A Conceptual Framework linking Learning Design with Learning Analytics

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University of Melbourne
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University of Melbourne
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University of Technology Sydney
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A Conceptual Framework linking Learning Design with Learning Analytics

Aneesha Bakharia
Information Systems School
Queensland University of Technology
Brisbane, Australia
aneesha.bakharia@qut.edu.au

Linda Corrin
Melbourne Centre for the Study of Higher Education
The University of Melbourne
Melbourne, Australia
lcorrin@unimelb.edu.au

Paula de Barba
Melbourne Centre for the Study of Higher Education
The University of Melbourne
Melbourne, Australia
paula.de@unimelb.edu.au

Gregor Kennedy
Melbourne Centre for the Study of Higher Education
The University of Melbourne
Melbourne, Australia
gek@unimelb.edu.au

Dragan Gašević
Moray House School of Education and School of Informatics
University of Edinburgh
Edinburgh, Scotland
dgasevic@acm.org

Raoul Mulder
School of BioSciences
The University of Melbourne
Melbourne, Australia
r.mulder@unimelb.edu.au

David Williams
Department of Physiology
The University of Melbourne
Melbourne, Australia
d.williams@unimelb.edu.au

Shane Dawson
Teaching Innovation Unit
University of South Australia
Adelaide, Australia
shane.dawson@unisa.edu.au

Lori Lockyer
School of Education
Macquarie University
Sydney, Australia
lori.lockyer@mq.edu.au

ABSTRACT

In this paper we present a learning analytics conceptual framework that supports enquiry-based evaluation of learning designs. The dimensions of the proposed framework emerged from a review of existing analytics tools, the analysis of interviews with teachers, and user scenarios to understand what types of analytics would be useful in evaluating a learning activity in relation to pedagogical intent. The proposed framework incorporates various types of analytics, with the teacher playing a key role in bringing context to the analysis and making decisions on the feedback provided to students as well as the scaffolding and adaptation of the learning design. The framework consists of five dimensions: temporal analytics, tool-specific analytics, cohort dynamics, comparative analytics and contingency. Specific metrics and visualisations are defined for each dimension of the conceptual framework. Finally the development of a tool that partially implements the conceptual framework is discussed.

Categories and Subject Descriptors

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Keywords

Learning analytics, Intervention design, Learning design

1. INTRODUCTION

Over recent years, learning analytics has emerged as a powerful tool for addressing a range of educational challenges and issues, including concerns over institutional retention (particularly for underrepresented groups), and continuous improvement of the student learning experience through personalised learning. However, the vast potential of learning analytics to influence and mitigate many of these concerns remains essentially untapped in terms of day-to-day teaching practice. Most analytics studies have drawn on historical data to identify patterns in students' learning behaviour which are then related to academic performance and/or retention. Much of this work, however, is lacking in an understanding of the pedagogical context that influences student activities, and how identifying patterns in students' learning behaviours can be used to influence and contribute to more positive teaching and learning experiences [16, 5]. Essentially there is a knowledge gap for teachers in attempting to bridge the divide between the information provided by learning analytics and the types of pedagogical actions designed by teachers to support student learning. The field of learning design offers a way to address this gap by helping teachers to articulate the design and intent of learning activities which can be used as a guide for the interpretation of learning analytics data.

In this paper we outline a framework that brings together both learning design and analytics to create more meaningful representations of data for teachers. In so doing we argue that an understanding of course context is essential to providing more adaptive and appropriate analytics visualisations to aid interpretation and translation into direct actions to support student learning. The framework development is situated within the context of a cross-institutional learning analytics study in Australia which investigated the pedagogical concerns and needs faced by teachers in their local contexts, and how learning analytics may usefully provide actionable evidence that allows them to respond to those concerns or needs. The interview data collected from teachers that informed the design of the framework will be presented as well as a description of an online analytics tool was developed which operationalised parts of the framework.

2. BACKGROUND

As the field of learning analytics evolves, the need to align both analytic approaches and outputs with a conceptual frame of reference and educational context has been acknowledged [6, 22]. The field of learning design offers the potential to do this. Lockyer, Agostinho and Bennett (in press) [14] define learning design as both a process of "creating and adapting pedagogical ideas" as well as the product of "a formalised description of a sequence of learning tasks, resources and support that a teacher constructs for students for an entire, or part of, an academic semester". The field of learning design allows educators and educational researchers to articulate how educational contexts, learning tasks, assessment tasks and educational resources are designed to promote effective interactions between teachers and students, and students and students, to support learning (see [7, 15]). Given this, well-articulated learning designs provide clear insight into teachers' pedagogical intent behind the learning activities and assessment tasks they provide to students [16]. These articulated learning designs can, therefore, provide a critical frame of reference for the interpretation of patterns of student interactions that are generated by learning analytics techniques. In other words, learning design can be said to provide "a semantic structure for analytics" [18, pp. 312].

While it makes conceptual sense to argue that articulated learning designs can provide a "frame of reference" for the interpretation of learning analytics outputs, questions remain about how this can be achieved in practice. This is complicated by the fact there are several ways such learning designs can be represented, including the Learning Design Visual Sequence [3] and the IMS Learning Design specification [10]. Thus a core challenge for the learning analytics community is to determine conceptual and practical frameworks that can link teachers' enacted practice (i.e., their learning designs) with data and evidence that emerge from learning analytics through the use of accessible learning analytics tools. This needs to be achieved in ways that ultimately are useful in informing ongoing educational practice.

3. METHODOLOGY

The development of the framework was informed by the outcomes of a study conducted across three Australian universities in 2014/2015. The study aimed to develop an online tool to provide meaningful analytics to teachers to support teaching and learning. Three main sources of information were used to help conceptualise and categorise the analytic needs and wants of teachers. These included a review of the literature on existing learning analytics tools, interviews with teaching staff across the three institutions, and specific user scenarios for each of the courses that were to be used to pilot the tool. The review of the literature identified several learning analytics tools that had been developed to provide learning analytics data to teachers. Each of these tools were then examined to determine if any theoretical/learning design foundation was present, the metrics used, and the methods of data visualisation employed.

The semi-structured interviews were conducted with teachers across the three participating Australian universities. The purpose of the interviews was to determine the ways in which learning analytics could be used to assist teachers to address the fundamental education problems or situations they face in the delivery of online and blended learning. The interviews explored the curriculum structures and learning designs teachers employed within their classes, the pedagogical problems they faced in their teaching, the ways in which they used technology-based tools in their teaching, and the role learning analytics could play in addressing some of their known concerns. The sample consisted of 12 participants, four from each institution, who were involved in the delivery of courses that used a range of tools within the Learning Management System (LMS). To ensure cross-disciplinary representation, the participants were course coordinators from across the arts, professions and science disciplines. Table 1 provides an overview of the discipline, number of enrolled students and tools used in the delivery for each participant's course. Once all interviews had been conducted a thematic analysis was performed on the interview transcripts to identify and group the needs and wants of teachers interviewed.

In addition to the review of existing analytics tools and the interviews, user scenarios were developed for each of the courses that were to be used to pilot the analytics tool. The case profiles contained more detailed information about the four pilot courses including: learning outcomes, structure of lectures/tutorials, assessment details, LMS tools used, the purpose of these tools within the curriculum, current curriculum evaluation methods, and suggestions for analytics that could be useful for the course. Additional suggestions identified through the user scenarios were then added to the outputs of the literature review and interview analysis. An important function of the user scenarios was to inform the prioritisation of development of the web-based analytics tool components.

The existing analytics tool review, interview analysis, and user scenarios combined to form the basis for the development of the conceptual framework which identifies different types of learning analytics that could respond directly to the kinds of issues and concerns that teachers expressed with the learning contexts, learning designs and learning activities they used in their online and blended learning environments. Each dimension of the conceptual framework was then used to identify the functional requirements of a learning analytics tool that would support enquiry-based learning design. The user scenarios were then used to prioritise the development of the web-based learning analytics tool.

4. RESULTS AND DISCUSSION

In this section, a conceptual framework that links learning analytics to learning design is presented. The conceptual framework consists of five dimensions: temporal analytics, comparative analytics, cohort dynamics, tool specific analytics, and contingency and intervention support tools. In the

Table 1: Course details for recruited participants.

Discipline	Year level	Class size	Digital resources	Discussion board	Lecture capture	Online quizzes	Turnitin	Facebook	Computer-aided learning	Online survey	Wiki	Blog	Twitter	Clickers	Virtual classroom
Arts (Education)	PG	30			X		X			X					
Arts (History)	UG	160	X		X						X				
Arts (Criminology)	UG	140	X		X		X								
Arts (Anthropology)	UG	1200	X	X	X	X	X	X		X					
Professions (Law)	UG & PG	70	X	X	X	X	X								
Professions (Accounting)	UG	450	X	X	X	X									
Professions (Property)	UG	300		X	X	X					X				X
Sciences (Statistics)	PG	40	X	X	X										
Sciences (Marine Biology)	UG	50	X	X								X	X		
Sciences (Physiology)	UG	570		X	X			X	X			X		X	
Sciences (Biology)	UG	250-300	X	X		X		X	X						
Sciences (Maths)	UG	400-600	X	X	X										

proposed conceptual framework the teacher plays a crucial role in bringing context to the analysis and making decisions on the feedback provided to students as well as the scaffolding and adaptation of the learning design.

4.1 Temporal Analytics

All the interview participants indicated that they valued the ability to see course, content and tool access statistics over the duration of the course within the LMS. The ability to see students' access to elements within a course (i.e., curriculum content and tools) and the duration of students' sessions was identified as important for teachers as they tried to reconcile how they have structured the overall course and scheduled key activities within it, with how the students have chosen to access the content, tasks and assessment tools within the LMS. In particular, they wanted to identify course material that was valuable to students and was being reviewed multiple times. They also wanted to check whether students viewed or posted in a discussion forum. Ten of the twelve interviewees indicated a need to review access statistics at an individual student level to be able to provide individualised support and/or to deal with student appeals.

Whilst teachers sequence and schedule content and activity according to their learning design, within the LMS there is no explicit way to represent this pedagogical intent when implementing content and activities. The LMS allows content and activities to be added in a hierarchical structure. Through the interviews and user scenarios it was clear that most teachers created weekly folders to contain the content and activities specific to the topic being covered in that week. Therefore the "week" was defined as the most relevant period for temporal analysis and the lense with which to review student activity allowing the teacher to link this back to the course structure and schedule.

An additional request, also within the temporal dimension, made by six of the twelve interview participants was the ability to see course and content access before and after key instructional events, such as the weekly lecture, tutorials, assessment due dates, or the start and finish of a quiz. As an example, one participant was interested in knowing whether students were accessing prescribed pre-reading material prior to the lecture and tutorial. Five other interview participants were also interested in seeing resource access (i.e., slides, notes, video recordings) prior to a quiz, and observing the impact this had on student grades. Temporal "events" specified by the participants fell into the following three categories:

Recurring Events
Events that occurred at the same time each week such as a tutorial or a lecture.

Submission Events
Events which included the due dates for the submission of assessment items and the dates on which an online quiz was made available to students.

Single Events
Events that only occurred once in the semester, such as a guest lecture or field trip.

4.2 Comparative Analytics

Comparative analytics allow the teacher to observe patterns or relations between two or more aspects of a course. Each of the interview and user scenario participants requested to be able to see how scheduled learning activities impacted on student participation (and thereby gain some insight into whether activities were achieving the desired learning design objective). In addition, nine of the interview participants wanted to be able to compare these activities and levels of participation with each other over time. This type of comparative analysis is only possible with a clear knowledge of the course structure and activity scheduling within the LMS. By being able to comparatively review activities and students' participation in them, activities can be identified that may be candidates for redesign, for a greater level of student scaffolding, or for other forms of intervention.

Comparative analytics in this context is defined as the provision of analytics in a form that enables the teacher to compare different types of activities that may occur within the same time period as well as the same types of activities occurring over different time periods. Examples include:

- the ability to compare access to content, communication and assessment tools over the duration of a week or the whole semester.

- the ability to compare access to each content, communication and assessment item by week.

- the ability to compare each student's course access by week.

Comparative analytics is not restricted to the temporal domain, and is equally applicable to social network, content or discourse analyses. For example, a social network diagram that describes the online discussion flows of a single small group could be the subject of comparative analytics, showing how the involvement of the group members shifts and changes over time and in relation to other components of the course. In this way, comparative analytics provides a lense through which the structure and sequence of designed activities within the curriculum, implemented through the use of LMS tools, can be evaluated.

4.3 Cohort Dynamics

Seven of the participants in the interviews expressed the desire to view which students had accessed or not accessed a specific item of content or tool. Similar to the request for course access statistics (as described in the Temporal Analytics section), this requirement on the surface seems relatively simple. However, while LMS reports provide simple access logs, typically they require extensive processing to be easily used and interpreted. Moreover, teachers would be required to drill-down and extensively filter data to gain insight into individual student's patterns of access and usage for content items. All of the interview and user scenario participants requested the ability to view tool specific metrics displayed by student. For example, they wanted the ability to view the number of quiz attempts, access to lecture recordings and forum posts made by a particular student.

The ability to view students' access to course items also relates to the ability to identify student pathways and the impact their patterns of activity may have had on learning outcomes. While the request for access to view students who had both accessed and not accessed course content and tools could be regarded as relatively simple, several participants requested the ability to analyse the access pathways that relate access patterns to student performance on assessment. As an example, one participant requested the ability to compare the performance of students who attended lectures and accessed online lecture recordings with students who only viewed the lecture recording. There was an expectation that there would be common access patterns for particular groups of students and that identifying these student groups would allow teachers to better understand the cohort dynamics. Another example of this was a request to compare the access patterns of successful and unsuccessful students, based on grades, to identify differences and advise the underperforming students on more effective approaches to study.

An understanding of the cohort dynamics can be helpful in determining how different groups of students interact and engage with overarching curriculum structures and the specific learning designs of elements of the course (e.g content, assessments, discussion). If different types of interaction patterns manifested for different groups of students, these may results in different learning outcomes. The implication is that the learning design may be more "accessible" by particular groups of students, resulting in different levels of success. This could help to highlight where learning activities may need to be scaffolded or interventions may need to be considered for particular cohorts. Cohort dynamics may also differ between course offerings with each semester bringing a different student dynamic that must be understood in realtime in order for learning designs to be adapted to better meet student requirements [20].

4.4 Tool Specific Analytics

While temporal analytics relate to all content and tools implemented in the LMS course sites, interview and user scenario participants also identified the need for analytics that were specifically tailored to the particular LMS tools they were using. Simple requests included the analysis of quiz scores, quiz attempts, and counts for discussion forum posts. More advanced analytics were requested for quizzes, such as, a need for quiz item analysis that can be more easily interpreted than what the LMS currently provides. The ability to map questions to concepts and provide aggregate reporting across these concepts was also requested. One participant suggested analytics based on content analysis would be useful to identify the topics that students were either exploring in a discussion forum. Six of the interview participants were interested in visualisations able to show the networks that were forming within collaborative activities involving forums. Sociograms, as illustrated by Lockyer, Heathcote and Dawson [16] provide a way to identify deviations between observed and anticipated interactions based on the learning design. There was also a need identified by four of the interview participants for the analysis of learning activities occurring outside the LMS with participants using a variety of social media platforms (i.e., Facebook, Twitter, Blogs). Interview participants who utilize lecture recordings or media resources in their learning design were interested in knowing whether the media was streamed or downloaded, and what portions were being played.

Tool specific analytics can clearly be used in conjunction with comparative analytics and cohort dynamics. In particular, there is potential to compare an emerging social network by week and include any specific tool related metrics as features to a clustering algorithm. The addition of tool specific metrics would allow additional types of student groups based upon similarity to be discovered.

4.5 Contingency and Intervention Support Tools

Eleven of the twelve interview participants highlighted the value of identifying and intervening when students were determined to be potentially "at risk" (because they did not access crucial content or achieve a pass score on a quiz or assessment). In most cases, the intervention proposed was sending an email to identified students alerting them to the fact they were falling behind and providing them with advice on the areas on which they should concentrate. Participants indicated that currently the identification and selection of students who were at risk was often a labour intensive and manual task. Groups of students were often determined by filtering a spreadsheet of data based on quiz scores, and then emailing specific feedback and guidance to students whose score fell within a certain range.

The contingency dimension seeks to address this issue by providing tools to help teachers identify and select an individual, a group, or multiple groups of students - based on some determined parameters - for the purpose of providing appropriate intervention and guidance. The contingency dimension is associated with the cohort dynamics dimension, in that patterns established on the basis of student similarity discovery algorithms will allow teachers to effectively select and identify student groups for some kind of intervention. Contingency is, however, seen as an outcome of cohort dynamics - only after the teacher has understood why students in a particular group or cohort were similar (e.g., they may not have participated in key activities or grasped a core concept) can he or she provide appropriate advice to both support students' understanding and scaffold their approaches to learning activities.

Contingency also requires a productivity element, in that, tools to facilitate the communication with students are needed. Particularly, the ability to select and email multiple students or send template messages with custom fields to personalise email with student details and scores (i.e., mail merge features). The provision of tools that simplify workload in terms of performing interventions is a necessity, potentially increasing the chance for teachers to adopt the use of technology in their teaching practice [8].

5. THE LEARNING ANALYTICS FOR LEARNING DESIGN CONCEPTUAL FRAMEWORK

Figure 1 illustrates the proposed Learning Analytics for Learning Design Conceptual Framework. The proposed conceptual framework aims to transform learning design into a teacher-led enquiry-based practice. In the framework, the teacher plays a central role in bringing contextual knowledge to the review and analysis of the learning analytics and then in making decisions in relation to contingency.

The framework incorporates the different analytical dimensions that emerged from the review of existing learning analytics tools, thematic analysis of the semi-structured interviews conducted with the study participants and the user scenarioss, namely temporal analytics, tool specific analytics and cohort dynamics. Each analytical dimension can be reviewed and analysed through a comparative approach by the teacher. Comparative analytics and related support visualisations are relevant across all other analytical dimensions and contribute to the teacher's ability to make sense of the data. Comparative analysis therefore provides the lense through which the teacher evaluates the learning design implementation within the LMS in direct relation to the activity scheduling and sequencing dictated by the course design.

The teacher plays a key role within the proposed conceptual framework in bringing teaching and learning context to the analysis. Firstly, the teacher must use their tacit domain knowledge and understanding of the macro (i.e., the course structure and higher level curriculum design) and micro (i.e., implementation of activities within the LMS) level learning designs while analysing and reviewing the learning analytics and visualisations. This view is supported by Lockyer, Heathcote and Dawson [16], who state that "The interpretation of visualizations also depends heavily on an understanding the context in which the data were collected and the goals of the teacher regarding in-class interaction." (p. 1446). Secondly, the teacher uses the insight gained from the analytics and contextual knowledge to make decisions on improving the delivery of the learning objectives, thereby adapting the learning design (i.e., contingency). Persico and Pozzi [20] see the teacher drawing analogies with similar activities and carrying out comparative evaluation. Pardo, Ellis, and Calvo [19] argue that analysis of the digital footprint cannot alone lead to informed learning activity redesign and that qualitative data on why the students have engaged in different ways leads to improved interpretation. The teacher is therefore crucial in being able to collate the required qualitative data and incorporate these findings in the learning design adaptation decision-making process.

In the proposed conceptual framework, contingency occurs as the output and is the result of learning design decisions made by the teacher. Contingency can take the form of restructured or scaffolded learning activities or recommendations and feedback provided to distinct student groups. Contingency requires the teacher to understand the different types of analytics and interpret the patterns emerging from the cohort dynamics dimension. Contingency also relies on the availability of tools to identify, select, filter and communicate feedback to students.

The cohort dynamics dimension needs to be supported by algorithms that are able to discover and provide interpretable student usage and similarity patterns to the teacher. Yi, et al. [24], define pattern detection as a "means to find specific distributions, trends, frequencies, outliers, or structure in the dataset" and go on to say that by using pattern detection, "people may not only find what they have been looking for but also discover new knowledge that they did not expect to find". Manual pattern discovery may however be a difficult and time consuming task, given the number of features to be evaluated. There are two types of machine learning algorithms that are suitable for inclusion in the cohort dynamics dimension:

Sequential Pattern Mining
: Sequential pattern mining algorithms are able to find not only what content and/or tools students are accessing but also whether there was an order in the way that groups of students accessed the content and/or tools [21]. The page flow visualisation [1] represents a useful way to visualise the output of a sequential mining algorithm.

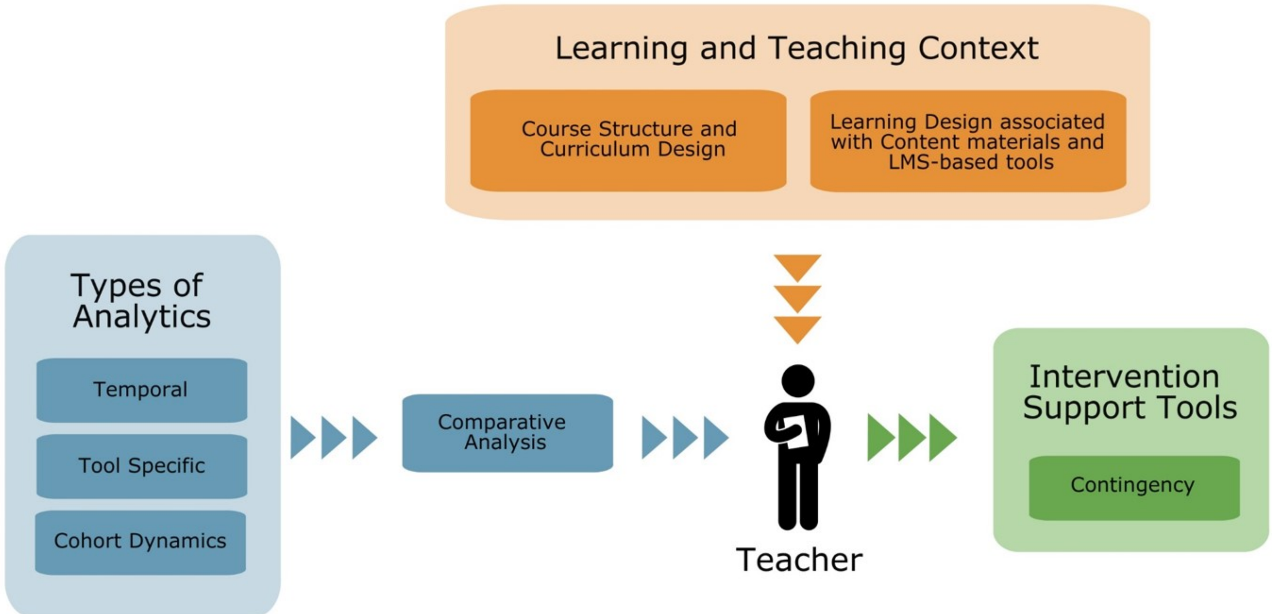

Figure 1: The Learning Analytics for Learning Design Conceptual Framework

Unsupervised Clustering

Unsupervised clustering algorithms are capable of finding similar students based on what the student accessed, when they accessed the items, and any other metrics such as quiz scores, forum contributions, and forum post vocabulary. Example algorithms include k-means clustering, dimension reduction, non-negative matrix factorisation and nearest-neighbour classifiers. These algorithms are commonly used in the educational data mining and learning analytics literature for student profiling [13, 17].

In Table 2, the specific types of analytics, metrics and visualisations that relate to each of the dimensions in the framework are included. Table 2 can be viewed as a blueprint for the types of analytics that need to be included in order to use learning analytics to inform enquiry-based learning design improvements.

6. THE LOOP TOOL - A REFERENCE IMPLEMENTATION OF THE PROPOSED CONCEPTUAL FRAMEWORK

The open source Loop tool is the reference implementation for the Learning Analytics for Learning Design Conceptual Framework (for more detail on the component of the tool see [4]). The Loop tool is programmed in Python and uses the Django web application framework. The Loop tool is made up of two components: (1) a data warehouse and (2) a web interface to display metrics and visualisations. The Loop tool supports the Blackboard and Moodle Learning Management Systems and is a partial implementation of the proposed conceptual framework. The Loop tool currently implements the temporal and comparative dimensions. The cohort dynamics, tool specific and contingency dimensions are currently being implemented.

6.1 Course Data Preprocessing

In order to perform the access-related analytics by person (i.e., teacher, tutor or student), by week, and by content item or tool, both a course access log and the course structure are required. In older versions of Moodle, the course export format contained both the logs and the hierarchical course structure manifest. In more recent versions of Moodle, the course export zip file and a csv export from the log tracking database table need to be processed. For Blackboard courses the IMS-CP archive format [9] (which includes forum posts) and an export of the Accumulator database table need to be processed. The IMS-CP archive format contains the manifest file in XML format that provides the course structure hierarchy.

Within the data warehouse, multidimensional cubes are created using a star schema architecture [2] commonly found in Business Intelligence applications. The star schema includes a fact table (i.e., a table with a timestamped entry for each course item accessed) with related dimension tables that store the dates (i.e., a table containing the the day, month, year and day of week), the course items by type and the users (students and teaching staff). The star schema allows analytics for aggregate calculations by week, tool and student to be stored. An additional categorisation for course items is performed to group items for analysis based upon whether the item is a content item, a communication tool or an assessment tool.

6.2 Dashboards

The Loop tool provides a dashboard for each week in a semester. The "week" was determined, through the inter-

Table 2: Metrics and Visualisations for the Conceptual Framework

<table>
<tr>
<td>Temporal Analysis

• Access by day of week and total access by week
• Access per course structure item
• Session duration and average session duration
• Unique page views
• Ability to visualise the impact of assessment and other events on activity
• Types of analytics/visualisation:
– Timelines
– Event Markers for recurring, submission and once-off events</td>
<td>Tools Specific Analysis

• The inclusion of metrics, analytics and visualisation specific to the type of LMS and social media tools being used.
• Quizzes
– Quiz scores
– Number of quiz attempts
– Quiz item analysis
• Forums
– No of forum posts
– Topics being discussed (i.e., Topic Modeling)
– Social network analysis
– Discourse analysis</td>
</tr>
<tr>
<td>Cohort Dynamics/Patterns

• Inclusion of weekly metrics, overall semester metrics and tool specific metrics as features for pattern discovery algorithms
• Analysis of student sequential access for patterns
• Session duration and average session duration
• Types of analytics/visualisation:
– Finding students who accessed content/tools and those that did not
– Cohort dynamics can be found by clustering student features by week and also by course duration whole of course.
– Allowing teachers to search for similar students
– Allowing teachers to search for students with specific attributes (e.g., Quiz score lower than, etc)</td>
<td>Comparative Analysis

• Need to compare the impact of different learning activities
• Week by week comparison of content and tool access
• Week by week comparison of student course content item access
• Comparison of access and usage of content, communication and assessment within the LMS course
• Comparative analysis with previous cohorts (i.e., group dynamics might change and learning design needs to adapt to it)
• Types of analytics/visualisation:
– Timelines and event markers
– Correlations between activities and measures of engagement eg correlation between communication tool access and session time or quiz scores
– Display of expandable hierarchical course structure tree with column counts for each week</td>
</tr>
<tr>
<td>Contingency and Decision Support Tools

• Inclusion of weekly metrics, overall semester metrics and tool specific metrics as features for pattern discovery algorithms
• Ability for teachers to easily recommend strategies and provide feedback to students
• Types of Contingency Tools:
– Finding students who accessed content/tools and those that did not
– Allowing teachers to search for similar students
– Allowing teachers to search for students with specific attributes (e.g., Quiz score lower than, etc)
– Allowing teachers to email groups of students using templates (e.g., mail merge)</td>
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</table>

views and user scenarios, to be a good period of activity measurement in terms of the way topics and activities are designed within higher education. Each weekly dashboard includes content, communication tool and assessment tool access graphs for each day of the week. Recurring, submission and single events can also be defined. These are displayed on the timeline graphs to allow teachers to see the pre and post event course access changes.

Figure 2 shows the weekly dashboard (temporal dimension). Summary statistics for session duration and average session length are included as sparklines. Top users and items assessed during the week are also displayed on the dashboard.

The Loop tool uses bubble charts to illustrate the percentage of activity that has occurred before and after an event (Figure 3). The teacher is able to define multiple events which they can then be selected to produce the pre and post event visualisation.

6.3 Comparative Visualisations

A tree table is used to display hierarchical course content access by week (see Figure 4). The inclusion of the tree table visualisation was inspired by Loco-Analyst, a tool identified in the literature review which integrated analytics with the course structure [11]. Weekly forum post counts, assessment item attempts and average scores are also shown by week.

6.4 Contingency

For each course item a teacher is able to see the students who accessed the item and those who have not accessed the item. Filtering by date is also provided. This is the only basic form of contingency that the Loop tool currently includes. In future versions of the Loop tool, the functionality for teachers to easily identify similar groups of students as well as recommend strategies and provide feedback to students will be provided.

6.5 Individual Course Item and Student Views

The Loop tools allows teachers to drill-down to view individual student access statistics and specific tool metrics (i.e., temporal and comparative dimensions). Figure 5 shows a timeline of total student access for a specific course item. Assessment attempts, scores and number of forum posts are also included (i.e., tool specific dimension).

6.6 Future Directions

This paper has detailed the progress made in Phases 1 and 2 of an Australian Government Office of Learning and Teaching funded project called "Completing the Loop" [12]. The first two phases involved collection of data to inform the development of the framework and design of the tool (as outlined above in the methodology section). Phase 3 of the project has commenced and a trial of the Loop tool is underway. Results from the trial using courses from Blackboard and Moodle will be used to validate and extend the proposed conceptual framework.

Additional functionality that supports the cohort dynamics and contingency dimensions are currently being investigated for inclusion in the Loop tool. Figure 6 shows the result of using the t-sne dimension reduction algorithm [23] to cluster students using using weekly course metrics (i.e., content access, communication tool access, assessment attempts and scores, forum posts and session duration in each week within the semester) as features. The aim is to provide visualisations that allow teachers to identify clusters of students and then provide insight on why students in each cluster are similar to help teachers interpret student groups and provide appropriate feedback and intervention.

7. CONCLUSION

In this paper, we have proposed a learning analytics conceptual framework for learning design. The framework was informed by an understanding of the types of learning analytics that would be useful to support the evaluation of learning designs. While clear dimensions for the types of analytics required emerged from interviews with teachers, it was evident that the teacher played crucial roles in bringing the learning and teaching context into the interpretation of the analytics and also in making decisions based upon the analytics. Five main types of analytics namely temporal, comparative, tool specific, cohort dynamics and contingency were identified.

The proposed framework makes a useful theoretical contribution, bridging the gap between learning design and learning analytics while establishing a platform to support enquiry-based evaluation and scaffolding of learning activities. The utility of the proposed framework, however, lies in its ability to direct the types of analytics and contingency support tools that are essential to support the learning design process. As illustrated in this paper, each dimension in the conceptual framework leads to clear analytics and visualisation requirements; which in turn were able to be implemented within the Loop tool. The Loop tool is currently being trialed and enhanced to incorporate analytics and tools for the cohort dynamics and contingency dimensions. The evaluation results of the Loop tool will be used to further develop, refine and validate the proposed framework.

8. ACKNOWLEDGEMENTS

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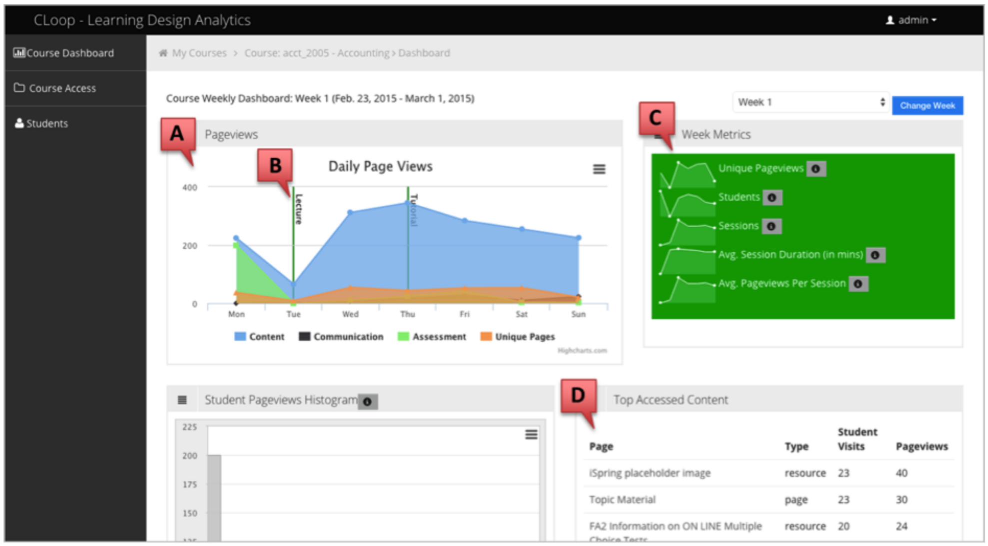

Figure 2: Weekly Course dashboard included in the Loop Tool (Temporal dimension): A = Daily page views; B = Critical learning events; C = Week metrics; D = Top accessed content.

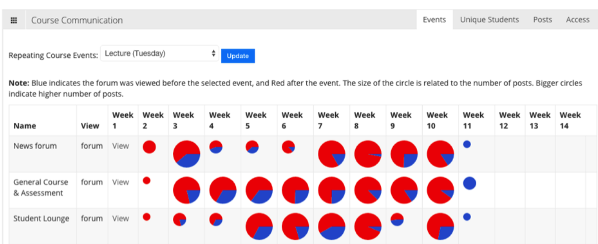

Figure 3: Individual course item access (Temporal dimension)

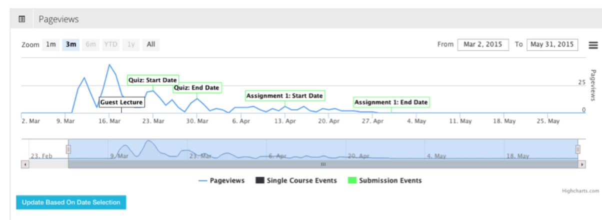

Figure 5: Individual course item access (Temporal dimension)

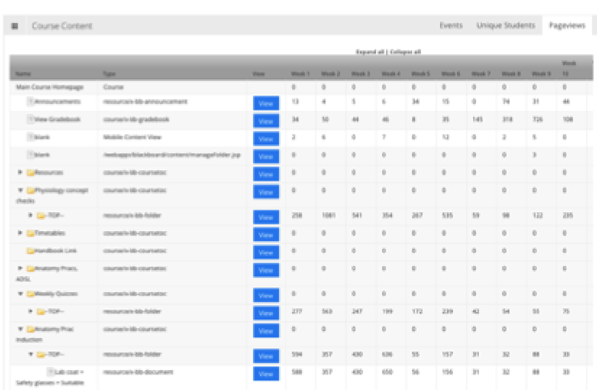

Figure 4: A tree table visualisation (Comparative dimension)

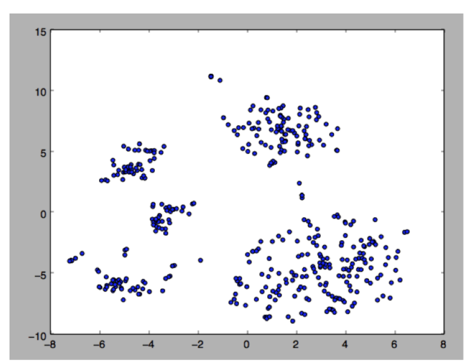

Figure 6: Student groups discovered by t-sne dimension reduction

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