Chapter 4

IMPROVING LEARNING BASED ON THE IDENTIFICATION OF WORKING MEMORY CAPACITY, ADAPTIVE CONTEXT SYSTEMS, COLLABORATIVE LEARNING AND LEARNING ANALYTICS

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Abstract: Working memory capacity and learning styles play key roles within adaptive learning environments. In addition, the concepts of collaborative efforts, context awareness, ensuring student engagement and the identification of students at risk of dropping out, play vital roles and are key to any successful learning environment. In this chapter, key concepts and mechanisms for each of them are discussed along with various approaches and frameworks. A means of utilizing artificial intelligence to improve working memory capacity identification and learning styles identification is discussed in the second section. Adaptation is discussed in both the third and fourth section, as it pertains to collaborative learning environments and adaptive context-aware expert systems. The final two sections address the problem of student drop-out rates as it pertains to improving the promotion of scientific competencies and the identification of students at risk of dropping out. All these concepts assist in providing learners with adaptive and improved learning environments that aid in supporting learners in the learning process.

Key words: learning style, working memory capacity, collaborative learning, context aware, scientific competences, learning analytics

1. INTRODUCTION

There is no single definition or template of a learner. Learners come from different backgrounds and have different skillsets, motivations environments and problems. The aim of our research is to facilitate the creation of more effective, adaptive and tailored learning systems that are conducive to learning at every stage of the learning process. In this chapter, we focus on five key areas and present research conducted in these areas: (1) the identification of working memory capacity and learning styles, (2) adaptive recommendations for collaborative learning, (3) adaptation based on context information, (4) adaptive recommendations for learning scientific competencies and (5) identification of students at risk of dropping out or failing.

Working memory capacity (WMC) play a key role is affecting a student's behaviour on how they perform in reading comprehension, decision making and problem solving (Ford & Chen, 2001; Broadway & Engle, 2011). The careful consideration of a student's WMC assists in the prevention of cognitive overload and thus able to affect student's learning in a positive manner (Gathercole & Alloway, 2008). The approach described in Section 2 of this chapter suggests a means of improving precision of learning style and WMC identification. This would permit students to benefit through more appropriate content matching or better advice from their teachers.

Collaborative learning is beneficial and crucial to the learning process (Koh, Barbour & Hill, 2010). In Section 3 we address the concept that collaborative learning can be enhanced by utilizing computer support. The research discussed in this section aims to provide adaptive recommendations to collaborative groups while they are working on a group project, focusing on support for project management and communication aspects.

Section 4 addresses the concepts of adaptive context-aware expert systems. Environmental and spatial conditions can have a significant impact on the way we learn. Although learning experiences, thanks to mobile technology, are able to take place anytime and anywhere (Shih et al., 2010), the increasing variety of locations and conditions where learning can occur has led to serious technical and contextual challenges. The research in this section describes the development of a framework that would facilitate the creation of adaptive context-aware systems that integrates with an adaptive engine.

The acquisition of scientific competences is a key issue in postgraduate programs. Section 5 suggests a solution to improve the experience of beginning researchers when they do research through the generation of recommendation in each step of the research process by the use of an ontology that represents practical and conceptual knowledge about research methods. The generated recommendations facilitate the decision-making process in the research process.

According to McNutt and Brennan (McNutt & Brennan, 2005) reports published in 2005, in the Chronicle of Higher Education (US) have found that post-secondary institutions are seeing dropout rates ranging anywhere from 20% to 50% for distance learners. Section 6 demonstrates means of determining variables that are the most relevant in the successful identification of students at risk.

2. IMPROVING PRECISION OF LEARNING STYLE AND WORKING MEMORY CAPACITY IDENTIFICATION WITH ARTIFICIAL INTELLIGENCE

The identification of students' learning styles, their preferences towards the learning task, and working memory capacity (WMC), the number of items they can store in short term memory, allows personalized content to be matched to the student. The student benefits from learning style identification with improved learning outcomes (e.g., Ford & Chen, 2001), satisfaction (e.g., Popescu, 2010), and a reduction in learning time (e.g., Graf, Chung, Liu & Kinshuk, 2009). Although there are many models for learning styles, this research used the Felder-Silverman learning style model (Felder & Silverman, 1988) which consists of four dimensions: active / reflective (A/R), sensing / intuitive (S/I), visual / verbal (V/V) and sequential / global (S/G).

Questionnaires exist which can identify students' learning styles and WMC; however, these have two notable drawbacks. Questionnaires are intrusive to the learning process. Also, questionnaires may be influenced by other factors such as a student's mood, so some students' characteristics will not be accurately identified. Automated approaches overcome intrusiveness by working in the background and by using students' behaviors they are less subject to other factors. The drawback to automated approaches is that they peak at about 80% precision leaving some room for improvement. This research aims to answer how artificial intelligence can be used to improve precision of automated approaches while being general to any learning management system.

One approach, DeLeS (Graf, Kinshuk & Liu, 2009; Chang, El-Bishouty Graf & Kinshuk, 2013), uses behavior patterns which are general to any learning management system to identify learning style and WMC and has a leading degree of precision (~80%). One issue with DeLeS is that it assumes that all behavior patterns are equally important by assigning each behavior pattern a weight of 1. If an optimal set of weights could be found then precision should be increased; however, the set of all weight combinations is a very large space (minimum 10^{12} combinations) and so three optimization algorithms are proposed to search more efficiently. Alternatively, the behavior patterns may serve as good inputs directly into a classification algorithm.

The three optimization algorithms selected were ant colony system (ACS), genetic algorithm (GA) and particle swarm optimization as each explores the solution space in a different manner and thus may give different results. The classification algorithm selected was the artificial neural network (ANN). Each of these approaches was named LSID (Learning Style Identifier) with the corresponding algorithm, for example LSID-GA for genetic algorithm. To assess all four approaches, 75 students' behaviour and learning style data and 63 students' behavior and WMC data was used. For each approach, the remainder of this process was repeated for each learning style dimension and WMC. Each algorithm has several parameters which greatly influence the ability of the algorithm to be trained properly. To optimize the parameters, each parameter was systematically altered one a time within ranges suggested from literature. Overfitting is a common problem with artificial intelligence algorithms where solutions are fit to the data's noise, so next overfitting reduction techniques were assessed. For all four algorithms stratification (Kohavi, 1995) was assessed and for the ANN future error prediction (Mitchell, 1997) and weight decay (Krogh & Hertz, 1992) were assessed additionally. To further promote a general nature to the algorithms, a 10 fold cross validation technique was used for every execution thus ensuring that the algorithms are able to work under a variety of data sets. For this reason, all the results are averages over the 10 folds.

With the optimal parameter settings and optimal overfitting reduction techniques, a final result was obtained shown in Table 1. These results show that, with two exceptions, all of the LSID approaches improve precision over DeLeS. The exceptions are LSID-GA in the A/R dimension which is worse than DeLeS and LSID-ANN in the S/I dimension which is equal to DeLeS. The best results were obtained by the ACS in the A/R and S/I dimensions while the ANN obtained the best results for V/V, S/G dimensions and for WMC. These results show that precision is improved by finding an optimal set of weights for the behavior patterns and that these behaviour patterns are successful as direct inputs into a classification algorithm.

Table 1. Comparison of precision results for LSID and DeLeS (ranking in parenthesis, and top result bolded

Approach	**A/R**	**S/I**	**V/V**	**S/G**	**WMC**

LSID-ACS	**0.819 (1)**	**0.797 (1)**	0.799 (2)	0.737 (4)	0.855 (2)
LSID-GA	0.795 (5)	0.796 (2)	0.794 (4)	0.774 (2)	0.836 (3)
LSID-PSO	0.805 (2)	0.794 (3)	0.796 (3)	0.768 (3)	0.835 (4)
LSID-ANN	0.802 (3)	0.790 (4)	**0.840 (1)**	**0.797 (1)**	**0.862 (1)**
DeLeS	0.799 (4)	0.790 (4)	0.788 (5)	0.702 (5)	0.809 (5)

By improving precision of learning style and WMC identification students would be expected to benefit through more appropriate content matching or better advice from their teachers. This would then lead to improved learning outcomes and satisfaction, and a reduction in the time needed to learn.

3. PROVIDING SUPPORT FOR STUDENTS THROUGH ADAPTIVE COLLABORATIVE LEARNING ENVIRONMENTS

Collaborative learning is an important aspect of the learning process. Learning goes beyond the learning material to teach students and builds upon other important indirect skills such as communication and interpersonal skills (Williams & Roberts, 2002). Collaborative learning can be greatly enhanced by the use of computer supported collaborative learning (CSCL) if it is properly implemented, especially when an adaptive learning system assists students along the way. Implementing a collaborative learning environment is both beneficial and crucial to the learning process if used correctly (Koh, Barbour & Hill, 2010). Learning management systems (LMS) are becoming widely popular with schools and education systems for both online and blended learning environments and while these systems are great for presenting information to students, they do not necessarily support collaborative learning or provide intelligent features to facilitate the collaborative learning process.

Our research aims to deliver adaptive recommendations to students working in groups in order to benefit and assist their progress. In this section, we introduce the Adaptive Collaborative Systems (ACS) which supports collaborative learning in learning management systems, focusing on two areas: communication and project management. ACS is different in terms of how other system have been designed and implemented as it is presenting adaptive recommendations to students and/or groups as they work on team projects. Other differences include that ACS is domain independent and the design can be integrated into any LMS.

3.1 Communication features in ACS

ACS monitors the communication between students to determine participation in a way that can ensure students are actively attending meetings as well as contributing to dialogues fairly. ACS looks at both ends of the spectrum of communication, high and low, in a variety of communication channels, including forums, chats and imported messages (e.g., from Skype). Brindley, Walti, & Blaschke (2009) discussed that not all communication will take place on the LMS and that other third party applications may be used. Therefore our system incorporates a utility that allows students to import third party chat logs for both participation analysis and centralized log to reference at later if needed.

If ACS determines that a student is not attending meetings frequently, it provides this student with an alert. Furthermore, if ACS determines that a student contributes significantly less than others to a dialog, ACS alerts the student privately to participate and contribute more to the dialog. ACS also uses the same monitoring techniques to determine if students are over participating and recommends those active users to improve their leadership skills by include other quieter members into the conversation, for example, by asking them direct questions about the content so they can elaborate further.

3.2 Project management features in ACS

ACS takes advantage of the information provided by the students on their progress for each task. This allows the system to help keep students on task in a timely manner by monitoring the amount of work done for each task and comparing it to the time that has passed. This information is presented to

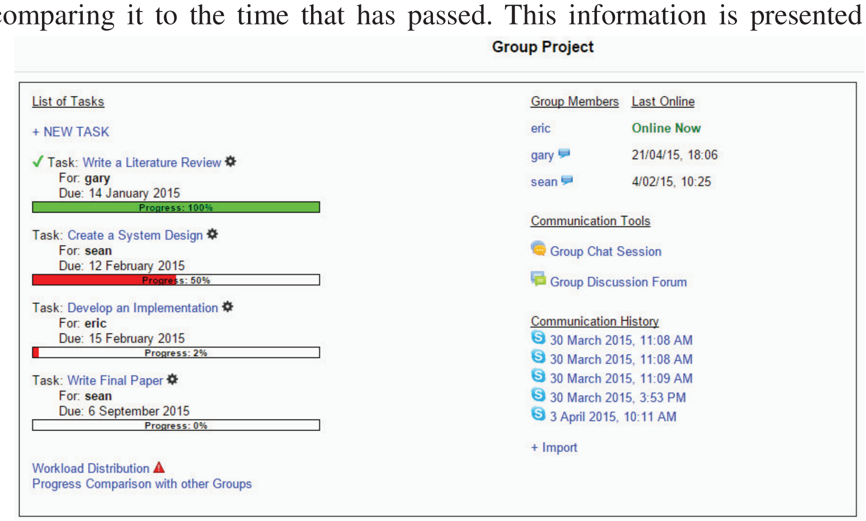

Figure 1. Main interface of ACS

students using an at-a-glance interface (see Fig. 1) so students can quickly and easily tell if they are on track on a specific task or not by displaying a progress bar in green or red, respectively. To motivate students, ACS also displays a group's current progress in comparison to other groups' progress in the current course. Furthermore, it monitors a group's risk of failing by comparing their progress to previous cohorts' progress at the same time and alerts a group if they become at risk of failing. ACS also ensures that an equal distribution of work has been assigned to all students by comparing the allotted amount of work between all group members.

Especially in online learning settings, group work is used more and more due to its many advantages and ease of use. ACS aims at ensuring that the potential of collaborative learning can be fully unlocked and all students are supported to participate and benefit equally from collaborative learning through personalized recommendations and information on how to effectively learn in collaborative settings.

4. A GENERIC PLATFORM FOR ADAPTIVE CONTEXT-AWARE EXPERT SYSTEMS

Collaborative learning has been seen as an important part of the learning process. It can take place over short distances in close proximity or with modern technology, between two places anywhere on the globe. Yet, our surroundings affect almost every aspect of our daily lives: from the mundane to the most elaborate task, where we are and what our proximate environment is like, affects us in many varied ways. This is also true for our ability to learn, specifically how and what information is presented to us. With the ubiquitous nature of smartphones worldwide, researchers are being provided enormous processing power in the hands of learners.

Although it has a great effect on us, people may not be always cognizant of their surroundings or its effect on their daily lives. For example, Schilit, Adams, and Want (1994) described a system that reacted to an individual's changing context. They stressed the importance of the limited information within a person's proximate environment.

Although proposed over 20 years ago, it is only recently thanks to technological advances that we are able to adequately investigate and apply this type of system as proposed by Schilit, Adams, and Want (1994) to the general public, specifically to aid in learning. Much work has been done since the 1990s to further the field, however there has not been much research done towards the creation of a framework that would incorporate context aware adaptive learning systems. For example, Anagnostopoulos and Hadjiefthymiades (2009) described an extension of context presentation that would help in the representation, classification and inference of sensor data obtained from a device. In the educational domain, Liu and Hwang (2010) described the paradigm shift between conventional e-learning to m-learning to context-aware ubiquitous learning.

This has extensive ramifications into learning in general, as environmental conditions can affect the way we learn, and the type of information we require changes with our environment. This raises the concern of how to provide advanced adaptive learning based on environmental and contextual information. In order to help find a solution for this issue, our research involves the integration of an adaptive context-aware learning system and an expert system.

As many current context-aware systems are designed to work with specific scenarios, when a different scenario is needed, the system typically needs to be re-built from scratch. Our research proposes a generic framework that integrates the inference engine of an expert system with a context-aware, mobile adaptive engine. This research aims to answer the following questions: How to automatically detect context information and create a generic rich context model for adapting to context and environmental factors? Furthermore, how does an adaptive context-aware system integrate with the inference engine of an expert system in order to allow for a generic platform between the two systems?

Figure 2 shows a brief overview of the main components of the framework and their basic functionality.

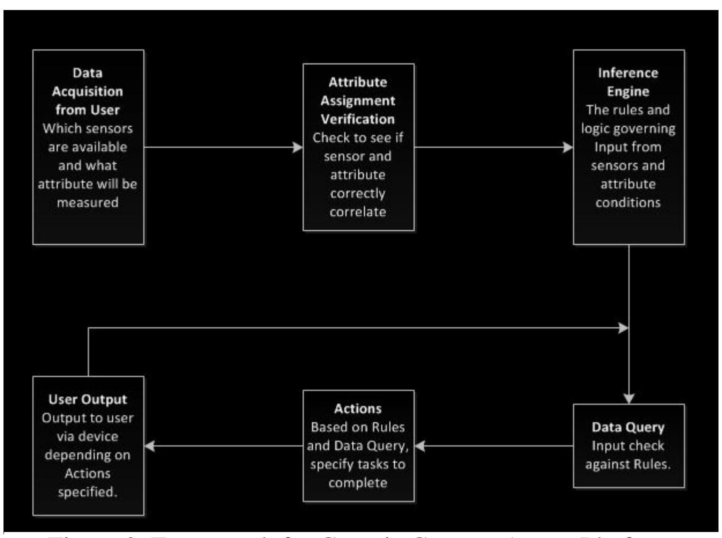

Figure 2. Framework for Generic Context-Aware Platform

The outcome of this research will be a generic platform that after minor configurations can be adapted to many different types of knowledge bases and inference rules, and therefore would be applicable in different scenarios.

5. IMPROVING THE EXPERIENCE OF BEGINNING RESEARCHERS WHEN THEY DO RESEARCH

How to promote the acquisition of scientific competences (NPA Core Competencies Committee, 2009) is one of the most important issues and permanent and persistent problems through the years in the context of postgraduate programmes. It is a relevant problem for postgraduate programmes because it causes reduction in the quality of postgraduate research as well as high drop-out and late submission rates. Important studies have been conducted with the purpose to identify causes of a very common problem that face beginning researchers as well as the attitude of postgraduate students toward research (Graves, 1976; Reeves, 2000; Shaukat, Siddiquah, & Abiodullah, 2014; Zuber-Skerritt, 1987). In general detected problems could be summarized in the following categories:

- Inadequate supervision
- Emotional and psychological problems
- Lack of understanding and communication between supervisor and student
- Student's lack of the fundamentals of scholarship due to a lack of background knowledge, training or experience in research methods
- Late completion and high drop-out rates

The origin of these problems arise in that it is "often assumed in postgraduate education that candidates have developed basic research and writing skills at undergraduate level (reading, note-taking, essay writing, problem solving, information and retrieval skills, etc.) and they are able to translate and apply these skills to their thesis research and writing…" (Zuber-Skerritt, 1987).

On the other hand, the generalized adoption of the single-supervisor model of postgraduate teaching that indicate "…whether and how well a student is guided in the research process and helped in developing skills in thesis writing, depends solely on the individual supervisor's available time, attitude and ability to teach these skills" (Zuber-Skerritt, 1987). In this way, if the supervisor does not have time or the necessary knowledge to support the student then, the research process could be unsuccessful, which frequently happens.

Several solutions that come from educational perspective have been proposed and validated to alleviate the described problem:

- The reviews of postgraduate programs to include educational strategies centered in the students' needs and preferences.
- The introduction of a workshop model for developing skills in dissertation research and writing.
- Many courses about challenges and methods in research have been created

Our hypothesis is that it is possible to conduce beginning researchers to a successful research if they receive appropriate recommendations, including conceptual and practical ones, based on the practical and conceptual knowledge about research methods represented in an ontology, that helps then to take high quality decision in each step of the research process.

Our solution includes:

- The generation of an ontology that represents practical and conceptual knowledge about research methods;
- The design of a recommender system that uses the generated ontology to give answers to typical problems or questions faced by beginning researchers.
- The evaluation of the system through an experiment with real students.

As recommended on by Shaukat et al. (2014) it is important nowadays to develop positive attitudes in the students toward research. Our research aims at contributing towards this goal by reducing the uncertainty that beginning researchers face when they do research.

6. RELEVANT VARIABLES FOR IDENTIFYING STUDENTS AT RISK

Several studies have shown that online distance students often have higher dropout and failure rates than students who attend classes in a physical environment (Lokken & Mullins, 2014; Schaeffer & Konetes, 2010). There are a number of aspects as to why online students do not succeed as frequently as their offline counterparts. Factors can include feelings of isolation, dissociation with the learning environment, differing learning styles, and technical difficulties (Schaeffer & Konetes, 2010). One of the major challenges of ensuring student success in an online environment is the lack of direct, face-to-face contact with instructors and other students.

Consequently, instructors are unable to observe when a student becomes disengaged or distracted from the learning process.

Fortunately, in an online environment the primary method of course delivery is through a learning management system (LMS), where activities from students, teachers, and course administrators, are automatically captured in database tables or log files (Mazza & Dimitrova, 2004). However, the online activity reporting functionality from an LMS is limited, primarily providing simple reports, including, for example, the last logins of students or the total number of logins for a specified date range. As with other organizations across industries, educational institutions have found themselves in the 'data rich, information poor' paradox.

Institutions have been employing learning analytics, which is 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 (Siemens, 2010), to develop prediction, risk identification, and intervention systems to increase student success (Chatti et. al, 2012). However, predicting student success at one institution is not guaranteed for predicting the success of students at other institutions. As more educational institutions and LMS vendors develop more learning analytic-style analysis and reporting tools, the field of learning analytics can benefit from research in determining variables that are the most relevant in the successful identification of students at risk.

6.1 Determining Relevant Variables

The intent of our study is to assist in furthering the development of the learning analytics research field by determining the relevancy of variables in the identification of students at risk. The three research questions that guided the direction of this study are:

1. What variables have been relevant in past studies?
2. Based on real student data provided for this study, which variables are accurate at identifying students at risk?
3. Based on real student data provided for this study, which variables are more relevant than others?

In addition to an online search of academic and scientific publications, this study included the analysis of student background and behavioral data over a period of five years. Past research has applied differing data mining or statistical analysis techniques on student behavioral data from a single institution, on a small number of courses, for a short period of time, typically one or two semesters, or for a specific student population, such as first year students or some combination of this sample. The data used in our study spans over sixteen semesters, nine courses, 94 classes, and 320 students at various points in their academic studies. The courses were fully dependent on internet and communication technologies for course delivery.

6.2 Methodology

To answer Question #1, what variables have been relevant in past studies, an online search and literary review of a number of academic and scientific publications was conducted. The online search consisted of the following key words and phrases: *learning analytics*, *educational data mining*, *academic* and *action analytics*, *student success* and *retention*, *predictive modeling software*, *tools*, and *online* and *distance education*.

To answer Questions #2, based on the student data provided for this study, which variables are accurate at identifying students at risk, and #3, based on the student data provided for this study, which variables are more relevant than others, student background and behavioral data from nine courses in a computer science graduate program, from the Fall 2007 semester to the Spring 2012 semester, was obtained. In total, there were 320 students comprising 1300 records, including their final course grades.

Two methods, Spearman's correlation coefficient for independent to dependent variable analysis and Pearson's correlation coefficient for independent to independent variable analysis was applied to partially answer Questions #2 and #3. Additional analysis was conducted by creating a Bayesian network for each course (i.e., each course revision). Descriptive statistics were used to determine the frequency, significance and direct relationships between all variables, and ultimately identify the variables that were the most relevant in terms of significance, strength and frequency of relationships.

6.3 Results

To answer Question #1, what variables have been relevant in past studies, over 200 variables from 22 studies were used in ensemble models to identify students being at risk. The number of discussion postings created was the prediction variable that was reported to be significantly relevant the most (61.5%) frequent in empirical research. A listing of prediction variables used in more than ten studies and the percentage of studies in which the variable was found to be relevant is displayed in Table 2.

Table 2 – Prediction variables appearing in ten or more studies and their reported relevancy percentage

Prediction Variables	Number of Studies Variable Appeared	Percentage of Studies Variable Reported as Relevant
Number of Discussion Postings Created	13	61.5%
Assessment Tests	13	53.9%
Number of Discussion Postings Viewed	11	45.4%
Number of Resources Viewed	22	40.9%
Grade Point Average	11	27.3%
Number of Mail Messages Created	11	27.3%

To answer Question #2, based on the student data provided for this study, which variables are accurate at identifying students at risk, the results of the correlation analysis and the number of direct relationships with independent variables to the dependent variable were combined. The variables for the total number of files uploaded to the LMS (average p value = .004, average $\boldsymbol{r_s}$ = .409) and total number of discussions viewed (average p value = .007, average $\boldsymbol{r_s}$ = .318) are identified as being significantly related to the final grade the most, appearing in 75% of the data sets, as displayed in **Error! Reference source not found.**3.

Table 3 - Correlation analysis results of relevant prediction variables with student final grade, including the percentage that direct relationships existed in the course data sets

Prediction Variables	p	r_s	Direct Relationships in Course Data Sets	Course Data Sets Appearance
Total Files Uploaded	0.004	0.409	56.3%	75.0%
Total Discussion Posts Viewed	0.007	0.318	68.8%	75.0%
Total Number of Log Activity Records	0.007	0.400	75.0%	68.8%
Percent of All Post Types	0.003	0.391	37.5%	68.8%
Average Number of Discussion Posts Viewed/Week	0.007	0.318	43.8%	68.8%
Total Number of All Discussion Post Types	0.004	0.422	56.3%	62.5%
Week 13 Logins	0.009	0.402	75.0%	62.5%
Week 11 Logins	0.013	0.372	75.0%	62.5%

To answer Question #3, based on the student data provided for this study, which variables are more relevant to others, the results of the correlation analysis and the independent variable that had the most direct relationships with the other independent variables was combined. Although the variables identified as being relevant were not similar between the correlation analysis and the Bayesian network graph, the results indicate that the successful student will be engaged with course material, and will revisit content frequently.

6.4 Discussion

With the projected adoption of learning analytics in the very near future within educational institutions (Johnson, et. al., 2011), the evaluation of prediction variables and their relevancy in identifying students at risk will assist with the continued development of student success models and prediction tools. Although student demographic information and previous academic history or performance data is often included in prediction models based on empirical research, our research showed that variables related to student behavior have often higher relevancy in successfully identifying students at risk. The findings of this study confirmed that student background data may assist in classifying students at risk early in a semester; however student behavioral data, specifically the engagement and interaction of students via discussion board forums are the most relevant variables in successfully identifying students at risk.

There are limitations with this research, specifically related to the size of the data sample and the student success rates. The data was provided from one single institution. Additionally, the course material and subjects from the nine courses used in the study was diverse but from the same program. The courses were only a subset of those available within the program, and even smaller from the total number of courses offered by the institution as a whole.

7. CONCLUSIONS

This chapter illustrates and identifies several key problems faced by learners. In Section 2 of this chapter, a means was described of improving the precision of learning style and WMC identification based on behavior patterns - which are general to any learning management system. Several algorithms were tested which improved the precision of identifying learning style and WMC. The results uncovered that precision is improved by finding an optimal set of weights for the behavior patterns. Furthermore, it was found that the behaviour patterns are successful as direct inputs into a classification algorithm.

The third section introduced a system that supports learners in collaborative settings, providing them with recommendations and information about how they can learn more effectively as a group. The system focuses on project management and communication aspects and supports individual learners as well as the whole group.

The concept of adaptation was also addressed in Section 4, the notion of adaptive context-aware learning systems was discussed. A framework was proposed that would enable the integration of an adaptive context-aware system with the inference engine of an expert system. The resulting framework would allow for quicker development of such systems with minimal work on the part of the researchers.

Section 5 proposed a solution that would help with the acquisition of scientific competences, which is a key issue in postgraduate programs. The proposed system provides recommendations to beginning researchers, supporting them in doing research.

In Section 6, the problem of high failure and dropout rates for online distance education courses was discussed. In the proposed research, a variety of variables was investigated in terms of their relevance for identifying students who are at risk of failing a course..

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