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Perceived benefits and barriers of a prototype early alert system to detect engagement and support 'at-risk' students: The teacher perspective

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ABSTRACT

Given the focus on boosting retention rates and the potential benefits of proactive and early identification of students who may require support, higher education institutions are looking at the data already captured in university systems. Student early alert systems are part of formal, proactive, early intervention communication initiatives that institutions have put into place to help with the timely identification and intervention (alert) of at-risk students. The significance of student early alert systems is that support could be offered to high-risk students while they are still enrolled in the unit and able to influence their success/failure before the unit completes. Delivering timely interventions to students via a student early alert system typically requires teaching staff to identify at-risk students, and act upon that information in a way that would encourage students to change their behaviours. However, little is understood regarding teachers' needs and attitudes towards the use of such a system. In the context of a prototype early alert system, this article reports the practices and opinions of a range of teaching staff across all faculties within an institution. The article sheds light on how teachers measure student performance and engagement in their units, and the perceived benefits and barriers of using the early alert system to identify and manage at-risk students.

1. Introduction

Blended and online learning have provided students with increased access and flexibility to participate in education. However, these come with the risk of a disconnect (or disengagement) between teachers and their students with each largely remaining no more than a name or even a student number to each other. Reduced contact with students makes it more difficult for teachers and institutions to manage student learning and measure the engagement of large numbers of students with the aim of retaining more students and improving student academic success rates (An, 2015; Bryson, 2016; Wintrup, 2017). There is a need to understand what factors teaching staff rely on to detect disengagement in the online context. Just as these problems are the result of technological innovation, technology can be used to provide solutions.

1.1. The role of learning analytics

The widespread use of e-learning platforms such as learning management systems (LMSs) (for example, Moodle, Blackboard, and Canvas) results in the accumulation of a vast collection of student data including interaction data between students, peers, instructors, and content. Stu-

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dents' data in an LMS can include information on the number of students' discussion posts generated and read, the number of times a resource is accessed, date and time of access, participation and progress through a range of tasks. This voluminous information can be used to understand student engagement, teaching efficacy and the learning environment in which teaching is performed. Despite the interest of researchers and educational institutions in learning analytics (Ferguson, 2012a; 2012b) and availability of this enormous data, these datasets from e-learning applications have been under-utilised in e-learning research (Phillips, Maor, Preston, & Cumming-Potvin, 2012).

Initial learning analytics developments have typically focused on providing student engagement and performance data to Higher Education Institutions (HEIs), most commonly for the purpose of improving student performance and retention (e.g. Arnold & Pistilli, 2012; Jayaprakash, Moody, Lauria, Regan, & Baron, 2014; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). This focus has recently been extended to include ways to understand students' learning behaviours (e.g. Gasevic, Dawson, & Siemens, 2015; Phillips et al., 2012; Wong, 2017), identify and contact at-risk students (e.g. Jayaprakash et al., 2014; West, Luzeckyj, Searle, Toohey, & Price, 2018; Wolff et al., 2013; Wong, 2017), providing personalised learning experiences (e.g. West et al., 2018; Author, 2019) and timely interventions (e.g. Author, 2017; Author, 2018). Here, we take 'at-risk' to mean students who have a high likelihood of failing a unit or dropping out altogether. As an emerging field of study, there is much research interest in and attention given to algorithms (correlational models and predictive analytics), the use of data mining for the analysis and presentation of data concerning students (Essa & Ayad, 2012a; Gasevic, Dawson, Rogers, & Gasevic, 2016; Papamitsiou & Economides, 2014; Wolff et al., 2013) and discussion of issues around the ethics of accessing and using student data (Gasevic, Dawson, & Jovanovic, 2016; Ifenthaler & Tracey, 2016; Pardo & Siemens, 2014; Prinsloo, 2017; Rubel & Jones, 2016; Slade & Prinsloo, 2013; Willis, Campbell, & Pistilli, 2013) as compare to identifying and contacting at-risk students.

Other researchers (Danilowicz-Gosele, Lerche, Meya, & Schwager, 2017; Dweck, Walton, & Cohen, 2014; Gasevic et al., 2016; Jayaprakash et al., 2014; Singell & Waddell, 2010) have shown that the earlier a student is identified as possibly being in need of support, the better the opportunity they have to improve their academic performance. To provide this early identification, one popular approach is the use of a student early alert system (Lynch-Holmes, Troy, & Ramos, 2012). Here, we consider student early alert systems as formal, proactive, early intervention learning analytics systems/tools that institutions have put into place to help with the timely identification (alert) and intervention of at-risk students.

1.2. Teachers and student early alert systems

The development of learning analytics tools (Siemens & Long, 2011; Viberg, Hatakka, Balter, & Mavroudi, 2018) has provided a much-needed foundation for the field. However, many of the tools have been developed without explicitly considering or applying the socio-technical aspects experienced by teachers actually using these systems to support their students (Author, 2019). The importance of a student early alert system that operates on unit[3]-level data in an LMS could be considered a step towards providing the support and help for teachers to find and reach out to high-risk or the most disengaged students while they are still enrolled. In our context, delivering timely intervention via a prototype student early alert system sought to provide teachers and student support staff (particularly those responsible for managing, monitoring and supporting student success) with access to real-time insights into the performance of students including students who are at-risk. Timely intervention requires timely identification and action on the part of the teacher first and then the student. The prototype student early alert system that we trialled in our study aimed to provide timely intervention. In this way, early alert systems and similar tools can be a significant help in the planning of approaches that would encourage students to change their behaviours. Some recent research has identified that effective teacher to student interventions improve students readiness to study, increase personal communication with students, offer early identification and intervention for at-risk students, enhance the quality of the learning experience, boost student engagement and quality of their higher education experience (Kennedy et al., 2014; Tinto, 2012; van Leeuwen, 2019; West et al., 2018).

For many years, higher education researchers and administrators have understood that teachers are the 'primary' people engaging with students and are the proxy in identifying students who may be at-risk and/or who may benefit from early intervention (Clow, 2013; Abdous, Wu, & Yen, 2012; Dietz-Uhler; Hurn, 2013; Falakmasir; Habibi, 2010). Delivering timely interventions to students via a student early alert system typically requires teaching staff to identify at-risk students, and act upon that information in a way that would encourage students to change their behaviours. While teachers already use an LMS for delivering teaching resources, managing assessments and communicating with students, it is unclear how willing and able they are to use the data associated with each student in the LMS to initiate further interactions with students. Given this, and the growing focus on learning analytics, we need to gain a deeper understanding of the perspective of teachers on using student data from the LMS. Knowing the teachers' perspective is important because if teachers are not favourable to the concept of an early alert system and if the barriers are too high, then they would not use such a system, even if students want them to, and benefits are perceived.

1.3. Aims and research questions

Therefore, the aim of this paper is to develop a greater understanding of teachers' perceptions of the early alert process and the use of a student early alert system to aid the process. Understanding these perceptions may identify any gaps, issues or barriers that inhibit student early alert systems from achieving their intended potential. Identification is an essential first step in allowing these matters to be addressed by individuals, departments, and institutions.

This paper aims to answer the following research questions:

1. What are the perceptions of teachers with respect to early alerts?
2. What information would teachers find meaningful to include in a student early alert system?
3. What are the potential barriers to early alert system usage?

4. What are the realised experiences and motivations of teachers with regard to usage, helpfulness and barriers/challenges to the use of a prototype early alert system?

The purpose of the study presented here was to investigate the perspectives of teachers regarding early alerts, the potential benefits, and challenges of an operational prototype system using institutional LMS data to improve the engagement and academic success of students within a unit. This paper will provide a detailed discussion of the teachers' perspectives and analysis of the data collected.

2. Method

This study used the taxonomy development model of exploratory sequential mixed methods (Creswell & Clark, 2007, chap. 4, pp. 62–79). In mixed methods, the advantage of using sequential design over concurrent design is that sequential designs use analysis of one form of data to inform the collection of the second form of data (Morgan, 1998; Myers & Oetzel, 2003). The sequential process of this study is graphically represented in Fig. 1.

During session 1 and session 2 of the 2015 academic year, a mixed-methods sequential exploratory study of the teachers' perspective was undertaken. The study design consisted of two different phases: *qualitative* followed by *quantitative* (Creswell, 2013). In this mixed-methods design, a researcher first collects and analyses the qualitative data whose findings are tested in the second quantitative phase. The justification to use this approach is that the qualitative data and their following analysis provide a general understanding of the research problem (exploratory). The quantitative data and their analysis further test (confirm) those qualitative results by exploring participants' views in more depth (Bergman, 2008; Bernard, 2012; Cameron, 2009; Creswell, 2013; Tashakkori; Teddlie, 1998). The pros and cons of this mixed-methods design have been widely discussed in the literature (Cameron, 2009; Creswell, 2013; Ivankova, Creswell, & Stick, 2006). The limitations of this design are that it requires a substantial amount of time to implement and analysis of the qualitative data must conclude with findings contributing to later stages.

Due to the paucity of research in this area, the first stage (1 A) was designed to be exploratory and involved capture of qualitative research interview (King & Horrocks, 2010) data from staff in the roles of unit convenor, teaching staff or student support staff (n = 9). In the context of our institution, a unit convenor is a member of academic staff responsible for managing and monitoring the academic activities and performance of the enrolled students in a unit. At other institutions, they may be referred to as unit or subject/course coordinators. At our institution, teachers in units with very large classes receive assistance from student support staff in the monitoring and support of their students. Thus, student support staff were also users of our prototype early alert system and part of this study. This phase one study enabled us to explore teachers' perspectives regarding the benefits and barriers to the use of early alert systems (Fig. 2). The priority of this phase is indicated by capitalising the term QUALITATIVE (Morse, 2003). The second stage (1 B) used the results from 1 A to develop a predominately quantitative instrument that was administered as a structured interview to a comparatively bigger group (n = 16) of academic and student support staff. This design has also been referred to as the quantitative follow-up design (Morgan, 1998). The second stage of the study not only increased the number of teacher viewpoints captured to answer our research questions, but also the use of a survey with answer options, rather than open-ended free text, required less interpretation by the researchers and enabled the use of statistical analysis methods.

2.1. Procedure

This study was approved by our institution's Human Research Ethics Committee (approval number 5201500031). In this teachers' perspective study, potential participants (teachers) were sent an email to take part in a 1-h interview. It is important to clarify that an invitation to participate

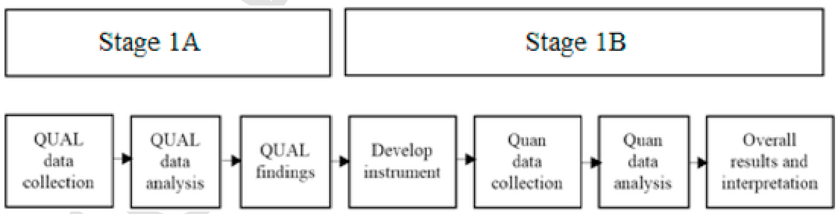


Fig. 1. Graphical representation of mixed methods sequential exploratory design (adopted from Creswell & Plano Clark, 2007).

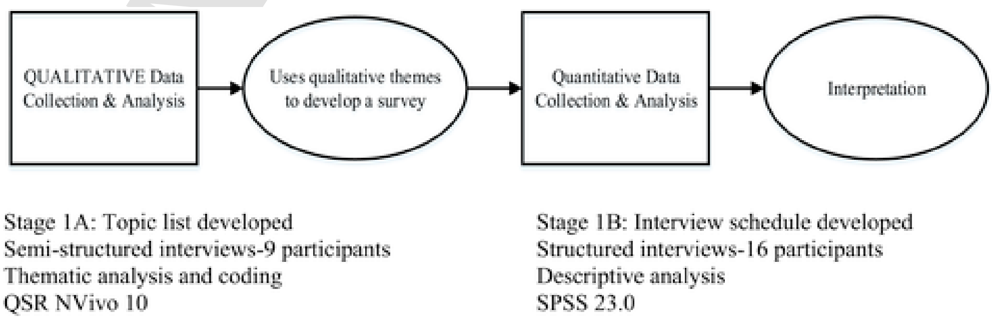


Fig. 2. A visual model of our mixed-methods sequential exploratory design.

in an interview was not distributed across the university, but targeted to individuals who had either expressed interest in using an early alert system or who had been identified to us. Prior to this phase, the Associate Dean Learning and Teaching for each faculty and other leading teaching representatives were contacted to identify who was teaching a unit with large class sizes and high failure rates and who was likely to be willing not only to complete a 1-h interview but to participate in a semester-long study that would involve training on the Moodle-based learning analytics plugin ‘MEAP’ (Moodle Engagement Analytics Plugin), also known as Moodle Engagement Block (MEB). Additionally, regular follow-up by the research team, use of the MEAP system, and various interaction with MEAP, students and tutors regarding the setting of thresholds, regular identification of students at risk and handling MEAP interventions and follow-up were expected from the participants.

The participants used MEAP with blended and fully online units in Semester 1 and Semester 2 of 2015 to trial its usefulness in informing unit convenors, and possibly student support staff, of students at risk of not completing their unit successfully. Teacher needs, attitudes, and preferences were gathered concerning the use of early alerts.

2.2. Illustrative Study-A prototype student early alert system

To ground the study and provide teachers and student support staff with a point of reference, the questions in our interviews and surveys were developed in the context of an LMS-based prototype student early alert system. The prototype student early alert system was designed and deployed at our institution. Our prototype is an extension of the Moodle-based learning analytics plugin MEAP (Authors 2017). To ensure fitness for purpose, initial validation using historical data from three introductory (first-year) undergraduate units was used to show that risk ratings calculated by MEAP could be correlated with students' final grades (Authors 2015). A design-based research approach was then used to extend MEAP, where we examined the experience of teachers with MEAP, together with its impact on student retention and learning. MEAP was enhanced and extended so that a new indicator (Gradebook) and an additional assessment type (Turnitin) could be used (becoming known as MEAP +). This improved its ability to identify students at risk of not completing their units. MEAP calculates the at-risk percentage for all the students in a unit as shown in Fig. 3.

MEAP was extended to monitor students' engagement behaviours (in a single unit) in the LMS on a range of indicators: including assessment submissions; forum interactions (are students reading and/or posting?); login metrics (how often, how recently, and how long are students logging in?); and grade book data (Authors 2015). All four ‘indicators’ or any combination of them can be used - these analyse assessment, login, discussion, and grade book data. Depending on the unit design, the unit convenors can weigh these indicators (Fig. 4).

Within these indicators, again depending on the unit design, the unit convenors can set the thresholds (or benchmarks) to calculate a risk score for students in their unit (Figs. 5–8). Please note that the numbers and percentages in Figs. 5–8 are examples of actual thresholds used by one of the teachers in the study. Thresholds will vary for each unit due to different contexts.

The prototype had a simple mail-merge engine that could also deliver personally-addressed emails (Fig. 9).

Emails could be composed from suggested snippets (Fig. 10) that provided short, specific, formative advice and all sent emails were logged to maintain a record of student contact (Authors 2015).

Stage 1 A (qualitative) was conducted prior to the implementation of the mailer component. Feedback from Stage 1 A was used to guide the design of the mailer. Stage 1 B (quantitative) included both the identification and mailer features of the plugin. The update of the prototype with Stage 1 A and 1 B findings adds a design-based research element to the larger project reported in other publications (Authors 2015; Authors 2016).

2.3. Qualitative data collection and analysis (stage 1 A)

The goal of the qualitative Stage 1 A was to explore the perceptions of teachers with respect to early alerts and their experience with using MEAP, how they currently and/or would like to identify if students are falling behind and how they do/might contact them. The participating teaching staff trialled MEAP in their respective LMS unit(s) in Semester 1 2015 to help identify and contact students that were disengaged and potentially ‘at-risk’. In this teacher perspective study, participants participated in 1-h initial and follow-up interviews. The initial and follow-up interview questions can be found in Appendix A. The process involved one-on-one induction training with unit convenors on using MEAP + fol-

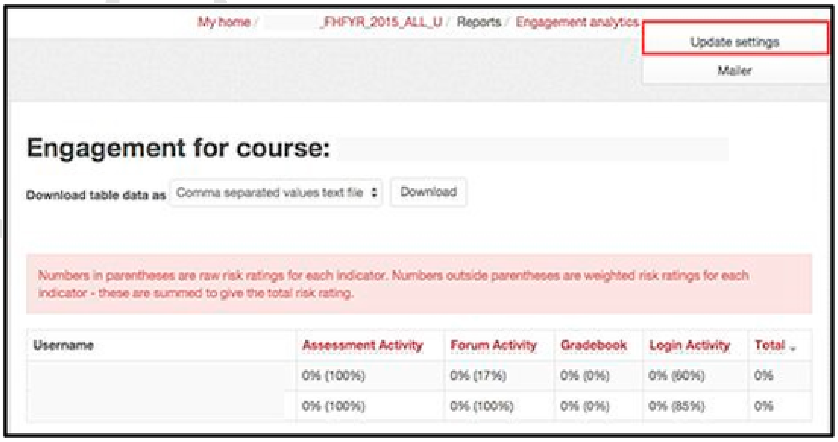


Fig. 3. A screenshot of MEAP + showing the indicators.

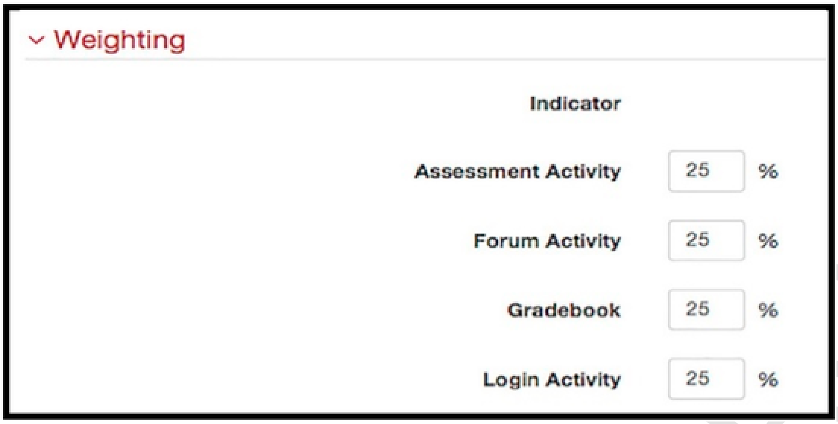


Fig. 4. Indicator weightings.

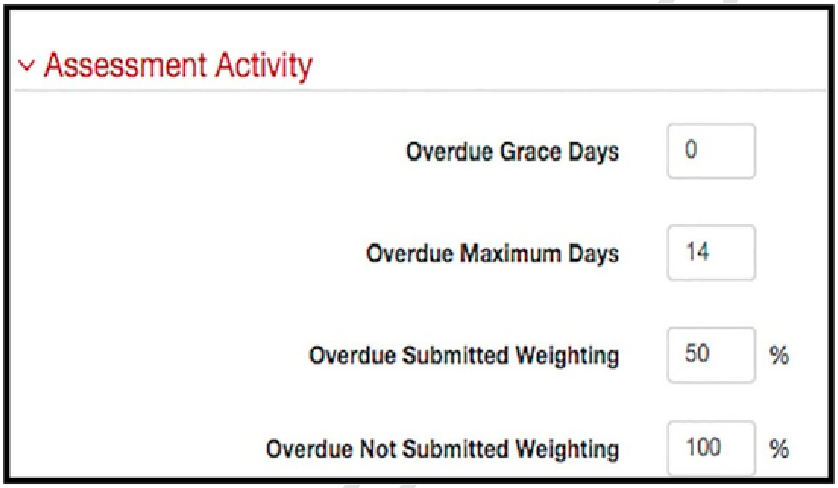


Fig. 5. Assessment activity thresholds.

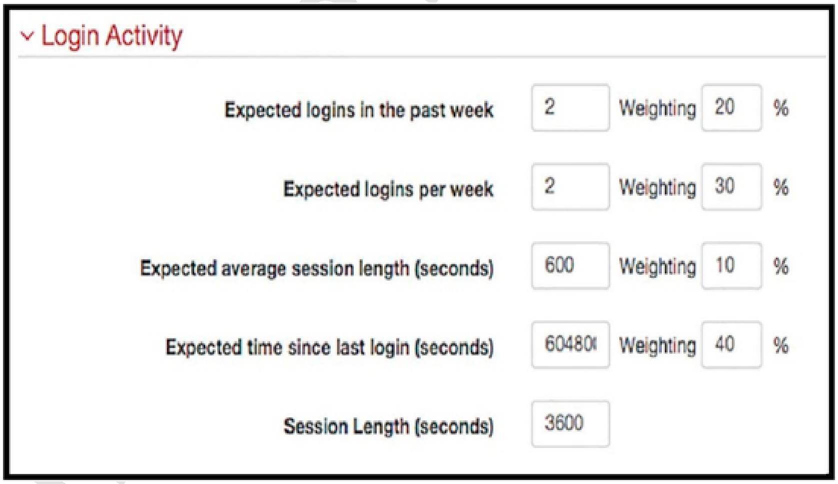


Fig. 6. Login activity thresholds.

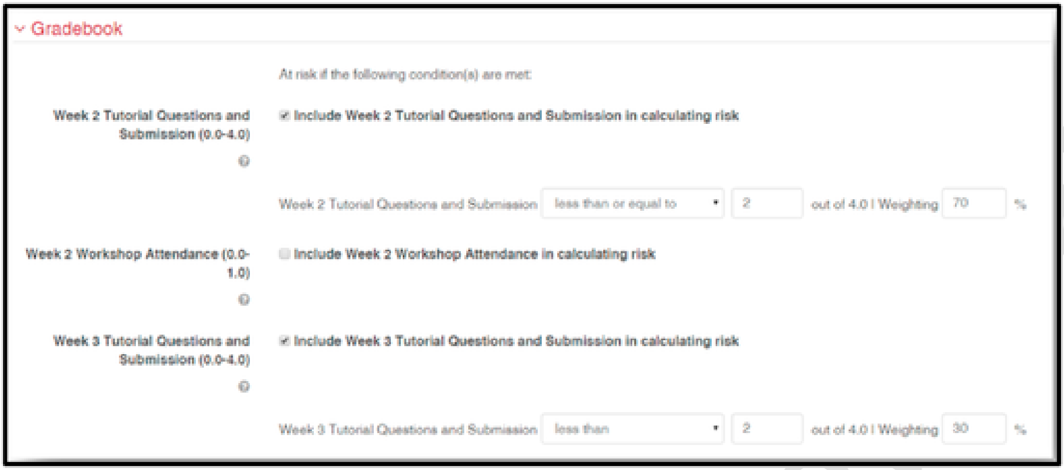


Fig. 7. Gradebook activity thresholds.

Fig. 8. Forum activity thresholds.

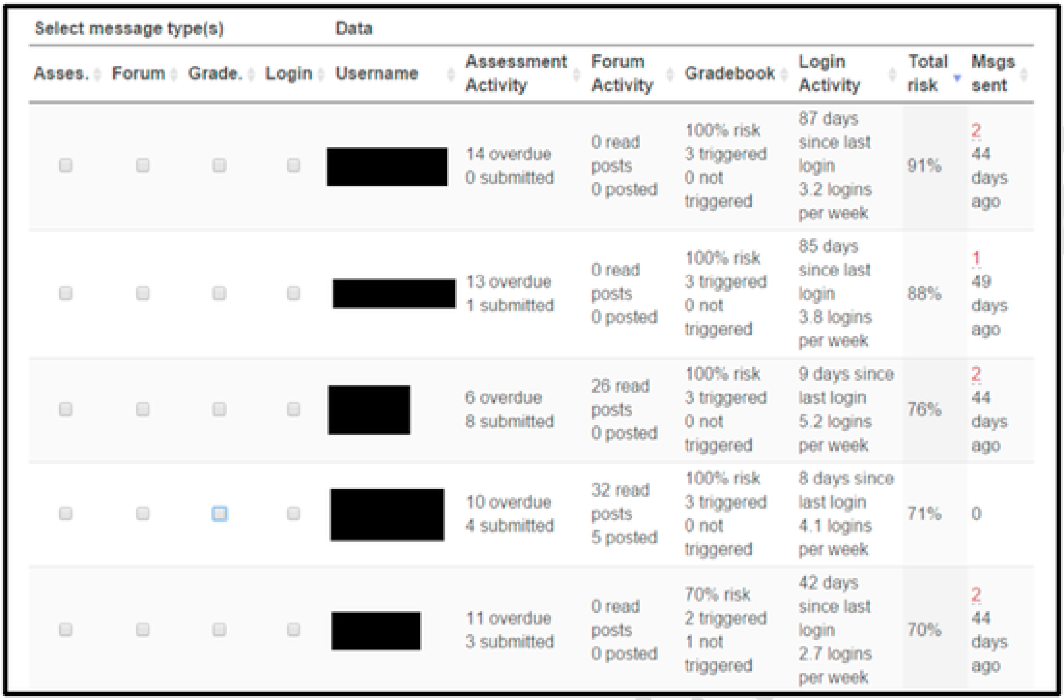
lowed by answering the set of questions from the initial interview. The research team continued to meet with and contacted the teaching staff throughout the semester (approximately every four weeks) to see how they were going with MEAP+ and also determine if they were sending any early alerts to their students (via emails or dialogue utility built-in service within LMS). If they were sending alerts, in a follow-up interview we sought to determine the nature of these alerts (how many, when, the trigger, and the content).

2.3.1. Interview guide development and pilot testing

During Stage 1 A, *semi-structured interviews* with teaching staff were carried out. Questions were designed to explore the perceptions of teachers with respect to early alerts and what information they found meaningful to include in a student early alert system, the potential barriers to early alert system usage, experiences and motivations of teachers with regard to usage, and helpfulness and challenges to the use of a prototype early alert system. Pilot testing of the interview guide was performed with two unit convenors (one from the Faculty of Science and Engineering and the other from the Faculty of Business and Economics) and a student support staff member from the Faculty of Business and Economics. The final interview guide used in the study is presented in Appendix A. Interviews were audio-recorded and data from all interviews were transcribed before it was imported to NVivo 10 (QSR International) for the coding process. The method of analysis chosen for this study was thematic analysis, which is presented next.

2.3.2. The use of thematic analysis

Interview data were analysed using an inductive thematic analysis where a rich thematic description (Boyatzis, 1998; Patton, 1990) and exploratory orientation of the topic was sought. Inductive thematic analysis is typically data-driven and so has some similarities with grounded theory (Price & Kirkwood, 2014). An inductive approach was chosen because: (1) the area under investigation was under-researched, and (2) little was known about the views of the particular participant group (academic staff) on this topic. For this study we used the rubric to do the thematic analysis adapted from Braun and Clarke (2006) such as (1) familiarising ourselves with the data; (2) generating initial codes; (3) searching for themes; (4) reviewing themes; (5) defining and naming themes; and (6) producing the report. The intention of coding was to link the identified themes to the data and not to try and fit the themes into a pre-existing coding scheme. The transcripts were reviewed and analysed by the first author (R1) using the three levels of coding: open coding, axial coding, and selective coding. *Open coding* is the first attempt of labelling segments of text to categorise them in the form of concepts. *Axial coding* is the reviewing of the data to revise the concepts identified through open cod-



Select message type(s)				Data						
Asses.	Forum	Grade.	Login	Username	Assessment Activity	Forum Activity	Gradebook	Login Activity	Total risk	Msgs sent
				[redacted]	14 overdue 0 submitted	0 read posts 0 posted	100% risk 3 triggered 0 not triggered	87 days since last login 3.2 logins per week	91%	2 44 days ago
				[redacted]	13 overdue 1 submitted	0 read posts 0 posted	100% risk 3 triggered 0 not triggered	85 days since last login 3.8 logins per week	88%	1 49 days ago
				[redacted]	6 overdue 8 submitted	26 read posts 0 posted	100% risk 3 triggered 0 not triggered	9 days since last login 5.2 logins per week	76%	2 44 days ago
				[redacted]	10 overdue 4 submitted	32 read posts 5 posted	100% risk 3 triggered 0 not triggered	8 days since last login 4.1 logins per week	71%	0
				[redacted]	11 overdue 3 submitted	0 read posts 0 posted	70% risk 2 triggered 1 not triggered	42 days since last login 2.7 logins per week	70%	2 44 days ago

Fig. 9. A screenshot of MEAP + showing the mailer component.

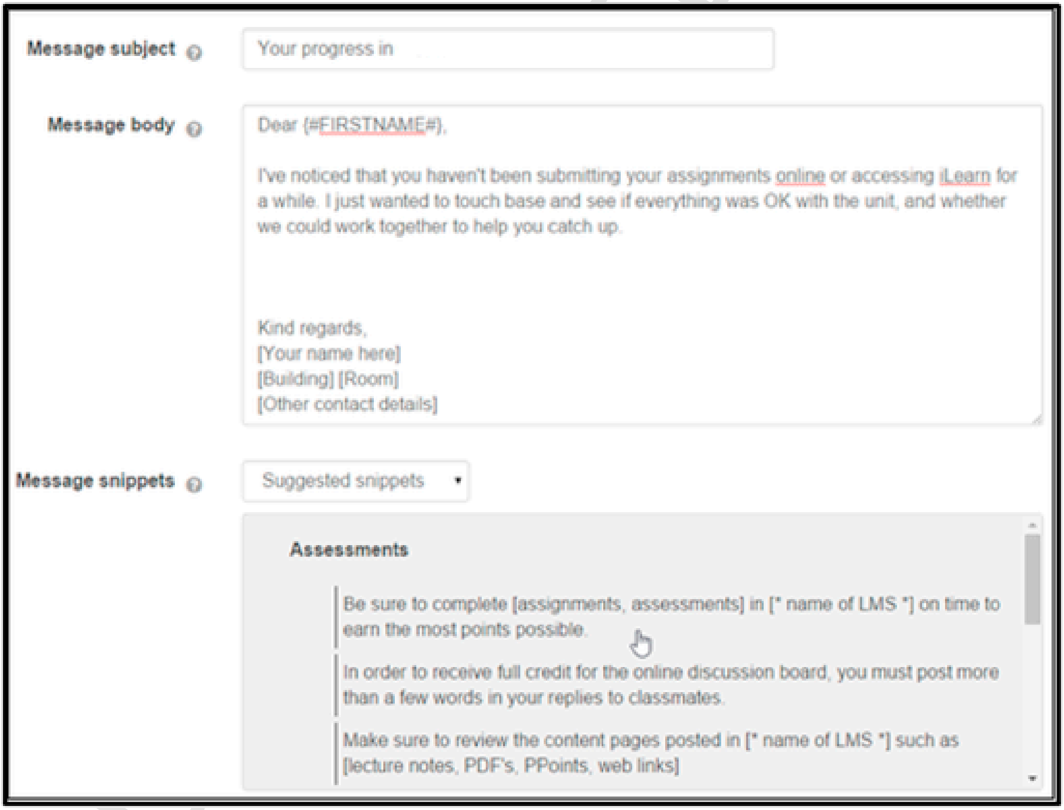


Fig. 10. A screenshot of MEAP + showing how to send an email from suggested snippets.

ing and organise them into themes. *Selective coding* is identifying core categories of data based on the aims of the study and the themes that emerged in the interviews.

As a first step in coding, the transcribed interviews were queried to determine the 50 most popular keywords with a minimum word length of 4 characters by ‘word frequency’ allowing some clustering of similar terms by adjusting the ‘grouping slider’ to halfway between similar and exact. Examples of most frequent keywords that related directly to the use of student early alert system included ‘triggers’, ‘motivation’, ‘features’, ‘concerns’, ‘alert’, ‘content’ and ‘usage’. The open coding phase helped to classify the perceptions of teachers with respect to early alerts into preliminary concepts (categories). These included themes such as triggers, motivation (for using student early alert system), usage, features, concerns/barriers, and early alert content. The axial coding phase reviewed the preliminary concepts from the open coding phase and involved an analysis of categories into (main) themes. The three main themes emerged were ‘(dis)engagement triggers/identifiers’, ‘student early alert system’, and ‘actions/responses’. The selective coding phase assisted to revisit the responses that may not have been representative but are related to the aims of the study such as the potential of perceived benefits of student early alert system rather than delivering timely interventions. Following the selective coding phase, the research team collaborated during the analysis in order to develop a mutually agreed coding scheme. The results of the coding process are presented in section 3.

Among the various approaches suggested by researchers for the qualitative research, Lincoln and Guba's (1985) criteria were used to assess the validity of the qualitative data. Confirmability, the inter-coder checks (Lincoln & Guba, 1985) ensured coded teachers' perceptions of the early alerts data were reviewed by three other researchers familiar with the student early alert system and early interventions at the later iterations of coding to confirm the author's understanding and coding decisions. Credibility, the confidence that can be placed on the information gathered rather than the amount (Maxwell, 1992), was enhanced by triangulating data sources such as interviews communication with the teaching staff (emails) and survey data. Transferability, the analytic generalisability to other (theoretically similar) contexts or settings (Yin, 2013) was achieved. This study did not seek to be representative of all teaching staff and units across all faculties (i.e. statistical generalisation), due to the selection of teaching staff using a particular criterion (selected sampling). Dependability, the stability, and consistency of the measures, research process, procedures and methodological techniques applied over time (Lincoln & Guba, 1985) was strengthened through the research design (including the operational detail of data gathering) and process including recording and retaining all data (e.g. interviews, recordings, transcripts).

For this study, the commonly used ‘coefficient of agreement’ also known as Cohen's kappa (Cohen, 1968) was used to assess the inter-coder reliability. The kappa measure can range from −1 to 1, with 1 indicating *perfect agreement* and 0 indicating *no agreement*. For this study, we used fairly rigorous cut-offs at kappa≥0.80 or 0.90.

2.4. Quantitative (survey interview) data collection and analysis (stage 1 B)

The goal of the quantitative Stage 1 B was to capture data from a larger number of participants and analyse the data more objectively and quickly. We collected the data via a web-based *structured interview* (also known as standardised interview or a researcher-administered survey) using Qualtrics (http://www.qualtrics.com) (Blackstone, 2012). The questionnaire consisted of items that required answers for binary (yes/no), open-ended, multiple-choice and Likert scale questions (Appendix B). The survey items were developed from themes identified in the interviews (Stage 1 A) and from a review of the current literature on using learning analytics tools to predict and improve student academic success (Arnold & Pistilli, 2012; Barber & Sharkey, 2012; Dietz-Uhler; Hurn, 2013; Essa; Ayad, 2012b; Verbert, Duval, Klerkx; Govaerts, & Santos, 2013). The quantitative interview data collected from sixteen participants included their demographics and their perspectives on the benefits, usage, helpfulness, and difficulties/challenges to the use of a prototype student early alert system. In a team review, we finalised the content validity of the survey items. We used the same criteria for unit selection as in the qualitative phase. SPSS 23.0 was used for quantitative data analysis.

3. Results

The findings are discussed in the following sub-sections. The perceptions of teachers with respect to early alerts are presented first by a thematic analysis, followed by information teachers find meaningful to include in a student early alert system, potential challenges and motivation to use.

3.1. Qualitative phase: stage 1 A

The interview sample for this study included nine unit convenors including three females and six males. The unit convenors were recruited from nine large (with enrolments ranging from 82 to 1159 and totalling 3861 students) undergraduate units (six first-year and 3 s-year) from four faculties: Arts (3), Humanities (1), Business and Economics (1) and Science and Engineering (4) units, delivered in either an online or blended mode. These units were selected because they had a relatively high number of at-risk students (at least 10% fail rate) in the previous study period and they used a range of online activities in their LMS (such as forum posts and assessment tasks). Unit convenors were mostly mid and late-career academics, however, no demographics were collected.

3.1.1. Coding perceptions of teachers with respect to early alerts

Coding themes were proposed by three researchers (R1, R2, R3) separately, based on the full set of interviews. The researcher (R4) collated and reviewed (by renaming of synonyms and removal of duplication) the three sets of coded data to clarify relationships (such as ‘is-a’, ‘is-part-of’).

After a team review, R1-R3 used the coding scheme to cross-code one randomly chosen transcript to check the inter-coder/independent agreement (Tinsley & Weiss, 2000). The Kappa value was calculated using the coding comparison queries in NVivo 10. The inter-coder agreement between the three researchers reflected high strengths of agreement (Table 1). It was not deemed necessary to do further cross-coding.

Table 1
Kappa coefficient values and value of agreement between the researchers.

Researchers	Agreement (%)	Kappa coefficient	Interpretation
R1-R2	99.69	0.901	Almost perfect agreement
R1-R3	99.67	0.899	Strong agreement
R2-R3	99.96	0.987	Almost perfect agreement

The finalised generated codes were applied to all transcripts by R1. At the end of the coding process, the researchers had found *3 main themes, 18 first-order, and 73 s-order sub-themes* (Table 2).

Table 2
Main themes and sub-themes from semi-structured interviews.

#	Main Themes	Sub-Themes (1st Order)	Sub-Themes (2nd Order)
1	Student Early Alert System	Motivation to use Frequency of usage When to use? Features Challenges	Contact at-risk students (6), identify at-risk students (4), understanding how students work (3), help as a program director (2), identify level of engagement (2), as indicator only (2), duty of care (2), provide checkpoint (2), address high failure rates (1), address falling enrolments (1), FYFS (first year-first semester) retention (1), identify online activity (1), validation of unit design (1), change student attitude (1), change student behaviour (1) Weekly (6), daily (2), Assessment tasks due (3), after semester (3), census date (2), before major events (2), halfway (2), throughout (1), after first third of course (1) Large scale coverage possible (1), uses available data (1), automatic detection and alert (1), efficient/time saving (1), personalisation (1), differentiation (1) Workload (10), interpretation of results (8), choosing benchmarks and weightings (4), learning new interface (2), false alerts (2), algorithm (1), improving accuracy (1), (lack of) confidence in reliability and validity (1), understanding how it works (1), what to suggest (1), not useful/ineffective (1), bombarding students (1), students not reading alert or taking action (1)
2	Engagement Triggers Or Identifiers	Final exam Assessment submissions Gradebook Forum Logins Assessment types Access resources Class attendance Contact	Attendance (1), mark (1) Late (1), missing (6), incomplete (1), repeated attempts (1) Grade/mark (1), inconsistent (1), declining (1) Posts (1), reads (1) Frequency (4), duration (2), Assignment (6), quiz (3), tutorial tasks (2), Watching videos (1), reading (1), downloading (1), duration (1) Lectures (5), tutorials (5), workshops/practicals (5) Via email (8), initiated by (3), with academic and support staff (2), content (1)
3	Actions	Send alert Ring Announcement Nothing/No action	Alert content (6), alert medium (5), recipient (1)

The three main themes identified from a preliminary analysis of the teacher interviews are 'student early alert system' that uses 'engagement trigger/s' to identify and take 'action/s'. Fig. 11 depicts the main themes with their sub-themes. The first main theme, student early alert system, had sub-themes of motivation, frequency, and timing of student early alert system use, as well as system features and concerns/challenges.

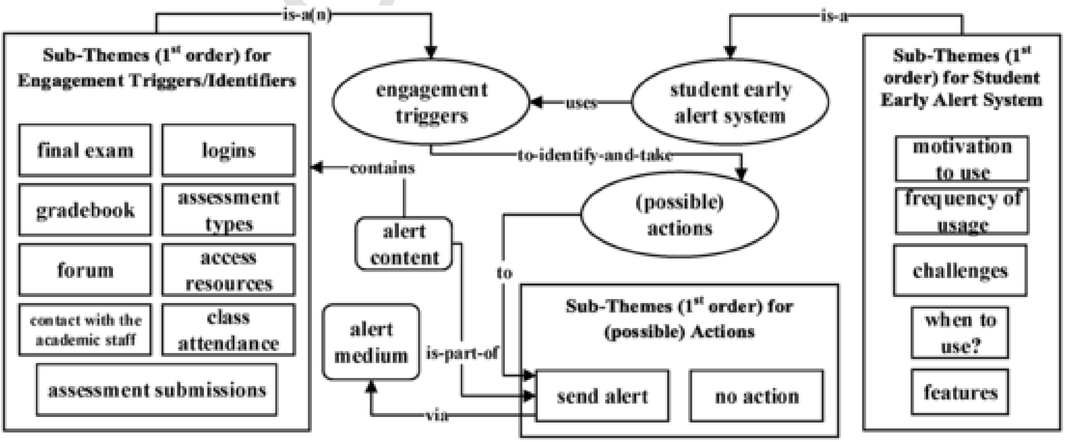


Fig. 11. The thematic map. Ellipses show the main themes, rectangular boxes show the 1st order sub-themes and rounded rectangular boxes show the 2nd order sub-themes.

The second main theme was the engagement triggers used by teachers (via student early alert system) to identify and take actions (the third theme) to aid students at-risk. The second theme included sub-themes around class attendance, assessment submissions, assessment types, forum, logins, grade book, final exam, access resources, and contact with the academic staff. The third main theme was the possible actions that an instructor could take to contact a student at risk such as send an alert via an alert medium (e-mail or phone). The map focuses on student early alert system and thus actions not involving student early alert systems are not modelled.

To keep the model simple and readable, for main themes 'student early alert system' and 'engagement triggers', 2nd-order sub-themes are excluded from the figure. See more about 2nd-order sub-themes in Table 2 column presented earlier. The arrows/lines linking the main themes and 1st-order sub-themes specify the relationships in the direction of the arrows.

The following extracts (Tables 3–6) from the interviews exemplify some of the themes in Table 2 and Fig. 11. Table 3 reports the reasons why teachers were motivated to use the prototype student early system.

3.2. Quantitative phase: stage 1 B

The sample for this study included sixteen participants (supervising a total of 7035 students in 17 units across all faculties) who used the extended prototype for all built-in indicators, i.e. login, forum, assessment, and grade book to contact the students. The participants came from all four faculties at our institution, Arts (2), Humanities (1), Business and Economics (8) and Science and Engineering (5). The participants' demographics are presents as counts and percentages in Table 7.

3.2.1. Engagement triggers and features teachers find meaningful to be included in a student early alert system

We specifically asked 'For the unit/s you are managing, in terms of identifying at-risk students which triggers did you consider?' We noted that the majority of the teaching staff consider assessment/assignment submissions (e.g. late, missing, incomplete or repeated attempts) (75%), attainment of certain grades (69%), task completion (62%), LMS access patterns (56%), and class attendance and participation (44%) as indicators for identifying at-risk students. One teaching staff selected others and said that they will consider special considerations and any student that attempted the unit previously (Fig. 12).

When the participants were asked how they used the prototype student early alert system, eleven respondents used the system for contacting students to send personalised intervention emails, two used the system only for viewing/monitoring purposes and did not send any emails, while 3 did not use the system at all. Reasons for not using the student early alert system included being busy and not having time to use it ($n = 2$) and that the prototype system was down when they tried to access it ($n = 1$). All respondents found the student early alert system useful as it enabled large scale analysis of individual student data. They commented that with a student early alert system they were able to identify and contact groups of similarly performing students and make personalised contact (including use of the student's name and mention of specific behaviours) through the drafting of a single email to that group.

3.2.2. Potential challenges to early alert system usage

While teachers mentioned that using student early alert system added a few extra hours to their workload, they felt that the time was justified because they would not be able to monitor and engage with their large classes without such an aid.

It is interesting to note that the main challenge, reported by 44% of the respondents was learning a new interface (Fig. 13). The respondents who selected other said that there were discrepancies between the student early alert system data from the LMS and the student information system data. This was because MEAP was a prototype so it was accessible only on campus and data was periodically updated (twice a week) so real-time data from the LMS was not available all the time. Sometimes the available data was four days old.

3.2.3. Experiences and motivations of teachers with regard to usage of a student early alert system

Respondents were then asked when the prototype system was of most use to them. The frequency of replies was in the following order: before census date[4] (75%), start of the semester (week 3–5) (44%), when the assessment tasks are due (31%), throughout the semester (31%), mid-semester break (25%), before exclusion date[5] (13%), and at the end of the semester (13%).

More than half of the respondents (10, 63%) said that the alerts mostly sent by them were of an academic nature such as missed classes, non-submission of assessment/s, poor performance on assessments or assignments and at-risk of failing the unit. Only six respondents (38%) said that they sent a combination of both academic and non-academic alerts (such as messages about the well-being or financial issues). Table 8 shows the actions/support for students suggested by the unit convenor or the student support staff as part of the early alert intervention. When the academic and support staff were asked whether they inform their students by other means that an early alert for them has been submitted, nine (56%) said that yes they do inform via announcements in the LMS, face-to-face in lecturers and tutorials, and seven (44%) said they did not.

In another question, eleven respondents mentioned that the early alert from them prompted student action (such as students returning to class or contacting them). The unit convenors also mentioned that they observed an increase in login and class participation activity. Eight out of eleven participants said that students acknowledged their lack of engagement and performance, were thankful for being contacted, intended to start working, and asked questions about how to get further support. Participants provided many useful insights on how the system could be improved such as to put the prototype on the live server to ensure data currency, to send the alert to multiple email addresses and to add more graphical and visual information. Thirteen respondents (81%) said that they wanted to use the prototype system in the future, two respondents (13%) were not sure, and one said no. Only two participants (tutor and support staff member) said that they needed to provide a report for the head of the department and/

4 It is the last date to withdraw from a unit without financial or academic penalty.
5 It is the last date to withdraw from a unit without academic penalty but financial penalty applies.

Table 3
Sample Quotes for Sub-Themes (1st Order) 'Motivation' showing the Sub-Themes (2nd Order).

Participant (Discipline)	Quote	Sub-Themes (2nd Order)
Male (Biology)	It will help me to identify students at risk quickly and that's good because at the moment it's something that I have to do relatively by hand.	Identify at-risk students
Female (History)	Focus on student retention … that's a big thing that we see particularly in our first-year first-semester (FYFS) units. Last year we had quite a big drop in who would enrol and then how many actually stayed in the unit and therefore who actually transitioned as well into our 200 level units.	FYFS retention
Male (Economics)	Well, I think this will be another significant tool and save some time to identify who are the students at risk and, hopefully again, by getting in contact with them to keep them in the unit.	Contact at-risk students; Identify at-risk students
Female (International Studies)	I'd be interested in seeing for the students who aren't participating in the forum I think I'd be interested in seeing what else they are participating in because I find that there's a range of participation.	Identify the level of engagement; Identify online activity

When considering the barriers or challenges in the use of early alert system, using unfamiliar technology and algorithms or learning new interfaces was less of a concern to participants than choosing benchmarks and weightings, interpretation of results, (lack of) confidence in reliability and validity (Table 4).

Table 4
Sample Quotes for Sub-Themes (1st Order) 'Barriers/Challenges' showing the Sub-Themes (2nd Order).

Participant (Discipline)	Quote	Sub-Themes (2nd Order)
Female (History)	… certain weightings on what I think is important for them but maybe my expectations of them might not be realistic.	Choosing benchmarks and weightings
Male (Economics)	I might envisage this, those weightings that I gave, and I could be totally wrong.	Choosing benchmarks and weightings
Male (Computing)	I think that would be interpreting the results and how to make them useable for future modifications.	Interpretation of results
Male (Psychology)	I would only be resistant to using it if I didn't believe in the results it produced or if I couldn't accept the results that were produced.	Confidence in reliability and validity

Teachers were asked how they determine if students need to be contacted or if they were falling behind. Many of them highlighted the non-submission of assessment tasks followed by late submission of assessment tasks, non-attendance at lectures and tutorials/workshops and not logging to iLearn (Table 5).

Table 5
Sample Quotes for Sub-Themes (1st Order) 'Engagement Triggers/Identifiers' showing the Sub-Themes (2nd Order).

Participant (Discipline)	Quote	Sub-Themes (2nd Order)
Male (Psychology)	Other times it's when people ask for extensions. They're indicators that they're falling behind.	Late submission of assessment tasks
Female (International Studies)	I check the logs. Well, the first thing I do, the online discussion is weekly and I assess that the day after its due and I dip in before its due to see how things are going.	Login frequency and duration; Forum posts and reads
Male (Biology)	The most effective variable to monitor student performance is the final exam.	Final exam attendance and mark
Female (History)	In many ways, it was actually quite difficult to identify when students were struggling in a course. Often they would get in touch with me. They'd ask for an appointment or their log-in activity.	Contact initiated by student; Login frequency and duration

Our prototype student early alert system used selected engagement indicators to identify relevant students and take action. Teachers were asked what information they would like to include in their alert to students other than information possibly from the LMS (Table 6).

Table 6
Sample Quotes for Sub-Themes (1st Order) 'Actions' showing the Sub-Themes (2nd Order).

Participant (Discipline)	Quote	Sub-Themes (2nd Order)
Female (Women Studies)	I'd probably like to know what the students think of being sent an email saying, you are potentially failing this unit, because I wouldn't want them to feel like they've been either targeted unfairly … the wording would have to be fairly neatly written that it wouldn't be seen as a negative in a way. It's more of a, we're concerned that you're not progressing in this unit. You've fallen behind in these ways. What can we do to try and assist you? That sort of … it's all in the tone and the way in which the alerts are written. The student survey might actually help us to work out well what do they actually want to know? I think that's going to be crucial before creating some of these alerts and I'm sure that you've got some guidelines on that.	Alert content Alert medium Recipient

Table 7
Summary of respondents' demographics.

Gender	Position	Current role	LMS proficiency level
Male 10 (62.5%)	Professor 1 (6.3%)	Unit Convenors 14 (87.6%)	Novice 1 (6.3%)
Female 6 (37.5%)	Associate Professor 2 (12.5%)	Teaching Staff 1 (6.3%)	Intermediate 1 (6.3%)
	Senior Lecturer 3 (18.8%)	Support Staff 1 (6.3%)	Advanced 12 (75%)
	Lecturer 5 (31.3%)		Expert 2 (12.5%)
	Adjunct Lecturer 2 (12.5%)		
	Fellow 1 (6.3%)		
	Teaching assistant 1 (6.3%)		
	Support Staff 1 (6.3%)		

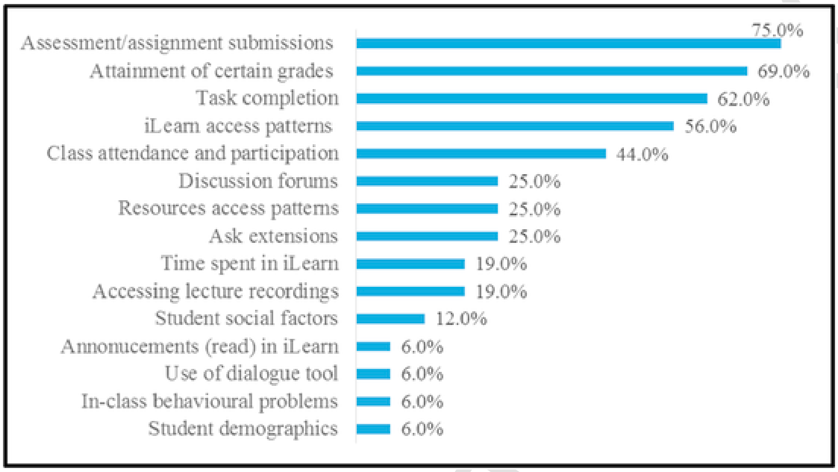


Fig. 12. Expectations and/or engagement triggers/indicators to identify at-risk students.

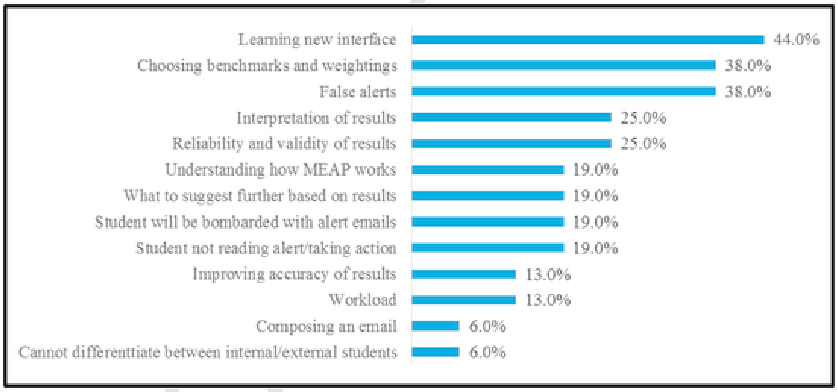


Fig. 13. Challenges faced using the prototype system.

or associate dean for learning and teaching with data on the numbers of identified and contacted students, types of contact made, and reason for contact. The remaining fourteen did not have any related reporting requirements.

4. Discussion

This mixed-methods sequential exploratory study aimed to gain a better understanding of the perceptions of teachers with respect to early alerts, and the potential benefits and barriers to early alert system usage. Our data collection was situated within an institution and within the context of a prototype student early alert system in actual use to provide alerts to students during one or more semesters of study. Compared to many of the current applications of learning analytic tools in higher education institutions which take a big-data view, we investigated unit-level student interventions, where data collated across the institution to inform students and departments or faculty when students are at risk and/or suggest opportunities (intervention) for improving their future performance to change their study behaviour. The interview and the survey (mentioned in Fig. 1) provided more insight into this. Both confirmed that understanding teachers' perceptions of the early alert process is useful to the higher education sector by contributing towards understanding the triggers and developing useful strategies to identify students at-risk, understanding why

Table 8
Actions/support suggested by teaching and support staff as part of the early intervention.

Actions/support suggested by teaching and support staff	N	%
Withdraw from the unit	13	81%
Offer of consultation for in-person with at-risk students	12	75%
Attend tutorial, mixed class, workshop or practical	11	69%
Referrals to specific resources or services designed to assist at-risk students	9	56%
Complete missing/late work	9	56%
Suggest consulting other teaching staff	8	50%
Attend lecture(s)	8	50%
Listen to online lectures	6	38%
Acknowledgement of positive progress	5	31%
Get external coaching	1	6%

they are at-risk, designing interventions accordingly to reduce that risk, and finally closing the loop by tracking the effectiveness of the applied intervention(s) to improve student success and retention.

The aim of the study was not to provide an evaluation of a specific student early alert system but to gather teacher perspectives based on actual experience, not perceived or envisaged advantages and disadvantages. The potential participants of this study were unit convenors who were teaching a unit with large class sizes (80+ enrolment) and high failure rates (10% or more in the last study period). It is important to note here that the participation did not just mean participating in answering our interview or survey question/s - it meant reviewing the assessment structure of their unit, ensuring student activity and assessment data were captured online, learning to use a new tool, learning to set thresholds and interpret the results, spend time to regularly run analyses, and contact students using a system that was a prototype with technical limitations including the data not being live. This added workload would have limited the participant pool, even though 25 teachers participated. The findings of the first stage interviews with 9 teachers were converted to a survey as a way of reducing bias and effort involved in subjective coding. As a first step, we aimed to find out the perceptions of teachers regarding early alerts (RQ1). To answer this research question, we analysed interview data (Qualitative Phase: Stage 1 A) using thematic analysis. The three main themes identified from the coding perceptions of teachers were 'student early alert system' that uses 'engagement trigger/s' to identify and take 'action/s' (mentioned in Fig. 11). The prototype student early alert system used selected engagement indicators to identify relevant students and take action.

The significance of a student early alert system is that feedback and support could be offered to at-risk students while they were participating in a unit and had an opportunity to modify their behaviour, rather than after they had failed one or more units. Therefore, the second research question was proposed: What information would teachers find meaningful to include in a student early alert system? (RQ2). The triggers identified in our study are consistent with expectations/indicators used by teachers to identify students at-risk reported in the literature (Falakmasir & Habibi, 2010; Macfadyen & Dawson, 2010; Minaei-Bidgoli; Kashy; Kortemeyer, & Punch, 2003; Smith, Lange, & Huston, 2012; West et al., 2016). However, rather than manual identification, a student early alert system is able to identify at-risk students automatically by utilising data from the LMS such as access patterns, time spent, discussion forum activity, assessment and task submissions and attainment of certain grades. Because much of this data was already available to teachers in our institutional LMS, it may seem that a *system* does not provide tangible benefits. However, this valuable data is time-consuming to access and evaluate. The raw data does not make the connection between student performance and behaviour with whether they were at risk. For small classes, the raw data could be used by teachers to understand their students and how the cohort, in general, were going. For small classes where teachers are in close contact, teachers are likely to know their students and be aware of issues without the use of the LMS data. On the other hand, for larger classes, this is not possible, so teachers need support to help them identify, interpret and act based on the LMS data. Our study sought to identify whether a student early alert system could, in fact, help teachers with large classes to identify and assist students at risk, or would it be too hard to use or require too much time and effort.

The majority of participants in our study found the prototype system useful (and helpful) in the identification of at-risk students and said that it did not add much to their workload. The few extra hours required to contact students at key points in the semester, such as census date, the start of the semester, and when assessment tasks are due were considered good time investments for providing timely feedback and support. When teachers take the time to contact students pro-actively in the first few weeks or at particular points in the semester, students feel connected to the teaching staff and the unit and they try harder to be successful in the unit (Campbell, 2007; Gasevic et al., 2015; Maher & Macallister, 2013). Research has shown that a teacher's initial personalised contact (email or phone call) early in the semester can ease student fears going forward into the unit/course and helps the student to understand that their teachers are there for help and they care about their performance (Achilles, Byrd, Strauss, Franklin, & Janowich, 2011).

The engagement triggers and features teachers find useful lead to answer the third research question related to the potential barriers/challenges to early alert system usage (RQ3). Respondents expressed that the challenges and difficulties they encountered with the use of the prototype system included learning a new interface, false alerts and choosing benchmarks and weightings (Fig. 13). This first difficulty (learning a new interface) is not surprising since research (Aldunate & Nussbaum, 2013; Price & Kirkwood, 2014) has also shown that in some cases, teachers feel the use of technology or learning a new interface may become a challenge. This can be traced to either a lack of confidence or a lack of computer usage skills (Bailey et al., 2004).

The second challenge concerned choosing the benchmarks and weightings. Authors (2015) suggests setting the thresholds for indicators using local (LMS) data wherever possible and re-examining the accuracy of the indicators and thresholds every semester the unit is offered since thresholds are likely to change. For example, if for a unit the teacher achieves positive results from targeting attendance, over time the teacher will most likely need to set higher expectations for student attendance. An accurate threshold can help flag students who can be assisted through interventions (Koenig & Hauser, 2011). While catching all of the at-risk students and being able to deal with large numbers via a single email is an attractive feature of our prototype student early alert system, unit convenors were very concerned about misidentifying students particularly since the prototype contained data that was up to four days old and there was no synchronisation between the LMS data and the student support system that tracks special consideration requests. This concern was not a surprise because MEAP+ was running on a parallel test server rather than a live server, with up to 96-h lag in data currency. The key strategy used by unit convenors was to experiment with their historical data in the unit to see whether changing thresholds made sense in their context and to look at detailed data for selected students, such as number of classes attended, last login, to confirm that the 'at-risk' scores made sense. Since MEAP + entered production in 2017, the concern over stale data is reduced but unit convenors still rely on timely entry of marks and attendance records and having to manually reconcile which individuals have special permissions such as assignment extensions.

Knowing the engagement triggers and potential challenges faced by teachers helped us to document the comprehended experiences and motivations of teachers with respect to usage, helpfulness and challenges to use of the prototype early alert system (RQ4). The participants (mostly unit convenors) were motivated to use the prototype system to understand their students, to identify students' level of engagement and to identify their online activity. One unit convenor mentioned that the use of the prototype will help in her other administration position as a program director to address responsibilities such as addressing high failure rates, falling enrolments and first-year first-semester retention. A few other convenors mentioned that they will use the prototype for the validation of their unit design because setting the weights requires careful planning and monitoring of assessments and learning activities. Some also considered the tool to be essential to fulfil their duty of care to students by helping to make students better aware of when they were falling behind and how to turn the situation around.

As unit convenors become more familiar with the MEAP + interface and the triggers and thresholds that work best for their units, these barriers to use are expected to decline. Possible improvements to the MEAP + interface and perhaps the use of machine learning to predict/suggest thresholds could reduce the learning curve for new users.

5. Conclusions, limitations, and future work

This paper presented the results of the perspectives of teachers (1) regarding early alerts and (2) the potential benefits and challenges of a prototype student early alert system using institutional LMS data to improve the engagement and academic success of students at a unit level. The research methodology used in this study was an exploratory sequential mixed methods in two stages, qualitative followed by quantitative. We performed thematic analysis on the qualitative interview data from nine teaching staff to gain an initial understanding of their perspective towards early alerts and student early alert system. A quantitative survey was then created from the themes to gather the perspectives of another sixteen teaching staff who utilised an extended version of the prototype.

The main contributions of this study are: (1) the development and use of 'exploratory instruments' for investigating the perceptions of teachers with respect to early alert process, and advantages and limitations to the use of early alert systems; (2) a better understanding of the practices and experiences of teachers across different faculties on how they could best support student learning and teaching using data; (3) a clearer picture of the perceptions of teachers on applied learning analytics in the real world.

There were some technical limitations of MEAP that impeded the use of the system and its use to identify and contact students at risk. The main limitation was the currency of the data, as the prototype was not on the live server and the data was up to four days old. Also, the prototype MEAP was taking data from LMS only and was not connected to other systems in the institution. Another practical limitation was that the use of any tool and approach requires some training, commitment, and expertise. The use of supporting tools like MEAP + are limited by the time constraints faced by teachers and support staff. Teachers who are adjuncts or sessional staff may not feel they are sufficiently remunerated and/or trained to identify students and send early alerts. Since this was an applied study, this practical limitation led to the issue of a limited participant pool, despite working through associate deans, heads of departments, and directors of learning and teaching. For example, in 'Quantitative Phase: Stage 1 B', approximately thirty unit convenors were recruited but only sixteen participated. Furthermore, some participating unit convenors did not use MEAP + to send alerts and/or use MEAP + frequently. Our experience reported here is consistent with the ever-present barriers of academic workload and unfamiliarity with new systems (e.g. Macfadyen & Dawson, 2012). Finally, since unit convenor participation was voluntary, the opinions of those who chose not to participate have not been captured. This data limitation impacts the volume and scope of our data and generalisability of the results.

The implications for higher education institutions, including our own, are that learning analytics systems such as early alert systems need to be made available to help teachers to gauge student behaviours and identify students at risk and enable teachers to contact students to improve student retention and their learning experiences because there is a real but unmet appetite in teaching staff. These systems need to afford both data integrity as well as student-facing action upon data. Additionally, any learning analytics development or implementation must work closely with teachers to determine their contexts and needs, as these will vary substantially even across a department or faculty. When further considering teacher perspectives of practical learning analytics tools, it may be helpful to triangulate the self-reported data with logs of how teachers actually use the tools, such as which analytics they access, which configurations are tweaked and how, and the style and content of messages dispatched to students. This is the first study in this area which can be also extended in the future investigating the impact of 'increase in issues with the teaching staff' on student academic performance and exploring the implications and impact of early alert tools in Massive Open Online Courses and other educational contexts.

CRediT authorship contribution statement

Amara Atif: Conceptualization, Software, Methodology, Formal analysis, Investigation, Visualization, Writing - original draft. **Deborah Richards:** Supervision, Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Danny Liu:** Methodology, Software, Formal analysis, Writing - review & editing. **Ayse Aysin Bilgin:** Supervision, Conceptualization, Methodology, Writing - review & editing.

Acknowledgement

We thank X (affiliated organisation) for assistance in developing the instrument and conducting the teacher initial and follow-up interviews.

Appendix A. Initial and Follow-Up Interview Questions

Pre MEAP implementation:
Background

- How would you rate your level of proficiency in the use of iLearn for teaching?

Novice/Intermediate/Advanced/Expert.

- On average during a course, how many students would you contact that are falling behind?

$<1\%/2–5\%/6–10\%/>10\%$

- How much experience do you have in convening this particular course (semesters) and courses in iLearn in general (years)?
- How similar is this current unit to previous ones? For example, are there more or different online activities? Are the assessments different?
- Before this project had you ever heard or been interested in learning analytics?

Planned use of MEAP.

- How useful do you think the Moodle engagement block will be to your role as an online convenor?
- How do you think you might use the MEAP?
- Do you think using the MEAP will add to your workload?
- What do you think will be your biggest challenge in using MEAP?
- When do you think MEAP will be of most use to you?

Student Alerts.

- If you had the capability would you like to send out alerts to students that were falling behind in the course?
- How do you think sending out student alerts would impact on your workload?
- What information would you like to see to help you decide what to include in your alert?
- How would you like to send out student alerts? Email, through iLearn, telephone, other?

Post MEAP implementation:Actual use of MEAP.

- When did you use MEAP?
- How did you use MEAP? Can you provide an example?
- Indicate to what extent you agree with the following statements, on a scale of 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree) and 5 (strongly agree). Mark one in each row.
  - o I found the information obtained from the MEAP about individual students valuable
  - o The MEAP enables me to get an insight into how the student is doing in the course
  - o The MEAP provides relevant information regarding the student's interactions within iLearn
  - o I found the MEAP easy to setup
  - o I found the MEAP easy to use
- How useful did you find the MEAP to your role as an online convenor?
- Did using the MEAP add to your workload?
- What was your biggest challenge in using MEAP?
- When was MEAP of most use to you?
- How could the MEAP be improved?
- Would you like to continue to use the MEAP in the future?
- Do you have any comments you would like to add about the MEAP?

Student Alerts.

- Did you send out any student alerts as a consequence of using the MEAP?
- What information did you send the student? How did you send it? (Perhaps keep a record of the information they send? For future purposes?)
- How did the student(s) react when they received an alert? Did it have the intended consequence or were there unintended consequences. Please describe it in detail.
- Do you have any comments you would like to add about student alerts?

Appendix B. Structured Interview Questions

Demographics:

Name/Gender/Academic level/iLearn Unit Code/s.

Role and Experience:

1. Currently, which of the following best describes your primary work role?

Unit Convenor/Lecturer/Tutor/Student Support Staff.

2. For how many years have you worked for X University and how much experience (such as <1 year, 1–5 years, 5–10 years, 11–20 years and >20 years) you have in your current role? Please select one response per row.

Working at X university/Experience in my current role.

3. How would you rate your level of proficiency in the use of iLearn for teaching?

Novice/Intermediate/Advanced/Expert.

4. Before this project had you ever heard or been interested in learning analytics?

Yes/No. If YES, what type of analysis did you do?

5. For this project, how many unit/s are you managing this semester?

Post MEAP + Use:

6. For the unit/s you are managing, in terms of identifying at-risk students which indicators did you consider? Please select all options that apply.

Class attendance and participation/iLearn access patterns/Time spent in iLearn/Discussion forums/Announcements (read) in iLearn/Use of dialogue tool/Resources access patterns/Assessment/assignment submissions/Task completion (e.g. quiz, tutorial questions)/Accessing lecture recordings/Attainment of certain grades/When a student approaches the academic staff concerned for their performance or ask for extensions/In-class behavioural problems/Student demographics (e.g. socioeconomic status, ATARs, enrolment status etc.)/Student social factors (hours of employment, family responsibilities, attitude towards learning, family and peer influence etc.)/Not sure/Other.

7. When/how often did you use the MEAP+? 0/1/2–4/>5. If not utilised, what is the reason?
8. For what built-in indicators did you use the MEAP+? Please select all options that apply.

Login/Forum/Assessment/Gradebook.

What process did you go through to decide on the threshold values? Did you change the thresholds throughout the semester? Yes/No. If YES, why?

9. How did you use the MEAP+? Can you provide an example? Please select all options that apply. Contacting students/Analysing/Viewing/Other. Did you send out any student early alerts as a consequence of using the MEAP? Yes/No. If NO, what is the reason?
10. How useful did you find the MEAP + to your current role in the identification of at-risk students?
11. Did using the MEAP + add to your workload? Yes/No/Not sure
12. Briefly, what problems/difficulties/challenges you have encountered with the use of the MEAP+? Please select all options that apply.

Learning new interface/Choosing benchmarks and weightings/Interpretation of results/Improving accuracy of results/Reliability and validity of results/Understanding how it works/What to suggest further based on results/False alerts/How the algorithm works?/Workload/Composing an email/Selecting snippet(s)/Students were bombarded with alert emails/Students not reading alert/taking action/Cannot differentiate between internal and external students/Other.

13. Have you experienced any difficulty while using the system? Yes/No. If YES, how did you solve the problem?
14. Did you view the MEAP + help resource? Yes/No/Not sure if there is any available

If YES, how did you find the help resource? Very helpful/Somewhat helpful/Helpful/Not very helpful/Not at all helpful.

15. When was MEAP+ of most use to you? Please select all options that apply.

Start of the semester, please say week #/Before HECS census date/Before exclusion date/Mid-semester break/When the assessment tasks are due/After the semester/Throughout the semester/Other.

16. What category best describes the nature of student early alerts sent by you?

Academic/Non-academic/Combination of both/Other.

17. Which of the following actions (information) did you suggest the student as part of the early alert intervention? Please select all options that apply.

Referrals to specific resources or services designed to assist at-risk students/Offer of consultation for in-person with at-risk students/Suggest consulting other teaching staff/Attend lecture(s)/Attend tutorial or practical/Listen to online lectures/Complete missing/late assessments/Get external coaching/Withdraw from the unit/Acknowledgement of positive progress/No suggestion/Other.

18. Do you inform your students by other means that an early alert for them has been submitted?

Yes/No. If YES, please describe the other means of communication.

19. Has an early alert from you prompted student action (such as student returning to class, contacting you or meeting with lecturer/tutor)? Yes/No/*Not*I am aware of/Not sure. If YES, please provide details.
20. Overall, is MEAP + been an effective intervention tool in changing/improving the success of alerted students in the unit/s you were involved in this project? Yes/No/Not sure
21. How could the MEAP+ be improved?
22. Would you like to continue to use the MEAP+ in the future? Yes/No/Not sure
23. Do you have any comments you would like to add about student early alerts or the MEAP+?
24. Should the name student early alert be changed? Yes/No. If YES, what is your suggestion?

Reporting:

25. What reporting requirements do you follow in relation to identified students and contacted students?
26. Are you required to generate and send reports about these support activities?
27. Who do you send these reports to and how often?
28. Have you generated and used the mailer log (report)? Yes/No. If YES, how you have used it?

MEAP + Evaluation:

29. Indicate to what extent you agree with the following statements. Please select one response per row on a scale of 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree) and 5 (strongly agree). Mark one in each row.
    - I found the MEAP + easy to setup
    - I found the MEAP + easy to use
    - The MEAP + enables me to get an insight into how the student is doing in the unit/s
    - I found the information obtained from the MEAP+ about individual students valuable
    - The MEAP + provides relevant information regarding the student's interactions within iLearn
    - It was easy for me to use the MEAP + to identify students that were at-risk
    - It was easy for me to identify why students were at-risk
    - The navigation through the MEAP+ was complicated
    - Using the MEAP + involves too much time doing mechanical operations (e.g. data input, time to compose and send an alert)
    - I feel apprehensive about using the MEAP + to identify and contact students at-risk
    - I hesitate to use the MEAP + for fear of making mistakes I cannot correct
    - The project team members were available for assistance with MEAP + difficulties
    - I could complete more efficiently the same task that the MEAP + allowed me to do on my own
    - I intend to use MEAP + for all students and not just at-risk students
    - Using MEAP + to enhance student academic success in a unit is a good idea
    - I intend to use the MEA + P next semester
    - Our institution should use the MEAP+

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