet (Ray et al. 2010; Jochen and Leidner 2004). Many supervised and semi-supervised machine learning algorithm, such as SVMNB, decision tree, co-training, are applied to classifying the questions (Li and Roth 2002; Huang et al. 2008; Yu et al. 2010; Zhang 2003). The typical features used in a classifier include: the words in the questions, the POS tags of each word and the named entities in the questions.

7.3.2 Response by Search

After understanding a query and searching the predefined textual materials (such as FAQs and discussion forums) through information retrieval (IR), a QA system returns a list of related documents.

The documents in the list are ranked according to the relevance between the query and the documents. The former a document is in the list, the more relevant it is to the query. The answer can be extracted from the relevant documents.

The relevance is evaluated by the similarity formula in vector space model (VSM). In VSM, documents and queries are all represented as vectors of features representing the terms (words) that occur within the collection (Salton and McGill 1986). The value of each term in the vector is called the term weight and the most commonly used weighting schema is tf–idf, meaning term frequency–inverse document frequency, which increases proportionally to the number of times a word appears in the document, but is offsetted by the frequency of the word in the corpus, which helps to control for the fact that some words are generally more common than others.

The cosine metric is used to compute similarity between a document and a query. If the query is identical to the document, the cosine is 1; if the query is not relevant to the document, the cosine is 0.

In order to search documents and add a document to database quickly, many special file structures have been developed in IR. Inverted Index is the kind of index found in most commercial library systems. An inverted file is a sorted list (or index) of keywords (attributes), with each keyword having links to the documents containing that keyword. Signature file is also a commonly used file structure. The "signatures" (hash-code bit patterns) of a document are stored in the "signature file." When a query is coming, the signature is scanned and many nonqualifying documents are discarded. Signature file is also used to check duplicated pages in IR (Salton and McGill 1986).

Although a collection of relevant documents for a question is obtained, the top-ranked document is probably not the answer to the question. Here comes the passage retrieval task, which includes two steps: segmenting a document into passages and ranking the relevance between the passages and the question. The important features used to rank a passage include: number of named entities of the right type in the passage; number of query words in the passage; number of question N-grams in the passage; Proximity of query keywords to each other in the passage; longest sequence of question words etc.

7.3.3 Response by NLP Generation

In order to extract an answer from passages, we need information about the excepted answer type to match the query. This information can be expressed by regular expression patterns which is called answer-question type pattern. For example: “Q: When was X born?,” a proper answer often has such relation “<X> (<Answer> …” with the question phrase X. The answer-question type identification has three steps: (1) aligning the question; (2) extracting the relevant answer; and (3) answer generation.

The matching of answer-question patterns strongly depends on the word ordering and distance in the text, which are too specific to the question type. So the first step is to reorder the question, for example, the sentence “What does Linda give to a student?” should be changed to “Linda gives what to a student” (Wen and Dou 2010).

In the second step, the most commonly used answer-question type patterns are the surface patterns which can be written manually or automatically (Soubbotin 2001; Ravichandran and Hovy 2002). Named entity recognizer is employed to identify the question phrase in the surface text. Predefined web-based open knowledge and some domain-ontology are used to effectively extract relevant answer. Zhou et al. (2013) used semantic relations in Wikipedia to compute the similarity between a query and its answer. Based on WordNet, Aqualog, a QA system used a novel ontology-based similarity services for relations and classes, make sense of user queries with respect to the target knowledge base (Lopez et al. 2007).

After extracting the relevant answers, the predefined template and syntactical structure for answers are used to generate a short answer text to user from the answer set.

7.4 Sentence Understanding and Generation Enhanced by Semantic Parsing

As above mentioned, semantic parsing is the task of mapping a natural language sentence into a complete, formal meaning representation or logical form (Meyers et al. 2004). The semantic parsing technology used in the question processing and answer extraction can help QA system better understand the question meaning and finding matching answers to the question.

Semantic role labeling identifies predicates and semantic argument phrases in a sentence. With this information, we are able to analyze and extract structure from both questions and their candidate answer sentences, which helps us identify more relevant and precise answers from a usually long list of candidate sentences. When searching for an answer to a question, we match the argument in the question to the semantic parses of the candidate answers. This technique significantly improves the accuracy of the question answering system (Shen and Lapata 2007).

Wen and Dou (2010) and Wen et al. (2012) have proposed a question answering system supported by case grammar theory and based on VerbNet frames which are applied to obtain syntactic and thematic information as well as semantic information in the question and candidate sentences. This system extracts the syntactic, thematic, and semantic information from the question to filter out unmatched sentences in semantic level and to extract answer chunks (a phrase or a word that can answer the question) from the answer sentence.

7.5 Automated QA

7.5.1 Key Components for QA

In the ubiquitous learning environment, students usually lack of physical personal contacts compared to a traditional classroom, and questioning via email often cannot get immediate replies. Thus providing a QA system to answer classroom questions is a good way to solve this problem. QA is designed to automatically analyze a large number of documents and gives concise answers to questions posed by users. A QA system employs many NLP technologies to provide relevant answer. Lexical analysis is used to formulate the questions and documents. The syntactic analysis is used to understand the meaning of questions and the sentences in the documents and find possible matching question–answer pairs from relevant corpora.

The typical QA system architecture consists of three main modules: question processing, information retrieval, and answer extraction, as shown in Fig. 7.3 (Wen et al. 2008).

Question analysis module: this module processes the question, analyzes the question type, and produces a set of keywords for retrieval.

Information retrieval module: this module takes the keywords produced by the question analysis module, and uses some search engine to perform document or passage retrieval. Lucene (http://lucene.apache.org/) and INDRI (http://www.lemurproject.org/indri/) are two of popular search engines used by QA systems.

Answer extraction module: given the top N-relevant documents or passages from the retrieval module, the answer extraction module performs detailed analysis and extracts the answer to the question. Usually, answer extraction module produces a list of answer candidates and ranks them according to some scoring functions.

Based on OpenEphyra (Schlaefer et al. 2006) which is an open-source English question answering system, Wen et al. (2008, 2012) and Wen and Dou (2010) designed QA systems for e-learning, where filtering and scoring algorithms based on FrameNet or VerbNet semantic role labeling and graph theory matching algorithm are introduced. Figure 7.4 depicts a processing flow in one of the systems (Wen et al. 2008).

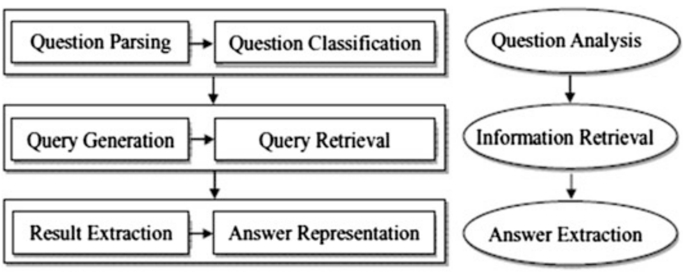

Fig. 7.3 The common architecture of QA system (Wen et al. 2008)

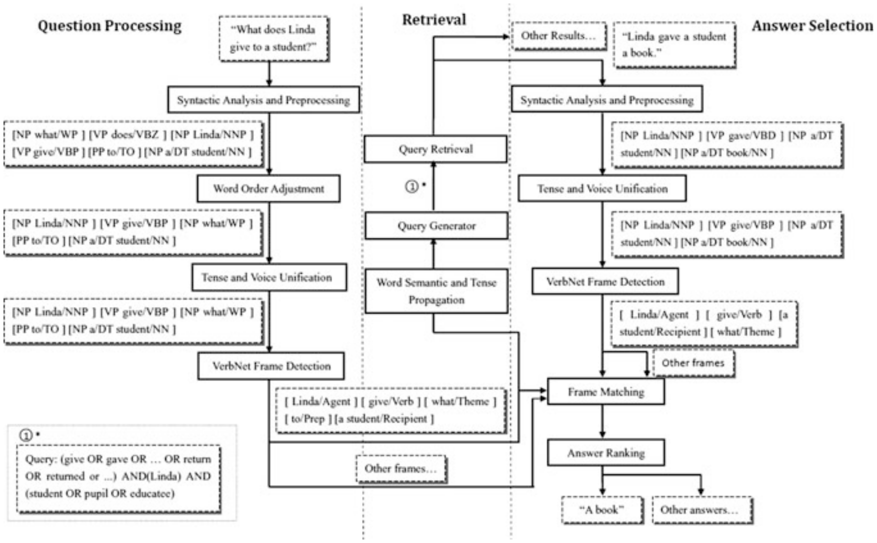

Fig. 7.4 The processing flow of a QA system (Wen et al. 2008)

7.5.2 *Semantic Analysis to Enhance Answers Finding*

Because the features for QA pairs are quite sparse and the content words in the questions are usually morphologically different from the ones with the same meaning in the answers, the traditional relevance computing methods based on word co-occurrence, such as Cosine similarity and KL-divergence, are not effective for QA's semantic modeling.

Word Semantic Matching and Relation Semantic Matching are introduced to solve the matching problem of question and answer. IBM machine translation model (Brown et al. 1993; Riezler and Liu 2010) is used to learn word translation probabilities, which actually denote semantic similarities between words. Given a new question, a translation-based information retrieval model exploits the word relationships to retrieve similar questions from Q&A archives. For Relation Semantic Matching, Sun et al. (2005) introduced the predicate-argument structures into semantic similarity matching. They used Jaccard coefficient to measure similarity between the sets of words that formed the arguments in the question and in the answer sentence. Bouma et al. (2005) measured the similarity between a question and an answer sentence by computing the tree edit-distance of the two dependency parse trees. With the development of SRL in NLP, Semantic Role Labeling is applied to improve question answering (Shen and Lapata 2007; Wen et al. 2012).

As above mentioned, the similarity score of question and answer can be computed using different features and different methods. Surdeanu et al. (2011) showed that the best ranking performance is obtained when several strategies are combined into a single model. They used SVM-rank to rank answers based on the combination features. The answer with high-ranking score will be the appropriate one to the question.

7.5.3 Challenges in Response Time and Usefulness

As stated above, semantic analysis, especially SRL can improve accuracy of the matching between the question and answer. But they are time-consuming and are too expensive. Wen et al. (2012) conducted the experiment using three SRL tools ASSERT (Pradhan 2004), SEMAFOR (Das et al. 2010), and Shalmaneser (Erk and Pado 2006) to semantically parse 1,000 sentences from the Reuters 21,578 corpus. Table 7.1 lists the speed comparison between three SRL tools.

The results listed in Table 7.1 shows that the time overhead makes the use of semantic role labeling troublesome in synchronous QA where near-instantaneous answers are expected. In ubiquitous learning environment, students can post the questions at any place at anytime, so the immediate answers are not demanded. The offline interaction between students and instructors that inherently involves a response delay between the time a question is asked and the time the answer is expected. It is within this delay where Wen et al. (2012) proposed an asynchronous QA system that can benefit from semantic role labeling while side-stepping the time complexity problem. In his system, OpenEphyra uses INDRI's very fast search engine for large lexicons with various syntactic capabilities that include POS tagging, sentence detection, and named entity recognition through the OpenNLP package (http://opennlp.sourceforge.net). PropBank semantic analysis is performed through the ASSERT software. This QA system proposed is seamless embedded in an LMS system (Moodle, http://moodle.org). A student submits a question to the LMS, and the LMS sends the question to QA system. The QA system based on OpenEphyra analyzes the question, performs semantic analysis for the question and document in the corpus, and filters and scores the answers. The extracted answers are sent to the student and the instructor. Referring the automated answers, the instructor sends the appropriate answers to the student. Figure 7.5 depicts the procedure of the QA system (Wen et al. 2012). This kind of solution can be easily delivered to a ubiquitous learning environment and support the interaction between learners and teachers.

Table 7.1 Speed comparison between ASSERT/SEMAFOR/Shalmaneser per 1,000 sentences (Wen et al. 2012)

ASSERT (PropBank)	SEMAFOR	Shalmaneser (FrameNet)
19 min	30 min	77 min

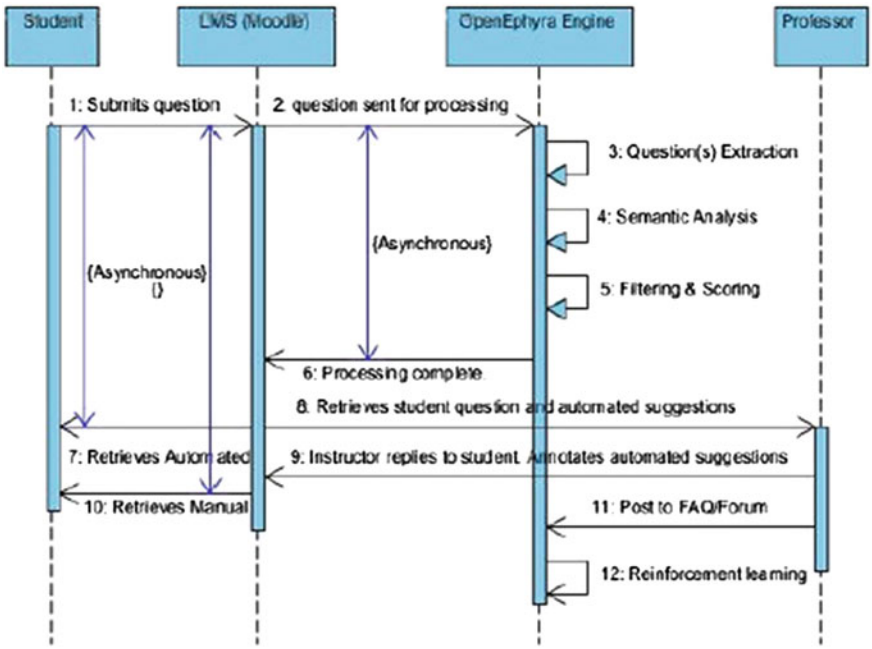

Fig. 7.5 Asynchronous semantic QA model (Wen et al. 2012)

7.6 Automatic Text Summarization

Ubiquitous learning environments have recently emerged as education solutions that provide learners interactive learning settings that combine mobile devices, learning content (especially Web-based learning content), learning related systems and applications with each other for better learning achievements. The successful establishment of this ubiquitous learning environment depends on how information can be shared and correlated smoothly among students, teachers, and mobile devices, and how students can be immersed totally in the learning process. However, due to the rapid increase of enormous amount of online information, the problem of the oft-decried information overload and duplication negatively impacts students' interactivity with and immersion in the ubiquitous learning environments. The concerns of how to alleviate these problems have given rise to interest in research on automatic text summarization (Yang et al. 2012, 2013b). A main task of text summarization is to determine the importance and semantic similarity between sentences in a set of documents.

7.6.1 Methods for Investigating the Importance and Semantic Similarity

The earliest research of text summarization starts with the Artificial Intelligence (Luhn 1958). From then on, many approaches have been addressed in this research area, and specifically, those approaches using structured probabilistic language models to summarize document content have obtained significant improvement in the performance of summarization (Barzilay and Lee 2004; Daumé and Marcu 2006; Haghighi and Vanderwende 2009). Several well-known, unigram-based summarization systems, such as SumBasic (Nenkova and Vanderwende 2005) and SumFocus, exploit frequency exclusively to create summaries. In their algorithms, a sentence is assigned a score that is the sum of probabilities of words appeared in the sentence. The system based on this algorithm has shown the highest performance improvement in a standard Recall-Oriented Understudy for Gisting Evaluation (ROUGE) (Lin 2004) at Document Understand Conference (DUC) 2006 (Vanderwende et al. 2007). Despite such achievement, this unigram distribution approach has significant disadvantages since it ignores distinction of word frequency in different documents.

In order to address the shortcomings in unigram distribution, generative probabilistic language models have been proposed recently. For example, BayeSum (Daumé and Marcu 2006) is a Bayesian-based, query-focused summarization model that adapts the query expansion technique in the language modeling for information retrieval framework (Ponte and Croft 1998). The topic-focused, multidocument summarization, often called query-focused or user-focused multidocument summarization, conceptualizes a common architecture that requires multiple documents to be clustered into subcollections of related documents and specifies text passages classified in terms of their subjects. In order to consolidate an approach, topic models in machine learning and natural language processing, especially the Latent Dirichlet Allocation (LDA)-based topic model (Blei et al. 2003), have been widely employed in multidocument summarization to identify the similarity and redundancy of text passages in terms of their topics that are classified by estimating the document collection (Celikyilmaz and Hakkani-Tur 2011; Eisenstein and Barzilay 2008; Haghighi and Vanderwende 2009). An example approach, namely TopicSum (Haghighi and Vanderwende 2009), imposes Latent Dirichlet Allocation (LDA)-based topic model (Blei et al. 2003), to indicate sentence similarity and reduce information redundancy. Experimental results in both ROUGE (Lin 2004) measurement and DUC manual user evaluation have shown that TopicSum can achieve similar performance as the BayeSum model.

Recent research in Bayesian-based topic models have suggested new approaches to incorporate the concept of latent topics in hierarchical Bayesian models into n-gram language models, such as a model for integrating topics and syntax (Griffiths et al. 2005), structured topic models (Wallach 2006), and topical n-grams (Wang et al. 2007). Experiment results have demonstrated that these techniques have achieved significant performance gains in information retrieval and document classification.

Although these methods are widely used in various applications of natural language processing, their utilization in the automatic text summarization is different due to the specific requests of the task of summarization and particular system architecture.

7.6.2 Main Components in Automatic Summarization System

Basically, our text summarization system consists of following main components: document preprocessing, query likelihood model, topic n-grams model, sentence ranking, redundancy removing, and summary generation. A high level view of the system architecture is shown in Fig. 7.6 (Yang et al. 2013a).

The first component is the document preprocessing. The features of this component include segmenting a document into a set of sentences. Then the system removes punctuations and labels stop words in all sentences, and then stem words to increase the possibility of similarity in word level. Finally, the system indexes sentences and marks the sequence number of the sentence that appears in the document. The reason that labels all the stop words in the corpus rather than deletes them is due to the words in sentences are sampled as a bigram distribution instead of a unigram, because a word will be sampled as a unigram if its immediately preceding term is marked as a stop word or this word itself is the first term in the sentence. If the stop words are removed from the corpus, those words that follow a stop word mislead the topical n-grams model to sample is as a bigram with the term that is actually not the immediate preceding.

The second component is used as query expansion for sentence ranking. In this step, a mixture model, which is the combination of topical n-grams model and the query likelihood model, is generated for sentence ranking.

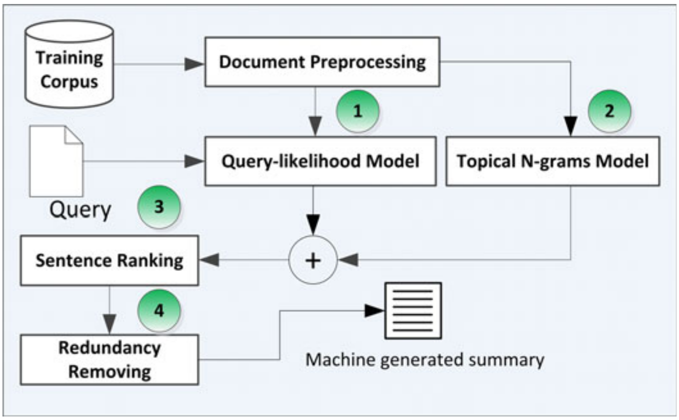

Fig. 7.6 Overall system architecture (Yang et al. 2013a)

The third component adapts topical n-grams model and provides an important process for effective expansion that can choose the topic words appropriately for the context (Croft et al. 2010, p. 201). In this component, the generated topics are selected as the expansion terms. But there are some redundancies between original query terms and the topic terms. To alleviate this issue, the expected mutual information measure (EMIM) (Croft et al. 2010) can be used to remove those redundant terms.

The fourth component uses the Maximal Marginal Relevance (MMR) model to reduce redundant sentences during the summary generation (Carbonell and Goldstein 1998). This component is important for multidocument summarization due to the similarity of sentences is based on various documents, and this situation can easily bring redundancy into the generated summary.

After this process, the sentences with the highest scores and the lowest redundancy are selected to create a final summary.

7.7 Conclusions

In this chapter, we have discussed the needs of natural language interaction in ubiquitous learning and some challenges that the ubiquitous learning environments bring to the design and delivery of NLI. By improving several semantic analysis techniques, including semantic role labeling, SRL-based question answering, and semantic similarity evaluating, we further developed several NLI-related applications, including the instructor-aided asynchronous QA system and automated text summarization system, which are integrated in a learning management system to help meet the learns' needs in finding answers to their questions and obtaining condensed textual contents in learning. The designed systems that are enhanced by semantic analysis demonstrate the significance of NLP for developing NLI systems that can fit for education and more specifically ubiquitous learning environments. We have shown that NLP technologies can help build different NLI systems in different learning situations, and thus benefit learners in the learning environments.

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Chapter 8
Big Data Learning Analytics: A New Perpsective

Vivekanandan Suresh Kumar, Kinshuk, Thamarai Selvi Somasundaram, David Boulanger, Jérémie Seanosky and Marcello F. Vilela

Abstract Learners' attainment of academic knowledge in postsecondary institutions is predominantly expressed by summative approaches. Instead, recent advances in educational technology have hinted at a means to continuously measure learning attainment in terms of personalized learner competency, capacity, and effectiveness. Similarly, educational technology also offers guidelines to continuously measure instructional attainment in terms of instructional competency, instructional capacity, and instructional effectiveness. While accurate computational models that embody these attainments, educational and instructional, remain a distant and elusive goal, big data learning analytics approaches this goal by continuously observing study experiences and instructional practices at various levels of granularity, and by continually constructing and using models from these observations. This article offers a new perspective on learning and instructional attainments with big data analytics as the underlying framework, discusses approaches to this framework with evidences from the literature, and offers a case study that illustrates the need to pursue research directions arising from this new perspective.

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Keywords Big data learning analytics · Data mining · Artificial intelligence in education · Feedback · Assessment · Modeling · Collaboration · Social networks · Curriculum assessment

8.1 Data and Learning

Whether observed or not, data is being continually produced in all phases of learning. For example, a classroom lecture could generate new data about the presentation material, learners' level of comprehension, conceptual associations, and insights. An online discussion, for example, could induce data about learners' awareness of the topic under discussion, their emotive states, learners' peer networks, and instructional challenges of discussion procedures. A blended training exercise, for example, could create new data on learners' confidence, their reflections, and new regulations of the industry. Lifelong work scenarios, for example, could generate data on recognition of new skills, refinement of competencies, work—study relationships, and models of studies. Instructional design efforts generate their own sets of data concerning course design models, development workflow, course guidance, adaptation opportunities, course comprehensiveness, and course quality. Ubiquitous learning environments could raise new datasets on perspectives and new behavior from learners, instructors, and software agents. Irrespective of where, why, how, and when learning happens, learning environments do create new learning experiences and correspondingly new sets of data.

Each learning experience can be measured. Be it personalized learning, formal learning, adhoc learning, classroom learning, or mobile learning, different types of learning environments offer different types of learning and instructional attainment datasets. The associations that evolve among these datasets on a day-to-day basis have conveniently and predominantly been ignored since the beginning of modern era. For instance, from a learner perspective, summative assessments, augmented with formative assessments, are used to only estimate competency of the learner. The capacity of the learner and the effectiveness of learning processes undertaken by the learner are not measured normally. This is not because of the challenges involved in obtaining and validating data on capacity and effectiveness, but because of the pervasive nature of 'lethargy' in teaching.

Learner competence can be measured to a greater extent using a variety of assessments. Learning capacity, on the other hand, depends on a number of personal factors including working memory, motivation, support, learning material, and learning styles. Learning effectiveness is a measure that mainly involves competence and capacity. Capacity and effectiveness have generally been ignored by contemporary instruction attributing to the lethargy mentioned above. Expectation of the "bell curve" as the norm of classroom performance is another factor that attributes to lethargy in teaching. Constraints placed on learning outcomes force instructional processes to be satisfied mostly with summative feedback-based associations, offering further attributions to lethargy.

Learning processes/activities undertaken by individual learners from the time a concept to be learned is introduced up to the time instructional efforts cease to teach that concept to that learner can potentially be observed using a variety of techniques and technologies. For instance, the behavior of classroom interactions of students attending a lecture can be recorded and analyzed at real time to estimate the level of comprehension of a set of concepts introduced in the lecture. The behavior of online interaction of students in a discussion forum can be analyzed at real time to estimate their writing competence. The behavior of social interactions of students can also be analyzed to estimate their sentiments on specific services offered by the institution related to learning. These exclusive observations, along with other traditional data, can supply the ``raw data' for learning analytics.

One of the early studies on big data was found in a report on a course titled "very large scale modelling" offered at the Simon Fraser University in 2004 (Kumar et al. 2007). The study was conducted as part of this graduate course, where students attempted to integrate datasets from "the entire gamut of modeling, from mathematical modeling, data modeling, process modeling, symbolic modeling (AI), social interactions modeling, to modeling the computation (distributed, grid, and parallel)." Students worked on individual projects across these topics and attempted to relate various datasets to extract meaningful conclusions. Raw data is being produced at an alarming rate in other domains including transportation, healthcare, geographic advertising, retail, banking, and energy.[1] A report on online learning in Canada[2] outlines the market share of LMS (learning management systems) that already produces large quantities of data on learning and the inclusion of online learning as part of core business plan of academic institutions across Canada. An infrastructure that supports learning resource discovery, sharing, and amplification indicates to a large volume of metadata and data (Bienkowski et al. 2012). At risk, students can be recognized based on data about the type of risk, interventions based on predictive models can be designed to mitigate that risk, and the utility of the models can be gaged by the trace data on applied intervention (Essa and Ayad 2012). A number of data-driven analytics drivers to mine effectiveness of learning have been reported for use in learning and academic analytics (Ferguson 2012). Social learning analytics offers access to a slew of data on informal conversations among students and instructors (Shum and Ferguson 2012). Raw data is not confined to formal and informal datasets, but also includes adhoc datasets with marginal overlap with learning. Adhoc datasets include browsing patterns, reading habits, writing style (including freehand writing), coding, posture analyses, collaboration drivers, thinking protocols, chats, domain-specific tool traces, recording of cognitive and metacognitive traces, and knowledge traces.

Among many others, raw data can be processed towards data mining (Romero et al. 2008), program evaluation (Hung et al. 2012), real-time classroom feedback

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[1] http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation.

[2] http://www.contactnorth.ca/online-learning-canada.

(Wood et al. 2012), prediction (Watson et al. 2013; Abdous et al. 2013), visualization (Mazza and Dimitrova 2003; Kim and Lee 2013), and modeling (Medeiros et al. 2013), among others. Potential observations and analyses of the aforementioned categories would shed light on instructional processes that indicate introduction, deliberation, assimilation, evaluation, and application of a concept or skill to various degrees by different types of learners. However, a holistic view of the rates of changes in adaptations, repetitions, and refinements of instructional processes and instructional resources, as well as the rates of changes in learning processes and learner capabilities have never been observed as a matter of fact—till now, till the arrival of learning analytics as the science of analysis that concerns learning, and the suite of tools that observe, validate, and semiautomatically associate datasets related to learning and instruction.

Learning analytics is the science of analysis, discovery, and utilization of learning traces in emergent and related levels of granularity. Analysis could include techniques ranging from data mining to machine learning and to big data analysis. The discovery of new relations and the discovery of even new data include unconventional data, for examples, the family income of a politically competing region, inherent economic drivers influenced by a curriculum, and rate of changes in motivation levels of students with respect to weather. Relations of interest include sentiments among learners across collaborating groups, interinstitutional credit transfer policies among institutions, and mutual respect among instructors. Trace data refers to observable raw data of study activities such as reading, writing, conceptualizing, critically thinking, solving problems, storytelling, and visualizing, where a network of study activities lead to a measurable chunk of learning. For instance, the types of sentence openers used by a learner, the range of errors that the student can confidently correct, the level of trust exhibited by the student in sharing information in a forum, and the depth of understanding in a set of concepts are examples of learning traces where one could measure learning over time. In learning analytics, data is expected to arrive continuously, typically in an interleaved fashion, subject to interpretation at various levels of granularity.

In general, learning traces translate raw data into incoming data for learning analytics, where incoming data are typically big, unstructured, unrelated, and fits multiple models and possibly multiple theories. Importantly, learning traces capture highly personalized study experiences. For instance, consider the example of studying about the notion of a pointed object penetrating better than a blunt object. The study goal is to understand why this is so. A visual-oriented learner may choose to study and explain this phenomenon using visual tools, while a fellow student may workout the mathematics behind pressure and explain the results in terms of equations. Thus, learning traces capture different types of skills and background knowledge exhibited by individual learners, the extent to which learners learned new concepts while studying a particular material, the amount of time (efficiency) learners took to study the material, the effectiveness of assessments to conclude that the concept had been learned efficiently, evidences of learning activities/experiences (e.g., a video of the learner trying a sharp pencil on someone's palm and the learner's answer to the question on pressure in the examination), and resources used by learner (e.g., the pencil, simulation run by the learner). While each learning trace is measurable, there is no standard scale of measurement that applies across different types of traces. A learning trace is the least common denominator for a measure of learning.

Data mining offers techniques that typically operate on well-defined, medium-sized datasets (up to gigabytes). Intelligent tutoring systems typically operate on limited-sized data (up to megabytes). Learning analytics aims to operate on large volumes of data (at least in the order of terabytes, hence the name, bigdata) as well as large volumes of models produced from the data. The models are dynamic, if not emergent, because more often than not, processing of data would include newly arriving, marginally related datasets. Examples of emergent models include 'reading habits across domains,' 'writing styles across contexts,' 'application of problem solving skills across tools' (SPSS, R, Eclipse, Matlab, and so on), 'social distances while collaborating with peers', 'comfort zone when interacting with instructors,' and 'research potential'.

Data can be gleaned with sensors. Contemporary technologies only offer sensors that observe a tiny fraction of data associated with these new learning experiences. In learning analytics, one could conceive of three types of sensors—instructional sensors, context sensors, and internal sensors. Instructional sensors have explicit association with the study as seen in LMSs. Intelligent tutoring offers a wide variety of instructional sensors such as sensors to observe self-regulation activities of learners and sensors that observe the interactions between learners and anthropomorphic pedagogical agents. Context sensors include the observable environment in which learning takes place. Examples of context sensors include autonomous software agents that act independently on students' behalf and data traces that cluster students from across multiple institutions based on specific competencies. Internal sensors include methods that estimate learners' ability to think laterally and critically, ability to strategize in a game environment or regulation exercise, ability to use working memory and comprehension techniques, and the ability to pace oneself and proactively study. The observations of these three types of sensors and the interrelations among individual data streams produced by each sensor yield the raw data.

While big data has been a recognized field of exploration in many domains such as traffic regulation, healthcare, geographic advertising, retail, banking, public sector, consultancy, energy efficiency, and policing, applications of big data techniques in learning is still in its infancy. Learning attainment and instructional attainment need to synchronize with each other to offer an optimal approach to learning. In addressing this very goal, this chapter highlights the application of learning analytics with a case study. The case illustrates the collection of raw data, the transforming the raw data into learning traces, the application of learning analytics techniques on learning traces, the use of results of analytics towards balancing learning and instructional attainment, and the measurement of impact of analytics.

8.2 Big Data Coding Analytics

Students taking an introductory computer programming class in an online environment, or in any course with a significant digital component, have access to learning activities associated with an array of media—including slideshows, reading material, audio/video lectures, interactive tutors, and automated tests. And, as they work through the course material in this digital environment, students generate learning activity traces that track their interaction with the course material, much like a web analytics system tracks visitors to a website. Similarly, as students complete the associated computer programming assignments, software development traces are generated which can be used to track the student success and coding competency. The same traces can then be used to assess the effectiveness of instruction.

Here we present a study that uses a combination of software tools to collect data generated from 240 students at the Madras Institute of Technology (Chennai, India) while they completed a course on "Introduction to Programming in C." The students interacted with the Moodle online education platform in addition to a number of software tools. The quantity of data collected using the additional software tools is much larger than the data that are traditionally collected from learning management systems. Thus, it approaches the realms of big data learning analytics. We present the types of data we collected, followed by details of the underlying technology, and some outcomes of the study.

8.2.1 Data Collection

A Moodle-based course was created to supplement the classroom instruction for the course on "introduction to programming in C." Student interactions with the Moodle content were captured from the Moodle database. Students also completed a built-in survey questionnaire in Moodle to indicate their experience with the Moodle course. Moodle's reporting module compiles learning activity analytics allowing for tracking of all logged on student interactions with the learning material.

Being a programming course, it required students to write programs in C language. Software development traces are generated by students as they solve computer programming problems, such as the number of compiles, warnings and errors encountered during these compiles, ability of the student to tackle these warnings and errors, the ensuing design changes, documentation efforts, and the testing of code can be captured from their development environments, along with the student learning traces from the digital course materials accessed for the duration of the course.

The limit to what can potentially be captured is determined only by the functionality of the Integrated Development Environments (IDE) and the data streams accessible in the IDE. The data generated from each learner's activities is owned solely by the learner. Learners have to explicitly consent to sharing this data with the researchers in each and every coding session. Learners also have the ability to

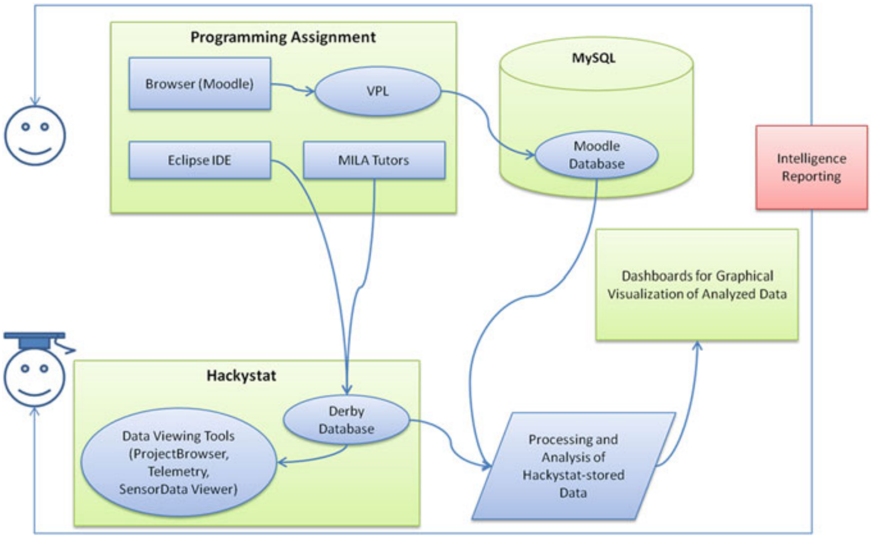

Fig. 8.1 EIDEE system architecture

withdraw any and all of their data from the repository at any time of their choice. Further, the system will only publish aggregated results and not individualized results. The individualized results are only shared with the individual concerned. Such a strict ethical guideline is important because of the implications that can be derived from the observed data on competencies and how these implications could be used (or misused) in a person's life.

A software system called Hackystat[3]—an open source project originally developed by Researchers in the University of Hawaii—acts as a central repository for collecting information on software development activities and logs from a variety of development environments, including Eclipse, Emacs, and Visual Studio.

An open source Moodle plug-in developed by University of Las Palmas de Gran Canaria called Virtual Programming Lab (VPL)[4] was altered to perform a similar data collection task from within Moodle itself for less intensive programming exercises.

Further, highly personalized software tutors called MI-LATTE (mixed-initiative learning analytics tutoring and training environment) have also been developed. Each MI-LATTE tutor targets a single assignment problem, where learners are expected to solve the problem by writing "one line of code" at a time. The tutor analyzes this single line of code and assesses the skill associated with the writing of that line of code. Data collected from learner interactions with each MI-LATTE along with any identified skills are collected.

[3] http://code.google.com/p/hackystat/.

[4] http://vpl.dis.ulpgc.es/.

Finally, learner interaction data with the Eclipse IDE Extension (EIDEE) captures data concerning code design steps (e.g., UML design), code writing, code debugging, code documenting, code testing, code review/reflection, and code optimizing. Figure 8.1 depicts the system architecture.

Using a combination of static analysis toolkits, depending on the language in use (for example, Java program analysis uses a combination of Checkstyle, FindBugs, and Junit, while C programs use a combination of Lint, and Virtual Programming Lab customizations), and manual grading by Teaching Assistants, the work of the students are graded and the results obtained from these tools are logged—along with the final grade on the assignment problem. These final grades and the marks scored by a student corresponding to each rubric in each assignment problem are also collected as raw data.

8.2.2 Technology and Datasets

Figure 8.2 presents the underlying technology used to collect continuous sets of raw data.

The key data in this flow is the continuously arriving student source code. Using the three tools, Eclipse extension (EIDEE), mixed-initiative tutors (MI-LATTE), and embedded coding interface (VPL), we collected a large quantity of data on students' coding habits. We also collected data from Moodle on browsing patterns, formal assessments (e.g., quiz and exams), student survey results, and student discussion contributions in forums.

To collect the raw data in a central repository, Hackystat sensors are embedded within Eclipse, within VPL, within EIDEE, within MI-LATTE, and within Moodle. All data are sent to the Hackystat sensorbase. The sensorbase, a Derby database, contains all the data collected from Hackystat sensors. Hackystat provides a helpful layer of abstraction through its Java API to query and display the data in a more intuitive way.

The raw data is processed continuously to populate two ontologies to discover and maintain a coding profile for each student and to track changes to this profile. Each ontology captures the mastery level of the concepts of a specific area within the coding domain. For instance, given a specific programming problem, the abstract syntax tree of the student source code will be time-stamped and stored in a first ontology. This ontology records the state of the abstract syntax trees generated by the student's code during the problem solving process. A second ontology captures all the errors made by the student. This ontology will store the results generated by code analysis tools such as Eclipse JDT[5]/CDT[6] compilers, FindBugs, CppCheck, Checkstyle, etc. To handle ontologies programmatically, we use the

[5] http://www.eclipse.org/jdt/.

[6] http://www.eclipse.org/cdt/.

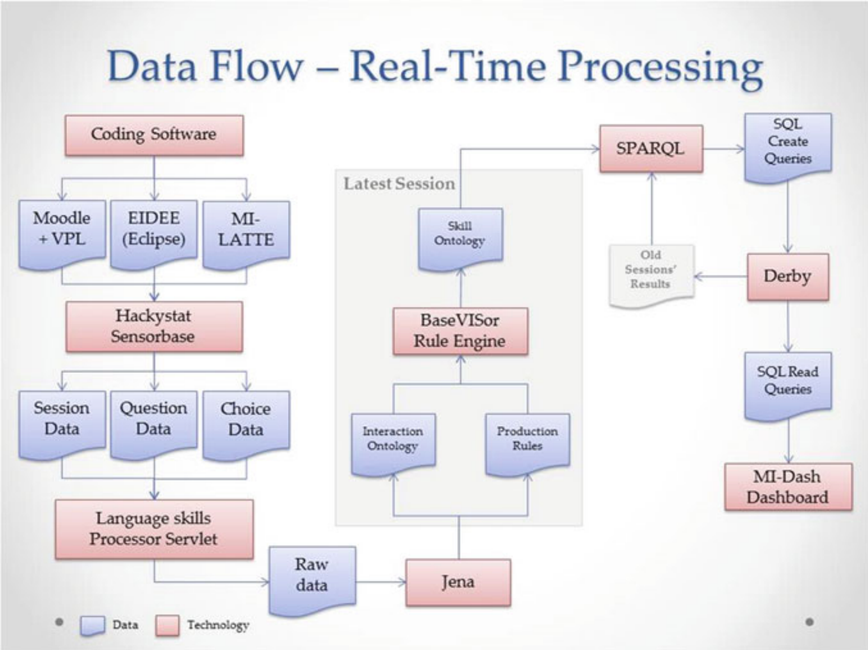

Fig. 8.2 Dataflow of the EIDEE system

Apache Jena framework. Ontologies are written in the RDF or OWL format depending on the needs of expressivity or power of inference engines.

Further, we built a knowledge base to interpret the performance of students and the results from code analysis tools in terms of skills, mastery of concepts, cause-effect relationships, and cognitive models. For instance, if Hackystat receives information about the student's struggles in debugging a particular type of error, the instances of struggles (from the second ontology) are recorded in the ontology along with the coding context (from the first ontology) in which these struggles were observed. This leads to an estimate of time it would take the student to solve a particular type of error could be estimated. This estimate is an inferred competency and further changes to such estimates are also recorded. BaseVISor,[7] an RDF-based forward-chaining inference engine, implements all the production rules in an XML format and records the state of the working memory of the student. The results of the inferences made by BaseVISor are stored in new ontologies.

These results serve as the contents of a dashboard called MI-DASH. The dashboard, we hope, will empower students to manage their own coding habits by interacting with their profiles. Ontologies can be queried with SPARQL, an RDF query language, and will be translated into a SQL database which will help in creating the contents displayed in the dashboard.

[7] http://www.vistology.com/basevisor/basevisor.html.

8.2.3 Hackystat Sensors

Hackystat provides a range of sensors to collect data from tools, such as Eclipse, Ant, Checkstyle, Clover, FindBugs, JUnit, Visual Studio, tools generating XML data, etc. Hackystat also provides a sensor shell Java API which supports the creation of customized sensors to increase the range of tools monitored by Hackystat sensors.

The main advantage of the sensor shell is that it has a built-in data integrity mechanism; that is, the sensor sends packets of data to Hackystat at specified time intervals or when an event occurs (clicking a button, pressing the return key, etc.) via a network (be it intranet or internet). However, if for some reason network connectivity is lost while data being sent, the sensor shell will temporarily store the data in XML files on the user's local machine until connectivity is restored. Then, any local sensor data is automatically pushed on the Hackystat sensorbase. This ensures that no data is lost due to some unexpected loss of connectivity.

Since Hackystat is open source, we modified its Eclipse sensor to suit the particular needs of our experiments. Essentially, we kept the data types originally designed with the sensor and added new ones. The sensor was also modified to fit various versions of Eclipse for various packages (Galileo, Indigo). Finally, we created our own Eclipse package with our customized Hackystat Eclipse sensor embedded. That package also contains course assignment projects ready to be monitored by the sensor. The purpose of this package is to hide the complexity of the sensor configurations from the students.

The Eclipse sensor enables the collection of different data types during code development. The three types of data captured by the sensor are Edit, Build, and Debug. It tracks any operations made on a file such as opening, saving, or closing a file. It also records any addition, renaming, removal, and move of programming constructs. Any failed compilation is also sensed and sent to the sensorbase. The sensor also reports debugging activities such as the start and termination of debugging sessions, the setting and removal of breakpoints, and the passage of the debugger into or over a block of code. We also modified the sensor, so that the source code may also be collected as the student types. The sensor collects the source code at 1-s intervals or whenever the student compiles his/her code (saves the code file), so that we might reconstruct his/her coding efforts and the evolution of the code.

As for the MI-LATTE tutor, we built a new sensor using the sensor shell API. The MI-LATTE tutor records the student interaction within its interface and forwards them to Hackystat. Each tutor is downloadable and consists of a client-side Java Web Start application and a server-side Java servlet. The Java Web Start application stores data collected from the student in a buffer and sends the data over HTTP post messages to the Java servlet. The servlet contains a customized sensor which sends to the Hackystat sensorbase all the instances of data types collected by the client application. The servlet also parses the final version of the student's source code to generate the corresponding abstract syntax tree and compiles the code using the Eclipse JDT/CDT compiler. Eventually, every capture of source code is built and parsed, so that we can track the evolution of errors during problem solving (for instance, which errors occurred and were solved properly by the student in the process and how much time it took him/her to solve them). Any error reported after a failed compilation is sent to the Hackystat sensorbase. Source code is captured as a DevEvent sensor data type, while errors are captured as CodeIssue sensor data types.

Developing the Moodle web sensors was a challenge. The Hackystat sensor shell (as well as all of Hackystat) is built in Java, but since Moodle is built using PHP, JavaScript, and AJAX, we used a framework called PHP/Java Bridge[8] which is designed to allow the integration of Java libraries inside PHP code and vice versa. Therefore, we used the sensor shell Java API inside the Moodle PHP code to build a Hackystat sensor for Moodle that uses the data integrity feature of the Java sensor shell. We created event handlers in Moodle's code that incorporate the Web Hackystat sensors which send data about the event that just occurred (action type, timestamp, action context, any user input, etc.) to the Hackystat sensorbase.

8.2.4 Feedback Mechanism

We define learning analytics as the science of analysis, discovery, and utilization of learning traces in emergent and related levels of granularity. Learning analytics is also defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."[9] The data collected are being processed and analyzed in order to improve the student's experience and increase the quality of tutoring services through human and software agents.

At this stage, the MI-LATTE tutor performs three tasks: provides instructions, points out errors, and offers corrective actions. The role of the human agent with the software agent will be to provide it with a set of alternative solutions. An alternative solution may follow a different algorithm, a different sequence of programming constructs, different variable names, etc.

The feedback from the software agent is optional. The student can solve the problem by himself/herself and submit his/her work for evaluation without resorting to any automated feedback from the software agent. Feedback will only be given on demand. Examples of types of MI-LATTE tutor feedback messages are given below:

- All the written code so far is correct. Here are the instructions for the next statement.
- The statement at Line 5 is incorrect. Please look at the instructions again.

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[8] http://php-java-bridge.sourceforge.net/pjb/index.php.

[9] https://tekri.athabascau.ca/analytics/.

- The statement at Line 5 is incorrect. Please look at the instructions again. You can also look at the reported compiler error message.
- The statement at Line 5 is incorrect. Please replace this section of your code with the following string.
- Here is the code section corresponding to what you have written so far. Please study it and try to solve the remaining part(s) of the problem.
- Here is the whole code. Please study it and try to solve the problem a second time by yourself.

Moodle and VPL also offer opportunities for providing instantaneous tutoring/feedback to students. This Hackystat-based technology allows us to customize Moodle to include feedback messages for the students as they work on a quiz or write a forum posting or view learning material on Moodle, or complete a programming assignment in VPL. By storing personalized messages in a database and even creating generic event handling sensor code that Moodle administrators can add or remove from the actual Moodle code at will to suit their individual needs, one can create a very powerful interactive tutoring feedback-based Moodle/VPL environment which, in addition to collecting data for later analysis and feedback, also provides just-in-time feedback to the student.

8.2.5 Ontologies

When a student works on a programming exercise, two ontologies are populated. The first ontology contains the abstract syntax tree of the final version of his/her source code while the second ontology stores the corresponding compile-time errors. We call the first ontology the AST (Abstract Syntax Tree) ontology and the second ontology the Error ontology. We currently use Protégé,[10] an ontology editor, to view the contents of the ontologies.

In the AST ontology, we can view the different programming constructs employed by a student, the relationships between the various nodes in the AST as well as the code corresponding to a specific node in the tree. We can also view graphically the abstract syntax tree through the OntoGraf[11] module, a plug-in installed by default in Protégé.

In the error ontology, we can view all the errors encountered by a student. The recorded information about a specific error will include the type of the error, the source code line number, the severity of the problem, the start and end character positions of the error, and an explanative error message. In brief, we can retrieve all the information generated by the Eclipse JDT/CDT compiler.

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[10] http://130.88.198.11/tutorials/protegeowltutorial/resources/ProtegeOWLTutorialP4_v1_3.pdf.

[11] http://protegewiki.stanford.edu/wiki/OntoGraf.

Since we propose to build the student's source many times per session, we want also to find a way to identify errors and keep track of them to study how students resolved them.

We manage the ontologies programmatically using the Jena framework. One of the most interesting aspects in the overall framework is the possibility to customize actions that will be carried out on the occurrence of a specific programming construct when the source code is parsed. The Eclipse JDT/CDT APIs offer a library of Java classes enabling to tailor the parsing process. Hence, we use the Jena framework to generate the AST ontology on the occurrence of all programming constructs. Interestingly, this enables us to build Hackystat sensors for Eclipse for the C and C++ languages as well as any other tools such as the MI-LATTE tutors which make use of the Eclipse API to implement its own features in a standalone Java application.

These ontologies play an important role in the analysis and report of the data collected from the students. These ontologies could be processed at multiple levels of granularity focussing on the assignment problem, or the student, or the course, or the institutions, and so on.

BaseVISor along with SPARQL provide key tools in performing large-scale inferencing and a detailed statistical analysis (using R) to help discover new patterns relating to a programming context. Based on the results of inferencing and statistical analyses, one could determine cause-effect relationships between various occurrences of specific constructs and/or errors. These could then be translated back into BaseVISor production rules to expand the knowledge base and enhance the results of later analyses.

The coding profiles of students have been assessed and modeled in the BaseVISor inference engine. Changes to the state of the working memory are brought back into the ontology. The resulting ontology can be translated into a SQL database by querying the ontology with SPARQL, an RDF query language, and translating SPARQL result sets into SQL queries to create SQL tables and insert values into those tables. A SQL database will be the repository of processed data where dashboards can retrieve information.

8.2.6 Sample Datasets and Analyses

Dataset collected through the Eclipse IDE and the MI-LATTE tutors are classified and stored in the Hackystat sensorbase. The data are then merely gathered and converted to ontologies for extensive inferencing in BaseVISor. Data are classified according to the tools which generated them and their type. Two data types exist at this point: DevEvent and CodeIssue. The DevEvent data type stores source code. The CodeIssue data type stores error instances generated by the Eclipse JDT/CDT compiler.

By time-stamping, the builds of a student's source code as well the error messages generated for the identified errors (see Fig. 8.3), an instructor could be

Error Type	Start Time	End Time	Duration	Error Message
MissingReturnType	Sat Sep 28 11:00:58 EDT 2013	Sat Sep 28 11:11:52 EDT 2013	10.90	Return type for the method is missing
ParsingError	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	Syntax error on token "that", ; expected
ParsingErrorInsertToComplete	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	Syntax error, insert ")" to complete MethodInvocation
ParsingErrorInsertToComplete	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	Syntax error, insert ";" to complete LocalVariableDeclarationStatement
ParsingErrorInsertToComplete	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	Syntax error, insert ";" to complete Statement
ParsingErrorInsertToComplete	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	Syntax error, insert "}" to complete MethodBody
ParsingErrorInvalidToken	Sat Sep 28 10:55:20 EDT 2013	Sat Sep 28 11:11:52 EDT 2013	16.53	Syntax error on token "==", invalid AssignmentOperator
UndefinedType	Sat Sep 28 11:00:58 EDT 2013	Sat Sep 28 11:11:52 EDT 2013	10.90	string cannot be resolved to a type
UnresolvedVariable	Sat Sep 28 11:00:58 EDT 2013	Sat Sep 28 11:11:52 EDT 2013	10.90	userIput cannot be resolved to a variable
UnterminatedString	Sat Sep 28 10:56:06 EDT 2013	Sat Sep 28 11:06:17 EDT 2013	10.18	String literal is not properly closed by a double-quote

Fig. 8.3 Errors types observed during coding

provided with a report (see Fig. 8.4) on errors made by a student when solving a specific problem and how long it took him/her to solve an error and which errors remained unsolved at the submission of his/her assignment.

Further, data on the number of compiles, the number of errors, the types of errors, the error correction patterns, documentation patterns, and test plan patterns can also be collected.

Figure 8.4 shows patterns of code submitted by students in VPL. We can go further to look at each student's submissions across multiple coding sessions. Within each session, we can investigate the code written by the student, the types of errors made by the student, the error correction behavior of the student (e.g., time to debug different types of errors), the pace of writing code, the types of competencies being gained (e.g., use of abstract data types), the ebb and flow of these competencies over time, and so on.

We classified the types of data being collected to course traces and student traces. Course traces offer analytics on how the course material and students are performing overall. This could include a semester-over-semester trend of some

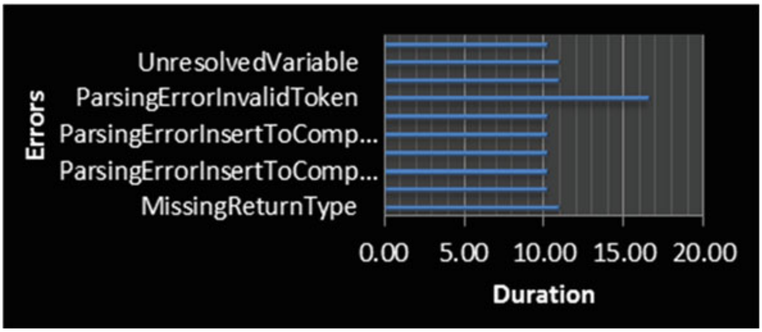

Fig. 8.4 Debug duration versus error types

measurements (e.g., competency growth), or as a yardstick against similar courses—an introductory C programming course against an introductory Java course. Some example course-wide traces include.

- Course interactions—how many actions (viewing pages, logging in/out, errors, adding forum postings, etc.) performed by each student ID on general course material
- Coding interactions—total actions related to coding in Moodle VPL (new code construct, compiling, deleting code, testing code, running code, etc.) performed by students in the setting of a course
- Course Assessment Performances Answered—successful completion of a programming assignments using VPL or EIDEE, performance in the quiz/assignment, and classification of forum interactions.

Course traces also include clues about the attractiveness and effectiveness of course content including lessons, assessments, and tools.

Student-based traces look specifically at how the student is performing in the course. This could be compared against the same metric for other students, or to look at different actions by the same student (i.e., were there fewer coding errors when the student first looked at the learning material, or is there a relationship between how long he looks at the learning material, and the number of errors made). Student-based traces include:

- All Moodle Actions—superset of all actions performed by each student on the Moodle website, including code-related actions
- Successful Submissions—total of all successful assignment submissions for all students collectively or each student individually
- Successful Submissions by Programming Problem—number of successful programming assignment submissions per programming problem in VPL
- All Coding Actions—all of a student's code-related actions in VPL
- Coding Actions by Programming Problem—number of code-related actions per programming problem
- Raw submitted/attempted program files—actual source (program) files students worked on both for submitted and attempted programming assignments

Student-specific questions might zero in on specific behaviors (number of actions, number of coding actions, time on Moodle, etc.), or even subdivide the course by section, and look at each section as a component to determine how helpful it was to the students.

Analysis includes relationships discovery across datasets. For instance, is there a reduction in coding errors over time when students first study the entire lesson for a significant time before attempting to solve the program? What are the predominant types of errors and how well they are addressed in the content? Are there different learning styles emerging from the Moodle browsing patterns among students who perform (based on marks scored) at different levels? Is there a significant improvement in coding submissions over time, as the student becomes more proficient, when instructors are informed about potentially demotivated students? Is there a relation between student performances and student self-regulation behavior (browsing their own profiles)? Is the level of student documentation an indication of their coding competency? Are there clusters of students who require special attention from the instructor? Are there clusters of students who progress faster through the course related to other students? Does the learner competency growth align well with the curricular goals of the institution? Do group study students perform better self-regulation than individual study students? Can performances of students be predicted based on initial patterns of study and progress? Is there a significant match between student competency levels and industry expectations?

The types of analyses, information, and data one could extract from learning related datasets is quite large and varied. The dashboards need to be customized to extract only the types that are of use and preferred by individuals. The progress reports of students generated by the dashboards need to not only show the current progress but also the means to reach a better competency growth. Shown below is one of results of our first controlled study in learning analytics outlined in Sect. 2.1.

A total of 75 first year students (batch 3) taking the C programming course were given access to learning analytics tools from within Moodle, in addition to traditional resources, at the end of Assessment 1. The rest, a total of 692 students, taking the same C programming course studied with access only to traditional resources such as lecture notes, text book, lab support, and assessment feedback. Table 8.1 shows the performance of batch 3, the experimental students and Table 8.2 shows the performance of the rest, the control students.

Comparison of Tables 8.1 and 8.2 indicate that, overall, the learning analytics tools, had a significant impact in improving grades of students in assignments 2 and 3. Further, learning analytics tools have also been instrumental in significantly reducing the percentage of failed students in assignments 2 and 3.

The theory and the practical exams target the full scope of the course and the impact of the learning analytics tools on these two assessments is inconclusive. Another study to investigate impact of individual analytics tools on student performances is currently underway.

Table 8.1 Performance of control students

	Assess 1	Assess 2	Assess 3	Theory	Practical
Average marks	64.44	60.96	59.55	6.41	7.44
No. of fails	146	221	151	99	24
% of fails	21.10	31.94	21.82	14.31	3.47

Table 8.2 Performance of experimental students

	Assess 1	Assess 2	Assess 3	Theory	Practical
Average marks	62.51	73.51	73.91	7.09	7.67
No. of fails	22	2	6	7	3
% of fails	29.73	2.70	8.10	9.46	4.05

8.3 Lessons Learned and Future Potential

One of the key challenges in big data learning analytics is data integrity that ensures the authenticity of the arriving data and the ethical nature of the data.

Data can be processed by any technique, whether it is a data mining technique or a machine learning technique, or a big data clustering technique, or a sentiment analysis technique. The point is, students and instructors should be in control of the choice of analyses and the corresponding techniques.

In addition to the students initiating interactions with the analytics tools, the tools themselves could also be initiating interactions with students.

Performance indicators, by themselves, offer reflection opportunities. Big data analytics enables students and instructors to proceed further towards regulation opportunities.

Analytics being offered are available without "any" intrusion on the student's course interactions. There is no controlled experiment as such. Instead, data are being collected in the background with students' explicit permission.

Students are welcome to relate different datasets to arrive at insightful analytics. The datasets and the associated analytics techniques are open for use by students. Students can request additional datasets or techniques for other types of meaningful analytics. Students and instructors can share their individual analytics dashboards with others.

Competency growth in programming can be observed within a specific language (say, Java) across multiple courses. Equally, competency growth in programming can be observed across multiple languages (say Java and C++). Competency growth in programming can be observed at the individual student level, or the course level, or the departmental level, or even at the institutional level.

Key inferences about intervention opportunities could be made available to instructors. These opportunities arise out of analytics with substantiating evidence. Intervention opportunities could be tuned towards learning efficiency of individual students and groups of students.

One of the substantiating evidences is the use of causal modeling in arriving at analytics. With sufficient data, coding activities, study activities, performances, and reflection/regulation activities can be causally connected. Such causal connections can be open to students and instructors to help determine intervention opportunities.

In addition to assessment outcomes, instructional effectiveness can be continually measured based on successful interventions and growth patterns of student performances.

The ontology-based analytics framework lends itself to develop analytics measures for learning efficiency and instructional effectiveness. The underlying mechanism that yields these measures (e.g., data mining, machine learning, or big data analytics) can be open for investigation but can be comfortably ignored by students and instructors.

The development of a comprehensive coding traces platform reporting on the efficiency of coding and effectiveness of coding instruction is a key contribution of this research. It reports not only on learner habits but also relates instructor habits.

The traces platform is quite conducive to the development of software agent-oriented guidance that can monitor the data sources on a student-by-student basis, to identify successful patterns of learning, based on a student's interaction with the digital learning environment, and suggest corrective actions, materials and behaviors that might improve performance, based on the past results of similar student behaviors.

The underlying datasets approach the quantities expected in the context of big data analytics. The platform that we have developed supports the inclusion of Hadoop[12]-based analytics that can handle large volumes of data. The platform also supports the use of causal modeling technologies (e.g., Tetrad IV) that can generate large volumes of potential competency models.

Coding efficiency encompasses aspects of coding style, metacognitive scaffolds, peer interactions, and interactions with instructors, among others. Instruction on effective coding encompasses aspects of intervention, guidance, content material, sensitivity to learner capacity, and timeliness of feedback, among others. Datasets corresponding to each of these aspects can be observed and relations among these datasets can be established using the platform.

With big data as the premise, we developed a sensor-based big data software platform that is open, inclusive, adaptable, and precise. It shows tremendous potential towards accountability of students' study tasks. Equally, the accountability and performance of instructors are also continually analyzed. Matching of these two accountabilities would yield optimal learning opportunities.

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Chapter 9
Recommendation Systems for Personalized Technology-Enhanced Learning

Mohamed Koutheaïr Khribi, Mohamed Jemni and Olfa Nasraoui

Abstract From e-commerce to e-learning, recommendation systems have given birth to an important and thriving research niche and have been deployed in a variety of application areas over the last decade. In particular, in the technology-enhanced learning (TEL) field, recommendation systems have attracted increasing interest, especially with the rise of educational data mining and big data learning analytics. Generally, TEL recommendation systems are used to support learners in locating relevant educational content according to their profiles. These systems may involve several phases, such as data acquisition and preparation, modeling, and recommendation computation, phases, which together, can describe a TEL recommendation system and distinguish it from others. However, such a description needs to be expanded and generalized in order to cover most of the TEL recommendation systems, especially, in the context of anywhere and anytime learning based on various Web-based learning environments, including Learning Object Repository (LOR), Open Courseware (OCW), Open Educational Resources (OER), Learning Management Systems (LMS), Massive Open Online Courses (MOOC), Educational Widgets, Educational Mobile applications, etc. In this chapter, we provide a generic meta-level framework for a common description of TEL recommendation systems. Then, we present an analysis of several existing TEL recommendation systems with respect to our defined framework.

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Keywords Personalized technology-enhanced learning · Recommendation systems · Automatic personalization

9.1 Introduction

One of the widespread trends in web personalization has been to provide appropriate recommendations to end-users. In particular, in the taxonomy of adaptive hypermedia technology (Brusilovsky 2001), two different classes of adaptation are considered: adaptive presentation and adaptive navigation support. Recommendation is considered as a subcategory of the adaptive navigation support category. Moreover, recommendation systems have attracted increased interest since the emergence of the first research paper (Resnick et al. 1994) on collaborative filtering in 1990 (Park et al. 2012). In general, recommendation systems aim to help end-users to find appropriate content, such as papers (Pitkow and Pirolli 1999), movies (Miller et al. 2003; Herlocker et al. 1999), web pages (Nasraoui and Petenes 2003; Nasraoui and Pavuluri 2004), music (Jäschke et al. 2007), books (Linden et al. 2003; Mooney and Roy 2000), restaurants (Burke 2002), scientific papers (Pavlov et al. 2004; Tang and Mccalla 2003b), learning materials/activities (Zaïane 2002; Romero et al. 2007; Khribi et al. 2007), etc. The majority of recommendation systems apply data analysis techniques in order to generate, progressively, a set of recommended items to a particular user. Furthermore, several knowledge discovery and data mining techniques have been used in recommendation systems. Most of them are based on the use of content-based filtering, collaborative filtering, or combined (hybrid) approaches. Other approaches such as demographic and knowledge based recommendation systems, can also be used (Khribi et al. 2012).

In the education area, Web-based learning environments are being increasingly used at a large scale, overcoming the restrictions of traditional classrooms and allowing students to learn anywhere and anytime. An increasing amount of educational content and activities are being incorporated continuously within ubiquitous learning environments that are accessed by a diversity of learners, with different needs and interests. Unfortunately, most of the current and commonly used Web-based learning systems are still delivering the same educational resources in the same way to learners with different interests, learning styles, or more generally, learner profiles. Therefore, several works have addressed the need for personalized technology-enhanced learning, putting an end to the traditional one-size-fits-all approach (Chorfi and Jemni 2004; Essalmi et al. 2013). One of the widespread trends in TEL personalization is to recommend relevant learning objects/activities for users through the online learning process (Boticario 2012; Khribi et al. 2012; Manouselis et al. 2011, 2013).

In this chapter, we propose a brief introduction to the field of recommendation systems for personalized technology-enhanced learning. Then, we provide a generic meta-level framework, cataloging the most important dimensions or criteria that should be considered when describing and analyzing TEL recommendation systems. The rest of this chapter is organized as follows. Section 9.2 reviews the background of TEL recommendation systems and identifies the different aspects or features that characterize these systems. Then, Sect. 9.3 presents a generic meta-level framework to use in the analysis and description of TEL recommendation systems. Section 9.4 presents an analysis of many existing TEL recommendation systems based on the dimensions that have been defined in Sect. 9.3. Finally, we conclude the chapter in Sect. 9.5.

9.2 Tel Recommendation Systems

Recommendation systems can be used in technology-enhanced learning for many purposes such as (1) supporting and scaffolding users (learners/teachers) in locating appropriate learning objects and/or learning activities through the learning/teaching process, according to their needs and interests; (2) predicting suitable ranks and rates; (3) recommending learning pathways or educational scenarios; (4) proposing users, i.e., peers with near or similar profiles, etc. (Bozo et al. 2010; Santos and Boticario 2010, 2012; Manouselis et al. 2011, 2012, 2013; Verbert et al. 2011; Boticario 2012; Khribi et al. 2012). However, all of these stated possibilities of recommendation systems' business objects imply the ability of these systems to understand the learners' online behavior from which their preferences, interests, needs, and characteristics are inferred or predicted. Moreover, the recommendation process can be outright considered as a prediction problem (Mobasher and Nasraoui 2011): In the context of TEL, the system must be able to predict the level of learning object suitability (or interest in) for a particular user and give it a predicted value. To accomplish such a prediction task and generate recommendations, most TEL recommendation systems generally apply machine learning or analytics techniques on usage data. Recently, interest in using data mining in the education domain has increased significantly, creating a new research niche, named educational data/web mining, and fostering a new growing research community. A detailed description about using and applying data mining in the education area was presented in Romero and Ventura (2010).

When comparing the main features of existing TEL recommendation systems (Zaïane 2002; Tang and McCalla 2003a; Shen and Shen 2004; Baloian et al. 2004; Lu 2004; Wang and Shao 2004; Romero et al. 2007; Wan et al. 2008; Khribi et al. 2008, 2013; Zhuhadar et al. 2010; Manouselis et al. 2011), etc., one can notice a shared composition in terms of their most essential phases, namely the data acquisition, modeling, and recommendation phases.

However, even with regard to these shared dimensions, various approaches, methods, and techniques, applied separately or combined, can lead to different types of TEL recommendation systems (e.g., collaborative filtering, content-based filtering, demographic, rule-based, ontology-based, attribute-based, hybrid, etc.). Moreover, some TEL recommendation systems rely on the user's data (preferences, interests, characteristics, etc.) that are gathered explicitly; while others tend to infer such information implicitly from tracked usage data. On the other hand, being in the educational domain, recommendation systems should normally take into account pedagogical features, which is, unfortunately, the case of only a minority of existing recommendation systems (Tang 2008; Khribi et al. 2009, 2013; Bozo et al. 2010). The pedagogical dimension refers, generally, to the learners' educational preferences, learning/teaching styles, as well as pedagogical rules and attributes, etc. All of these elements may be considered, separately or combined, in the modeling and/or recommendation phase.

In Khribi et al. (2012) and Khribi (2013), we considered a set of selected significant features for analyzing and describing educational recommendation systems (Input Data, Data Acquisition, Educational Attributes, Modeling Operations, and Recommendation Strategies), and we used them as criteria to compare some of the existing recommendation systems. Thereby, several similarities and dissimilarities, according to these common and recurrent dimensions of TEL recommendation systems, were revealed, so that, each system can be seen as an instantiation of a common generic meta-level extended description containing all underlying key dimensions to be considered in TEL recommendation systems.

9.3 A Generic Meta-Level Framework for Tel Recommendation Systems

In the literature, we can find several intuitive classifications of recommendation systems, based mainly on their related fields (e-commerce, tourism, e-learning, social networks, etc.) (Park et al. 2012; Schafer et al. 2001), applied approaches and techniques (Web mining, collaborative, time framed, association rules, etc.) (Mobasher 2007a; Nasraoui 2005; Sieg et al. 2010; Burke 2002), objectives (recommending papers, learning objects, documents, etc.), underlying environments (mobile, context aware, etc.) (Verbert et al. 2011), the final user category (students and/or teachers) (Bozo et al. 2010), and many other key features (Khribi et al. 2012).

Since most recommendation systems have been initially characterized according to the adopted recommendation strategies that they use, we tend, intuitively, to recognize them according to these strategies, which include content-based filtering systems (CBF), sometimes also referred to as item-based filtering systems, collaborative filtering systems (CF), rule-based filtering systems, demographic systems, hybrid systems, and Web usage mining-based Web recommendation systems (Mobasher 2007a; Nasraoui 2005; Burke 2002). Another possible classification that was reported in Park et al. (2012), relied on the kind of techniques used in Web mining-based recommendation systems (association rule mining, clustering, decision-trees, neural networks, Markov models, etc.). It is important to note that the aforementioned classifications were rather based on an *algorithmic* point of view, in contrast to say, an alternative classification stemming from a *machine learning* *strategy* point of view (Mobasher 2007b). Two main categories of recommendation systems are considered in this latter classification: model-based systems and memory-based systems. *Memory-based systems* (also known as *lazy learners*) store all the needed data, then use it directly at run time (or online) when producing recommendations; while *model-based systems* (also known as *eager learners*) invest in the relatively more costly learning phase offline and then generate online recommendations, based on the learned model predictions, at run time.

Another intuitive classification can also be considered, this time related to the final user for whom the recommendations are produced. In this case, we can consider for instance the following categories: Student recommendation systems versus Teacher recommendation systems (tutors and/or authors) (Bozo et al. 2010). It is also possible to categorize recommendation systems based on their purpose, meaning *what* they tend to recommend: links, ratings, papers, persons, etc. Finally, especially in the realm of ubiquitous learning environments, recommendation systems can be categorized based on whether or not they are sensitive to context data (geographic location, network bandwidth, time, device computing power, etc.). This latter emphasis has generated a new research branch, named *context aware* TEL recommendation systems (Verbert et al. 2011).

All the aforementioned possibilities for intuitive categorization or classification of TEL recommendation systems motivate the need to have a broader description gathering and modeling all the known categories and features of TEL recommendation systems. In the literature, some attempts have already made directions toward addressing this issue. For instance, Manouselis (Manouselis and Costopoulou 2007) presented a framework for analyzing recommendation systems based on three categories: supported tasks, adopted approach, and performed operations. In Manouselis et al. (2013), the authors used this framework and extended it slightly to the TEL recommendation system domain. On the other hand, in Verbert et al. (2011), authors focused on a specific family of TEL recommendation systems, namely context aware systems. In this treatment, a context framework was adopted for the analysis of context aware TEL recommendation systems, whereby the categorization was based on a delineation of context categories and their elements.

Based on the criteria that we have adopted in (Khribi et al. 2012; Khribi 2013) for the description and the analysis of TEL recommendation systems, and drawing inspiration from existing frameworks, such as (Manouselis et al. 2013), that do not cover all the relevant features of educational recommendation systems, we attempt to propose a simplified generic meta-level (GML) framework providing abroad description of most known and commonly used dimensions that can be used to delineate different classes of TEL recommendation systems (Fig. 9.1).

In the proposed framework, we distinguish 11 key dimensions which can be summarized as follows: *Recommendation Purpose, Pedagogical Strategies, Predefined Rules, Context Loading, Data Acquisition, Modeling Operations, Recommendation Strategies, Recommendation delivery, Recommendation Output, Current online user Objectives,* and *Technical Model*. In what follows, we briefly describe each of the stated key dimensions:

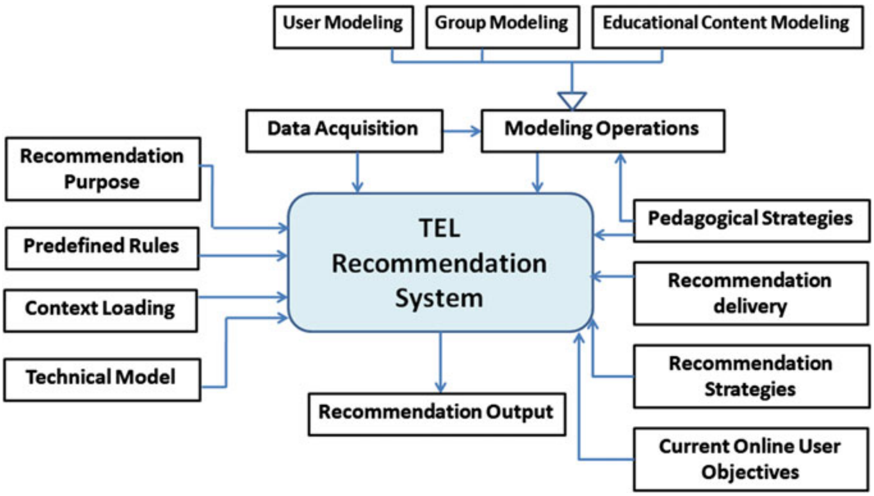

Fig. 9.1 Generic meta-level (GML) framework for technology-enhanced learning (TEL) recommendation systems

1. The *Recommendation Purpose* refers to the usage objective of the recommendation system i.e. its objective for a specific category of users (Students and/or Teachers), which can be one of the following:

   - Locating and suggesting relevant links: proposing a set of related and appropriate educational objects to the users, e.g., learning object, learning activity, etc.
   - Building suitable learning pathways: proposing suitable learning paths or scenarios throughout an online course in order to accomplish some underlying objectives.
   - Predicting the user's item ratings: suggesting to the user, a list of predicted item ratings or using the ratings to rank the items according to these predicted ratings.
   - Recommending a learner's action: proposing the next action that should be done by a user after his/her current click.
   - Locating users (student/teacher): recommending a set of users with similar profiles and interests, leading to the creation of an educational social network.

2. The *Pedagogical Strategies* refer to the pedagogical dimension that should be taken into account in educational recommendation systems. This could be done by considering one or more of the following elements in both the modeling and recommendation phases: learning styles, teaching styles, educational interests and preferences, educational content attributes, educational standards, and instructional rules.

3. The *predefined rules* imply a dictionary of rules, set up earlier by teachers, as well as course administrators and creators, in order to personalize the recommended course delivery with respect to these rules.
4. The *Context loading* refers to the ability of the recommendation system to be aware of context data either on the user side or on the server side. Several contextual categories can be considered such as location, time, computing, and physical conditions. The latter include conditions such as noise, brightness, network bandwidth, and device features.
5. The *Data Acquisition* dimension concerns user data as well as content data acquisition and collection. Such gathered data can be acquired following three modes: implicitly (from tracked usage data and from educational content), explicitly (directly from users and educational content attributes or descriptions), and combined (hybrid).
6. The *Modeling operations* refer to the modeling phase in the recommendation system framework. It covers the user modeling, group modeling, and educational content modeling operations. Each subcategory can be described based on the following elements: Mode, Representation, Building approach, and Update process.

   - The *user modeling* (student modeling/teacher modeling) operation can be achieved offline, which is by default the case of a model based category; or it can be achieved online when considering the user profiles in memory based systems. Two modes of user modeling can be distinguished: automatic user modeling (based on implicit data) and collaborative user modeling (based on explicit data) (Brusilovsky 1996). In some cases, we can have a hybrid mode for building user models. Automated building of user models implies the automated detection of all basic information composing the model. Indeed, the user model is composed of a set of components (Brusilovsky 1994) that can be summarized mainly in the user competency profile (knowledge, skills, and attitudes) and the user personal characteristics, such as learning style, interests, needs, etc. (Sampson and Zervas 2013). User models can be represented using several representations such as vector-based or ontology representations. Models can be created, in the beginning and initialized using specific techniques or left empty waiting for the learning phase. With regard to the user model building process, many approaches can be used from the entire arsenal of data or web mining and machine learning fields. Once the user models have been built, it is necessary to update them as new users' data is acquired. The model updating process can be accomplished by following an online learning (continuous updating), by rebuilding a model from scratch or by incremental learning (by adding new data into the model following specific scheduled periods).
   - The *group modeling* operation means that user models can be grouped or classified into several discovered groups, in order to assign users with common preferences and interests to the same group, so that feedback from one user can serve as a guideline for information delivery to other users

within the same group. Web usage mining techniques, such as clustering, are widely applied in order to generate group models.

- The *educational content modeling* operation implies building a summary representation of the available educational content, to make this content easy to access, search, and recommend for users. This task can be accomplished explicitly (i.e., the content is described and categorized and indexed manually by humans) or implicitly (i.e., the content is automatically crawled, indexed, and categorized using text mining and information retrieval techniques) or hybrid. Generally, specific representations are used to depict the educational content model (e.g., inverted index, term-document, matrix, term lists, ontology, etc.).

7. The *Recommendation strategies*. Most recommendation systems apply learning analytics techniques in order to provide a set of suitable recommendations to users. Furthermore, several knowledge discovery and statistical techniques are used in recommendation systems. Most of them are based on the use of content-based filtering, collaborative filtering, or combined (hybrid) strategies. Other approaches can also be used, such as demographic, knowledge based, and rule-based recommendation strategies. From a learning point of view, these strategies can be applied as part of model based or memory-based learning categories. On the other hand, based on the similarity or correlation mechanism used to compute recommendations (item attributes or ratings, user attributes or ratings), these stated approaches can be based on several types of correlations: item-to-item, attribute-based, user-to-user, or any combination thereof.
8. The *Recommendation delivery* describes how the recommendation system output is delivered. This can be done:
   - Synchronously: online recommendations are provided while the user is interacting with the system;
   - Asynchronously: recommendations are provided when the user is not interacting with the system (for instance, sent by email);
   - On-demand: online recommendations are provided only when the user requests them.
9. The *Recommendation Output* refers to the kind of output provided by the recommendation system. Commonly, we distinguish the following: Top-N or suggested Links (documents, papers, learning materials, learning objects, learning activities, courses, etc.), Actions (next action to do), Learning Pathways, Ranks, and Users.
10. The *Current Online User Objectives* refer to the request and needs of a current user asking for recommendations. This request represents two types of user objectives: short-term and long-term objectives. These objectives can be expressed either explicitly by the user, or inferred in an implicit mode from his/her online activities. User objectives can be depicted as a vector-based (term-vector or weighted-link-vector) representation, or ontology-based representation, etc. Several approaches that are used in user modeling and content

modeling, if slightly tweaked, can also be used for building and updating discovered current user objectives.

11. The *Technical Model* covers all the technical features related to the recommendation system, which includes, among others, the following:
    - The learning type, which can be model based or memory based.
    - The architecture of the recommendation system, which can be either centralized or federated.
    - The software properties of the recommendation system, such as portability, interoperability, adaptability, modularity, and extensibility.
    - The relation with the E-Learning System (ELS), such as dependence, ELS name, and ELS type, with which the recommendation system is concerned.

9.4 Overview of Tel Recommendation Systems Based on the Proposed GML Framework

This section reviews and categorizes several TEL recommendation systems that have been documented in the literature over the course of the last decade, based on the proposed generic meta-level framework description that was presented above.

The Recommendation Agent for e-learning systems is one of the first collaborative filtering educational recommendation systems that have been established (Zaïane 2002). The recommendation purpose of the proposed recommendation agent is to suggest links and shortcuts of appropriate learning activities to students for helping them when browsing the learning material. Data acquisition is ensured in an implicit mode based on tracked usage data gathered in web server logs. Extracted visited links and actions are grouped into sessions that are modeled using web mining techniques. Association rule mining is applied to the learner transaction set in order to discover associations between actions, URLs, etc. Then, during the recommendation phase, the recommendation agent, when activated, consults the mined association rules and looks for a match between the rule's antecedent and a current learner's event. Thereby, a collaborative filtering recommendation strategy is applied to deliver relevant recommended links and actions to students. The proposed recommendation agent was developed and used under the e-learning system WebCT. In this early system, no attention was paid to pedagogical considerations or to student personal traits.

The Smart Recommendation system for an evolving e-learning system (Tang and McCalla 2003b) aims to recommend relevant papers for students. The data acquisition mode is ensured in a hybrid mode relying, simultaneously, on explicit data reflecting the students' appreciation of visited papers, and implicit data inferred from student access histories. Similar students are grouped into the same cluster. Then, the prediction of paper suitability and its recommendation are ensured based on a collaborative filtering approach. The recommendation system also attempts to retrieve relevant papers from the Web based on the system's observation of its learners, as well as their situated learning characteristics and their accumulated ratings. The Smart Recommendation system has later evolved to take into account some pedagogical considerations for students (Tang 2008).

Lu presented a Personalized e-Learning Material Recommendation System (PLRS) (Lu 2004), which recommends appropriate educational resources for students. In the proposed framework, data about students is obtained in both modes: implicitly (clickstream data) and explicitly (feedback). The PLRS framework is based mainly on four tasks: gathering data about students, identifying active learners' needs, learning material matching analysis, and producing learning material recommendations. Two related technologies were developed under this framework: the first was a multi-attribute evaluation method to justify a student's need, and the latter was a fuzzy matching method to find suitable learning materials, best meeting each student's need.

An advanced recommendation system based on time-framed navigation clustering was proposed in Wang and Shao (2004). This recommendation system is based on a collaborative filtering strategy and applies two web mining techniques: time-framed navigation clustering and association rule mining, thus integrating user clustering and association-mining techniques. Historical navigation sessions for each user are divided into frames of sessions based on a specific time interval. Then, time-framed navigation sessions are clustered based on a clustering method, called HBM (Hierarchical Bisecting Medoids Algorithm). Sessions contained in the same groups are later analyzed using an Association Rule Mining method, in order to be used next to make recommendations for similar students. A prototype of the proposed recommendation system was developed as part of a web-based Virtual Classroom at Ming Chuan University.

Another recommendation system, proposing suggestions of learning materials, was presented in Baloian et al. (2004). The authors presented a collaborative filtering recommendation system that suggests suitable multimedia material for learners according to their profiles and the technical environment features. Data acquisition is ensured explicitly based on the learners' ratings and evaluation of materials. Learning materials are first analyzed by human experts, in order to capture the essential learning potentials of underlying learning objects, then, evaluated by learners. In addition, a methodology for characterizing multimedia learning material, based on the use of collaborative techniques defining vectors of documents' characteristics, was presented. These vectors are supposed to reflect the opinion of people who explored them. Learner preferences are collected explicitly and assigned into two categories of properties describing the learner's profile: learner preference properties, which describe the learner's preferences for a certain type of material, and learner hardware properties describing the hardware and software available at the user side. This means that the system is context-sensitive to hardware properties and it is able to provide appropriate learning materials according to these properties.

Chen et al. proposed a recommendation system called PEL-IRT Personalized e-learning system using Item Response Theory (Chen et al. 2005), which estimates the abilities of online learners and recommends appropriate course materials to them using Item Response Theory (IRT). This recommendation system relies on explicit learners' feedback from their responses to questionnaires and their collaborative course voting. PEL-IRT provides personalized Web-based learning according to course material difficulty and learners' responses and votes. The maximum likelihood estimation (MLE) is applied to estimate learner ability based on explicit learner feedback.

Markellou et al. proposed a Recommendation System using Semantic Web Mining Technologies for personalized e-Learning (Markellou et al. 2005). This framework combines content-based filtering and collaborative filtering recommendation strategies to produce a recommendation set, which consists of links to pages that the student may want to visit. Data acquisition is ensured implicitly from students' online activities stored in web log files, used to build aggregate user models in an offline mode. The framework distinguishes between the offline tasks of data preparation, ontology creation, and usage mining, and the online recommendation tasks. The domain model is represented by a common ontology and the different learning objects of the corpus are expressed as subgraphs of this ontology by labeling the nodes accordingly. Recommended links are produced by first matching the current student's active session (short-term student objectives) to the domain ontology, and then filtering this obtained set through frequent itemsets.

AHA! (Adaptive Hypermedia for All) (De Bra and Calvi 1998) was initially an adaptive hypermedia system aiming to provide support to students by guiding them through their exploration of educational hypermedia. This system has received a number of extensions and evolutions in order to satisfy new emerged needs of online learning (De Bra et al. 2000). Later, in Romero et al. (2007), the authors describe a personalized recommendation system that uses a web mining approach to recommend next links to visit for students in an Adaptive and intelligent Web-based educational system. The proposed framework is composed of a specific mining tool and a recommendation engine, and it was initially designed and integrated in the AHA! system. Data acquired by the system is gathered implicitly from log files where each student visit is depicted as a set of attributes (including session ID, visit timestamp, and visited page), and student profile files containing for each student the number of visited pages and the average knowledge obtained from these pages. A collaborative filtering strategy is applied in the proposed recommendation system, and Web mining techniques are used to first group similar students in a same cluster (clustering), and then to extract frequent co-occurrences of their visited pages (association rules). One of the special properties of this framework is that the modeling phase can be triggered manually by teachers having the possibility, first, to select the users' data (historic log and profile data), and second, to launch the mining process. Once sequences have been discovered and saved, all related recommended links are shown to the teacher for eventual validation in order to select which links should be used by a recommendation engine to the student.

Koutrika et al. (2008) presented an example of a closed-community social system named CourseRank, which is an educational and social site where students can explore learning materials. Students can search for courses of interest, rank the accuracy of each other's comments and receive personalized recommendations. Recommendations are produced for students based on content-based filtering and collaborative filtering strategies. Data acquisition is done explicitly from students' evaluation and comments. In fact, useful information is extracted from several aspects of user interactions and user-contributed content in the site, such as activity levels, user behavior and user content quality.

Wan et al. (2008) presented a recommendation system called Collabo-eNOTE supporting social learning by recommending exchanged student notes. This system is developed under a multimedia document repository E-NOTEBOOK offering to students several search facilities to access and retrieve relevant documents, and to annotate and comment collaboratively these documents. Collabo-eNOTE was initially designed to overcome information overload about student contributions and notes on visited documents. Thus the recommendation system aims to help students in locating appropriate contributions from each other. Data acquisition is ensured implicitly from usage data stored in the Database. The recommendation system relies on a hybrid approach based on the combination of content-based filtering and collaborative filtering strategies. This combination is accomplished when final similarity measures are computed based on a CombSIMsimilarity method which uses both content-based similarity measures (SIMContent) and collaborative-filtering-based similarity measures (SIMCollaborative). It is also important to note that the system also recommends a list of students having similar profiles to the current student, by matching his/her profile (term vector) to other student profiles.

Hsu describes an English learning recommendation system aiming to provide ESL students with appropriate reading lessons and aspirations (Hsu 2008). The proposed system applies content-based analysis and collaborative filtering recommendation strategies. Data acquisition is accomplished implicitly from usage data. Data mining techniques are applied to analyze students' reading data and assign weights to visited lessons. A clustering algorithm is used to cluster the students into different groups, so that students belonging to a same group exhibit similar study behavior. Then, an association rule mining algorithm is applied to discover associations between lessons in each cluster. For each lesson of a given group, an initial score is set, using the content-based method. Collaborative filtering is further applied to adjust the score of each student's lesson.

In (Tan et al. 2008), Tan et al. propose a design of an e-learning recommendation system of courses for learners. Recommended courses are produced based on similar learners' preferences i.e. ratings. However, these ratings are not provided explicitly by learners, they are rather inferred implicitly from learners' access histories (web logs). To this end, the duration of visit is considered as a suitable heuristic which is used to imply the learner's interest i.e. rating on a given course. The learner modeling phase is done offline, creating a matrix of learner ratings for available courses. In the recommendation phase, a user-based collaborative filtering strategy is applied, so that the learner neighborhood formation is performed. Then, top-N recommendations are produced using association rule-based recommendation.

HyperManyMedia is an open-source platform for automated discovery, categorization, and retrieval of personalized semantically enriched e-learning resources (Zhuhadar et al. 2008, 2010; Nasraoui and Zhuhadar 2010). HyperManyMedia represents both learning content (course lectures) and user profiles, using an ontology of the content available within the e-learning platform. The ontology is seeded with the course and college metadata, then refined using clustering of the textual content of the individual lectures. The system collects and analyzes user activity data to build student profiles that are furthermore allowed to evolve with time. The system also clusters user profiles and later matches the current learner's query to the profile clusters (collaborative filtering) and/or content clusters (content-based filtering) to provide recommendations. The system also gains scalability by using indexing and retrieval with open source indexing and search engines, a concept proposed for recommender systems by Nasraoui et al. (2006).

Bin et al. (2009) proposed an e-learning recommendation system based on a vector space model. This recommendation system aims to recommend Top-N similar documents to the current viewing document, scored with ratings related to viewing documents. The recommendation of suitable documents is based on a content-based filtering approach. The learners are represented using content based profiling of the highly rated visited documents. Recommended documents are those which are similar to the learner profile. The predicted ratings of viewing documents are based on the good learners' average rating of these documents. Otherwise, a document that has not received any ratings from the good learners, receives an assigned default prediction rating.

Gomez-Albarranand and Jimenez-Diaz (2009) proposed a recommendation system based on a Case-Based Reasoning (CBR) approach. The CBR recommendation system provides suitable Learning Objects to learners from existing educational repositories. The recommendation approach combines content-based filtering mechanisms and collaborative filtering processes. Explicit ratings of learners are taken into account with a set of other characteristics such as learning goals and knowledge level. An ontology-based indexing scheme for learning objects is used. As a consequence, it provides a general indexing scheme that includes knowledge about the similarity between concepts, which is fundamental in the similarity-based search and ranking contexts employed by the recommendation.

Under the ISIS project (Drachsler et al. 2009), PRS, a personal recommendation system, applies a combined recommendation strategy based on stereotype filtering and ontology-based recommendation strategies. The ontology matches learner personal characteristics with the domain knowledge to recommend the most suitable *Learning Activities* (*LA*). *Stereotype filtering* uses learner profile attributes to create different classes containing similar learners, and then recommends appropriate LAs to these learners. The recommendation system relies on an ontology-based recommendation technique if only information about the interest of a learner is available; otherwise the stereotype filtering technique is applied.

In Shelton et al. (2010), the authors propose a recommendation system for Open Educational Resources (OER). The OER recommendation system is a content-based system that recommends related resources based on their semantic relatedness to available resources. Educational resources are indexed using advanced functionalities of indexing in open source search engines, a concept proposed for recommender systems by Nasraoui et al. (2006). Indeed, in addition to metadata which is harvested by utilizing and extending the ROME and other open source libraries for feed parsing, the Lucene open source full-text search engine is fully used for indexing and retrieving resources, as was earlier done by Khribi et al. (2007, 2008) and by Zhuhadar and Nasraoui (2008), Zhuhadar et al. (2010), Nasraoui and Zhuhadar (2010). The current user's objectives are inferred from his/her clickstream data. Resource title, tags, and descriptions are taken into account and weighted differently when tracking user actions. Moreover, the system tracks user clicks and time on page data, and uses it to adapt the ordering of recommendations based on this user data.

Bozo et al. proposed a hybrid approach for recommending suitable learning objects to teachers, taking into account their context which is modeled with an ontology, used as the basis for the Los' metadata and the teachers' profile (Bozo et al. 2010). The hybrid recommendation approach is a combination of an ontology based collaborative filtering technique and content-based filtering technique. The information used for generating recommendations includes the LO metadata, the teacher's profiles, the LO evaluations, and the statistics on the LO usage.

Hu et al. (2013) outline an educational context-aware recommendation system architecture, which is mainly based on social tags assigned to learning materials and users. These tags represent the user contextual information, current interests, learning goals, and knowledge levels. Moreover several rules defining relationships between users, tags, and items are created, composing thus a heterogeneous object network model. A specific rules engine is used to manage these sets of rules related to each user in order to produce personalized recommendations. Rules are further updated and refined based on user feedback on initial recommendations. Graph-based algorithms can be applied on the heterogeneous object network to generate precise recommendations according to the similarity of the objects. The proposed recommendation system is expected to deliver three types of recommendations: learning materials to learners and tutors, tutors to learners, and users to users.

Khribi et al. (2007, 2008, 2009), developed an e-Learning recommendation system (RPL Recommendation system) named HARSYPEL (Hybrid Automatic Recommendation System for Personalization in e-Learning), relying on web mining techniques and scalable search engine technology to compute recommendations against a massive repository of indexed RPL educational resources of the Virtual University of Tunis. The authors (Khribi et al. 2009) studied the possibility of integrating educational preferences in the learner model, thus considering a learner model trilogy: learner's profile, learner's knowledge, and learner's educational preferences, which is expected to enrich the quality of learning object recommendations, especially from an instructional point of view. Later work in Khribi (2013), Khribi et al. (2013), extended the proposed recommendation system to (1) be included in a learning management system, and (2) take into account the learners' educational preferences including their learning styles. This should lay the foundations for a new recommendation approach for learning management systems

LMSs, taking into account both learners' educational preferences and learning styles that are inferred automatically from their usage data. Hence, compared to earlier work in Khribi et al. (2008), the learner's educational preferences component, *LEPi,* was added, including the learner's preferences and learning style, as well as considering the duration and frequency of visits in the learner's knowledge component building. On the other hand, compared to the work in Khribi et al. (2009), the learner's educational preferences component was extended by adding their learning style and preferences on visited learning objects. Furthermore, the learner's preferences and learning style are automatically inferred from tracked usage data, collected from the learning management system database, based on web usage mining techniques and a literature-based approach. Once learner models are built, a hierarchical multilevel model based collaborative filtering approach is applied, in order to gather learners with similar preferences and interests into the same groups. On the other hand, the content modeling phase consists of automated indexing of all available learning objects within the LMS course. In the recommendation phase, the recommendation system first recognizes the active learner's knowledge component (i.e., his/her learning style and educational preferences) and then infers his/her short term usage history, considered as an implicit query, and represented by a vector of referred learning objects or a vector of relevant terms. Then, the recommendation engine progressively classifies the active learner using, first, his/her educational preferences, and then, a sliding window to determine the closest cluster or group of clusters, from which related association rules are extracted. Moreover, the recommendation engine submits the inferred implicit query to the index module in order to retrieve similar learning objects. Finally, the Top N recommended links are determined by combining collaborative filtering and content-based filtering.

Based on our review of the TEL recommendation systems above, one can identify several important and crucial aspects characterizing existing recommendation systems according to the proposed GML Framework description. Three main intuitive observations can be drawn first: (1) difficulties in understanding the organization and working principles of several existing recommendation systems due to their complicated original descriptions and lack of clarity in stating their internal and external components relationships, (2) several similarities and recurrences can be observed in their adopted strategies and applied techniques, and (3) many other unexplored key dimensions remain. The interpretation of identified aspects upon this analysis would help in highlighting the necessity to define a common and generic meta-level framework description for TEL recommendation systems, regardless of the related e-learning system, its vocation type, delivered items, low-level specifications, etc. This is expected to alleviate efforts to comprehend the operation of TEL recommendation systems, their fundamental organization, their features and components, and their relationships with each other and with the educational environment. In addition, this could initiate further research to explore new challenging directions, particularly, from an instructional point of view, and to design and develop TEL recommendation systems with open and evolved multi-featured architectures. A comparative analysis of the recommendation systems described previously, can reveal to the following properties:

- Most of the reviewed TEL recommendation systems use the collaborative filtering recommendation strategy, thus favoring the collaborative evaluation and exchange between users, under several types (ratings, annotations, comments, votes, implicit evaluation, tagging, etc.); while other systems rely only on content-based filtering, and the remaining systems apply some kind of hybridization strategy.
- Most of the user or content model representations are vector based. However, in some cases, an ontology representation is used.
- Several systems apply a data/web mining approach for the user/group and content modeling operations. In particular, clustering and association rule-based techniques seem to be recurring methods.
- Explicit student data harvesting (ratings, peer evaluations, comments, etc.) is still widely used in data acquisition.
- The domain model is built either using automatic indexing or manually, using concepts and an ontology representation. Yet, a few systems apply automated methods to extract item information from content and/or metadata.
- When it comes to the learning paradigm, more systems follow the model-based approach than the memory-based approach.
- Usage data, logging data, clickstream data, online interactions, ratings, evaluations, etc., are stored in an e-learning system database, rather than generic log files. The majority of the recommendation systems exploit this data via the data acquisition phase.
- In most cases, the reviewed systems deliver recommended links to learning objects; and regardless of their granularity, format or type, each system has its own terminology: learning material, learning course, learning activity, lesson, document, URL, action, web page, etc.
- The majorities of the TEL recommendation systems have a centralized architecture, and are closely dependent on the related e-learning system. Consequently, software properties such as portability, reusability, or interoperability with other systems are not considered.
- Most of recommendation systems deliver recommendations to a specific category of final users: students. On the other hand, teachers, tutors, or content authors, are barely considered as potential beneficiaries of recommendations, despite the increased interest of teachers and educational practitioners in using various types of e-learning systems, especially Learning Object Repositories (LORs) for search and retrieval of educational resources. This is also the case for users with disabilities.
- There is not yet a deep understanding of the context data representation. Indeed, some authors consider solely such data in the case of physical conditions and computing characteristics at the user or server side. Meanwhile, other authors assume that context data must cover all exchanged data around users, and

propose a specific framework to represent such context data, while yet others differentiate between learner context (design and profile) and system context.

So far, there is no effective well-known TEL recommendation system which is used commonly within e-learning systems. Existing systems are neither portable nor adaptable, and they are generally based on a specialized predefined recommendation strategy. Moreover, most educational recommendation systems, though named "educational," still do not take into account the necessary pedagogical considerations, neither through the modeling, nor the recommendation phases, except for a few attempts that are still confined to research labs.

9.5 Conclusion

There is no doubt that the TEL recommendation systems field constitutes one of the most fruitful and active research niches in personalized e-learning. However, after a decade of research in educational recommendation systems that has given rise to systems that adopt different approaches, strategies, and techniques, we notice that most of these systems are still confined to research labs. To this extent, we think that it is time to make a comprehensive inventory and reflection of what has already been done, in order to compile their benefits and address the obstacles hindering a wide and common use of recommendation systems in e-learning, as has successfully been the case in the realm of e-commerce.

Having, generally, a common foundation deduced from the analysis of their functioning, organization, and features, TEL recommendation systems' design and development need to be described and understood within a well-defined, unified, and comprehensive framework, according to which, their analysis, survey and comparison can be done more accurately and efficiently. In this perspective, we proposed, a generic meta-level GML Framework for a common description of TEL recommendation systems. Then, we presented an analysis of some existing TEL recommendation systems with respect to our defined framework. This analysis has led to the identification of several critical properties of TEL recommender systems, as well as challenges that need to be taken into account in further research, development, and validation of these systems.

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Chapter 10
Use of Dashboards and Visualization Techniques to Support Teacher Decision Making

Alex Mottus, Kinshuk, Sabine Graf and Nian-Shing Chen

Abstract Learning environments have evolved rapidly in the past decade growing the encompass Learning Management Systems, rich digital content, and multiple forms of access including new mobile technologies. In the process students have moved further and further away from traditional classrooms where teachers have historically provided face-to-face learning content and supports. Digital information sources have vastly exceeded the capacity of any one content specialist but learning supports have been harder to establish in a decentralized education model. Communication methods have become moved to asynchronous types in the form of e-mail, texts, and discussion forums. This has left teachers with a serious disconnect that has not, as yet, been reconciled by technology or methodology. This indicates a gap which learning environments and teachers' alike need to bridge before ubiquitous learning environments can fully achieve the goal of successfully meeting learner needs outside of the classroom paradigm.

Keywords Ubiquitous learning · Interactive dashboard · Teacher support system

10.1 Introduction

The world has undergone radical changes in the past 100 years as new technologies have reshaped the face of the culture, industry, and even human interaction. Strangely over the same period, educational institutions, and teaching mechanisms have remained largely unchanged until relatively recently. With the advent of the

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Internet combined with an explosion in the prevalence of home computers, personal devices, and readily available network connectivity the very bedrock of education has sustained a significant shift. In today's world, educational opportunities abound both in digital and physical formats that can be utilized at any time under a vast range of circumstances. Education is no longer bound to a physical location as handheld network devices have become commonplace, allowing students to not only access, but in turn, create content that can be interacted with directly and socially. This has created a fully ubiquitous learning environment which students are now immersed in by means of devices that are available 24/7. This has been reflected in educational environments as hybrid courses which combine online and real-world aspects have quickly become the majority of post-secondary offerings (Li 2009). The introduction of real time connectivity has also added location and media supports that can tie directly to physical elements unlocking the full potential of real-world learning objects. This is a dramatic departure from classroom-based education which dominated the last century where teachers led content delivery as well as learning support. In a current scenario, learning artifacts can be found in anywhere at the tap of a finger providing students with more choice than they could ever effectively consume. Ironically, this has become part of the problem as educational opportunities can become overwhelming by their sheer quantity. It is also notable the other key role of teachers, that of providing learning support, has been compromised in most ubiquitous learning environments. This stems from the fact that teachers and students no longer need to share the same physical proximity as learning has moved outside the classroom and, in extreme situations, even around the world. This means that teachers can no longer rely on direct observation to monitor students and identify learning challenges. Instead it is possible and even probable, that a teacher may not be aware of what their students are doing at any given time. While that may not be an issue on a regular basis it can create serious impediments when learning problems arise. An example would be a student who has been unable to develop a competency because they can't find a suitable resource or explanation. Normally they would simply ask a teacher for help but in a distance or distributed learning scenario that teacher might not be available or the student might not know how to make contact appropriately.

The absence of teacher support is compounded by the fact that ubiquitous learning situations also tend to have a much higher student to teacher ration making instructional time much or precious. In order to mitigate the challenges provided by such a situation it makes sense to leverage the skills which teachers have developed over the years. However, to do so, they need some way to reconnect with their students in a timely and effective manner that can provide a teacher with operational knowledge as well as learning options. This challenge is further complicated by the learning process itself. While many automated systems take a transactional approach to problems that can be extremely difficult to accomplish with knowledge acquisition. The primary problem is that learning is by its very nature an internal process, meaning that it has to be evaluated by external methods. This can be prone to errors created by the metrics, tools, and methods used to measure knowledge levels. Learning is also seldom incremental meaning that simply spending time on a task is no guarantee of success. Instead learning can often occur in stops and starts which may not correspond to any predefined pattern. This suggests a reliance on constant monitoring and the evaluation of educational processes in order to properly support and enhance student learning.

One possible solution to the problems outlined is to develop a tool specifically for teacher use. This would capture and display student information in a way that is accessible and meaningful. This includes the need to aggregate complex data structures in a way that is friendly and easy to use. Visualization techniques have been used extensively to provide supports to domain specialists who may not have particular expertise in information technology (Lavrac et al. 2007). That type of approach has been evidenced in commercial and scientific tools which have rendered large amounts of decision support information in dashboard formats. Likewise this type of tool has been used in Learning Management Systems (LMS) and Student Information Systems (SIS) but on a very basic level. Normally these tools focus on specific metrics that are directly tied to the application they support. In this discussion, a dashboard approach would need to illustrate a global environment by consuming and displaying educational information regarding as many aspects of student activity as possible. Finally, it would need a recommendation component to provide teachers with options, drawing on possibilities as broad as those their students are utilizing in learning. In this way it should become possible for ubiquitous learning to be effectively supported while students enjoy all the advantages of rich and infinitely diverse educational choices.

10.2 Review of Learning Supports

Before starting to explore tools and other solutions it is important to take a look at the various options that have been researched to provide students with supports in today's learning environments. These range from automated approaches to those based on examining information sources to explore learning activities. In most of these instances, teachers or educational researchers take an active role in development but have varying degree of interaction in the actual use of learning support methods. An interesting contrast in much of this research has to do with whether it seeks to replicate or support teacher function. Work in this area is seldom black or white but instead exists along a spectrum between the two extremes. This provides a good set of different results taken from the various methods.

One of the leading areas of research aimed at automating teaching activities revolves around the work on Intelligent Tutors. This type of mechanism has been utilized in a number of different domain areas to deliver educational services on demand without the need to have a teacher present. Generally, Intelligent Tutors have been shown to result in good success rates with positive feedback from students (Mitrovic 2006). They are normally built with the assistance of domain specialists and educators to try and replicate the learning process as closely as possible. This style of learning support has the advantage of providing students with near instant feedback and by supplying tools for dealing with previously identified problems. The challenge of these systems is that they tend to be very complex requiring extensive programming to create and maintain. This has proven very time consuming even with experimental work on automated interviewing methods for capturing knowledge and skills from human domain experts (Hwang et al. 2011). They are also domain specific meaning that they are focused on specific knowledge areas making them difficult to modify for other purposes. They are also built for specific problems and scenarios meaning they may not be able to adapt to new learning challenges. Other methodologies such as using constraints and fuzzy logic to make ITS systems more generic have simplified the programming but not enough to make them realistic on a large scale (Mitrovic et al. 2007). While they may be paired with more traditional teaching methods this still leaves a gap in that they are difficult to modify meaning that, even if teachers identify new approaches, they are unlikely to be able to implement them.

Another automated approach comes in the form of learning companions which are a more social tool that seeks to pair learners with an automated system. This methodology has been shown to reduce learner confusion in virtual environments resulting in better outcomes. These systems also seek to address the social aspect of learning as they provide individual students with a source of communication that they can use to develop new ideas (Wu et al. 2012). These can exist in a number of different formats as the companion may function as another student, a teacher, or even as a friend. These different variations provide flexibility in terms of approach as the can be used to evaluate as well as assist students. While they are certainly useful, there are limitations to how much impact they can have on the learning process. In some cases they are used as a supplementary component for modeling and ITS approaches (Limoanco and Sison 2002). They provide a supplement to an existing program of study adding a social component which can be available any time a student enters the "system". Once again the programming involved in these tools is specialized and in most cases would be beyond most teachers' ability to customize. This creates another situation that makes adaptation difficult and requires the use of some sort of human intervention to handle unique scenarios.

The automated tools can make use out of student information but the purest form of that research comes from Educational Data Mining (EDM) and Learning Analytics. These fields leverage previous research in scientific and business data mining but take an education centric focus to develop techniques specialized for working with student and learning information. Research has shown that these types of systems have been highly effective at evaluating student progress and determining what content best suits a learners needs (Hatzilygeroudis et al. 2005). EDM and LA initiatives have also developed a number of different algorithms and heuristics for extracting complex data patterns from vast repositories of information that would otherwise be nonsensical. In many of these cases, the sheer volume of information can be overwhelming rendering it effectively useless. This is a significant problem given the prevalence of information now available from SIS, LMS, and web logs representing all kinds of student activities. From these sources rich outcomes can be drawn such as developing learning styles and preferences which can be used to customize and delivery educational content. Unfortunately, these tools once again represent a high degree of specialization requiring training and years of practice to use effectively. In the case of teachers this detracts from instructional time and forces them to develop an entirely new skills set to simply access the information. Instead it makes much more sense to allow them to consume the outcomes or develop questions that can be sourced by other tools or specialists. To make these outcomes more useful it also makes sense to render them in a way that is easier to understand and manipulate. Elements of LA have focused on this problem turning to visualization techniques to provide information in a way that can easily be interpreted and used. Like the dashboards seen in the LMS they do tend to be more localized focused on specific outcomes rather than a holistic approach. This suggests that while the approach has considerable value there is still work remaining to be done to deal with a fully ubiquitous scenario. There has also been research completed to support the belief that there is general a need for the increased use of visualizations in data analysis (Ali et al. 2012).

As mentioned in the introduction one of the challenges of working in distributed or distance learning environment is the ability to gain awareness of student activities. This is perhaps the most critical for those students in need who have either encountered a learning difficulty or have ceased to be engaged. Ideally any such process would locate students before reaching a critical point at which a student begins to fail or ceases to be engaged. An example of work in this area was provided by the Signals project at Purdue where researchers explored student data to attempt to identify those who were at risk (Arnold et al. 2010). Likewise Macfadyen et al. provided a proof of concept for a similar system in order to find students with risk attributes (Macfadyen and Dawson 2010). Both of these cases focused on a fairly Boolean concept but one that could be invaluable to a teacher trying to prioritized the need levels of their students. In turn this suggests that a high-level overview of student information could prove valuable by quickly supplying information. This has been expressed in the form of dashboard tools which have proved useful for administrative leaders as the make key operational decisions (Lavrac et al. 2007). Dashboards have been utilized with great success in business, health case, and operations to both consolidate and display datasets. Given the complex and dynamic nature of student information it would seem reasonable to a similar approach would be helpful to teachers monitoring and assisting students who they might have no direct contact with.

In all of these examples educational expertise is critical to developing a solution for supporting student learning. While automated approaches provide excellent supplements they essentially replicate teacher function which can be very complex and difficult to achieve. Instead a hybrid solution seems more likely to succeed at least in the short team. In terms of data mining, there are endless possibilities but this information must be accessible and usable to be able to make a different in a real time learning context. Thus, a teacher support tools seems logical to allow teachers to find and support students using a variety of content and supports. The ubiquitous nature of learning makes this even more necessary to avoid simply overwhelming teachers with details and making decision processes impossibly complex.

10.3 Teacher Tools Requirements

While a formal set of requirements are difficult to ascertain at this point it is possible to draw out high-level details that can be used to construct a prototype design. The literature review has already identified some important trends that have driven research in student learning and supporting educational mechanisms in a non-classroom environment. Specifically, these would include providing timely support and refining information for use in customizing learning environments. In some ways these two requirements can be at odds with each other as one is immediate while the latter can require large amounts of processing time to achieve the appropriate outcomes. This suggests a hybrid strategy which can split information into different categories which can be handled differently but in conjunction with one another. In other words, information being displayed can be real time or aggregated but related by a common thread such as student preferences. In this example, immediate data may show what a student is currently engaged in but in the context of their preferences, a determination can be based on large collections of aggregated data.

Awareness of student states or conditions is most commonly expressed by risk assessments which determine whether or not a specific learner needs immediate assistance. This concept has been explored in previous research (Arnold et al. 2010) but not necessarily in terms of a ubiquitous environment which presents a highly malleable scenario with numerous inputs but potentially a lack of formal structure. This suggests the importance of context to give teachers not only just the "what" but also the "how" and the "where" their students are experiencing difficulty. This also needs to be able to drive navigation to allow teachers to access additional details and even recommendations to assist with their teaching practice. This speaks directly to the need to provide teachers with relevant information but in a timely fashion that can be utilized immediately. This can be seen as similar to automated approaches which seek to provide immediate feedback but those are based on defined problems and learning situations. In the proposed case, the teacher can act as a mediator who can use previous experience and knowledge to evaluate student needs in real time and provide solutions. This makes support mechanisms much more flexible as they no longer need to rely on predefined scenarios which have been programmatically rendered.

Once, a specific student has been selected it is critical that a teacher can get a full picture of what that student is doing, what environment they are in, and what resources and problems they are exposed to. This implies a highly complex dataset which lends itself to the use of visualization techniques to make information more accessible and efficient to digest. This needs to communicate a summary of the potential factors that a student can encounter in a ubiquitous learning environment. Location data and a cataloging of the learning objects and opportunities in a geographical area represent a new challenge and highlight the absence of physical contact between teacher and student. Specific student information about learning styles, preferences, and knowledge levels begin to augment and replace the direct evaluation processes that are a normal part of classroom education. This can then drive recommendations by providing a context which allows teachers to understand a student's needs and make informed decisions leveraging their own expertise in combination with relevant data.

A complementary approach is the ability to search and determine patterns based on collective data which involves entire classes or identified subsets. In this type of situation, a teacher can search for outliers or unique patterns that may not have been flagged by the system. This allows the teacher to use their own knowledge and expertise to drive investigative processes which locate student issues and lead to improvements in educational delivery. For this approach, information needs to be common to the group in terms of their behavior, progress, or results. This is to allow for effective comparison of larger groups which can the subsequently be used to create a subset to allow teachers to draw out smaller working groups or specific individuals. The flow from large class groups to smaller groups sharing certain attributes needs to be seamless allowing teachers to once again move quickly and efficiently between different functional areas. These would need to be treated slightly differently as summary visualization tend to focus on trends and larger patterns where smaller groups can use techniques to directly compare students in groups of 10 or less. This is to avoid providing overwhelming data which can hide key points within larger bodies of information. From an operational point of view, trends and status updates are both important aspects which have provided tool users with a real time awareness of where the information they are monitoring is going (Mahendrawathi et al. 2010). The identification of exceptions has also proved important as those elements which stray outside the norm can offer quick flags as to what is going wrong or identifying new patterns that may be emerging (Sachin and Vijay 2012).

Due to the variability of such an environment it also makes sense to allow teachers the ability to customize and manipulate visualizations in order to meet as broad a range of possibilities as possible. This still needs to be done within a clear and concise, point, and click interface which can easily be learned based on transferable skills from other applications. While this environment puts a high emphasis on data use and manipulation the purpose is to create an abstraction between data consumption and data mining construction. This means that the programming around data aggregation and defining useful patterns is out of the scope of this discussion even though it is critically important. Instead an optimal situation is portrayed in which information is readily available which can be manipulated with a standardized interface.

10.4 Development Environment

As the support of teachers turns to technology considerations there are a range of different possibilities to consider. Many dashboards are simply add-ons to a larger tool which they directly support. For examples, most LMS have a dashboard component which has been built with the same programming language and architectural concern patterns. Since, the proposed solution is ambivalent toward specific tools it becomes much easier to make choices which support ease of use, open access to technology, and the ability to easily change or modify toolsets. In the context of a ubiquitous approach, it is logical to take a community approach which would allow researchers and practitioners from any area to utilize a final project. These ideals promote a source approach which provides full access to both source code and documentation. As with many LMS it also suggests a web-based approach which is platform independent but with a focus on selecting industry standard and community supported toolsets. To this end, the use of HTML5 and JavaScript-based technologies makes excellent sense as these areas represent the natural evolution of Internet technologies in a format that is accessible to developers and users alike. A quick survey of the open sources community also reveals a plethora of JavaScript visualization libraries that offer a broad range of techniques and functions (Google Developers 2013; Graph Visualization Library With jQuery—Arbor 2013; Introduction to Using Chart Tools 2013).

10.5 Technical Details

In terms of specific tools, there are some clear choices that can be used to form the backbone of the development environment. From a data repository perspective there needs to be an intermediary location which can be used to refine data elements. This approach was selected to reduce the real-time overhead needed to present data elements drawn from data mining activities. Previous research has explored this topic looking at data structures that can be used to collect information from different sources (Yang et al. 2010). In the example provided here the Personalized Adaptive Dashboard (PALD) illustrates this idea and has been used as a local repository to house information suited toward a dashboard function

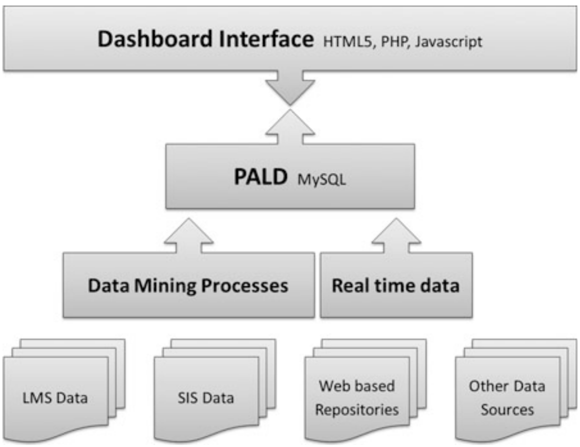

Fig. 10.1 Architecture diagram

(Fig. 10.1). The use of PALD can be expressed from an implementation perspective by either MySQL (Oracle Corporation 2013) or PostgreSQL (The PostgreSQL Global Development Group 2013) offer robust solutions that can be used easily at a very low cost.

Web servers are also freely available although the Apache Foundation offers one of the most commonly utilized which comes with a number of plug-in options including PHP (The Apache Software Foundation 2012). The latter is an important consideration as it offers a highly flexible technology option for manipulating data and providing dynamic content. While HTML5 and JavaScript may be better suited for a final implementation, PHP can be used accelerate the prototyping process based on its ease of use. Finally, from a visualization perspective three leading candidates can be drawn from the rich JavaScript library community to provide mechanisms for rendering information in highly salient manner. Of these the Google API emerges as the most suitable for prototyping as it contains excellent documentation, a rich collection of functions and the ability to manipulate data in a modular fashion which can be shared between objects. With these tools at hand it is possible to engage in a functional prototyping exercise to illustrate what elements an educational decision support tool could and should have.

In terms of actual construction, there is an interesting dichotomy between the need for elements which are standalone and yet interrelated. Discrete data collections related to a specific subject such as knowledge levels would need to be displayed in such a way that they could provide insight on their own. At the same time, it should also be possible to connect to visualizations of other data elements such as learning object preferences and learning styles. In a highly mature example it would be ideal to be able to select a knowledge level and automatically subset to the learning objects used to develop that understanding. One way to approach this type of functionality is based on a "widget" style of development where individual visualizations can be built as unique modules in terms of function and interface. It is possible to add and remove these items from the parent display and related them to the other widgets based on underlying data. This provides a highly flexible framework which can be used to display any number of items which can be customized in terms of selection. Thus, widgets could be built individually and then made available to larger dashboard by means of dropdowns or other screen management functionality.

10.6 Proposed Model

In terms of creating a working example a tabular interface provides a mechanism for cleanly dividing functions while simplifying navigation and workflow. Based on the requirements outlined earlier, four primary areas can be highlighted as providing a fundamental functionality. The first would be the at risk area which identifies students at risk and their categorization, next a focus on details specific to individual students, third information on the class cohort as a whole and finally a tab focused on specific groups extracted from the class. These form complementary areas which can flow from one tab to another as a teacher selects information and gains insights to enable them to make educational decisions.

The first case focuses on an “at risk” or overview tab in which information needs to be very timely and organized to draw a teacher’s attention quickly. It also has to give them a high-level context of where students fit within a class. To do this different visualization elements have to be combined to provide a united interface which can drive follow up actions. The first visualizations need to organize students “in need” by category; in the example below (Fig. 10.2) students are flagged based on low social activity and prerequisites. There is another complementary grouping based on students who have stalled in their course work. A similar visualization also lists students who have self-identified by requesting help from the teacher along with the question or issue they are facing. At this point the teacher should be able to prioritize and focus their attention on a specific subset of students. This makes them more efficient and allows them to utilize the scare resource of instructional time in the most effective way possible. This is further enhanced with a real-time component which lists students as they become active or inactive in their learning environments. In the ubiquitous scenario proposed this could involve logging into an LMS, tweeting, or even using location technologies to recognize when a student enters a study area or physical learning object repository like a library. This gives the teacher an awareness of whether a student in need is

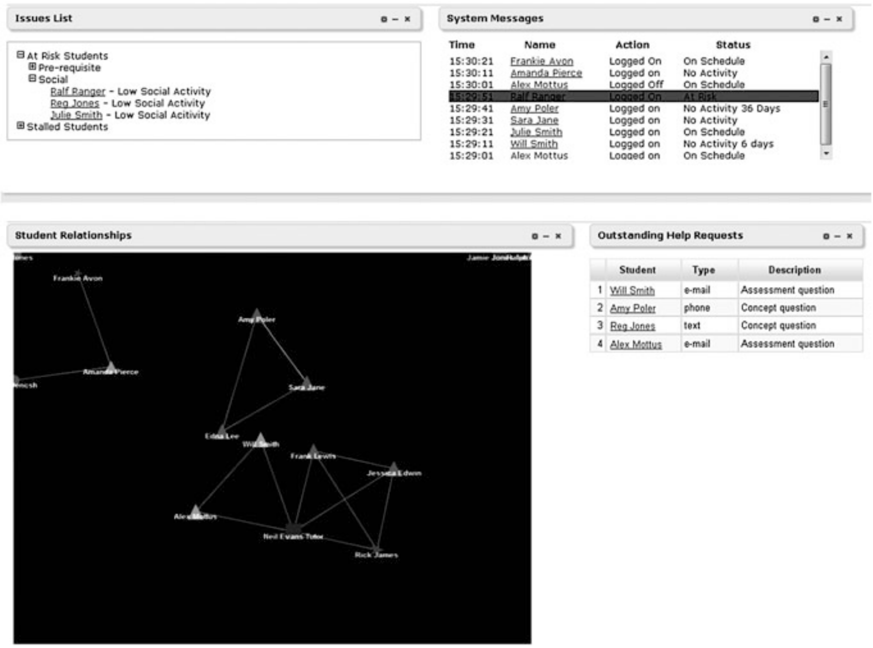

Fig. 10.2 Screen design for an overview tab

accessible. This real-time logging feature provides additional visual cues by the using the color (red) to draw the teacher's attention when an "at risk" student becomes active. Finally, a node diagram is used to aggregate and relate a number of different elements to provide contextual information across groups of students in the class. This shows relationships as well as high-level attributes such as at risk categories and current performance in the class. In this way, the teacher can gain a high-level awareness at a glance. In all visualizations the student names are clickable to drive navigation and give the teacher the ability to quickly select individual students. In this manner the teacher can quickly identify, find and select a student so they can take immediate action.

In the second tab, the focus is on specific students where details can be aggregated and collected to provide insights on demographic, preference, location, and performance information. Student selection could be based on activities in other tabs such as choosing a student at risk or simply by working through a list of existing students examining traits and attributes. This supports workflow between tabs so that teachers can very quickly move from discovery to investigative to decision-making tasks. This is an important as factor as students in a ubiquitous environment are only available sporadically for direct interaction. In order to capitalize on these moments the teacher must be able to move quickly and efficiently between different activities. Once the teacher has selected a student they can be shown a data portrait of the student which gives them a much higher awareness of the student and their activities (García-Solórzano et al. 2012). Different elements can be observed in combination to show who students are, what they are doing, and how they prefer to learn (Fig. 10.3). By showing details like learning styles and preferences, teachers can determine which resources best suit a student's specific need (Graf et al. 2008). Location information can also indicate if physical learning objects or learning environments exist in the immediate area. These form the basis for providing supports and intervention opportunities from a content perspective. As mentioned earlier, ubiquitous environments provide a wealth of learning opportunities but not necessarily the details necessary to select which ones would best suit a certain learning situation. In this situation, the teacher can begin to use their own expertise to sort through options in the context of student information to form intervention plans and supports. Another benefit to location information is to be able to see whether other students and tutors exist in the area and who might be able to work collaboratively. This provides the ability to form social supports and groups which can augment learning and provide a richer experience. In terms of learning achievement, knowledge levels can be used to create concept maps of student's understanding, both in terms of performance and relating concepts. All of this supports a simple example of a functional recommendation mechanism which provides the teacher with an awareness of what options are available and allows them to select and provide feedback on how those actions work out. In this manner, the environment moves beyond information display and begins to create and collect its own actions for later feedback and support of decision-making processes.

The third tab takes a more exploratory view of student data by looking at classes as a whole. This collection of visualizations seeks to show different groupings

Fig. 10.3 Screen design for student information tab

which comprise the full cohort of students. In order to avoid too much diversity, the groups of students are displayed based on distinct classes which can be selected from a drop down list at the top for the tab. This is helpful in situations where teachers may be supporting a set of different classes. The introduction of the “class” dataset also allows a teacher to use their own background and experiences to draw out specific patterns and find outliers. In the case of the overview tab, at risk students are brought to the teacher's attention but at the potential exclusion of other individuals who may also require assistance. Like the example of the Intelligent Tutors there are a fixed number of options which can be programed into the system. Thus, it makes sense to provide a flexible means for a teacher to be able to explore and identify groups and individuals based on their own observations. Assessment and progress information figure prominently as these are common items which can easily be compared and contrasted (Fig. 10.4). An example of a simple visualization would be to compare multiple assessments across different cohorts using graphing techniques (Friedler et al. 2008). Taking this one step, further each element, whether a piece of a pie chart or a block in bar diagram, becomes clickable to allow a teacher to quickly select and preload that group for further analysis in another tab. This creates easy navigation by surfacing distinct groups. Scattergrams also show student grouping or clusters which can be used to highlight outliers which form distinct plot points that can be clicked on to select specific students for the analysis described in the previous (student) tab. In this way, the teacher can choose how specific to get in terms of the number of students they want to analyze. Map visualizations also provide an excellent overview, especially in cases where students may be located in a variety of different cities and even countries. This can very quickly illustrate the diversity of a class and the challenges that students may face working with one another. One of the other potential challenges of manipulating this type of scenario stems from the fact students may be starting at different times during the calendar year. There are many examples of courses which are open intake which can create distinct cohorts within an individual class making it important to observer the rate at which students are proceeding through course materiel. This creates another opportunity for developing subsets and allowing teachers to observe different learning patterns.

The final tab focuses on groups of students who have been selected from the class visualizations in the previous tab or from a dropdown which displays predefined sets of students. The latter could be project groups generated by class activities who are working on the same assignment or subsets of students who are collaborating on various discussion groups. The differentiation of these two groups is quite important as the ability to provide recommendations can be a very intensive task from a computer processing perspective. That means it is extremely difficult to generate any sort of recommendations for Ad Hoc groups. Instead recommendations are only provided for predefined groups which can be analyzed in advance to generate solutions to potential learning problems (Fig. 10.4). In both cases the groups can be summarized as the same raw data can be leveraged to show progress, understanding, and learning preferences. In this way, a teacher can observe and work with groups collectively or once again drill down one more layers to work specifically with individual students. While this tab is quite similar to the class tab, it allows for greater detail and comparison in order to further analyze student activities and behavior. The bubble chart example in the top right corner (Fig. 10.5) illustrates this quite effectively as it combines a variety of different elements such as performance, progress, and learning styles. This is somewhat similar to the node

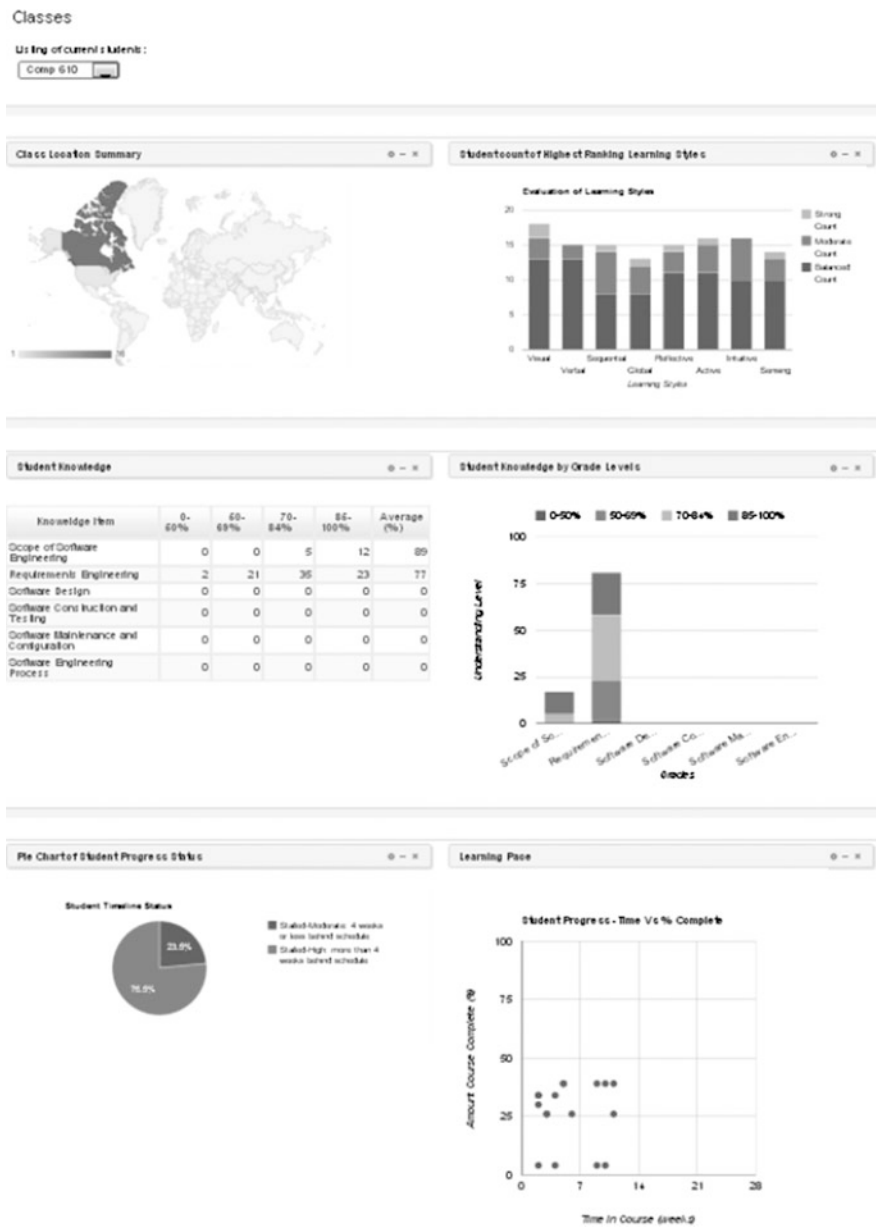

Fig. 10.4 Screen design for a class tab

diagram presented in the overview tab. The goal of both these visualizations is quite similar as they provide a number of attributes which can be observed quickly in order for a teacher to gain understanding and make determinations about student need and potential solutions.

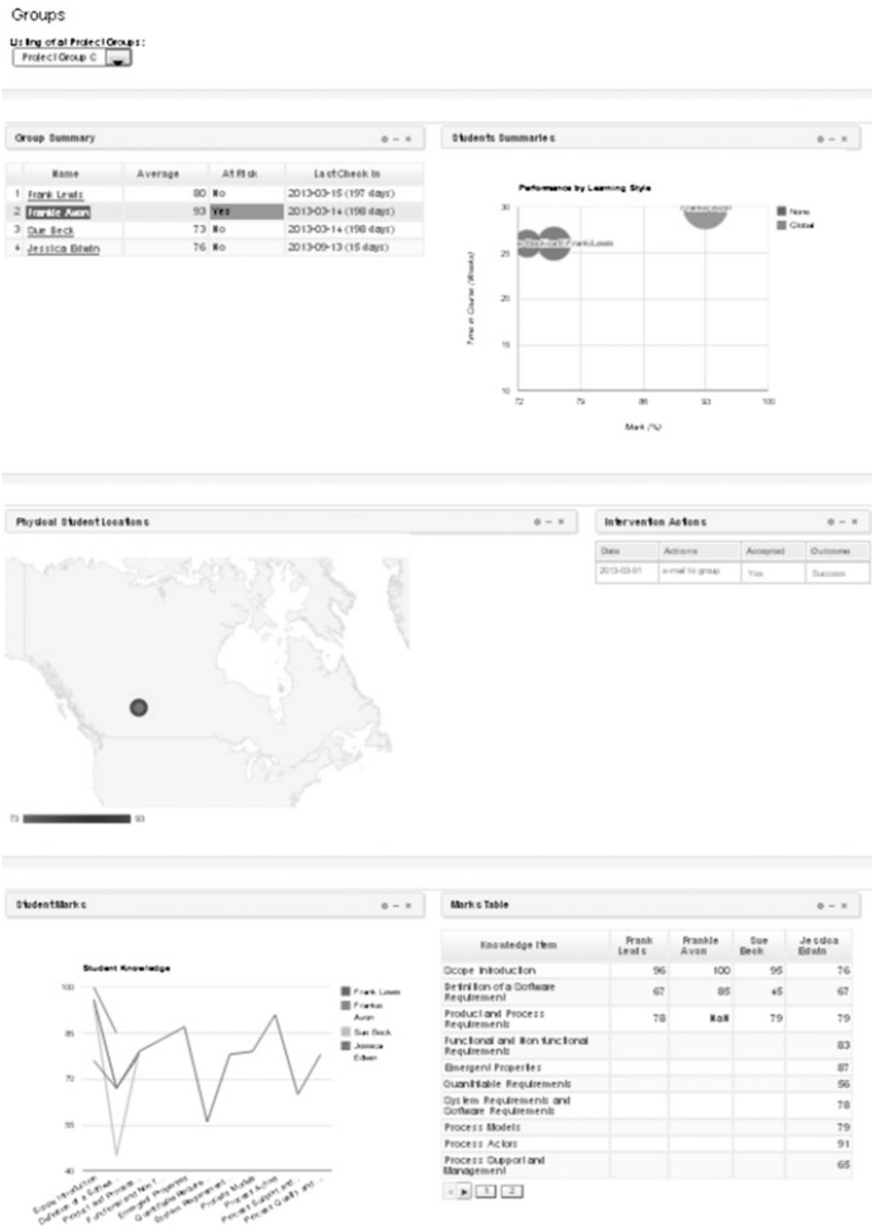

Fig. 10.5 Screen design for a student groups tab

The proposed interface provides a working example of how a teacher might observe and work with information to find and assist students. It does this from both a system generated perspective and from a user driven mechanism which allows teacher to locate and generate the own groups based on personal experience and knowledge. This provides the best of machine and human intelligence by leveraging the strength of each. Workflow is designed to jump between tabs as teachers may need to move quickly from investigation to decision making as students come to their attention. This is aimed at maximizing teacher's time which become diffused in a ubiquitous learning environment. It should also allow them to make better decisions by providing contextual information which can focus on group and individual student's needs with the specific details of their learning scenarios.

10.7 Discussion

In examining student learning, a number of elements have emerged. While new supports have been developed to assist students there is still no comprehensive mechanism that can handle a fully ubiquitous environment. This can be problematic due to the complexities of the learning process and the vast number of options that students are presented with. Automated systems are already challenged when it comes to dealing with new scenarios and a variety of different domain knowledge sets. Likewise data analysis techniques are also constantly evolving to deal with problems related to managing vast data sets coming from a variety of different sources. The current trend is toward collecting more information about location and interaction details as new and more effective devices become available and are used by students and teachers. Managing all of these items suggests the need for a different approach which can leverage human intelligence in combination with machine. The proposed solution in this chapter takes this position as it demonstrates how a tool could be created to display information and assist a teacher in real time and for investigative purposes. This leverages the work done in automated and data analysis systems, while reintroducing the teacher as a critical agent in the learning process. In this situation, a teacher can utilize the benefits of highly complex components without requiring additional training or skills. The use of visualizations facilitates this by rendering information differently and in a range of alternate methods. This allows for customization which can allow for differentiated teaching as well as differentiating instruction methods. It also has the side benefit of increasing human interaction within ubiquitous learning by increasing the opportunity for teachers to interact with students in their classes. This stems from awareness as teachers can access information in order to simulate a face-to-face encounter which in term provides the ability to make connections. This can also provide an important validation mechanism for confirming automated actions which have generally been locked in machine driven systems (Mitrovic et al. 2007).

One of the other trends in technology as whole is the concept of integration which relates to systems becoming increasingly linked with one another. As this happens it also increases the complexity level as more and more factors begin to interact with one another. This draws a strong parallel to ubiquitous learning where different learning objects and systems are being to be drawn together to create a richer and more effecting educational environment. Much as with Executive Management Systems (EMS), educational decision making needs to be supported in order to make it accurate and flexible in the face of increasingly complex problems. As students encounter problems individually or collectively, strategies need to be implemented which can solve learning difficulties and provide resources that address a variety of challenges. This has the advantage of making teachers aware of what options actually exist for intervention or solution to problems. In the same way that a teacher may be unaware of details about a student, they may also be unfamiliar with the different supports that are in place, especially when learning environments become highly technical. In many cases, teachers are functioning as consumers of services themselves rather than creating different tools to help their students.

One of the key aspects of introducing new tools is that they become generators of information themselves. That is particularly true in a decision support system where choices can be captured in the context of specific problems. This creates the opportunity for creating an incredibly sophisticated source of data which draws on the expertise of teacher as they work with the learning process itself. This is an important factor as learning occurs in relative isolation within the mind of each student. There is really no way to directly measure it as a process as it must be implied from behavior or by means of assessment tools which may be imperfect or potentially create impediments. Since, the process of evaluating leaning is deductive itself contextual information is invaluable as it generates scenarios which can be compared and contrasted. This mapping of complex patterns can provide significant which feedback into the decision-making cycle to help newer teachers as well as improve systemic suggestions. While it may never be possible to fully map learning as a discrete activity it should be possible to cover the range of potential outcomes in a meaningful way. As this body of knowledge develops ubiquitous learning environments should become more effective as the combine limitless learning options with supports that can recognize and assist with the challenges faced by individual students.

10.8 Conclusion

Education as a whole has undergone huge transitions in past few years. The introduction of technology has allowed students to turn their everyday surroundings in a wealth of learning opportunities with which they can interact and evaluate for themselves. As they engage with different systems and learning objects, a wealth of information is captured providing the ability to analyze interactions in great detail and extract complex observations about learning styles, preferences, and other habits. The goal is to use this information to provide a learning environment which can be adapted to the individual student and their needs. Unfortunately this has led to a number of challenges which can be identified by the lack of supports generally seen in these environments. Automated systems have yet to fully encompass these learning environments and mechanisms for utilizing information generally require complex skills sets outside of normal professional training. In order to bridge this gap, teachers need to be supported and allowed to function effectively in ubiquitous learning environments so that they can gain operational knowledge and the ability to make decisions that can influence student learning. This suggests the need for a tool which can aggregate and display data in a friendly way that can easily be utilized and then applied to specific problems in a decision-making scenario. To do this visualization mechanisms have been proposed in a unified interface to supports the teacher even as they support students. This provides a meaningful way to address complexity in the learning process and handle problems discretely. This provides one potential solution for unlocking the full potential of ubiquitous learning environments and allowing students to follow their own learning which being fully supported and encouraged.

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Author Biography

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Chapter 11
National Palace Museum Adventure—A Mobile Educational Role-Playing Game for Museum Learning

Chun Chang, Maiga Chang and Jia-Sheng Heh

Abstract Most of the classroom learning is teacher-lead which students cannot observe and touch learning objects in real environments. Different from the traditional learning, the informal learning is student-lead and takes place outside of the traditional classroom. Students can choose learning objects which they are interested in at any time and in any sequence they want (Lelliott 2007; Tough 2002). When students do informal learning, they must be so thoughtful in order to obtain some knowledge and skills (Clough et al. 2008). Museum tour is informal learning, covers knowledge in variety of domains such as historic, cultural, and art (Nikolaos et al. 2008) and this research chooses museums to be the learning environment.

11.1 Introduction

Most of the classroom learning is teacher-lead which students cannot observe and touch learning objects in real environments. Different from the traditional learning, the informal learning is student-lead and takes place outside of the traditional classroom. Students can choose learning objects which they are interested in at any time and in any sequence they want (Lelliott 2007; Tough 2002). When students do informal learning, they must be so thoughtful in order to obtain some knowledge and skills (Clough et al. 2008). Museum tour is informal learning, covers knowledge in variety of domains such as historic, cultural, and art (Nikolaos et al. 2008) and this research chooses museums to be the learning environment.

There are three issues needed to be taken into considerations on museum learning. First issue is mobility issue. Students in an informal learning environment

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like a museum always keep moving around and learn relevant knowledge. The learning devices that students use for museum learning need to be able to be carrying by the students and to be capable of providing students learning content for different learning objects from time to time. Both of personal digital assistant (PDA) and Smartphone are ideal devices. The second issue is motivation issue. How can we make museum leaning interesting and get students motivated? Embedding game elements into museum learning seems a good solution because games are fun, enjoyable, and beneficial to learners (Ardito et al. 2007). This research tries to develop a game to give students immersion experience while playing the game and to make them learn knowledge implicitly during the game-play. The third issue is activity design issue. How can we design personalize activities for students according to the learning goal they choose? This research analyzes the relationships among the artifacts and its embedded knowledge in a museum and designs an activity generation method accordingly.

A mobile educational role-playing game called National Palace Museum Adventure has been implemented and a pilot has been conducted to evaluate the effectiveness of doing informal learning in the museum via the game-playing. The results show that the game does engage students doing learning activities in the museum continuously and help students learn the knowledge embedded in the artifacts.

This chapter is organized as following. Section 11.2 first reveals the relevant literature of informal learning and mobile learning; then goes through the theories like rough set and information theory which can be used for finding the relations existed between artifacts and knowledge and storing learning contents; at the end, talks the procedures of activity generation. Section 11.3 explains the game design includes the roles the students can play as and the interactions happened between the student and the NPC in the game. Section 11.4 talks the game's architecture and the game-play. Section 11.5 starts with hypotheses and the pilot design, followed by the data analysis and findings discussion. Section 11.6 makes a summary of the research; discusses the pros and cons of the research according to the experiment results; and, finally plans the next steps for the research.

11.2 Making Informal Learning as Game

11.2.1 Informal Learning and Museum Mobile Learning

Many researchers have found that it is very difficult to define informal learning due to the informal learning involves many conceptual and methodological challenges (Lai et al. 2013; Hofstein and Rosenfeld 1996). Eraut (2004) argues that the informal learning is different from formal learning and emphasizes that suggests greater freedom for learners. Other researchers further argue that informal learning is being open-ended and free choice, intentional and interest-based, a self-directed and learner-centered, non-assessment-driven, and non-qualification-oriented endeavor (Hofstein and Rosenfeld 1996; Csikszentmihalyi and Hermanson 1999; Eshach 2007; Laurillard 2009).

Table 11.1 Difference between informal and formal learning

Informal learning	Formal learning
Voluntary	Compulsory
Intentional effort	Unintentional effort
Non-measured	Measured

Informal learning may happen at anytime and anywhere, is a learner-lead pedagogy. For example, students in a museum can choose to take a look at the artifacts which they would like to understand and know more (Lelliott 2007). Taking a course in traditional education setting as an example of formal learning, teachers must prepare materials and syllabus depending on their teaching styles. Hence, formal learning is a teacher-lead pedagogy (Folkestad 2006). Lelliott (2007) argues that formal learning is a structured educational system and students must get tested after learning. Moreover, students are asked to take identified courses even they do not have interests on the courses.

Wellington (1990) identifies the differences between informal and formal learning as Table 11.1 lists. Students learn with formal learning will always write homework and/or take exams, teachers can assess the students' learning performances via mark their homework and exam papers. On the contrary, there is no homework and exam for the students who learn via informal learning, e.g., museum visits and informal discussions happened in lunch.

Informal learning is different from formal learning because it takes place outside of the traditional classroom. Therefore, there are more social opportunities within informal learning (Tough 2002). There is no teacher to tell learners what to do. Students gain knowledge, skills and attitudes via reading newspapers, visiting exhibitions and chatting with friends (Lelliott 2007). Hence, Students may not be aware that they are learning.

Researchers usually categorize museums and wildlife centers into informal learning environments, as these places provide learners direct access to the natural world and scientific phenomena to help students practice and learn skills (Martya et al. 2013; Holmes 2011; Rivera Maulucci and Brotman 2010). Scanlon et al. (2005) think informal learning in museums makes learning being causally and autonomously.

Museums are places which have plentiful opportunities for learning (Nikolaos et al. 2008). Museums provide a free-choice learning experience which learners can ignore contents that they are not interested in. However, if the learners do not interest with too many things, then they probably will feel bored or leave the museum shortly. Students will have sympathetic responses to the learning contents which are enjoyable and understandable to them (Hawkey 2004). Therefore, *motivating students is important*.

Regarding Museum Learning, there are two definitions which have been proposed (Hawkey 2004): (1) Abungu proposed in 1999 that "Museums in twenty-first century are the environments in which learning takes place while exploring exhibits. The exhibits do not offer all answers, but motivate students to think and ask questions"; (2) Sheppard proposed in 2001 that "Museums enhance discovery. Students can learn visual thinking skills through the contents and context of the exhibits. Moreover, students can realize the variety of phases of the world by observing real learning objects." Hence, *designing museum learning through exploration* is a significant issue.

Mobile devices can support museum learning very well due to: (1) mobile devices can be context-awareness because it can sense the artifacts and ask relevant information from the server; (2) mobile learning processes and interactive contents are interesting to visitors and students (Tsung et al. 2006). Mobile applications already used in museums are (1) delivering information to the visitors and students (2) providing tools that can support learning processes, and (3) presenting educational scenarios.

Many mobile applications have been developed to assist learners visiting and learning in museums. First, Kwak (2004) finds that sending information of the artifacts to students' handheld devices can make them have better experiences in the museum. Yatani (2004) proposes the Musex system which was embedded into mobile devices (Yatani et al. 2004). The Musex asks children questions regarding museum exhibits and Children discover the exhibits and learn collaboratively in the museum. Feix et al. (2004) developed DinoHunter to construct a mobile edutainment activity in the museum via storytelling. Klopfer et al. (2005) proposed Mystery at the Museum with four features: (1) allowing participants to discover the exhibits they have never seen before; (2) enabling participants learn the knowledge of the exhibits while searching in the museum; (3) making participants understand the relations among exhibits; and (4) making participants collaborate with each others.

11.2.2 Information Theory and Rough Set

Students can learn everything that they are interested in a museum. Hence, the critical problem of informal learning is how to design the program in which people are interested. Information theory is a method regarding logarithmic base measurement. The base chooses '2' used to fit the computer basic unit such like a bit is 1 or 0 (Düntsch and Gediga 1998). The importance of data depends on the probability, as the data which is commonly to be seen and found or an event which commonly happens may not so important to the users. In this research, the probability can be used for indicating how often and common a feature or a characteristic is to been found among artifacts, i.e., the probability is higher, the feature/characteristic is more common to be seen in the museum. The information value of a feature then can be noted as:

$$I(f_i) = \log_2(\frac{1}{p_{f_i}})$$

where p represents the probability of the feature f_i.

Rough set is an approach regarding ambiguity. Rough set is used in the knowledge discovery and pattern recognition. The advantage of the rough set is that researchers do not need to have additional information to analyze the relationships among data (Pawlak and Skowron 2007). Three sets are involved in the rough set: positive, boundary, and negative sets. The definitions of these three sets are:

1. Positive set: All elements within positive set can be classified uniquely.
2. Boundary set: All elements within boundary set cannot be classified uniquely.
3. Negative set: All elements within negative set are not interesting to analyzer.

This research uses the three sets to distinguish if an artifact has all features that a learner needs. An artifact will be put into boundary set if it covers only part of necessary features and will be put into negative set and not be considered while generating activity for learners if it doesn't have any needed feature.

11.2.3 Activity Generator for Informal Learning

This section reveals how to design the activity generator for informal learning. Museum learning is informal learning. Many scholars of informal learning consider that learning resources in museums are abundant, as the resources in museum cover history, art, cultural, and others. However the question is how to make those learning resources interesting and get students engaged to learn. Game is fun and enjoyable (Ardito et al. 2007). Hence, the research team tries to integrate museum learning with the game characteristics such as challenge and control. To do that, there are two things that must be considered.

First, the artifacts of a museum (i.e., National Palace Museum in our research) which are considered to be used for learning are needed to be preprocessed. Four features of artifacts are categorized and are used for the proposed museum learning game; they are "material", "dynasty", "purpose", and "shape". Second, a museum learning game with four learning activity chains which take different feature as its main feature is designed. The activities in the learning activity chains are called "main learning activities". The main learning activities are what users must complete. After the users accomplish a series of main learning activities, i.e., conquer a learning activity chain, they would learn all of the knowledge related to the particular learning topic.

In this research, 46 artifacts on the 2nd floor of National Palace Museum are chosen to be learning objects and ten feature relevant learning characteristics such as vase and bowl for the shape feature and bedding and decoration for the purpose feature are found. In order to know which artifacts can help the learning of particular topic, this research uses "Rough Set" to analysis the relationships among artifacts as Fig. 11.1 shows.

The artifacts are listed at the right hand side and the features are listed at the left side of Fig. 11.1. The feature of the learning activity chain the user chose, for instance, "material" feature in this case and other three features become secondary feature candidate while generating activities for the user. In the example shown in Fig. 11.1, the main feature is "material" and the secondary feature is "purpose". If we want to generate learning activity for learners to learn "pottery" artifacts which can be used for tasting wine, then the artifacts can be categorized into three different rough sets according to their connections to the main and the secondary features:

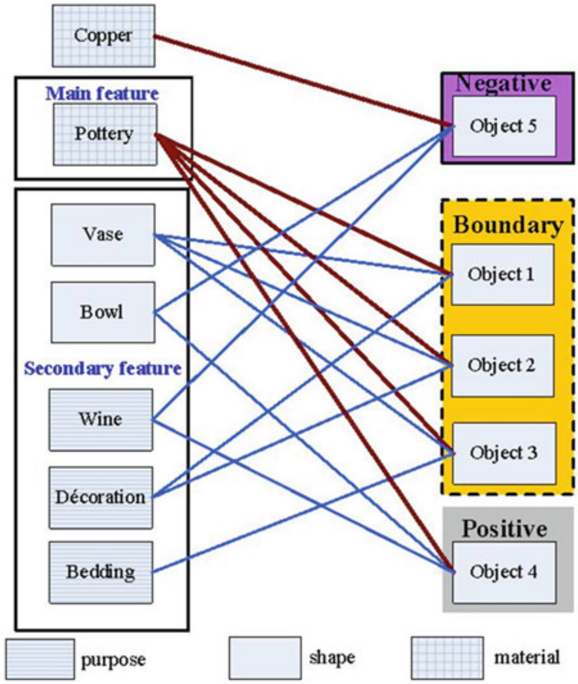

Fig. 11.1 Relation analysis by rough set

1. Boundary Sets: Although the artifacts in this set are pottery products, they are not mainly used for drinking or they are not used for tasting wine at all.
2. Positive Sets: The artifacts in this set are pottery and their purpose is for drinking.
3. Negative Sets: The artifacts in this area set are not even pottery products.

Due to the artifacts in both of the Positive and the Boundary sets are pottery products, they are selected to generate the activities for the learners. Each activity in the chosen activity chain has same main feature and secondary feature.

Once the artifacts have been selected and related activities have been generated, we use Information theories to decide the priority of each activity. The information theory is used to measure the difficulty of activity in terms of finding an artifact which has the required features, as the information value represents how common a feature can be seen on the artifacts in the museum. More details of activity generation algorithm and mechanism can be found in (Chang et al. 2008).

11.3 Generating Role-Playing Quests for Museum Learning

In this research, A mobile game—National Palace Museum Adventure (NPMA)—is designed and the activity generator is embedded into it. The game has game features such like “control”, “curiosity”, “fantasy” for learners by

1. allowing learners to choose different roles with different story, learning contents and goals;
2. automatically generating activities as game quests so learners may see different quests and can not predict what kind of quests they will see for next; and,
3. allowing learners to interact with the NPC in the game world.

11.3.1 Playing Roles

The game content influences what players would do and what they would complete and achieve (Adams and Rollings 2006). This research designs the proposed game a role-playing game, as the role-playing game could make learners explore the world, gather required quest items and find answers by themselves via solving quests one by one. The characteristics of role-playing games fit our needs in developing a mobile game in National Palace Museum and our intention in asking learners to find out the correct artifacts for particular quests by reading the description and explanation of the artifacts.

The game has two roles which learners can choose to be: “Cinema Property Handler” and “Artist” before they can start to play as Fig. 11.2 shows.

Figure 11.3 shows the four responsibilities that a cinema property handler and an artist has. There are four movies need the cinema property handler’s help: “Journey to the west”, “Dear and cauldron”, “Condor hero”, and “Heaven sword”. Each movie is associated with a dynasty and needs the learners to find the movie director some artifacts with different features. On the other hand, the four responsibilities that an artist has are “Gorgeous aristocrat”, “Populace art”, “Religion art”, and “Sculpture skill”, and each responsibility is associated with a particular material. Similar to the movies, learners may need to help virtual client authenticate some artifacts with different features.

Fig. 11.2 Career selection

Fig. 11.3 Different roles' responsibilities

After learners select a responsibility, they would see the correspondent available quests of that particular responsibility. At the top right-hand side of the screen as Fig. 11.3 shows, an NPC introduces the background of the chosen role for the learners. The background is used for giving learners an immersive experience and getting them motivated. After the learners choose a responsibility, they can enter into the game world and start to play the game.

11.3.2 Quest Design

The embedded activity generator introduced in Sect. 11.2.3 then generates responsibility relevant activities for the learners.

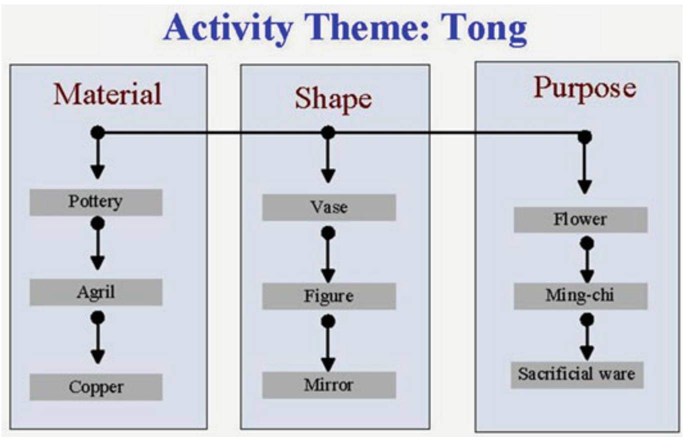

Fig. 11.4 A result of activity generator

Table 11.2 Quest description templates for different careers

Career	Principle model	Noun	Verb
Archaeologist	You must [verb] the [noun] about [Main Feature] and [Secondary Feature] at this quest	1. Antique 2. Ancient civilization	1. Find 2. Recognize 3. Discover
Cinema property	To [verb] which [noun] are [Main Feature] and [Secondary Feature]	1. Antique 2. Ancient civilization	1. Find 2. Discover 3. Bring
Tomb raider	To [verb] which [noun] are [Main Feature] and [Secondary Feature]	1. Artistic 2. Production antique	1. Steal 2. Find
Artist	You need to [verb] the [noun]s are [Main Feature] and [Secondary Feature] to learn new art skill	1. Antique 2. Ancient civilization	1. Find 2. Ensure 3. Authenticate

As Fig. 11.4 shows, the main feature is dynasty when the learner chooses to be a cinema property handler and the other three features—material, shape, and purpose—become the secondary features. The research calculates and arranges the quest in a sequence and the learners need to complete the prerequisite quest before they can take the follow-up quest. For instance, the artifacts in Tong dynasty were made by three different materials—pottery, argil, and copper. The learners need to complete quests of pottery material then are allowed to take quests of argil material. The learners can see the available quests on the bulletin board in the association of adventurers in the game world. After learners choose to pick-up a quest, the quest principle provides them the quest's description includes the amount of artifacts they are required to find in the museum.

The quest description is consisted of three parts: principle models, nouns, and verbs. This research designs the templates, listed in Table 11.2, for the three parts according to the careers.

11.3.3 Interaction and Feedback Mechanism

This section explains the interactions and feedback happened between the learners and the NPC in the game. First of all, the NPC introduces the role's background and the responsibilities for the learners after the learners chose a role to play in the game as Fig. 11.3 shows

After the learners choose a responsibility, they will interact with the NPC in the Association of Adventurers in the game worlds. The NPC will tell the learners that they can pick any quest listed on the bulletin board at the bottom-left hand side on the screen as Fig. 11.5 shows.

Fig. 11.5 The NPC in the association of adventurers

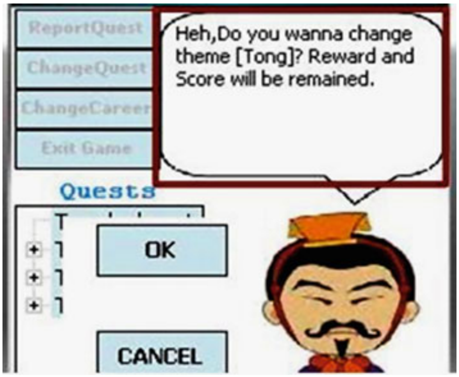

Fig. 11.6 The NPC's response toward the responsibility change request

The learners can also interact with the NPC in the association of adventurers to report the solved quest, try another responsibility, try another role, and stop playing the game. Figure 11.6 shows the NPC's response when the learners want to try another responsibility by clicking the "Change Quest" button.

When the learners want to try to play another role by clicking "Change Career" button. NPC will remind players of their current career. When the learners confirm their willing by clicking the "OK" button, the NPC will tell the learners what other roles they can play. Figure 11.7 shows how the NPC doesn't want to see the learners leaving when they click "Exit Game" button—the NPC begs players to stay. With such interaction, the learners may stay and play more. As playing the game is the process of learning, longer the learners play this game much more they may learn via their game-play.

When the learners come to see the NPC to turn in the quest results, there are four situations could happen. The first situation is successful turning in the quest results,

Fig. 11.7 The NPC begs the learners to stay and to keep playing

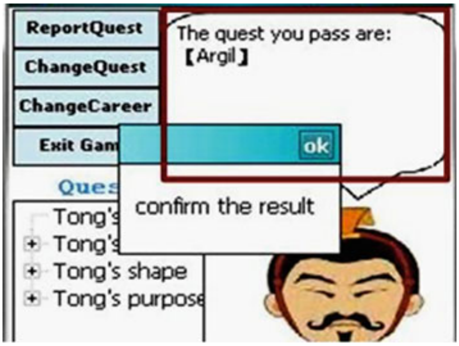

Fig. 11.8 Successfully turn in the result of a quest

as the learners have found all necessary quest items as Fig. 11.8 shows. The second situation is that there is no further quest existed in the same secondary feature after the players turn in a quest successfully.

The third situation is the NPC finds that the learners complete all quests generated for the chosen responsibility. Under such situation the NPC will congratulate their victory and ask them to try another responsibility that the chosen role has. The last situation is they players try to turn in the quest but without correct or have no all required quest items yet. Under such situation, the NPC will ask the learners not to cheat. Figure 11.9 is the Petri net diagram of the possible interactions which could happen in-between the NPC and the learner. A node is an action that the learners may do in the game. A sentence aside of a node is the NPC's response.

The proposed game uses reward as feedback. Four kinds of rewards are given to the learners when they solve the quests of particular features as Fig. 11.10 shows. When the learners complete a quest, the game gives the learners the correspondent reward and score as Fig. 11.11 shows.

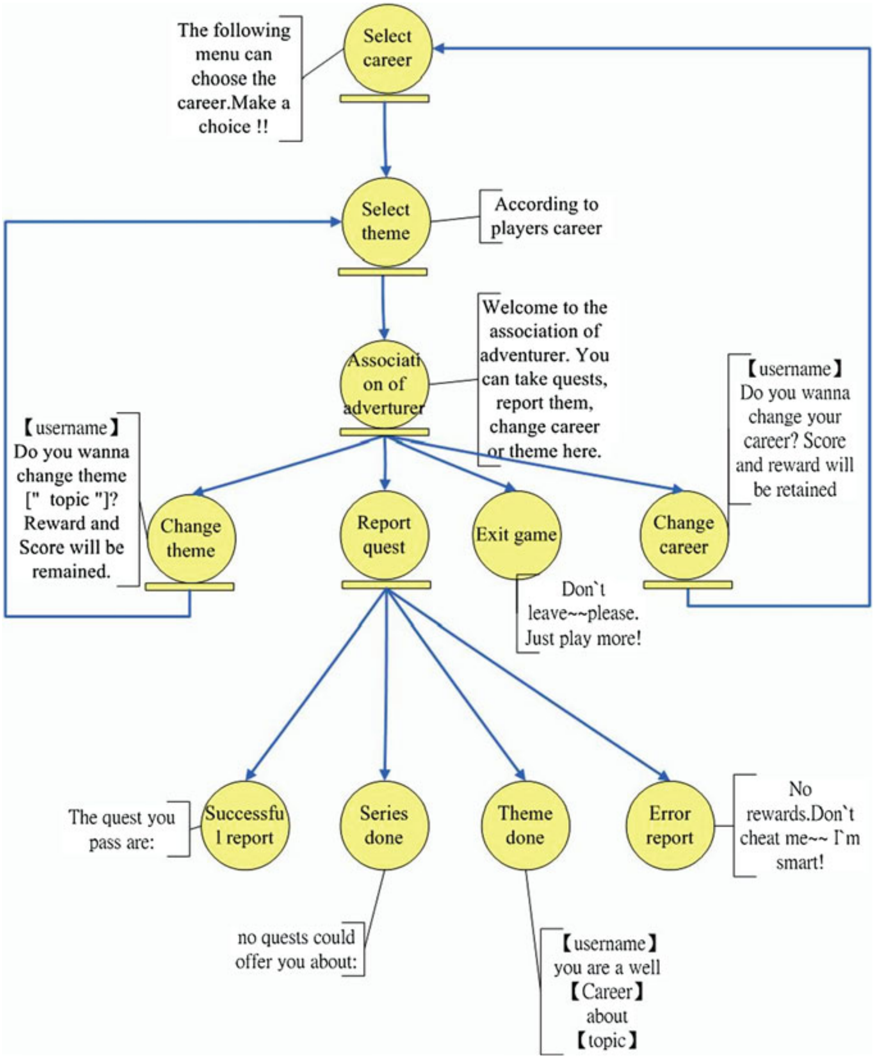

Fig. 11.9 The Petri net diagram of the NPC's responses

11.4 National Palace Museum Adventure—The Game

This section uses the experience of a mocked kid—Bruce—in National Palace Museum as case to explain how a student plays the game and learns in the museum.

One day, Bruce comes to National Palace Museum with a PDA pre-installed the National Palace Museum Adventure (NPMA) game. After he goes through the entrance, he starts the game and sees the main menu as Fig. 11.12 shows.

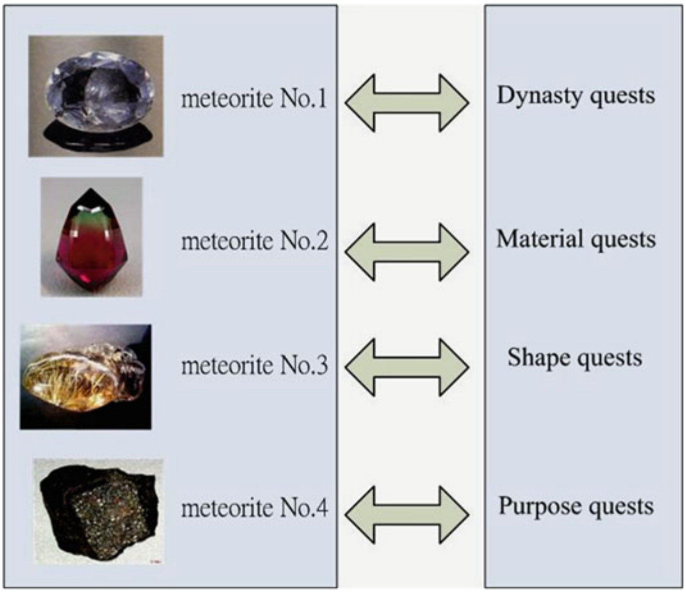

Fig. 11.10 The feature related rewards

Fig. 11.11 Reward and score that the learners receive for the completion of a quest

Fig. 11.12 Main menu of the game

Fig. 11.13 Registering an account and choosing a role

He has never played the game before so he clicks the “New Player” button to register an account and choose a role to play the game as Fig. 11.13 shows.

He chooses to be an artist and the NPC tells him the responsibilities of being an artist. He wants to try the “Gorgeous aristocrat”. The NPC asks him whether Enamel or Jade he want to try as Fig. 11.14 shows.

As Bruce chooses Enamel, the game then starts to generate Enamel-related activities for him. Bruce finds himself is teleported to the association of adventurers in the game world and he has nothing in the bag at this moment because Bruce has never completed any quest yet. Bruce takes a look at the bulletin board and tells the NPC that he wants to take the Qing quest. When he takes the quest, the screen is switched to the Map page as Fig. 11.15 shows. Bruce can see the quest principle and the possible location clue for solving the quest.

According to the quest principle, Bruce understands what kind of artifacts he needs to find and the possible room he should go. He reads the descriptions of the

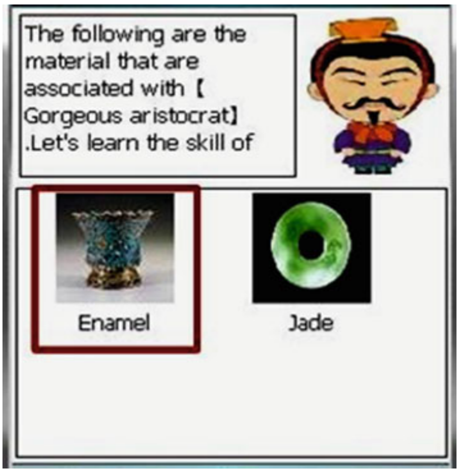

Fig. 11.14 Quest menu of gorgeous aristocrat

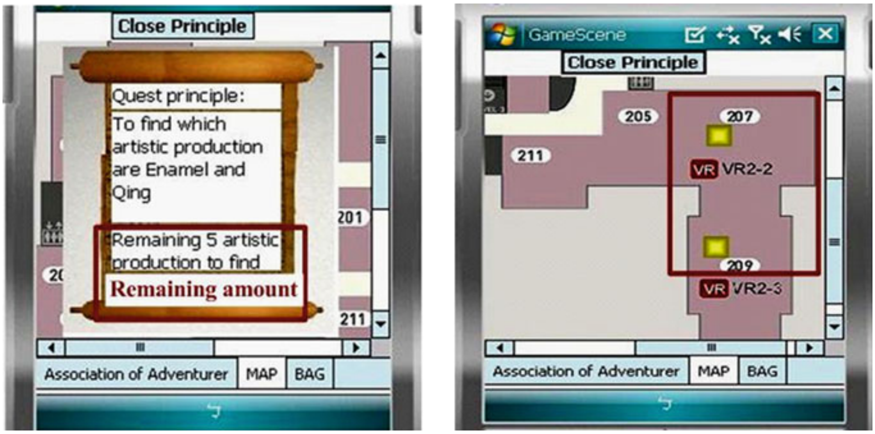

Fig. 11.15 The quest principle and the map for location clues

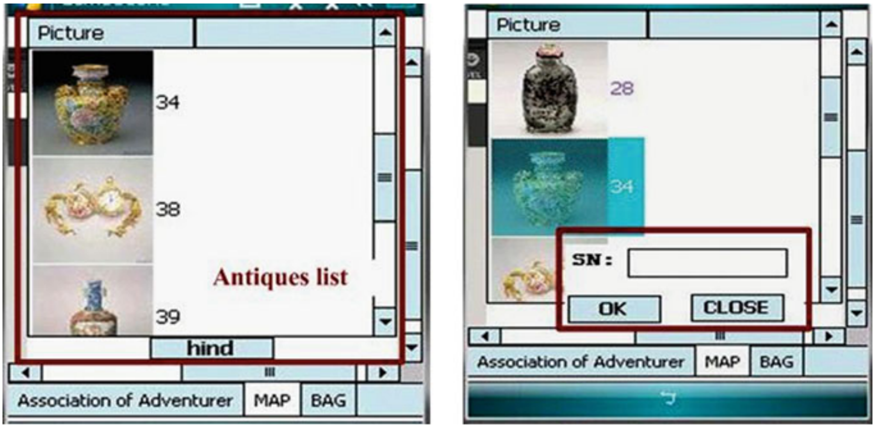

Fig. 11.16 Selecting an artifact candidate and entering the artifact serial number to confirm his decision

artifacts to see which the quest is asking for. When he finds one and believes the one is correct one, he opens the “antiques list” and chooses the one he believes is correct by entering the correspondent artifact serial number as Fig. 11.16 shows.

Bruce finds the right one; therefore, the game updates the numbers of remaining required artifacts as well as the antique list for him. When he finds out all required artifacts for the Qing quest, the game gives him a correspondent reward and score as Fig. 11.17 shows.

Bruce then comes back to the association of adventurers and reports to the NPC. After NPC verifies the turn-in quest results, the NPC updates the bulletin board and offers a new dynasty quest—Ming quest. Bruce can take this new quest or take any

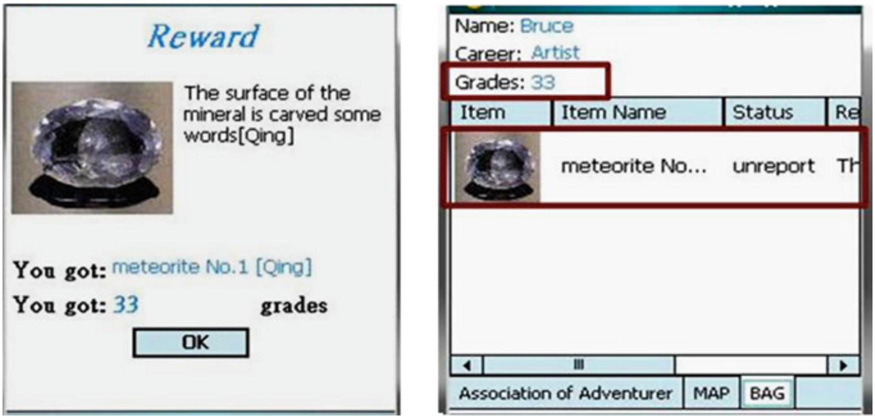

Fig. 11.17 Reward page and the updated bag

other quest listed on the bulletin board until all quests have been done. Once Bruce completes all quests, the NPC tells him that he can try another topic of "Gorgeous aristocrat". Bruce returns to the "quest menu" and finds the "Enamel" is gone. He can choose another topic to conquer until no topic exists.

11.5 Evaluation and Discussion

11.5.1 Hypotheses and Pilot Design

There are three hypotheses this research wants to prove:

- **Hypothesis 1**: learners can learn through playing the game in National Palace Museum
- **Hypothesis 2**: the proposed game makes learners spend more time in National Palace Museum
- **Hypothesis 3**: the knowledge learned through playing the game can be remembered longer.

The pilot recruits nine subjects include four elementary school students and five high school students to form the experiment group. The experiment group students play the game in National Palace Museum. Also, the pilot recruits two subjects to visit National Palace Museum with pre-designed paper-based learning activities. Table 11.3 lists the details of experiment group students.

The chosen experiment site the east side of second floor in National Palace Museum. The east side of second floor has six rooms (i.e., 201, 203, 205, 207, 209, and 211). Figure 11.18 shows the floor plan.

Table 11.3 Details of experiment group students

Item	Description
Age	9–16 years old
Gender	1 girl, 8 boys
Educational level	Four elementary school (denoted by E1–E4), two junior high school (denoted by J1–J2), 3 senior high school (denoted by S1–S3)

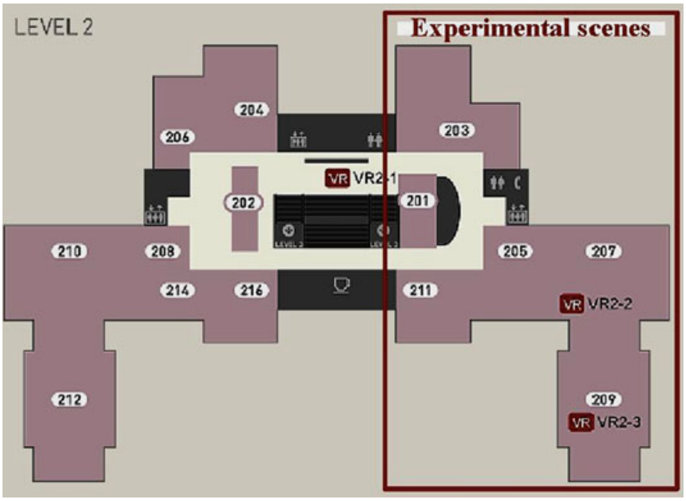

Fig. 11.18 The second floor plan of National Palace Museum

Forty-six artifacts in the six rooms are collected and four features—“dynasty”, “shape”, “material”, “purpose”—that the artifacts have are chosen for activity generation. The activity generator which the game uses can generate 121 quests with these data. Table 11.4 lists the quest distribution.

Table 11.4 Quest distribution

Theme	Quest amount	Theme	Quest amount
Tsin	3	Argil	3
Tong	9	Copper	8
Six	3	Lacquer	7
Jin	3	Stone	3
Sung	12	Bamboo	3
Ming	21	Ivory	6
Jade	7	Pottery	23
Enamel	10		

The experiment procedures are:

1. A research assistant explains the game for the subjects.
2. The subjects are allowed to try the game to get familiar with it before they start the museum visit.
3. The assistant show the subjects how to solve a quest.
4. The assistant double checks if the subjects really know everything about the game.
5. The subjects start the game play and solve quests around the east side of second floor. The assistant accompany the subjects to provide supports like room finding, quest principle explanation, and technical problem shooting and solving.
6. The pilot only stops when the subjects decide to exit the game and to stop playing. Hence, each subject's time spent on playing the game in the museum is different from others.
7. The subjects are asked to fill a questionnaire and to take a post-test when they decide to stop playing.
8. Two weeks later, the subjects are asked to do a delayed post-test which is identical with the post-test.

The questionnaire is designed and used for getting the subjects' perceptions toward the game. The questionnaire has ten five-point likert scale questions, where five indicates the subjects strong agree with the question description and 1 indicates they strong disagree. The pilot has a post-test and a delayed post-test because the research team wants to see if the knowledge learned through playing the game can be remembered longer. The post-test and the delayed post-test are identical..

11.5.2 Data Analysis and Findings

The descriptive statistics results of the questionnaire responses are summarized in Table 11.5 and several findings can be told from it:

1. The subjects were engaged to learn in National Palace Museum (Q4 and Q10).
2. The subjects felt that they did learn knowledge in National Palace Museum through the game play (Q8); therefore, *Hypothesis* 1 *is supported*.
3. The subjects do find the hints and the location clues are useful for them to solve quests (Q3 and Q5).
4. The game does provide the subjects an immersive experience (Q7).

Table 11.6 lists the *t*-test result of the time-spent on the museum between the control and the experiment group. The result shows that the time-spent of experiment group students in the museum is significantly longer than control group students, which means, the game does engage students learning in the museum; therefore, *Hypothesis* 2 *is supported*.

Table 11.5 The descriptive statistics results of the questionnaire responses

	Question	Mean	S.D.
Q1	Does the game work well?	4.22	0.971825
Q2	Are quests too difficult to solve?	2.44	0.881917
Q3	Do you need hint for solving quests?	4.22	0.833333
Q4	Do rewards and score motivate you to keep playing?	4.00	1
Q5	Does the location clue help you solve quests?	4.22	1.20185
Q6	Do you feel the difficulty of the quests is getting higher?	3.33	1.224745
Q7	Do you feel you are the role you play in the game?	3.67	0.866025
Q8	Do you learn knowledge while playing the game?	4.33	0.866025
Q9	Do you think the NPMA is a game?	3.89	0.927961
Q10	Can the game attract you to visit National Palace Museum?	4.11	0.927961

Table 11.6 *t*-Test results of two groups' the time-spent on the museum

Experiment group		Control group			
Mean (h)	S.D.	Mean (h)	S.D.	*df*	*t*
2.7	0.5	2	0	9	1.92[a]

[a] $p = 0.04 < 0.05$

Table 11.7 *t*-Test result of experiment group's post-test and delayed post-test score

Post-test		Delayed post-test			
Mean	S.D.	Mean	S.D.	*df*	*t*
0.66	0.24	0.54	0.26	8	1.27

Table 11.7 lists the *t*-test result of the score that the experiment group students received for the post-test and the delayed post-test. The result shows the delayed post-test score that experiment group students received is not significantly different from the post-test score ($p = 0.12 > 0.05$), which means, the learning effect via playing the game in the museum can retain; therefore, *Hypothesis* 3 *is supported*.

11.6 Discussions

The research team expects that the learners will be enjoy their visit in National Palace Museum because of the game. Several observation and interview results do confirm our expectation.

(via observation)
E3: How many quests did you remain, brother (E4)?
After checking brother's progress
E3: I am better than you.
E3 then tried to help E4 complete quests. After E3 and E4 finished every quests that cinema property handler has, They seemed to be satisfied with their achievement.
(via interview)
E1: that the automatically generated quests are fun. I like the process of finding answer via quest solving.
E2: I felt that I was the role I played.
S1: Wow, time flies. We spent almost 3 h to play. The game provided us goals which are more interesting than last time (without the game) (S1, S2 and S3)

The research team also believes the game can get learners motivated to learn in the museum. The interview results show that the game does have such potential.

(via interview)
E1: I like to visit a museum with the game instead of without it.
E2: I would like to play the game again. I want to finish the cinema property handler's quests which I haven't completed yet.
S3: I enjoy collaborating and competing with my friends in terms of playing the game in the museum. Yes, it is a game. Playing the game is better than teacher-lead learning in the museum. I know what I should find and read in the museum because the chosen topic is what I like.
J2: I agree that I can actively visit the museum with the game. The most attractive parts of the game are the reward and the role-playing.

NPMA is a game which the artifacts' knowledge is embedded into quests. Hence, the game can help learners learn while playing it. Several evidences can be proofs.

E1 and E2 try to conquer Tong's Ming-Chi quest. However, they did not understand what Ming-Chi is.
E1 and E2: assistant, what is Ming-Chi?

Assistant: Ming-Chi is a kind of mortuary objects. You can go to Room 201 and see which one can be used as mortuary object. Did you ever hear the story of Emperor Qin-Shihuang's terracotta warriors and horses? The required artifacts are similar to that.

E2: (thought for a while) I got it.

She went to see the artifact—"Pottery figurine of a standing lady painted with colors Tang dynasty" and put the artifact's serial number into the game and she was right about that.

And then, E1 and E2 were capable of finding out all required artifacts in Room 201. They actually understood what Ming-Chi is.

In this research, the generated quests' priority in a chain is decided based on the information value of the artifacts involved. The research team expects to see the later quests in a chain are more difficult for the learners. Some observation results show that it seems to be true.

(via observation)

When J2 saw a follow-up quest, he even wanted to change to another topic to play.

E1 and E2 had higher failure rate while solving later quests and the times they asked the assistant for help are also higher.

S1, S2, and S3 completed the beginning quests in the quest chain individually by themselves. However, for the later quests they solved through collaboration.

11.7 Conclusion

This chapter first reveals the design of mobile educational role-playing game for doing informal learning in museum and then explains the game-play with mocked user's experience so readers can have clear idea of how the things work. A pilot has been done for assessing the usefulness of the game and for verifying some hypotheses. Many interesting and important findings have been found. For instance, the game does make the learners spend more time in the museum. Moreover, the learners do learn the knowledge associate with the artifacts but still treat the game a game. With such finding, museums and exhibitions may consider to provide their visitors similar mobile role playing game apps to not only make visitors learn something while visiting the places but also make them come again and again—to make informal learning continue and become life-long.

In the future, the game can be enhanced by automatically generating collaborative activities for the learners. Learners in the museum can work on the quest together with their devices, for instance, a quest may involve artifacts located at different floors and rooms so individual learners in a group can have different tasks but all help the completion of the quest. On the other hand, the learners can see how others perform and such competition may get them engaged. The limitations of the current research include the small number of subjects and the unbalance numbers of subjects in different genders and groups. Also, the academic background and interests the subjects have are needed to be considered, as subjects have higher interest in history and arts may be more interested in the game-play and/or may perform better. The future pilot design should take these issues into consideration.

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Chapter 12
Teaching Improvement Technologies for Adaptive and Personalized Learning Environments

Moushir M El-Bishouty, Kevin Saito, Tingwen Chang, Kinshuk and Sabine Graf

Abstract Due to the widespread of online learning, learning management systems (LMSs) contain many of online courses but very little attention is paid to how well these courses actually support learners. Teachers build courses according to their preferred teaching methods; on the other hand, learners have different learning styles. The harmony between the learning styles that a course supports and the actual learning styles of students can help to magnify the efficiency of the learning process. In this chapter, an interactive tool is presented for analyzing existing course contents in learning management systems based on learning styles. This tool allows teachers to be aware of the course support level for different learning styles. It visualizes the suitability of a course for students' learning styles and helps teachers to improve the course support level of their courses. It aims at supporting teachers

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in adaptive and personalized learning environments to decide-making efficient modifications in the course structure in order to meet the need of different students' learning styles.

Keywords Interactive course analyzer · Learning styles · Learning management systems

12.1 Introduction

With technologies becoming more and more available and user friendly, educators have been using different technologies in teaching such as computers, courseware, and the Internet to teach students in new and interesting ways. Web technology enables courses to be delivered online to a large number of geographically distributed students, which allows students to learn anywhere and anytime; in addition, designers can produce interactive course materials containing online activities such as self-assessments, animations, and simulations. These can improve learning and are often more enjoyable and meaningful for learners (Hamada 2007). Teachers play a vital role in online learning, they should act as facilitators who guide the students in their learning and offer help tailored to the needs of individuals and groups (Galusha 1997). Despite the popularity of online learning, many problems, such as the students' feeling of isolation and teachers' communication overhead and difficulty in addressing the needs of individuals and groups, may hinder the success of online courses (Rivera and Rice 2002).

In order to successfully fulfill teachers' role in online learning, they need to gain an understanding of what is happening in online courses and become aware of problems experienced by individuals or groups of students (Galusha 1997; Rivera and Rice 2002). However, monitoring students' activities and deciding which actions are most appropriate can be both cognitively demanding and time consuming, and can therefore significantly increase teachers' workload (Helic et al. 2000). Therefore, there is a high demand for automatic feedback for teachers in online courses to highlight important situations, point at potential problems, and recommend appropriate pedagogical activities (Kosba et al. 2007; Macfadyen and Dawson 2010; Romero and Ventura 2007; Romero et al. 2009).

In adaptive learning systems, the common goal is to help students in a personalized way to guide their learning process. An adaptive learning system automatically provides different suggestions, courses, or activities to learners with different characteristics and needs. However, usually the goal of adaptive learning systems is not to replace teachers but to give them more time to devote more one-on-one time to each student and to work with students of varying abilities simultaneously (Gaudioso et al. 2012).

Several approaches for supporting teachers in adaptive learning systems have been presented (Romero and Ventura 2010; Tsai et al. 2001; Vialardi et al. 2008).

The main objective of these approaches is to provide feedback to support teachers in decision making (about how to improve students' learning, organize instructional resources more efficiently, etc.) and enable them to take appropriate proactive and/or remedial action. Gaudioso et al. (2012) presented a research to show the importance of the teacher support in adaptive educational systems and the usefulness of both descriptive and predictive models in this assistance. On one hand, the predictive models help the teacher to detect or anticipate problematic situations in the students' learning process. On the other hand, descriptive models allow the teacher to analyze what has happened in a course or in a learning situation. A teacher module was implemented which includes a reporting and data analysis tool (with both predictive and descriptive models). It is concluded that the use of this teacher's module improves the learning process. Moreover, Kosba et al. (2007) presented an approach to support distance learning teachers by offering advice that points at problems faced by students and suggests possible activities to address these problems. This approach utilizes student, group and class models derived from tracking data in web course management systems, and follows a taxonomy of feedback categories to recognize situations that are brought to the instructors' attention. The results of an empirical study in an online learning course point at benefits of the generated feedback to both instructors and students. This, in turn, can have a positive effect on students who can receive feedback tailored to their needs and problems.

In this chapter, we present an interactive tool for supporting teachers in adaptive and personalized learning environments. This tool utilizes our proposed mechanism for analyzing existing course contents in learning management systems based on students' learning styles. It supports teachers to improve the course by making efficient modifications in the course structure. The aim of these modifications is to meet the need of different students' learning styles, which helps adaptive and personalized learning environments to provide personalization and adaptation based on students' learning styles.

Section 12.2 introduces related work that focuses on providing adaptation based on students' learning styles. The course analysis mechanism is presented in Sect. 12.3. In Sect. 12.4, the design and the implementation of the course analyzer tool are illustrated. Section 12.5 concludes the chapter.

12.2 Learning Styles and Adaptive Learning Environments

A student's learning style is defined as a unique collection of individual skills and preferences that affects how a person perceives, gathers, and processes information (Clay and Orwig 1999). Once a learner's particular learning style is detected, it is possible to identify ways to help in improving the learning process (Onyejegbu and Asor 2011). There are many models about learning styles in literature such as Kolb (1984), Honey and Mumford (1982) and Pask (1976). In this research chapter, we utilize the Felder and Silverman's learning style model (Felder and Silverman 1988) because of its applicability to e-learning and compatibility to the principles of interactive learning systems design (Kuljis and Liu 2005). Furthermore, the Felder and Silverman's learning style model (FSLSM) is one of the most often used model in adaptive educational systems in recent times and some researchers even argue that FSLSM is the most appropriate model for use in adaptive systems (Carver et al. 1999). In this model, Felder and Silverman describe the learning style of a learner in great detail, distinguishing between preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global), where each learning style corresponds to (matches with) one of four teaching styles (active/passive, concrete/abstract, visual/verbal, and sequential/global). By using dimensions instead of types, the strengths of students' preference toward a particular learning style can be represented. Moreover, FSLSM is based on tendencies, enabling the learning style model to consider exceptional behavior.

Many studies have been conducted to provide recommendations and adaptations for online courses based on learning styles (Paredes and Rodríguez 2004; Graf and Kinshuk 2007; Mejía et al. (2008). Adaptation process to deliver content based on user learning styles. International Conference of Education, Research and Innovation (ICERI 2008). Most of the previous research focuses on identifying students' learning styles and adapting courses based on the identified learning styles. Graf and Kinshuk (2007) introduced a concept to enhanced LMSs with adaptivity based on learning styles. They used the open source LMS Moodle as a prototype and developed an add-on that enables Moodle to automatically provide adaptive courses that fit the learning styles of students. Paredes and Rodríguez (2004) presented a framework that collects explicit information about the students by means of the Index of Learning Styles (ILS) questionnaire developed by Felder and Soloman (1997), adapts the course structure and sequence to the student's profile and uses the implicit information about students' behavior gathered by the system during the course in order to dynamically modify the course structure and sequence previously selected. Experimental results of evaluations of such adaptive systems indicated that providing adaptive courses based on students' learning styles plays an effective role in enhancing the learning outcomes by reducing learning time and increasing learners' satisfaction (Graf and Kinshuk 2007; Popescu 2010; Tseng et al. 2008).

The previous related work presented systems for providing adaptation based on students' learning styles. When a system adapts a course to fit better with particular learning styles, the original course itself should contain suitable learning objects that support such learning styles, otherwise the adaptation mechanism will not be able to provide efficient adaptive course. In order to measure the ability of a course to be adapted for particular students' learning styles, we present a mechanism and a tool to analyze existing course contents in learning management systems. This tool allows teachers to be aware of the course support level for different learning styles. It visualizes the suitability of a course for students' learning styles and helps teachers to improve the course support level of their courses. In addition, the tool can be used to evaluate how well-adapted courses support targeting learning styles.

12.3 Course Analyzing Mechanism

This mechanism aims at analyzing existing course structure and contents in LMS based on the literature from Felder and Silverman (1988), who provide a clear description on how learners with particular learning styles prefer to learn. The mechanism considers which types of learning objects (LOs) support particular learning styles and at which place/location in the course these types of LOs can support such learning styles (El-Bishouty et al. 2012). Basically, this mechanism considers eleven types of learning objects; however, it is flexible so that new types of LOs can be added if necessary. The following list shows the currently considered types of LOs.

- *Commentaries*: provide learners with a brief overview of the section.
- *Content Objects*: are used to present the learning material of the course.
- *Reflection Quizzes*: include one or more open-ended questions about the content of a section. The questions aim at encouraging learners to reflect about the learned material.
- *Self-Assessment Tests*: include several close-ended questions about the content of a section. These questions allow students to check their acquired knowledge and how well they already know the content of the section through receiving immediate feedback about their answers.
- *Discussion Forum Activities*: provide learners with the possibility to ask questions and discuss topics with their peers and instructor. While a course typically includes only one or few discussion forums, the course can include several discussion forum activities as LOs that encourage learners to use the discussion forum.
- *Additional Reading Materials*: provide learners with additional sources for reading about the content of the section, including, for example, more detailed explanations.
- *Animations*: demonstrate the concepts of the section in an animated multimedia format.
- *Exercises*: provide learners with an area where they can practice the learned knowledge.
- *Examples*: illustrate the theoretical concepts in a more concrete way.
- *Real-Life Applications*: demonstrate how the learned material can be related to and applied in real-life situations.
- *Conclusions*: summarize the content learned in a section.

It is assumed that a course consists of several units and a unit can (but does not have to) consist of several sections. One or more instances of the types of LOs described above can exist in each section. A section may (but does not have to) start with a commentary. Subsequently, there is an area before content (ABC) that may include some LOs that aim at motivating the learners and making the section interesting for them. After this area, the content is presented. In the next area, namely area after content (AAC), different types of LOs may be presented. The conclusions of the section can be either right after the last content object or at the end of the section.

The presented mechanism recognizes how well a section of an existing course fits to each of the eight poles of FSLSM (i.e., active, reflective, sensing, intuitive, visual, verbal, sequential, and global) by calculating the average of three factors: the availability, the frequency, and the sequence of the learning objects in that section. Consequently, the calculations are applied for each section and then summarized for each unit and for the whole course.

$$\mathrm{Ava}_{\mathrm{ls}} = \frac{(\#\ \text{of existing LO types that support ls})}{(\#\ \text{of LO types that support ls})} \tag{12.1}$$

$$\mathrm{Freq}_{\mathrm{ls}} = \frac{(\#\ \text{of existing LOs that support ls})}{(\text{frequency threshold})} \tag{12.2}$$

$$\mathrm{Seq}_{\mathrm{ls}} = \frac{\sum_{i=1}^{n} f_{\mathrm{ls}}(\mathrm{LO}_i) \times w_i}{\sum_{i=1}^{n} w_i}, 0 < w \leq 1 \tag{12.3}$$

Certain LO types can support diverse learning styles; on the other hand, it is possible that they have no effect. Table 12.1 shows the learning object types that fit with each learning style. The availability of types of LOs is considered as a factor to infer the learning styles that a section of the course fits well. The availability factor measures the existence of LO types that can support each learning style (ls) in a section with respect to all types of LOs that support the particular learning style. The availability factor is calculated using Formula 12.1. On the other hand, the frequency factor measures the number of LOs in the section that support each learning style in respect to the frequency threshold. The frequency threshold represents the sufficient number of LOs in a section to fully support a particular learning style. This threshold is predefined and can be adjusted by the teacher if needed. If the number of LOs that support a particular learning style (ls) in a section is less than the value of the frequency threshold, then the frequency factor is obtained by Formula 12.2, otherwise the frequency factor takes the value 1, which means a full frequency support level for that learning style. The obtained values for both, the availability factor and the frequency factor, range from 0 to 1, where 1 indicates a strong suitability for the learning style and 0 means no support.

The sequence factor measures the suitability of the sequence of LOs for different learning styles. The sequence factor is calculated for each LO according to its type, location (ABC or AAC), and position within ABC/AAC. It is determined according to how well this object type in that place fits with each of the eight learning styles of FSLSM. The sequence factor for each learning style is calculated using Formula 12.3. In this formula, f_{ls} (LO) = 1, if the LO is suitable for that learning style at that location, and f_{ls} (LO) = 0 otherwise. n is the number of LOs in the section. The weight w

Table 12.1 The relation between the learning object types and the learning styles

Learning object/learning style	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Reflection quizzes		x		x				
Self-assessment tests	x		x					
Discussion forum activities	x					x		
Additional reading materials		x		x		x		
Animations	x		x		x			
Exercises	x		x					
Examples		x	x					x
Real-life applications			x					x

represents how well the position of a learning object in AAC/ABC fits to the learning style; it is calculated by measuring how far the position of the LO is away from the content. Formula 12.3 represents the weighted mean of f_{ls}(LO). Its value ranges from 0 to 1, where 1 indicates a strong suitability for the learning style and 0 means no support.

12.4 Course Analyzer Tool

The course analyzer is a tool for visualizing the suitability of a course for students' learning styles (El-Bishouty et al. 2013). Furthermore, it provides the teachers with an interactive graphical user interface (GUI) that allows them to play around with the course structure. This interactive interface supplies the teachers with drag and drop utility to add, move, and/or remove LOs, and based on any modification simulates the expected changes in the course support level for diverse learning styles. This interactive interface aims at helping teachers in improving the support level of their by making efficient modifications in the course structure. The course analyzer tool is implemented as a web application. It is mainly developed using MySQL relational database management system and PHP scripting language. In addition, Google charts online library is utilized for building the visualization component.

12.4.1 System Architecture

The proposed system architecture of the course analyzer tool is designed to extend the functionalities of any LMS. As shown in Fig. 12.1, the system architecture is illustrated in three layers. The first layer is the data layer; in this layer an internal database is created to store additional data independently from the LMS database. This internal database facilitates a reliable way of storing and exchanging the data among the tool components. The internal database stores extra metadata about the types of learning objects, enrolled students' learning styles, and the analysis results of LMS courses. Let us consider Moodle LMS as an example. Nine Moodle database tables (page, question, quiz, label, lesson, resource, url, user, and course) are extended and linked to the corresponding tables in the internal database (page_extend, question_extend, quiz_extend, label_extend, lesson_extend, resource_extend, url_extend, user_extend, and course_extend). For example, each LO that exists in the page table has a corresponding record in the page_extend table to store its type (one out of the 11 types of LOs illustrated in Sect. 12.3). Also, the course analysis results are stored in the course_extend table and students' learning styles are stored in user_extend table.

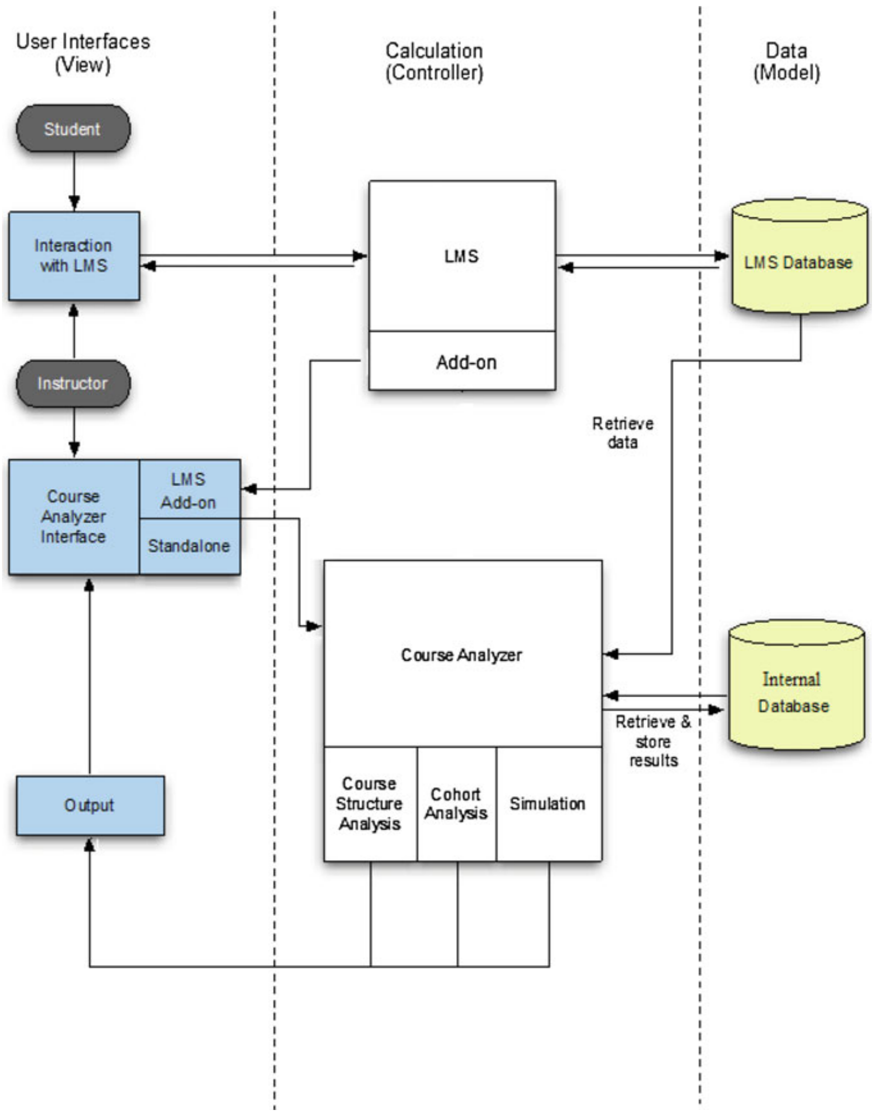

Fig. 12.1 System architecture of the course analyzer

The second layer contains the calculation components. The calculation layer of the course analyzer is comprised of three modules:

- Course Structure Analysis module: it connects to the LMS database, retrieves existing course structure data, applies the proposed analysis mechanism for the course (as illustrated in Sect. 12.3), and stores the analysis results in the internal database.

- Cohort Analysis module: as students' learning styles can be calculated through, for example, the ILS questionnaire (Felder and Soloman 1997) or by a tool like DeLeS (Graf and Kinshuk 2009) and then stored in the internal database, this module connects to the LMS and the internal databases, retrieves the list of students enrolled in each course and their learning styles, and analyzes students' learning styles in comparison with each course support level. This module aims at identifying the course support level for the students based on their learning styles.
- Simulation module: this module considers the teacher's proposed modifications in the course structure and simulates the changes in the course support level for students' learning styles. These modifications are not actual modifications in the course but are only visible in the course analyzer to show how the course support level would change if such modifications would be done in the course.

The third layer is the user interface. There are two methods to access the course analyzer interface. The first method is embedded into the LMS interface through an add-on that works for a particular LMS (a block in case of Moodle), which provides a direct link to the course analyzer interface. This method automatically retrieves the teacher's authentication information from the LMS, and adapts the interface for the teacher's current course and students enrolled in that course. The second method is a standalone web application that requires entering the authentication information manually (such as the user name and password to access the LMS and the internal databases). The later method considers all existing courses in the LMS database; it targets administrators, who would like to access the analysis results for different courses. This chapter focuses on the first method, which is embedded into the LMS interface. The course analyzer interface allows teachers to modify the course structure and visualizes the analysis results.

12.4.2 Visualization Component

The visualization component presents the analysis results and shows how well a course fits with students' learning styles. There are two visualization modes: the General Mode and the Cohort Mode.

The General Mode visualizes the support level of a course for diverse learning styles based on FSLSM. Figure 12.2 illustrates the visualization component of the course in General Mode. This component consists of two parts. The upper part of a component consists of a set of bars to show the strength of the harmony of the course with each of the eight learning style poles (i.e., active, reflective, visual, verbal, sensing, intuitive, sequential, and global), in terms of percentage (calculated by the average of the three factors illustrated in Sect. 12.3). Each learning style dimension is represented by two horizontal bars, one for each pole, where the two poles show the two different preferences of the dimension. The longer the bar, the more the course fits with the learning style. The lower part of a component contains

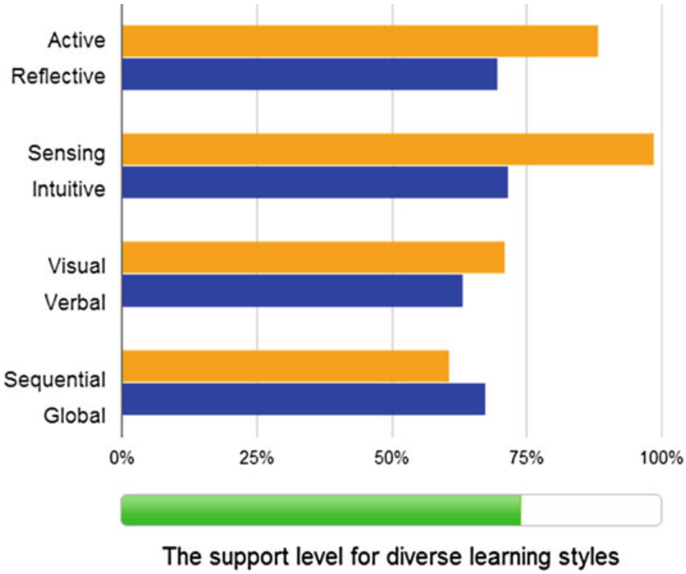

Fig. 12.2 Visualization of general mode

only one bar that shows the overall support level of the course for diverse learning styles (calculated by the average of the support level of the eight poles). Once the teacher moves the cursor over any bar, a tooltip appears to display more details about the analysis factors illustrated in Sect. 12.3.

The Cohort Mode visualizes the support level of a course in respective to the learning styles of the cohort of students enrolled in that course. Figure 12.3 illustrates the visualization component of the course in Cohort Mode. The component visualizes the data about students' learning styles in comparison with the course support level (calculated by the average of the three factors illustrated in Sect. 12.3). As shows in Fig. 12.3, each learning style dimension contains two bars; the upper one shows the course support level for each poles of that dimension (e.g., the active/reflective dimension); the lower bar shows the learning styles of the respective cohort of students on this learning style dimension. In case that all students are fully supported in the course/section, the bar will be displayed in green color, otherwise a gap will be shown in red. The intensity of the red color indicates the number of unsupported students.

12.4.3 Interactive GUI

As shown in Fig. 12.4, the course analyzer interactive GUI consists of two parts: the settings part (at the left side of the interface) and the visualization part (at the right side of the interface). The Analysis Settings area, allows the teacher to switch

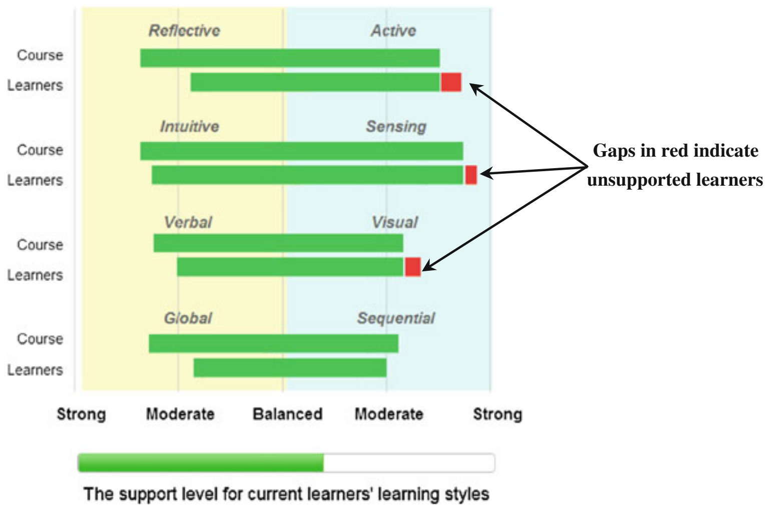

Fig. 12.3 Visualization of cohort mode

Fig. 12.4 Course analyzer interactive GUI

between general and cohort visualization modes (that are explained in Sect. 4.2). In the Course Structure area, the course structure is displayed in terms of units, sections, and a list of LOs in each section. The teacher can browse the course and select a particular unit/section by clicking on it. The Simulation Settings area allows the teacher to simulate modifications in the course structure. By utilizing drag and drop functionality, the teacher can drag learning objects from the list of learning object types and place them in certain positions in the Course Structure area (displayed in blue), drop learning objects from the Course Structure area to remove them, and/or move leaning objects from one place to another in the Course Structure area (displayed in brown). Once the teacher has completed the modifications on the course structure and wants to analyze how his/her modifications change the support level of the course, he/she can click on the Test button. Then the tool analyzes the course structure and updates the visualization part respectively. Furthermore, in the Advanced Settings area, teachers can set the value of the frequency threshold and select the learning object types to be considered while analyzing the course support level.

The visualization part consists of four similar visualization components according to the visualization mode (for example, the General Model), as shown at the right side of Fig. 12.4. The visualization part shows how well the course and a particular selected unit/section fit with students' learning styles. The upper two of the components visualize the course support level for the whole course before and after the modifications made by the teacher in the course structure. Similarly, the other two components show the selected unit/section support level before and after the modifications.

12.4.4 System Usage

In order to be aware of how well an online course fits with students' learning styles, a teacher needs to login into the LMS using his/her username and password, and then navigate to the course webpage. In that webpage, the teacher can easily find a link for the course analyzer tool (given that the add-on of the tool is already installed on the LMS). The teacher can click on that link to launch the course analyzer. Consequently, the course analyzer retrieves the course structure data, analyzes the course based on learning styles, retrieves the learning style data of students enrolled in that course, and then visualizes the course support level for diverse learning styles in General Mode. The teacher can switch to Cohort Mode to visualize the course support level for enrolled students' learning styles. The teacher can use the simulation settings to improve the course support level for particular learning styles and fill any gaps by adding, moving, and/or removing LOs, and then can click on the Test button to visualize the expected changes in the course support level. Once the required support level is reached, the teacher can navigate to the course webpage in the LMS and actually can implement the necessary modifications in the course structure to improve the course support level for students' learning styles. Consequently, the course will be ready to apply personalization and/or adaptation mechanism (for example, using one of the illustrated systems in Sect. 12.3) based on students' learning styles.

12.5 Conclusions

Despite the popularity of online learning, very little attention is paid to how well these courses actually support learners. When designing instructional material, it is important to accommodate elements that reflect individual differences in the learning process. One of these elements is learning styles.

Several systems have been presented for providing personalization and adaptation based on students' learning styles. When a system adapts a course to fit better with particular learning styles, the original course itself should contain suitable learning objects that support such learning styles, otherwise the adaptation mechanism will not be able to provide efficient adaptive course.

In this chapter, we present an interactive tool for supporting teachers in adaptive and personalized learning environments. This tool utilizes our proposed mechanism for analyzing existing course contents in learning management systems based on students' learning styles. Furthermore, it provides the teachers with an interactive graphical user interface that allows them to play around with the course structure. This interactive interface supplies the teachers with drag and drop utility to add, move and/or remove LOs, and thus simulates the expected changes in the course support level for the learning styles. This supports the teachers to decide which modifications should be implemented in the actual course structure. The aim of these modifications is to meet the need of different students' learning styles, which helps adaptive and personalized learning environments to provide personalized and adaptive courses based on students' learning styles. In addition, the tool can be used to evaluate how well-adapted courses support targeting learning styles.

The future plans of the research includes proposing a mechanism to provide teachers with recommendations on how to best extend their courses to support more students with different learning styles, and to fit the course to the current cohort of learners. In addition, experiments with teachers are planned to evaluate the efficiency and the user-friendliness of the tool.

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Chapter 13
Improving Learner Experience in the Technology Rich Classrooms

Ronghuai Huang, Yongbin Hu and Junfeng Yang

Abstract With more and more technology equipped in classroom to facilitate teaching and learning, Technology Rich Classroom (TRC) gradually became a hot topic for educational researchers, practitioners, and policy makers, especially when it was looked as one important learning space or learning environment. However, some predicaments had emerged in current multimedia classrooms, which resulted in lower learner experience for the new generation. In this chapter, we first investigated the development and definition of user experience and based on that we defined learner experience in TRC as learners' perceptions and responses that resulted from physical environment changes. Then we proposed the five elements of learner experience: value, usability, adaptability, desirability, comfortability. Finally, considering the connotation and extension of the five elements for learner experience, as well as the factors associated with the equipping and furnishing classroom, we brought forward a framework for analyzing learner experience. We also identified the indicators for evaluating learner experience in TRC by deeply investigating the changing factors of classroom and the five elements of learner experience.

Keywords User experience · Technology rich classrooms · Learning space · Leaner experience · Framework

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13.1 Introduction

Classroom is the most important supporting elements in teaching and learning processes, which is designed by the architect to accommodate various elements such as chair, desk, cupboard, whiteboard, and audio-visual equipment (Udin and Rajuddin 2008). In the mid-1990s, schools began to implement programs to bring technology into the classroom, and with the development of technology and pedagogy, classroom has now been equipped with various technologies to support teaching. The use of desk computer, laptop computer, interactive whiteboard, projector, Internet access, productivity and curriculum-related software, and a printer have enabled great changes of teaching methods and strategies in classroom. The emerging models of "technology enhanced learning environments" (TEAL)—first introduced at MIT in 2003—proposed that acoustics, furniture, lighting (both natural and artificial), mobility, flexibility, air temperature, and security must support the educational technologies being designed for those spaces (Fisher 2010). Since more and more educational researchers have seen the importance of classroom environment and the influences that technologies have played on students' learning in classroom, there have been lots of research and practice to explore the impact of classroom equipment. At the same time, the rapid advances in technology have revolutionized the way in which the children learn, play, communicate, and socialize (Mouza and Lavine 2013). The teaching model must adapt to students' learning preference, and the classroom equipment should support and promote diverse teaching strategies. The classroom equipped with various technologies is always called Technology Rich Classroom (TRC), which has enabled the emergence of a true synchronous/asynchronous and virtual/physical matrix of learning opportunities for which our existing learning environment infrastructure is not well suited for children to learn (Mitchell 2003). In order to study on how to design a TRC, we investigated TRC both at a background of a learning space in supporting social forms of student interaction, and at a background of smart learning environment in response to the "new generation" learners.

13.1.1 Research in Learning Space

Learning spaces are designed to support, facilitate, stimulate, or enhance learning and teaching, which encompass formal, informal, and virtual environments. Learning space involves the intersection of the design of physical and virtual spaces, the appropriate technology with which to populate newly configured spaces and the impact such spaces have on how faculty teach and students learn in them (Lomas and Oblinger 2006; Montgomery 2008). According to the literature, early researchers have been engaged in developing theoretical models, formulating a common terminology, encouraging to rethink pedagogical approaches, and developing effective

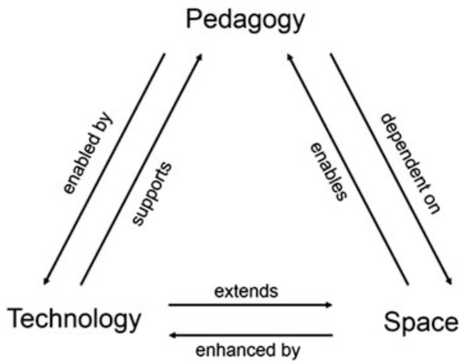

Fig. 13.1 Pedagogy-space-technology (PST) design and evaluation framework

assessment and evaluation tools related to learning spaces (Hunley and Schaller 2009; Jorn et al. 2009; Lippincott 2009).

Radcliffe et al. (2008), a Professor from the Next Generation Learning Spaces group in the University of Queensland, had developed a simple interrogative approach—called the Pedagogy-Space-Technology (PST) Design and Evaluation Framework—to help guide conversation among the disparate members of a building-project team, as shown in Fig. 13.1.

Perkins (2009) proposed a framework which clearly placed the individual learner at the center of the teaching and learning process, as shown in Fig. 13.2. In conjunction with the desired new knowledge and ways of working, the learner drove the learning agenda where the digital technology, digital pedagogy, and twenty-first century learning spaces were dependent elements meeting the individual needs. This theoretical framework, presented as a Venn diagram, also offered some notable "intersections" for consideration, particularly between spaces-technology and spaces-pedagogy.

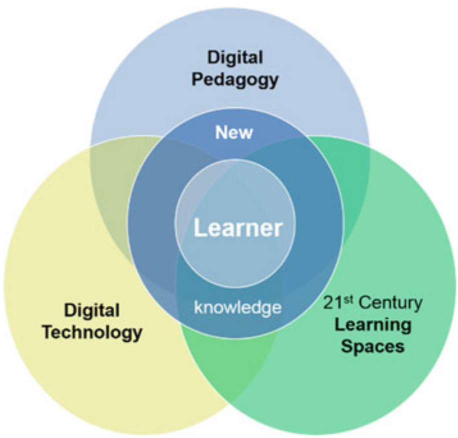

Fig. 13.2 Framework of twenty-first century learning spaces

Learning space is a new emerging research area, with the aim to promote independent, flexible, and engagement learning by providing leaner appropriate technology and pedagogy. The core value of constructing learning space is to prepare today's students for tomorrow's environment, and to enable learners to adapt in the future work and life. Learning space research includes the planning, design, implementation, and evaluation of all spaces for learning. The United States and the United Kingdom and other developed countries have made useful attempts, and Australia has implemented several successful programs on learning space with the Government's support.

13.1.2 TRC as a Learning Space

Classrooms, which have engendered a host of conversations, were by far the single most important space for learning (Brown 2005). Technology Rich Classroom is always considered as a learning space and the principles for building learning space could be used for building a TRC. In practical field, several research projects were carried out and their implications had been assimilated by the academic community.

The Massachusetts Institute of Technology started Technology Enabled Active Learning (TEAL) project incorporated a redesign of both course approaches and the space to facilitate student interaction and problem solving by employing round student tables, laptop connections, display screens, marker boards, software-based simulations and visualizations. Dori and Belcher (2005) implemented a quasi-experimental design and found that students in the TEAL programs had lower failure rates and higher rates of conceptual understanding than students taking the course in a traditional environment with a lecture-based approach.

North Carolina State University initiated Student-Centered Activities for Large Enrollment Undergraduate Programs (SCALE-UP) to enhance in-class problem solving and increase faculty–student interaction by employing large round tables for students, laptop connections, projectors, pedagogical approach, and teaching materials for cooperative learning. Beichner et al. (2007) found that the top tier of students increased levels of conceptual understanding, and both the overall and at-risk student improved problem-solving skills, attitudes, and class attendance rates.

University of Minnesota built Active Learning Classrooms (ALC) with round tables for nine students, switchable laptop technology for presenting student' work, two large projector screens for displaying teaching materials. By a quasi-experimental research, Brooks (2012) indicated that (1) space shapes instructor behavior and classroom activities; (2) instructor behavior and classroom activities shape on-task student behavior; therefore, (3) space shapes on-task student behavior.

The analysis of projects on TRC showed that the fusion of technology, pedagogy and space has changed learning behavior and teaching behavior. However, the emphasis of TRC research and practice mainly focused on the design method, and the evaluation methods were always missed in the research. Especially, with the emerging technologies equipped in TRC, such as tablet PC, wireless communication, multiscreens projectors, and e-textbooks, as well as flexible furniture layout, a new perspective for evaluating TRC should be developed.

13.1.3 Research on Smart Learning Environment

Today's learners differ from those of learner even 10 years ago in attitudes, expectations, and constraints. (Oblinger 2006) Many of today's learners favor active, participatory, experiential learning; they are also highly social, connecting with friends, family, and faculty face-to-face and online; they appear to have no fear of technology (Shinde et al. 2012).

Based on the demands of new generation of students for the reform of learning environment and the analyzing of challenges for both the online learning environments and classroom former environments, Huang et al. (2012) proposed the concept of "smart" learning environment which is the high level of digital learning environment with the aim at facilitating "easy, engaged and effective" learning for learners. After analyzing the differences of smart learning environment and digital learning environment from learning resources, learning tools, learning communities, teaching communities, ways of learning, and ways of teaching, they put forward a system model and TRACE[3] functional model of "smart" learning environment, which stands for tracking, recognizing, awareness and connecting for promoting easy, engaged and effective learning (Huang et al. 2012).

The background for emerging of "Smart Learning Environment" is the predicaments of current learning environments in formal educational settings. The current learning environment only supports the low-order cognitive objectives, such as knowledge, comprehension, and application, while not supporting higher-order cognitive objectives, such as analysis, synthesis, and evaluation. First, in a multimedia classroom, instructors present their teaching content with serialized presentations, which hinders students' understanding of the learning content. Second, multimedia consoles are always fixed in the front of the classroom, which limits the flexibility of teaching. Third, a unified and fixed seating layout is not conducive for teachers to carry out diverse teaching activities. Fourth, computer-networked classroom's equipment does not meet the needs of the students' inquiry learning. Fifth, a gap exists between teaching with electronic whiteboard applications and expectations of deeply interactive teaching. All these factors result in that students don't have a good experience while they study at classroom.

13.2 The Concept of Learner Experience

Experience in using a product or object exists in our daily lives. We perform activities with them, e.g., a knife to cut an apple; we express part of our identity with them, e.g., wrist watches; and we use them as a medium to interact with other people, e.g., mobile telephones. In 1940s, UX was raised in the field of human-–computer interaction with the foundation of usability and user-centered design (UCD). The connotation of UX was brought to wider knowledge by Norman et al. (1995), who is a user experience Architect in the mid-1990s. Recent advances in mobile, ubiquitous, social, and tangible computing technologies led to a shift away from usability engineering to a much richer scope of user experience, where users' feelings, motivations, and values are given as much attention than efficiency, effectiveness, and basic subjective satisfaction (Wikipedia 2013).

Up to now, more than 30 influential definitions of UX have been raised by the academic community, including some international organizations and companies such as Wikipedia, Microsoft, W3C, etc. Existing definitions are different as they are defined from different context, however, most of them mainly focused on product, system, and services. In the perspective of "product", user experience refers to the experience that a person gets when he/she interacts with a product in particular conditions. In practice, there are numerous different kinds of people, products, and environments that influence the experience that interaction evokes. (Alben 1996; Arhippainen and Tähti 2003; Desmet and Hekkert 2007) In the perspective of "system", user experience is about how a person feels about using a system (Wikipedia 2013), which highlights the experiential, affective, meaningful, and valuable aspects of human-computer interaction (HCI) and product ownership.

As devices, products, software systems, and services are included in experience when learning happened in TRC, it is important to see learner experience in a macro view to include all the aspects of experience. User experience was defined as "a person's perceptions and responses that result from the use or anticipated use of a product, system or service" by ISO (2009), which is the most closed definition to the concept of learner experience that stands for the user experience to educational products or environments, especially in a new classroom.

In a healthy classroom learning environment, the student, teachers, and designers will be turning to concepts of sustainable design to address comfort-related issues such as hygiene, safety, acoustics, and availability of space, natural daylight, and natural ventilation (OECD 2006). For a TRC, the learning technology in classroom encompasses virtual technologies, such as online presence and online resources, installed appliances, such as media presentation systems, remote interaction systems and room-scale peripherals, and mobile devices (Milne 2006). So the user experience in a TRC includes the experience of learner in using new classroom furniture, equipment and device, software system, and services.

Therefore, we can define Learner Experience in a TRC as learners' perceptions and responses that result from physical environment changes, such as decorating classroom and changing layout, equipping by providing audio-visual system, computers, devices, and software, and services in gaining technologies gradually involved for learning.

13.3 Elements of Learner Experience in TRC

The structure and elements of user experience can reveal the connotation and extension for the definition, which could enlighten us the structure and elements of learner experience in TRC. Morville (2004) proposed a conceptual framework, which is called User Experience Honeycomb as shown in Fig. 13.3, to describe the elements of UX in designing websites.

In order to create a meaningful and valuable user experience, the information in a website must be: (1) Useful: content should be original and fulfill a need; (2) Usable: website must be easy to use; (3) Desirable: image, identity, brand, and other design elements are used to evoke emotion and appreciation; (4) Findable: content needs to be navigable and locatable onsite and offsite; (5) Accessible: content needs to be accessible to people with disabilities; (6) Credible: users must trust and believe what you tell them; (7) Valuable: website must deliver value to our sponsors.

Rubinoff (2004) proposed that user experience is made up of four interdependent elements: branding, usability, functionality, content. Branding includes all the esthetic and design-related items within a Website. It entails the site's creative projection of the desired organizational image and message. Functionality includes all the technical and "behind the scenes" processes and applications. It entails the site's delivery of interactive services to all end users, and it's important to note that this sometimes means both the public as well as administrators. Usability entails the general ease of use of all site components and features. Subtopics beneath the usability banner can include navigation and accessibility. Content refers to the actual content of the site (text, multimedia, images) as well as its structure, or information architecture. We look to see how the information and content are structured in terms of defined user needs and client business requirements.

To help define the objectives and scope of user experience efforts, as well as enable their meaningful measurement, Guo (2012) suggested a conceptual framework that describes four distinct elements of user experience, including value, usability, desirability, and adoptability, and how they interact with one another in driving better product designs, as shown in Fig. 13.4.

Learner experience in a TRC needs to consider classroom as an integrated system with classroom furniture, equipment and devices, software systems, and services. The four elements of user experience for products can be used to express the learner experience in a TRC. While, learner experience should consider the diversity of learners in learning environment, so we use "Adaptability" to replace "Adoptability" to show the diversity needs from students. Also, the physical environment factors, such as light, temperature, and acoustics, play an important role for experience. So "comfortability" is also included in learner experience. Through the above analysis, the elements of learner experience include value, usability, adaptability, desirability, comfortability, as is shown in Fig. 13.5.

Fig. 13.3 User experience honeycomb (for designing websites)

Fig. 13.4 Four elements of user experience (for products)

Value Is it useful?	**Usability** Is it easy to use?
Adoptability Is it easy to start using?	**Desirability** Is it fun and engaging?

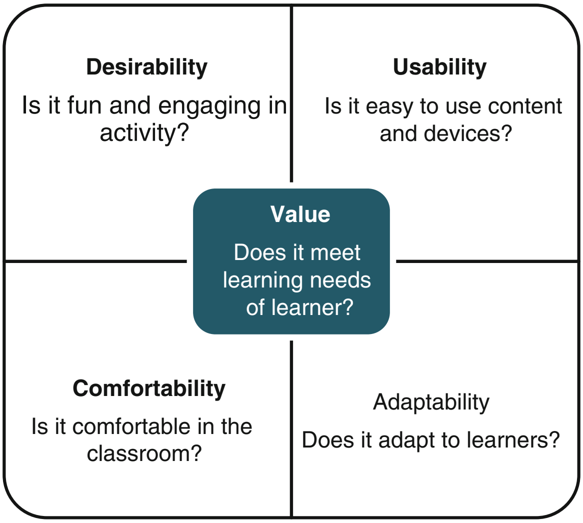

Fig. 13.5 Five elements of learner experience in TRC

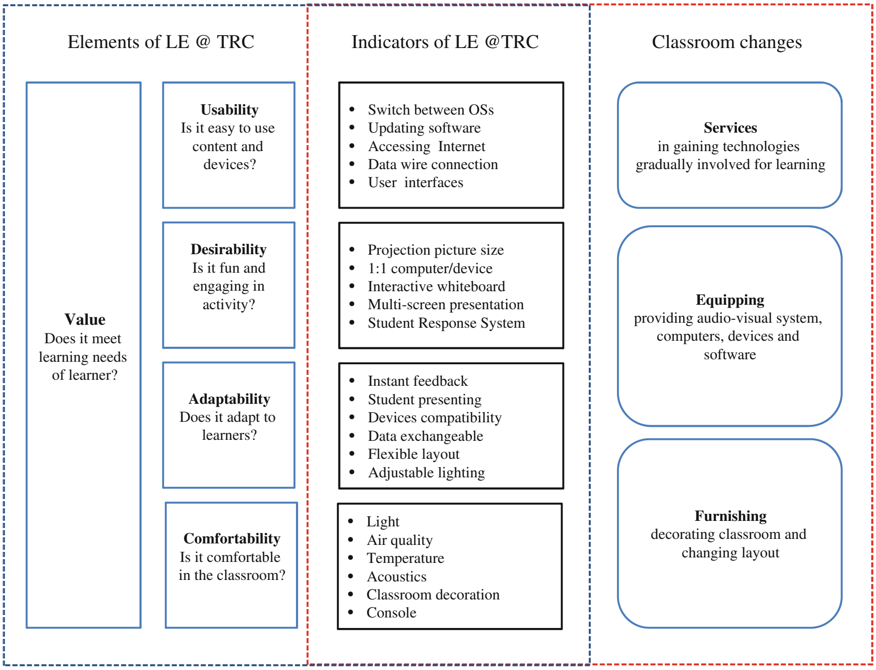

Fig. 13.6 Framework for analyzing learner experience in TRC

13.4 Indicators to Evaluate Learner Experience in TRC

Learner experience in TRC could be designed, improved, and evaluated by considering the connotation and extension of the five elements of learner experience, as shown in Fig. 13.5 the framework for analyzing Learner Experience in TRC. Value is the most core indicator for learner experience, and other four elements should support it. Services, equipping and furnishing are the main factors in a TRC changes, of which the indicators of learner experience derived from (Fig. 13.6).

13.4.1 Value: Does It Meet Learning Needs of Learner?

From the holistic perspective, value of learner experience refers to the positive or negative quality that renders the changes of classroom, such as classroom furnishings and layout changes, the use of equipment, desirable or valuable for the learners.

What drives a TRC's value to learner? TRC features must be in alignment with learning needs. If a classroom change is designed to support learning needs, teacher and learners may consider the layout changes and equipment valuable. Learning needs encompass more than just their explicit needs—things that learner know they want, but to include learners' implicit needs—things that learners don't express as needs, which might be hidden in learning activities and be recognized by their teacher. In order to meet learners' unexpressed needs, TRC should not only be easy-to-use products, such as devices and software, but also services that add much value to student learning.

13.4.2 Usability: Is It Easy to Use Content and Devices?

Usability refers to the ease of use and learnability of a TRC, which is composed of: (1) learnability: how easy is it for teachers and students to accomplish basic tasks the first time they encounter the TRC, (2) efficiency: once teachers and students have learned the design of a TRC, how quickly can they perform teaching and learning tasks? (3) Memorability: when teachers and students return to the design after a period of not using it, how easily can they establish proficiency? (4) Errors: how many errors do teachers and students make, how severe are these errors, and how easily can they recover from the errors? (5) Satisfaction: how pleasant is it to use the design?

The design factors of a TRC include systems, facilities, and software which have a significant influence on usability. Operating Systems provide a software platform for the application programs to run. Microsoft Windows, Mac OS X, GNU/Linux are examples of popular modern operating systems being used in personal computers (Ukessays 2013). Operating Systems, with diverse features, provide different software to support different resources and learning activates. The facilities include devices, audio-video control system, projector, interactive whiteboard, student response system, access of wireless network, etc. Software systems include learning management systems, resources providing system, collaborative learning platform. Classroom network tools offer new possibilities for classroom interaction; they present ways of rapidly distributing information, exchanging ideas, and constructing shared artifacts that can support a variety of engaging and mathematically rich activities that would be difficult or impossible to implement in conventional classrooms (White 2013). Within the context of learning tasks, a large part of desirability is attributable to innovative and recognizable design in user interface and interaction. User interface design includes well-organized navigation, nice looking graphics, and sleek designs. Meanwhile, interaction design includes the convenient, smooth, and multiple operations. More important, a desirable TRC must engage learner in relation to their purpose of using.

Based on the above analysis, we proposed the following indicators for evaluating usability in a classroom. (1) Is it easy to switch to a different Operating System? (2) Updating software with new version appearing frequently. (3) Is it easy to access to Internet? (4) Are data wires available for connecting different types of devices, such as USB, AV, VGA, HDMI, etc.? (5) Are the user interfaces friendly?

13.4.3 Desirability: Is It Fun and Engaging in Activity?

Desirability in a TRC refers to the attractiveness and engagement of the activities in a TRC or the pleasing perception from teachers and students. A pervasive goal in education is to engage students in learning so that they are attentive and mindful (Lavigne and Mouza 2013). Engagement involves three dimensions (Fredricks et al. 2004): (a) behavior (e.g., participation in activities such as number of times students interact with virtual world characters, embedded tools, objects), (b) cognitive-motivational (e.g., putting forth effort, belief of competence in content area or self-efficacy, desire to be optimally challenged), and (c) emotions (e.g., interest, curiosity, sense of belonging, and affect). Engagement in a TRC depends on the content presentation methods, the digital resource, software systems, and interactive design.

Vahey et al. (2013) leverage four key benefits of using dynamic-representation environments in mathematics classrooms: (a) providing multiple representations for student understanding, (b) providing a shared focus of attention, (c) supporting the use of narrative as a representation, and (d) engaging students in the mathematics. Dynamic-representational environments have also been shown to increase student engagement in mathematics. Focusing on young children's collaborative communication and thinking in classroom science activities, Kershner et al. (2010) suggests that the IWB can be used collaboratively in a variety of science activities closely related to familiar classroom practice and the children can engage effectively in the collective learning experience. The research on multi-image presentation revealed that multiscreen presentation having split-attention effect followed the cognitive load theory, which means that learners obtain better learning performance by integrated information (Ayres and Sweller 2005).

Therefore, the indicators for desirability in a TRC could include the following aspects: (1) Does the size of projector screen match the classroom? (2) Do 1:1 computers/devices match the content? (3) Do interactive whiteboard match the activities? (4) Is the content presented on the screen using multiscreen technology? (5) Does Student Response System provide active learning?

13.4.4 Adaptability: Does It Adapt to Learners?

Adaptability for a TRC mainly deals with the diversity of students and their learning preferences. In order to meet the diverse needs of students, room layout should be flexible to meet the teacher's instruction and learner's collaboration, software system should adapt to learning styles of the learners, and physical environment factors, such as the lighting, temperature, ventilation, could be adjusted automatically.

Hill (2008) recognized that flexible, modern learning environments could encourage students to fully participate in activities with others as they acquire knowledge for themselves. With regard to classroom layout, Lippman (2002, 2003) in his study of schools mentions that providing a variety of spaces within a classroom supports student–teacher/child–adult relationships. Jamieson (2007) recognized that formal spaces such as lecture theaters, classroom, and labs should have flexible layouts that support a diversity of teaching and learning approaches.

From the above analysis, combined with considering the emerging technology equipped in TRC and the main furnishing elements, we proposed the indicators for evaluate the adaptability of a TRC could include the following aspects: (1) Does the software system provide instant feedback? (2) Can students present and share their learning outcome easily (3) Are the systems compatible with common devices? (4) Does data between the student and teacher change easily? (5) Is the classroom layout flexible for different learning activities? (6) Can the lighting system adapt to learners needs with the changes of nature light?

13.4.5 Comfortability: Is It Comfortable in the Classroom?

Comfortability in TRC relates to providing or experiencing TRC's physical well-being, i.e., the user interface and environmental conditions consisting of various elements such as temperature, humidity, noise, thermal, air pressure, ventilation, air quality, acoustic, dust, vibration, lighting, air flows, radiation, etc.

Due to the increased use of media and technology in classrooms, the design of easy-to-use, adjustable lighting systems is more important than ever. Lighting should be designed in accordance with the Illuminating Engineering Society's and the National Electrical Code's current recommendations. Lighting should be designed to meet the special program requirements for each instructional space (Clabaugh 2004). In addition, many studies showed that the following factors are important design considerations (Filardo and Vincent 2010): (1) Indoor air quality (IAQ)—mold and airborne bacteria have adverse effects on children's and teachers' health. (2) Temperature and humidity—creates conditions which lead to Sick Building Syndrome, relative absenteeism and lowered mental acuity. (3) Ventilation and air flow—is an occupational health and safety issue because children require more air in proportion to their body weight than adults. Studies indicate that air flow from windows is inadequate in schools to remove or prevent the buildup of carbon dioxide. Poor air flow leads to poor performance of tasks. (4) Thermal comfort—there is an optimum temperature for learning, retention, task performance, and job satisfaction. (5) Acoustics—good acoustics (quality rather than amount of noise) are fundamental to academic performance. (6) Building age, quality, and esthetics—affect student and teacher perceptions of safety and well-being. Building age is not as important as the quality of building conditions. Students generally perform better in modernized or new environments but it is difficult isolating mediating factors, and therefore, inconclusive. (7) Furniture and carpets—dampness and pollutants can lead to health problems, e.g., asthma.

Based on the important factors for comfortability in a classroom, we proposed the following indicators for evaluating classroom comfortability. (1) Does the lighting system support reading healthy? (2) Does air in the classroom meet the air quality standard? (3) Is the temperature in the classroom suitable for learning? (4) Does the classroom have good acoustics? (5) Does classroom decoration meet the students' preference? (6) Is the teaching console easy to operate?

13.5 Conclusion

New generation of learners appeals for technology-rich, flexible, and comfortable learning space. TRC as a learning space should consider the new generation student's needs. Considering the digital learner's needs, we proposed the concept of "learner experience" to show learners' perceptions and responses that result from physical environment changes. With the fusion of technology, pedagogy, and space, learner experience in a TRC gradually became important for ensuring students' engagement and performance.

We proposed value, usability, adaptability, desirability, and comfortability as the five elements in a TRC that will influence learner experience, which should be considered when build or rebuild learning space. Learner experience will change when the Furnishing (providing audio-visual system, computers, devices, and software) and Equipping (decorating classroom and changing layout) in a TRC changed, and service was one of the most key factors for improving learner experience in a TRC. The framework for analyzing Learner Experience in TRC we proposed in this chapter presented the most important factors for improving students' experiences in a TRC, which could become the guideline for optimizing classroom environment supported by technology. It is believed that the framework for analyzing learner experience will become a significant direction in learning space design and evaluation, but the framework we proposed were not perfect and should get improved in future.

The indicators in the framework for analyzing Learner Experience in TRC indicated the detail information for each element, which will help designers and practitioners to build an advanced TRC for learner. However, these indicators were yet in the rough and should be refined and enriched with more empirical study. The next step of this research should be (1) to develop the scales for measuring learner experience in TRC; (2) to investigate the relationship between learner experience and students' performance; (3) to test and verify the framework for analyzing Learner Experience in TRC by cross-cultural collaborative empirical study.

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