An enhanced learning analytics plugin for Moodle: student engagement and personalised intervention

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Moodle, an open source Learning Management System (LMS), collects a large amount of data on student interactions within it, including content, assessments, and communication. Some of these data can be used as proxy indicators of student engagement, as well as predictors for performance. However, these data are difficult to interrogate and even more difficult to action from within Moodle. We therefore describe a design-based research narrative to develop an enhanced version of an open source Moodle Engagement Analytics Plugin (MEAP). Working with the needs of unit convenors and student support staff, we sought to improve the available information, the way it is represented, and create affordances for action based on this. The enhanced MEAP (MEAP+) allows analyses of gradebook data, assessment submissions, login metrics, and forum interactions, as well as direct action through personalised emails to students based on these analyses.

Keywords: Moodle, learning analytics, students at risk, engagement, indicators, intervention.

Introduction

Higher education institutions are increasingly offering units in online and blended delivery modes. However, the typical heuristics that staff rely upon to detect disengagement are not readily transferrable to, or available in, the online context. The reduced contact and immediacy makes it more difficult for them to be aware of how their students are engaging (Swan, 2003). At the same time, the ubiquity of learning management systems (LMSs) means that many interactions between students, peers, instructors, and content are captured in databases. The relatively young field of learning analytics (and the closely aligned field of educational data mining) seeks make sense of these and other data to better understand and optimise student learning (Siemens & Baker, 2012). For example, participation in online discussion forums, LMS login frequency, and assessment completion have some predictive value for a student's final grade (Dawson, McWilliam, & Tan, 2008; Falakmasir & Habibi, 2010; Macfadyen & Dawson, 2010; Smith, Lange, & Huston, 2012; Romero & Ventura, 2013) or engagement (Black, Dawson, & Priem, 2008). Indeed, the majority of work in learning analytics to date has focussed on improving student performance and retention (Arnold & Pistilli, 2012; Romero & Ventura, 2013; Jayaprakash, Moody, Lauría, Regan, & Baron, 2014) by determining variables that are indicative of issues in these areas.

To close the analytics loop and enact change, student data need to be appropriately understood and acted upon (Clow, 2012). To this end, a number of staff-facing dashboards that graphically represent student data have been conceptualised and developed (Arnold, 2010; Duval, 2011; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Pardo, 2014). These typically seek to assist in deciphering complex student interactions and provide information for decision making processes about learning and teaching (Siemens et al., 2011). Such decisions may involve triggering and sending interventions, facilitated by systems that allow staff to contact students and provide timely advice and feedback (Tanes, Arnold, King, & Remnet, 2011; Mattingly, Rice, & Berge, 2012; Jayaprakash et al., 2014).

The learning analytics landscape in Australasian higher education

In the Australasian context, a number of higher education institutions are starting to use learning analytics to help students and staff understand and optimise learning. A number of recent Office of Learning and Teaching projects have focussed on constructing institutional frameworks around advancing learning analytics (Dawson, n.d.; West, n.d.), analysing data from social media interactions (Kitto, Cross, Waters, & Lupton, 2015), and understanding how data can be used by teachers (Kennedy et al., 2014). A recent project supported by Ako Aoteorea involves examining how data from LMSs can be used to answer common learning and teaching design questions (Gunn, Donald, McDonald, Milne, & Nichols, n.d.).

A number of institutions have also developed bespoke systems for learning analytics (Atif, Richards, Bilgin, & Marrone, 2013; Siemens, Dawson, & Lynch, 2013). For example, the University of South Australia has staff-facing dashboards reflecting LMS and other online activities (T. Rogers, pers. comm.), while Western Sydney University leverages a commercial business intelligence tool to predict students at risk based on indicator variables (Barwick, 2014). Analysis, identification, and referral systems exist at Edith Cowan University (Jackson & Read, 2012) and the University of New England (Leece & Hale, 2009). Systems that combine analysis and identification with direct student intervention have been developed at Central Queensland University (Beer, Tickner, & Jones, 2014; Jones & Clark, 2014), the University of Sydney (Liu, Bridgeman, & Taylor, 2014), and the University of New South Wales (Siemens et al., 2013). These typically combine data from various sources and allow instructors to contact students through electronic and other means.

In addition to these bespoke systems, an alternative approach is to leverage the capability of an institution's existing LMS to support learning analytics (Sclater, 2014). The two main LMSs in the Australian higher educational sector are Moodle and Blackboard Learn, which together command between 78-90% of the market share (Kroner, 2014). Blackboard Inc. markets the proprietary Blackboard Analytics for Learn, which some institutions such as the University of Sydney, the Western Sydney University, and James Cook University are investigating. Moodle, an open-source LMS used in 222 countries with 1442 installations in Australia (Moodle, n.d.), has a small collection of learning analytics plugins made by its developer community. GISMO is an interactive graphical monitoring tool that helps staff understand how students are interacting with unit resources (Mazza & Milani, 2005). From the same team is MOCLog, which analyses and visually represents log data (Mazza, Bettoni, Faré, & Mazzola, 2012). Similarly, Analytics Graphs graphically summarises students' access in a Moodle unit (Singh, 2015), while SmartKlass is a nascent staff and student dashboard that tracks online interactions (SmartKlass, 2014). Finally, there is an engagement analytics plugin (Dawson & Apperley, 2012), which is the focus of this paper.

The Moodle Engagement Analytics Plugin

The Moodle Engagement Analytics Plugin (MEAP; https://moodle.org/plugins/view/report_engagement), originally developed by Phillip Dawson, Adam Olley, and Ashley Holman and released under the GNU General Public Licence, provides staff such as unit convenors (who are academically responsible for a unit of study (or course), also referred to as course coordinators, unit coordinators, or similar) and student support staff with information about how students are engaging with a Moodle unit site based on a range of indicators (Dawson & Apperley, 2012). The original MEAP uses three indicators, which analyse students' login activity, assessment submission activity, and forum viewing and posting activity to produce a total risk rating (**Figure 1**). Although some authors have queried the ability of such traces of online activity to fully reflect student learning (Lodge & Lewis, 2012; Gašević, Dawson, & Siemens, 2015), these readily measurable and accessible data from an LMS can provide insight into student engagement (e.g. Black et al., 2008; Lonn, Krumm, Waddington, & Teasley, 2012; Fritz, 2013) and predict performance (e.g. Macfadyen & Dawson, 2010). However, because MEAP can only access Moodle LMS data, users need to be aware of the limitations when configuring and interpreting proxy measures of engagement as represented in the MEAP indicators.

To allow customisation of the MEAP analysis for each Moodle unit, the three indicators can be weighted relative to each other according to the perceived relative importance of each activity type to students' engagement in a particular unit. In addition, each indicator has parameters that allow further customisation. For example, the calculated risk rating for the forum indicator can be set to include parameters around number of posts read, posts created, and replies. Even though the reported total risk rating has predictive value for students' final grade (Liu, Froissard, Richards, & Atif, 2015), currently MEAP does not offer the same level of functionality as other learning analytics tools such as those with complex visualisations and/or in-built intervention systems (e.g. Beer et al., 2014; Jayaprakash et al., 2014; Liu et al., 2014).

Username	Assessment Activity	Forum Activity	Login Activity	Total
[redacted]	35% (71%)	8% (31%)	11% (46%)	55%
[redacted]	18% (37%)	25% (100%)	10% (39%)	53%
[redacted]	27% (53%)	25% (100%)	1% (3%)	52%
[redacted]	13% (26%)	25% (100%)	9% (37%)	47%

Figure 1: Screenshot of existing MEAP user interface.

Aims and research questions

There have been a number of frameworks suggested for assessing the functionality and quality of learning analytics approaches. Scheffel, Drachsler, Stoyanov, and Specht (2014) proposed a quality indicator framework around the objectives, learning support, learning measures and output, data aspects, and organisational aspects of learning analytics. Jones, Beer, and Clark (2013) proposed a framework which examined the relevancy of information, meaningfulness of the represented information, the affordances for action based on this information, and the scope for change. We selected this IRAC (information, representation, affordances for action, change) framework to assess and enhance MEAP using a design-based research approach. Initial evaluation suggested that the representation of data as percentage risk ratings lacked direct meaning, and there were no affordances for action. Therefore, working in collaboration with staff who were the intended users of this system, our overall aim was to improve the utility and impact of MEAP for staff and students through applying the dimensions of the IRAC framework. Specifically, the questions we wanted to answer were: (1) what additional information would be meaningful to include in MEAP, (2) how might information be better represented, and (3) how can affordances for action be implemented to allow staff to enact necessary interventions?

Methods

As our research necessitated working closely with unit convenors and student support staff to design, test, and refine MEAP, we followed a design-based research (DBR) methodology. DBR “integrates the development of solutions to practical problems in learning environments with the identification of reusable design principles” (Reeves, 2006, p. 52) in collaboration with practitioners. Here, we describe research that was situated in practitioner contexts (identification of potentially disengaged students within units), integrating design principles with technology to create solutions (application of the IRAC framework to MEAP), and iterative processes to test and refine the innovations (user testing and evaluation of the enhanced MEAP, MEAP+) (Reeves, 2006).

Context

We worked together with unit convenors and student support staff at a large metropolitan public university on the east coast of Australia with just under 40,000 students and 3,000 staff. The units investigated were at the undergraduate level with between 59 and 1455 students, delivered through either an online or blended mode. These were selected because their Moodle unit sites consisted of a range of activities which students needed to complete (such as online forums, quizzes, and assignments) and they had a relatively high number of at-risk students (at least 10% non-completion and fail rate in the last study period).

Design, development, and testing process

To better understand the needs of unit convenors (n = 9) and student support staff (n = 3), they were individually interviewed and asked about how they would measure performance and determine if students were engaged. MEAP was then demonstrated, and staff were asked how they might use it, what the challenges may be, how and when it would be useful, and their needs in a system that could help them contact students. Interview transcripts were coded in NVivo 10 (QSR International) using an inductive approach (Thomas, 2006).

Initial codes were identified through review of the terms and concepts found in each of the interviewee’s responses to each question. The interview questions sought to elicit the motivations for using an early alert system, the variables and triggers for identifying students at risk, and how best to contact students. Additionally, we sought to identify concerns and barriers to using an alert system such as MEAP. Given the focused nature of each question, responses to each question tended to represent a code family, which grouped codes that were related (a process considered to be selective coding). To create the codes and code families, three of the authors independently reviewed the transcripts and for each question proposed a set of codes. The remaining author combined the three sets of codes into the final code families which involved renaming of synonyms, removal of duplication, and some restructuring to clarify relationships (such as “is-a”, “has-a”). After review by the team as a whole, the coding scheme was finalised.

Based on the needs analyses from these data, and informed by the IRAC framework, we conceptualised any additional information that staff needed, as well as the interfaces that would allow them to identify and contact students. Simple mockups of the screens that staff would use to do these were produced, and the interview data were used to evaluate these in terms of the information and actions that staff wanted to take. This iterative process refined the mockups, from which functional software prototypes of MEAP+ were developed. We undertook usability testing of MEAP+ prototypes by asking staff to work through typical use case scenarios, a widely used approach in user interface design (Constantine & Lockwood, 2001). Findings from usability testing were used to further refine the prototypes. We present here the results of the user needs analyses, the enhancements to MEAP, and an evaluation of MEAP+ based on user needs and the IRAC framework.

Results and discussion

User needs analyses

Three top-level code families were created: (dis)engagement triggers and indicators, the learning analytics system itself, and actions and responses arising from use of such a system. The themes identified as main (dis)engagement triggers and indicators were class attendance, assessment submissions, forum usage, LMS logins, interim grades, the final exam, access to resources, and interactions with the academic staff. The themes relating to the system itself were frequency and timing of usage, motivations for usage (e.g. improving first year retention), features (e.g. automated notifications to students), and concerns/challenges (e.g. increased workload and selecting benchmarks). For actions and responses, the themes identified were the content of intervention messages (e.g. reason for contact and suggested support), and the mode of delivery (e.g. email or phone). As a results of our analyses, we identified one minor and two major enhancements to MEAP, discussed next. A full analysis will be presented in a future publication.

Enhancements to MEAP

Minor enhancement to identify students: addition to assessment indicator
Like many others, our institution predominantly uses Turnitin submissions instead of native Moodle assignments for receiving student work, which were not detected by the existing MEAP. This enhancement therefore targeted the assessment indicator, augmenting it so that it could additionally identify Turnitin submissions along with quizzes and native Moodle assignments to calculate a risk rating based on whether submissions were absent or late.

Major enhancement to identify students: gradebook indicator
Needs analyses and consideration of the information dimension of the IRAC framework revealed that MEAP was also unable to analyse the data recorded in the Moodle gradebook, the place where students’ marks for the unit are stored. While interim assessment data are commonly neglected in learning analytics (Clow, 2012), these data can yield valuable information in determining a student’s current academic status. Therefore to address this requirement, we developed an indicator which allowed comparison of gradebook item data against customisable parameters (e.g. quiz 1 mark less than 5/10). Each comparison is associated with a user-defined weighting, which together are used to calculate a risk rating by the gradebook indicator based on which comparisons are triggered (**Figure 2**).

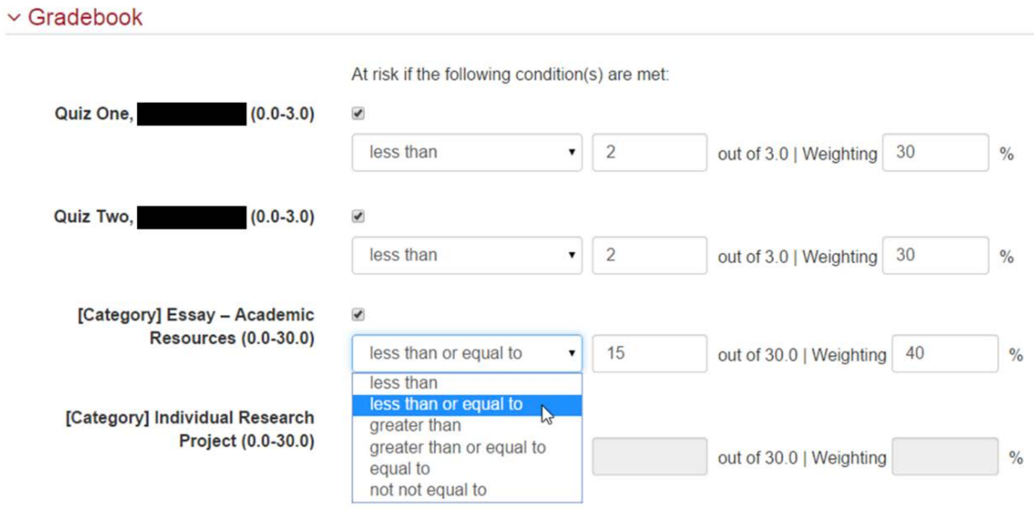
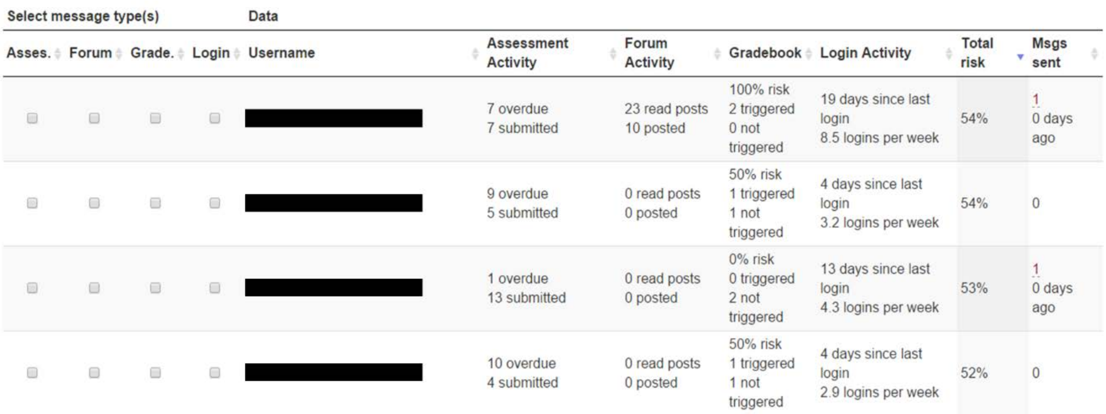


Figure 2: Screenshot of additional, gradebook indicator allowing items from the gradebook to be queried and compared.

Major enhancement to improve information representation and afford contacting students
Other questions raised by the IRAC framework, namely the abstracted representation of information and affordances for action, were also supported through the needs analyses. Therefore, to provide a clearer picture of student engagement and address the representation challenges around information abstraction, MEAP+ was developed to display some of the raw information that was otherwise just shown as percentage risk ratings (**Figure 3**). MEAP+ was also designed to afford action based on provided information, in the form of a student contact system that could deliver customisable and personalisable intervention emails, addressing a key component of the learning analytics cycle (Arnold & Pistilli, 2012; Clow, 2012; Jayaprakash et al., 2014). Emails could be composed from suggested snippets that provided short, specific, formative advice (Croton, Willis III, & Fish, 2014) (**Figure 4**), and all sent emails were logged to maintain a record of student contact.



Select message type(s)				Data						
Asses.	Forum	Grade.	Login	Username	Assessment Activity	Forum Activity	Gradebook	Login Activity	Total risk	Msgs sent
				[redacted]	7 overdue 7 submitted	23 read posts 10 posted	100% risk 2 triggered 0 not triggered	19 days since last login 8.5 logins per week	54%	1 0 days ago
				[redacted]	9 overdue 5 submitted	0 read posts 0 posted	50% risk 1 triggered 1 not triggered	4 days since last login 3.2 logins per week	54%	0
				[redacted]	1 overdue 13 submitted	0 read posts 0 posted	0% risk 0 triggered 2 not triggered	13 days since last login 4.3 logins per week	53%	1 0 days ago
				[redacted]	10 overdue 4 submitted	0 read posts 0 posted	50% risk 1 triggered 1 not triggered	4 days since last login 2.9 logins per week	52%	0

Figure 3: Screenshot of the information representation in MEAP+.

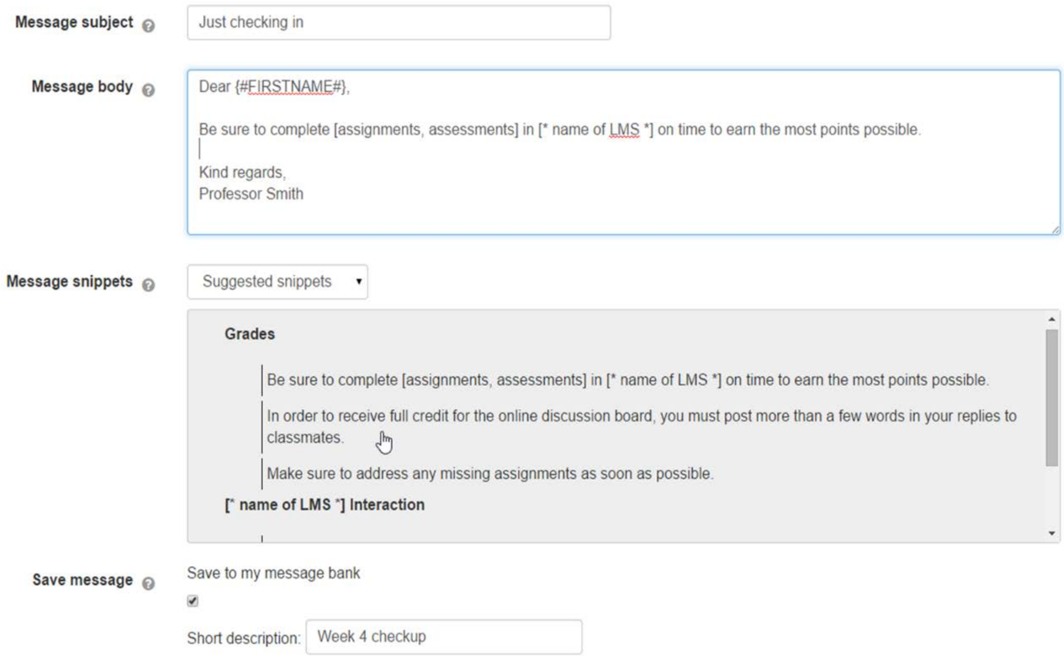


Figure 4: Screenshot of part of the embedded student contact system.

Evaluating MEAP+ from staff perspectives

As part of the evaluation process, a project reference group provided feedback on the user experience for MEAP+. This group was constituted of associate deans and directors of learning and teaching from faculties, the head of learning and teaching infrastructure, unit convenors, online teaching coordinators, and student support staff. This group endorsed the developments in MEAP+ and recognised that it was a positive step in providing staff with relevant information that was also directly actionable through the interface. The group requested further rollout within the university to interested staff, who will be contacted through faculty and departmental meetings, ad hoc workshops, and other channels. Based on more widespread usage, we will further investigate the uptake and impact of MEAP+ on students and staff.

Evaluating MEAP+ using the IRAC framework

Information

Currently, MEAP+ is able to consume and display available information on grades and measures of online discussion, assessment submission, and accesses to the unit site. Posts to discussion forums, assessments submitted, and LMS sessions have been correlated with student performance (Macfadyen & Dawson, 2010; Jayaprakash et al., 2014) and are commonly used in learning analytics and educational data mining (Romero & Ventura, 2013). Since performance, often measured as final grade, is calculated from interim (or partial) grades collected during the unit, using these as intermediate variables can potentially provide valuable insights and predictive power (Clow, 2012; Jayaprakash et al., 2014). MEAP+ can access these data as long as they are available within Moodle, but other data that are important in many learning analytics applications such as grade point average, prior academic history, current academic standing, or demographic information (Arnold & Pistilli, 2012; Jayaprakash et al., 2014) are inaccessible. However, the design of the new gradebook indicator within MEAP+ is customisable to the extent that one could conceivably upload these data to the gradebook as manual data points and take advantage of the ability of the gradebook indicator to perform basic comparison analyses (**Figure 2**). This could also be applied to attendance data, which was identified through the needs analyses and is closely related to student performance (Massingham & Herrington, 2006). Although not developed as part of MEAP+, an attendance indicator that plugs into MEAP is available (https://github.com/danmarsden/moodle-engagementindicator_attendance), drawing data from another Moodle plugin for attendance capture.

It is important to recognise that the information available in MEAP+, as well as in most other learning analytics tools, are essentially static counts or averages of user data such as average online session time, number of forum posts contributed, and delays in assignment submission. These may fail to take into consideration the full complexity of learner activity, paint a limited picture of student engagement and learning, and be difficult to derive relevant interventions and recommendations from (Gašević et al., 2015). An alternate approach to counts and averages of these data involved aggregating and classifying them as a number of interactions between agents, such as student-student, student-content, or student-teacher (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014). These measures were significantly correlated with final unit grade, and this approach presents another perspective on information that can be made available through learning analytics. Interestingly, this study and others (e.g. Jayaprakash et al., 2014) highlight the importance of unit-independent models, even though differences between learners in different units (Wolff, Zdrahal, Nikolov, & Pantucek, 2013) or the pedagogical design of units (Gašević et al., 2015) may have substantial impact on the accuracy of learning analytics. Further comparative research is therefore needed to determine the value of unit-independent and unit-dependent systems and models, and MEAP+ contributes to evidence of the efficacy of the latter.

Representation

Representations of information in learning analytics systems are also important to aid analyses and decision making - in particular, being able to understand and use the information are crucial (Jones et al., 2013). Highly abstracted representations such as traffic lights can provide students and staff with a quick indication of progress or predicted risk (Arnold & Pistilli, 2012). More elaborate dashboards can provide visual representations that offer quantified insight into student interactions with resources (Duval, 2011; Pardo, 2014). MEAP also has a traffic light interface, but this may not be as informative for reflecting student disengagement compared to the calculated risk ratings that are used to derive the light colour (Liu et al., 2015). Although the MEAP parameters are presumably determined by an instructor before viewing the risk ratings, this abstraction fails to provide a nuanced representation of student interactions. This is especially important if action will be taken based on an instructor's understanding and application of these representations. In fact, confusion around percentage risk ratings and the need for less abstraction was seen in the staff interviews. Since feedback with explicit suggestions for improvement are more impactful (Tanes et al., 2011), a more nuanced understanding of information will allow more targeted and valuable feedback to be provided to students. As such, the alternative representation in MEAP+ gives instructors deeper and human-readable visibility of variables that have an existing evidence base around student performance and engagement. Since the aim of representation is to allow a learning analytics user to intuitively understand information in a few seconds (Pardo, 2014), the descriptive summary in MEAP+ is more intelligible than percentage risk ratings, and easier to understand than graphical visualisations. However, these representations are currently not customisable (for example, the instructor cannot choose to show number of replies instead of number of posts), so the importance and impact of this would be an area of future investigation.

Affordances for action

Action based on available information is a critical and often neglected aspect of the learning analytics loop (Clow, 2012). Specifically, affordances for integrated intervention are needed so that the efficiency and workload barriers to adoption are adequately addressed (Macfadyen & Dawson, 2012; Jayaprakash et al., 2014). For example, the Early Alert Student Indicators project at Central Queensland University integrates the sending of 'nudges' directly into the informational interface which helps to encourage engagement between staff and students (Beer et al., 2014). In a similar way, MEAP+ integrates information delivery and affordances of action into one coherent touch point, lowering this barrier for adoption. The composition of the messages themselves is also an important consideration, since their summative or formative nature and motivational or instructional focus impact upon the success of interventions (Tanes et al., 2011). In MEAP+, message composition is supported by 'message snippets' which appear as suggestions based on the indicator(s) that is/are flagged as triggering the intervention. We derived some of these snippets from PassNote, a repository of short comments based on research-supported good practice which staff can readily select and use (Croton et al., 2014), and composed a number of snippets ourselves. We are conducting further research on the use and customisation of messages delivered through this system, especially in terms of the content and nature of these interventions and their impact on students. This last point not only reflects the efficacy of MEAP+, but also the ethical implications of intervention-based learning analytics, such as ensuring only positive outcomes for students, recognising student agency and autonomy, and appreciating that student success is complex and unlikely to be causally linked to any one intervention (Slade & Prinsloo, 2013; Sclater, 2015).

Change

The IRAC framework allowed us to critically evaluate MEAP in the context of blended or fully online units at our institution to perform the task of assisting staff to identify and contact potentially disengaged students. Based on this, we took advantage of the open source nature of MEAP to undertake one cycle of development (Jones et al., 2013), and have released the resultant MEAP+ back to the open source community to encourage further change informed by wider implementation and development. The source code for the beta MEAP+ is available upon request.

Conclusions and future directions

Using a design-based research approach, we report the design and development of enhancements to MEAP based on needs analyses involving unit convenors and student support staff, supported through the IRAC framework for learning analytics functionality and quality. We extended the informational reach, improved the representation of data, and provided affordances for action directly within MEAP. Our next goal is to implement and evaluate the impact of MEAP+ in a range of units at our institution, and seek to address wider learning analytics quality indicators such as efficiency, helpfulness, availability, and effectiveness (Scheffel et al., 2014). We will explore how best to support staff to interact with the system, how it may be further modified to optimise the task of identifying and contacting students, and how it should be used to meet the needs and expectations of students. Through this more widespread usage, we will investigate the nature of feedback provided by staff, as well as the impact of these interventions on student success.

Acknowledgements

The authors would like to thank the unit convenors and student support staff who participated in this research. We would also like to acknowledge the technical support staff who provided advice and assistance. This project was funded by a Macquarie University Teaching Development Grant.

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Note: All published papers are refereed, having undergone a double-blind peer-review process.