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Towards Understanding Learner Experiences in eLearning Tools

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Abstract

An understanding of how learners interact with eLearning tools and the relationship of different forms of interaction on subsequent learning outcomes is fundamental to improved learning outcomes as well as the effectiveness of eLearning tools. In this paper our main objective is to present methods to extract and analyse some crucial experiences and patterns, from an eLearning tool, that have significant effect on students learning. The proposed methods are presented in the context of a study conducted with undergraduates and postgraduates taking a course in an information system discipline. We demonstrate how the extracted experiences and patterns can be used as feedback to learners to improve learning. Academicians and lecturers can also use the analysis as a gauging instrument to measure the effectiveness of the eLearning tool thereby allowing the tool and learning practices to be improved.

Keywords : eLearning, learning experience, learning patterns, recommender, kiviart chart.

1 INTRODUCTION

eLearning systems are widely recognized to present characteristics such as providing alternative modes of interactions between learners and instructors as well as amongst learners, removal of the limitation of time and space, high availability and access to materials and so on. These characteristics fulfil evident needs and demands of learners in a modern digital knowledge society. However, recent studies and surveys suggest that despite the popularity and huge investment in eLearning, eLearning in higher education (HE) has yet to make a significant impact on the quality of teaching and learning and pedagogical innovation; even though it is most commonly cited as key driver (Homan and Macpherson 2005; Keller et al. 2009; MacKeogh and Fox 2009; Nagy 2005). As a result many of the eLearning systems developed today are mostly focussed on the automation of the process and management of teaching and delivering of courses with the advantages of eliminating the time and space barrier. The value towards better learning outcomes is still an area of study, although some researchers have recognized the issues and provided innovative solutions to solve some related problems (Brusilovsky and Millan 2007; Peter Dolog 2008; Yalcinalp and Gulbahar 2010).

Most HE institutes in Australia are still conducting courses in the conventional way while encompassing some form of blended learning strategies (Graham and Valsamidis 2006; Sadiq et al. 2004) in which lecturers deliver face-to-face lectures supplemented with tutorials, laboratory works and some forms of eLearning tools. Learning Management Systems (LMS) are common for the management and administration of courses, for instance, tracking progress of students, providing repositories for learning materials as well as tracking of courses (Allen et al. 2008). On the other hand eLearning tools are increasingly being introduced to complement learning of concepts and providing a platform for students to test their understanding and application of the concepts they learned as a result of attending lectures and tutorials.

Typically in eLearning face-to-face contact with educators, lecturers, facilitators and tutors are at a minimal. Thus the opportunity to observe, understand and respond to the behaviour and outcomes of the students is rather limited for both the teaching staff as well as for fellow learners. The values of sharing experience which is often neglected in eLearning can be of great benefits to learners, teachers, academicians and practitioners epistemologically and financially (Helic 2007; Helic et al. 2004). We argue that the capturing and utilising of experiences of learners, referred to as learners' experience (LE), as knowledge available or sharable to peers and academicians would be a critical catalyst in making learning more efficient and to produce better outcomes for students learning in a variety of ways.

In this paper our aim is to develop methods to effectively and efficiently capture, analyse and utilize knowledge relating to LE. More specifically, our focus is on how to analyse important patterns of LEs and learners' behaviour in the context of eLearning that pose potential effect on students' learning. Essentially the patterns are an indication of various interactions of the learners with an eLearning system. We posit that these learners' patterns when reused in the form of knowledge and feedback implicate the transformation of knowledge to action. This transformation can motivate as well as accelerate learning efficiency for learners and their peers (due to the ability to compare). Additionally, we also propose a visualisation instrument for learners to reflect on their own learning experience as a form of feedback.

The proposed methods are primarily algorithmic in nature and hence follow a design science research methodology. The proposed methods as well as the results derived from their implementation are presented in the context of a study conducted over a semester within an information systems course. The course involves both undergraduates and postgraduates, and has a student body spanning across IT, business, engineering, science as well as a number of other disciplines.

In the subsequent sections, we first present the background and related work on learning experience and learning patterns in the context of eLearning. We then discuss the study context and methodology for our work. The proposed methods of extracting and analysing the learning experiences and patterns are described and examined in the subsequent sections. The results and future extensions of this work are summarized in the last section.

2 BACKGROUNDS AND RELATED WORK

Experience in general can be considered as knowledge or skill gained through the observation or exposure to some phenomena or some events. When applying to learning it is the process, systematic or random, of exploring and active or passive cognitive engagement with a domain knowledge with the objectives of gaining skill and knowledge (thereby fulfilling the Bloom's Taxonomy of educational objectives (Krathwohl 2002)). There is also a fundamental difference between experiential learning and learning experience (LE) in an academic eLearning environment. In its simplest definition experiential learning is learning by doing whereas LE (as presented in this paper) refers to learners' experiences (interactions) with an eLearning system. We posit that knowledge of LEs can help improve the effectiveness of learning for the learners, as well as their peers.

We note however, that knowledge related to LEs is not just concerned with material that exists, the interactions with the technologies such as computers and Internet, but also related to many experiences that are human oriented. Therefore the experience also encompasses into it the human learning behaviour and patterns. In his sociocultural theory, Vygotsky (Vygotsky 1980) argues that individual mental functioning is inherently situated in social interactional, cultural, institutional and historical contexts, and learning occurs through social interactions with peers, mentors and experts. Explicit knowledge in the form of instructional materials, course notes, quizzes, etc. are normally abundant and excessive. Therefore the real value is in the meta-information. That is, knowledge of the type of information, when it is useful, what to do with it and how to reuse it. LE and behaviour of learners holds the key to the answer because it reflects a learner's cognitive, behavioural and psychological learning pattern, which is in fact a form of tacit knowledge (Nonaka 1994; Ronchetti and Saini 2004).

Michael D. et al. (Derntl and Mangler 2004; Derntl and Motschnig-Pitrik 2005) in his work tried to model the processes of blended learning as patterns and produce a web template based on social-technical and pattern-based approach. His later work (Derntl and Calvo 2011) is to ultimately produce and use an e-learning framework approach capable of enhancing the usability and usefulness of educational design patterns. Similarly Teo and Gay (Teo and Gay 2006), use concept and formal concept analysis to tap and externalise expert's or mentor's tacit knowledge, a form of patterns of teaching, and use it in personalising eLearning system. Peter Dolog's (Peter Dolog 2008; Peter Dolog 2004) research works focus more on the framework and infrastructure of eLearning system that enables personalised access to distributed heterogeneous knowledge repositories. He addresses the key issues of choosing appropriate learning repositories with a vast number of federated learning offers. Many of the existing works provide frameworks and approaches in designing personalised eLearning but do not address the issue of learning experience and patterns that if extracted, could be used to improve learning and teaching through feedback. There are a few works that identify the differences of learning patterns of learners using LMS (Learning Management Systems) statistics but not specifically using eLearning tool in a blended environment (Campbell et al. 2007; Coates 2005; Dawson 2010) which is the common practice in most teaching environment currently.

In this study we conducted an experiment with an existing eLearning tool in a blended environment running for an information systems course and collect users' data on interactions with the eLearning Tool. We analysed the collected data with our algorithms to extract patterns and experiences that are of interest in terms of their impact on learning outcomes. Lastly, we demonstrated how these can potentially be used to improve learning and teaching.

3 STUDY CONTEXT AND RESEARCH METHODOLOGY

Students' interactions with an interactive eLearning tool called Learning Database Management System (LDBM) is the main source of data used to assess the students' engagement and subsequently the learning experience and patterns. For every student the eLearning tool registers the answer to each question, the time taken and the number of attempts, and the marks the students received for each attempt. Each question is related to one or more examples from the topics of the course. The questions in the interactive activities deal with a concept within a broader topic. Thus engagement with a particular topic can be seen through the collection of concepts $\{C_1, \dots, C_n\}$ where each concept C_i is

further composed of a set of questions $\{Q_{i_1}, \dots, Q_{i_k}\}$. Additionally for each concept there is a list of examples $\{E_{i_1}, \dots, E_{i_n}\}$.

Thus the complete set of interactions for a concept i can be viewed as:

$$C_i = (\{E_{i_1}, \dots, E_{i_n}\} * \{Q_{i_1}, \dots, Q_{i_k}\})$$

At a particular time of a course, a student may have not answered all the questions $\{Q_{i_1}, \dots, Q_{i_k}\}$ related to a concept C_i . Therefore for a student S_j , a concept C_i at time t of calculation we consider the following:

$$A_{ij} = \{Q'_{i_1}, \dots, Q'_{i_r}\} \subseteq \{Q_{i_1}, \dots, Q_{i_k}\}$$

where A_{ij} is the set of questions about C_i attempted by the student j .

This simple approach allows LDBM to conceptualize students' learning experiences (LE) with topics through their interactions with concepts, examples and questions available in the eLearning tool. Topics are in turn later assessed through various assessment types including quizzes, assignments, group work and exams. This represents the context and environment for the study.

The methodological design for the study is accordingly based on the above context. The aim as explained previously is to develop methods to effectively and efficiently capture, analyse and utilize knowledge relating to LE. More specifically we have focussed on the following four aspects of LE and respectively designed methods to capture, analyse and where relevant visualize the data relating to the aspect.

1. Engagement of eLearning (learning experience) and output performance,
2. Importance and effectiveness of eLearning components designed,
3. Learners' chronological pattern and trend of engagement, and
4. Patterns and engagement as feedback to students and course facilitators.

The rationale for the choice of the above four aspects is further discussed below.

The first aspect relating to the study of learning experience is the degree of engagement of students with the eLearning tool. Student engagement is generally considered to be among the better predictors of learning and personal development. The premise is simple and self-evident: the more students study or practice a subject, the more they tend to learn from it. The very act of being engaged also adds to the foundation of skills (Shulman 2002). We estimate the degree of engagement from the frequencies of interactions in our studies and this is thought to be a better way of measuring the learning experience than time devotion because it is common that learners may be idle on a web site for hours and without doing anything productive (Brennan et al. 2009). LDBM is designed to register an entry in its log only when students interact by submitting answers to questions.

Secondly, it is widely known that students may not directly relate course concepts to various aspects of their personal, professional and social experiences. This is especially true for technical courses. The evaluation of the usefulness or the appreciation of the importance of the course concepts usually takes a few cycles for students attending the course. In this study we try to gauge the development of this understanding of importance through the examples presented in the eLearning tool. These examples are derived from a variety of domains indicative of the diversity of the student body such as examples from business, scientific, and social domains. An example that is widely used indicates a better fit for student learning. We use the data collected to formulate a simple equation based on the users' specified interactions data, for instance the examples students used $\{E_{i_1}, \dots, E_{i_n}\}$ to predict the effectiveness of the specified component of the eLearning tool and in turn the course concept that it represents.

Despite relative ease in extracting log data on student online interaction, the visualization and aggregation of this data is highly challenging (Mazza and Dimitrova 2007; Mazza and Milani 2005). This limits staff (and students) in understanding the linkage between student's online interaction and

implementing pedagogical innovation. In eLearning Helic et al.(Helic et al. 2004) argue that good online tutoring requires monitoring of a learner's progress with the material and assessing the acquired knowledge and skills on a regular basis. Thus from the lecturers' point of view, the chronological pattern of engagement represents the trend of learning experience of the students. This data allows the course facilitators to understand the progression of learning experiences over the duration of the study period and in particular around assessment activities. Hence our third aspect of study relates to the study of learners chorological patterns and trends of engagement. .

Lastly, we used a visual representation called Kiviati diagram which has common application in the control of quality improvement to display the performance metrics of any ongoing program (Basu 2004). Kiviati figures are histograms arranged in a circular shape. Usually 5 to 8 spokes (which represent multitudes measured) are arranged in a wheel and intersect with imaginary cycles. The rim represents the maximum value of the magnitude. An intersection close to the rim indicates a large magnitude; close to the core indicates a small magnitude. Subsequently a glance at the shape of the Kiviati figure resulting from linking intersections in each spoke can quickly convey a great deal of information about the underlying metrics. Kiviati figure usually represents a static picture that is they do not have time axis, but represent an instantaneous state or a time-integrated state (summary). Hence we use Kiviati figures to assist in providing feedback and subsequently studying the impact of feedback instruments on changes in study patterns in general and eLearning interactions in specific.

4 METHOD DESIGN

The eLearning tool LDBM was a 24/7 web based tool developed for addressing the growing need for database literacy in graduates across a range of disciplines in the School of ITEE, The University of Queensland. The tool was designed around concepts and examples closely aligned to the curriculum. For instance when learner chose to learn a concept i.e. ER-to-Relational Mapping, a list of examples was shown that he/she was free to select from. A set of questions would be presented for the learner to answer. Feedback on the correctness of the answers was shown immediately after each question was submitted.

The study was carried out over a 13-week semester with 135 undergraduate and postgraduate students of diverse backgrounds and disciplines who were taking the course. The course consisted of 3 hours lecture, 1 hour tutorial and 1 hour lab per week. Students could make use of the tool to supplement their conventional learning. The students would be assessed through 2 quiz tests, 1 assignment and 1 final semester exams. Students had been well informed of the benefits of using the tool at the beginning of the course especially towards the learning milestones.

Our data collection approach was non-intrusive and whenever the students interacted with the LDBM, it would register the concepts, examples and questions attempted as explained previously. Student's attendance for lectures and tutorials and students performance outcomes after each milestone was also collected manually.

4.1 Learners' engagement and performance output

We measure the learning experience by extracting the degree (%) of engagement of students with the eLearning tool against the performance outcomes using the following pseudo code and the results were plotted in figure 1:

Pseudo code C1:

```

Performance output = W
Sj = Student {j = 1, 2, 3 ..... n}
Ai = Questions attempted or the learning engagement
UP(Y) = degree of engagement in percentage (Y=y%)

```

```

For i = 1 to n
Do
{
i ++

```

```

    Execute UP(Y)
    Print W
}
End

```

4.2 Effectiveness of eLearning component

As for the measurement of the effectiveness of eLearning components (examples in this case), first we used the following pseudo code to extract all the examples done by the students and their performance outcomes. The results were plotted in figure 2.

Pseudo code C2:

```

Eih = examples { h = 1, 2, 3 ..... k}
UP(Y) = degree of engagement in percentage (Y=y%)

For i =1 to n
Do
{
i ++
Count E
For h = 1 to k
Do
{
h ++
execute UP(Y)
Print W
}
}
}

```

Given that:

$$E(e) = \alpha * \text{gradient}(e) + \beta * \text{StudentNumber} \dots\dots\dots (1)$$

$E(e)$ is the overall weighting or effectiveness,

gradient is the performance of learning for each example, over specified threshold outcomes (1 to 7) and eLearning engagement (0-100%), and is determined from the output in figure 2,

StudentNumber is the number of students, over specified threshold outcomes (1 to 7) and eLearning engagement (0-100%), and

α and β are arbitrary values or the weightage assigned. (refer to section 5.2 for values assigned)

Equation (1) determined the overall weighting or the overall effectiveness of each example. The higher the value the better the students learned from the example.

4.3 Learners' chronological pattern and trends of engagement

The same pseudo code in C1 was used to investigate the trends and patterns of learners' engagement and the results are plotted in figure 3. Except that two outputs were chosen to reflect and compare the chronological patterns of students with low engagement of eLearning and high engagement of eLearning. In both cases the plots were performance output vs. the date of interactions.

4.4 Patterns and engagement as feedback

As for the visual feedback, we collected learners' overall interaction data as well as the concepts covered, the attendance for tutorials and lectures and the performance outcome at each. Based on the Kiviati diagram for each student we used a simple "if then" rule to generate a recommendation for each student.

Providing a good and sensible recommendation system can increase the user trust of the system

(Santos and Boticario 2008; Swearingen and Sinha 2001) and therefore influence the attitude of users towards the system. Research also shows that constant feedback and guidance from instructor is crucial in eLearning (Ragan 1999) where learners are impaired by lack of face to face contact with instructors. Therefore in our design metrics the Kiviati figure consists of attendance, overall eLearning engagement to date, engagement with specific concepts and the grades achieved for each student.

5 RESULTS AND DISCUSSION

5.1 Learners' engagement and performance output

Performance output and learners' engagement are closely correlated as indicated in many researches. The question is there is much more in-depth valuable information about the learning experience that can be derived for the academicians.

The results presented in figure 1 are using scatter plots. Development of scatter plot is a useful approach for identifying potential initial trends between variables. The scatter plots in figure 1 was generated using excel and the best polynomial line was estimated to reflect the overall experience and patterns of engagement of learners using the tool against the academic performance grades. The performance grade of 0 indicates the lowest scoring and 7 the highest while the passing grade is 3.

The results indicate that engaged students are more likely to complete the course successfully than their less interactive peers. But the results also indicate that the line intercepts the y-axis at about 3.5 when the eLearning engagement is at 0%. This makes legitimate sense in a blended environment because students can still learn from other means like lectures and tutorials when they are not using the eLearning tool. In fact there are students who use the tool very little and still able to score a 6 in their final grade. We attribute this to the diversity of student body where there are a number of students who have prior knowledge or work experience related to the topics.

Generally the results indicate that the tool helps students to learn quite effectively once they start to engage until it reaches an optimal point at about 70% when it does not help students to achieve a significantly better result. The "cut-off" point at 70% corresponds to performance output of 6 in the figure. This also gives an opportunity for course administrators and academicians to ponder on the issues of redesigning some components of the tool to try to raise the optimal learning point to make the tool even more effective for the learners.

The figure also showed that students who engaged with the tool 100% would score a 4 at least in the final grade. It also indicated that with a minimum eLearning engagement of 40%, the students should pass the course. Our findings were actually in line with many previous studies (Campbell et al. 2007; Goldstein and Katz 2005; Morris et al. 2005) which identified students as having high, medium and low risk of failure or attrition based on student time online. With this information we can make timely recommendation or intervention.

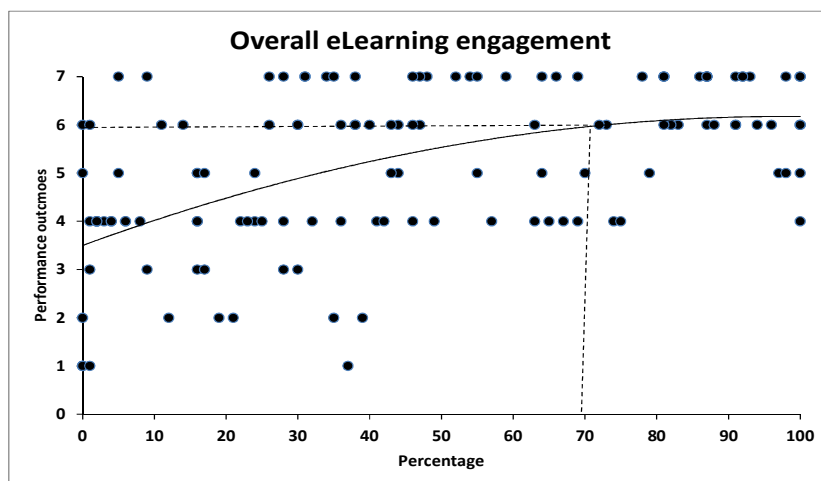


Figure 1 Performance Outcomes vs. Overall engagement

5.2 The effectiveness of eLearning component

The effectiveness of the eLearning component we were investigating was the examples attempted by the students in our study. The engagement of each example for every student was examined and the results were plotted and an estimation of the best linear equation was calculated with the aid of excels. Figure 2 shows the output for example 1, 7 and 8.

Using equation (1) discussed in previous section we estimated the importance of the examples and the results were tabulated in table 2. We consider performance of learning (gradient) more important than the *StudentNumber* and therefore set $\alpha = 2$ and $\beta = 1$ for our calculations. *StudentNumber* was the number of students who scored more than the threshold outcomes (we chose 4) as well as engaged more than the required value of eLearning engagement (40%). These values were chosen based on figure 1 in which students scored at least 4 at 40% eLearning engagement

In table 2, N-grad and n-student are both normalised values of the gradient from the regression line and the number of students. E in table 2 indicates the overall effectiveness of learning from the examples. A higher value indicates a better design of the example. Example 8 has the highest value meaning that students learn best from this example whereas example 7 is the least effective one. We could use the same technique to find out which learning components (in this case the examples) are inferior/better for students' learning and thereby feedback to academicians for possible pedagogical innovation and learning improvement.

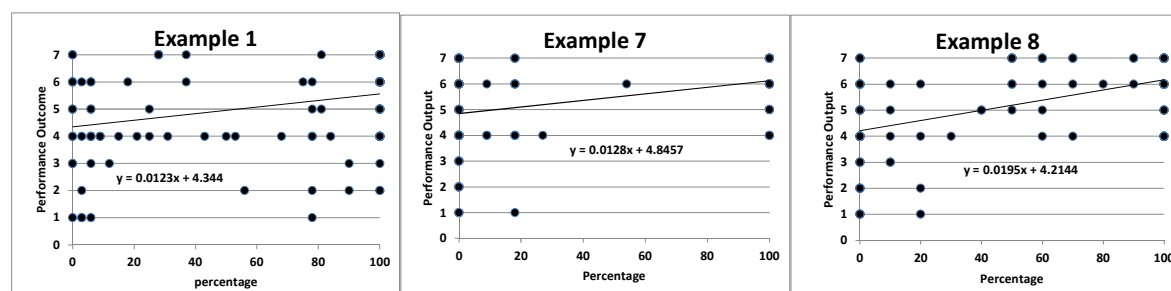


Figure 2 Examples Vs. eLearning engagement

Examples	Gradient	n-grad	No.of.Student	n-student	E
1	0.0123	0.63	78	1.00	2.26
2	0.0174	0.89	53	0.68	2.46
3	0.0179	0.92	54	0.69	2.53
4	0.0157	0.81	66	0.85	2.46
5	0.0149	0.76	47	0.60	2.13
6	0.0144	0.74	56	0.72	2.19
7	0.0128	0.66	29	0.37	1.68
8	0.0195	1.00	72	0.92	2.92
9	0.011	0.56	53	0.68	1.81

Table 1 Importance of examples in the tool

5.3 Learners' chronological patterns and trends of engagement

The date and time of access are helpful for evaluating the usefulness of the eLearning tool and also the patterns of when the tool is the most effective to use for different achievers. In figure 1 optimum learning approximately occurs at 70% engagement and also learners scored at least 4 at 40% engagement. Therefore figure 3 chose the values of percentage of engagement at 70% and 30%. The

scatter plot represents bivariate data of students and dates where a bullet represents at least one interaction with the tool made by students.

Immediately apparent from the figure were two discernible and one not so obvious intense interaction peaks. These peaks directly correspond to the course milestones - the assessment for quiz 1, 2 and final exams at 6 September, 11 October and 20 November respectively. An interesting trends and patterns to observe was that high performance learners tend to use the eLearning tool more consistently throughout whereas low performance learners used less consistently in periods of intense use.

While these findings appear to support the notion that students are likely to be more involved at times when assessment performance is looming, the data can also be used to highlight peak periods for staff intervention.

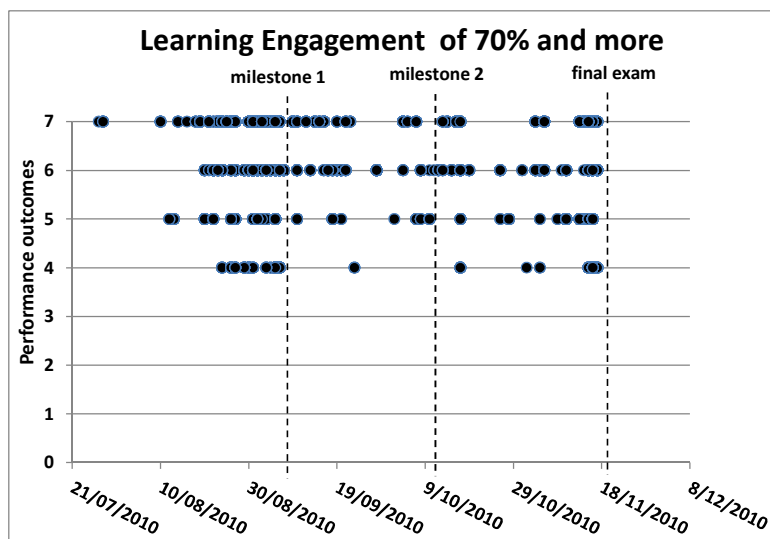


Figure 3(a) 70% Engagement with eLearning tool

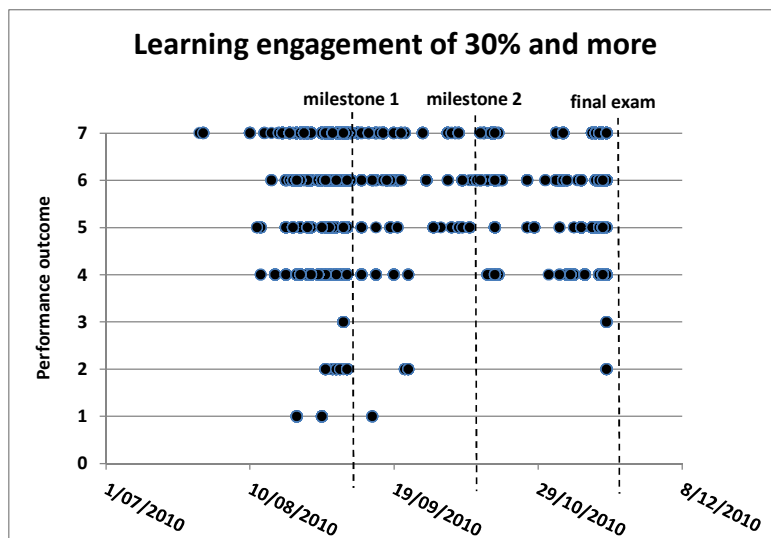


Figure 3(b) 30% Engagement with eLearning tool

5.4 Feedback for learners and teaching staff

In Figure 4 student D Alex (not real name) learning metrics were all above class average. For example his grade is 7 and his engagement with concept 1 and concept 2 components of LDBM are higher than average. On the other hand student M Joseph (not real name) was somewhat unsatisfactory. We would recommend him to engage with the eLearning tool more often throughout especially towards the

milestones. We could also use Kiviatic chart to highlight what components of the course s/he needed to catch up with for instance lecture attendance and engagement with “concept 3”. Further we would recommend the student to pay more attention to those particular components or to direct them to the right learning paths for instance the recommendation for D Alex:

“You are doing well. You could improve further by trying the online LDBM more in particular Concept 3. Attending lectures and tutorials more regularly should also help you understand better.”

As for the teaching staff there are a few valuable feedbacks from the analysis of the results. For instance in figure 1 course designer could try to raise the optimal learning beyond 70% point. The results in Table 2 and the class average in the Kiviatic figure provide some insightful information on the effectiveness of the tool for possible pedagogy innovation and improvement too. The class average shown in Kiviatic figure could allow the learner to do appropriate adjustment in his learning behaviour.

The comments from the students are also quite desirable from the Kiviatic figures. Here are some of the excerpts:

“The system is useful and it’s the first subject I’ve seen this information actually graphed.”

“I thought this was a great feature of the course. It’d be great to see this across other subjects as it’s great to see how you stack up against the rest of the class. Great work there, I thoroughly admired it.”

“It’s very useful. I think all courses should have this. It’s Very well done.”

By providing recommendations together with the Kiviatic figure our system could:

- Motivate the learner when working in the course so he/she does not get frustrated if the results were lower than expected.
- Enable collaboration- fosters sharing contributions, communicating with course members etc.
- Promote self-reflection through visualisation of the learning metrics.

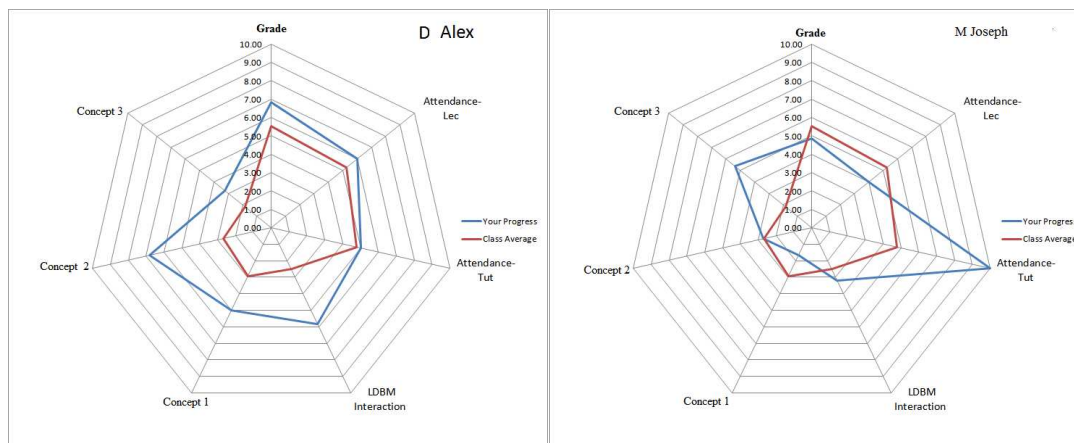


Figure 4 Kiviatic charts showing two students with 7 metrics of their learning

6 CONCLUSION

The purpose of this study was to detect and extract students’ learning patterns and experiences from an eLearning tool in a blended learning environment. The patterns and experiences are important in providing insightful information about the effectiveness of students’ learning and also effectiveness of the tools developed. This information can be used in a variety of ways such as providing an extended and where possible visual feedback to the learners to reflect on their own learning patterns and their impact on performance and also benchmarking their progress and metrics against others in the class. Furthermore appropriate actions could be suggested through some form of recommendations for

learning improvement. From an academician point of view, the analysed data can also provide a gauging benchmark to help improve certain components of the eLearning tool to make pedagogical improvement to the teaching to provide early detection of at risk students and lastly to be able to develop a learning profile to identify at risk students in the future. An envisaged future extension of the eLearning tool is to support collaborative work, wherein the impact of group learning can be studied against a variety of individual learning profiles.

Although the data examined here are indicative at this stage, the results to some degree may be influenced by a number of exogenous variables. We acknowledge this, and in our future work, are aiming to factor further variables in our study as well as assess the impact of recommendations and perceived reflection from the developed feedback and diagnostic methods. The findings nonetheless provide some important insights into students learning patterns and how they can be studied to improve learning outcomes. We hope that this study can be used as a platform for future investigation into new diagnostic methods and to develop extended means for improved learning outcomes and pedagogy innovation.

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