Students’ perceived course outcomes in E-Learning (LMS)

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Abstract:
This study examined the factors that influence students’ perceived course outcomes in e-learning using the Learning Management System (LMS), and the extent to which the factors significantly predict course outcomes. A total of 255 university students completed an online questionnaire measuring their responses to 5 constructs (lecturer support, interaction with peers, perceived ease of use, perceived usefulness and course outcomes). Data analysis was conducted using structural equation modelling. Results showed that perceived usefulness and interaction with peers were significant predictors of course outcomes, whereas perceived ease of use and lecturer support did not. However, perceived ease of use had an indirect relationship with course outcomes through perceived usefulness. Lecturer support also had an indirect relationship with course outcome through interactions with peers. Overall, the four antecedent variables contributed to 77.0% of the total variance in course outcomes. Based on the study findings, implications for educators and researchers are discussed. This study also looks at Moodle Engagement Analytics Plugin (MEAP), Moodle, an open source Learning Management System (LMS), collects a large amount of data on student interactions within it, including content, assessments, and communication. 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: Course Outcomes, Learning Management System, University, Students

I. Introduction
Electronic learning (E-learning) is becoming prevalent in tertiary education, with many universities increasing their provision and higher number of students signing up for online learning (Liaw, 2008). The growth in e-learning is attributed to the inherent advantages in terms of manpower, cost, flexibility, and convenience (Ozkan & Koseler, 2009). As (Sun, et al., 2008) described, e-learning has ‘liberated’ interactions between learners and educators from the limitations of time and space through the asynchronous and synchronous learning possibilities. The e-learning system can be viewed as having several human and non-human entities interacting together in an LMS environment to achieve the intended course outcomes (Eom, Wen, J., & Ashill, 2006). As enrolments in e-learning courses continue to increase in higher education, it is pertinent for educators to be aware of the factors that contribute to student success in e-learning. Despite the numerous studies on the various factors that predict successful e-learning (e.g. (Johnson, Hornik, & Salas, 2008); (Sun, et al., 2008)) few of these studies were conducted in the LMS environment. 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.
context. The reduced contact and immediacy make 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). 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, Lauria, Regan, & Baron, 2014) by determining variables that are indicative of issues in these areas. There is also a plethora of studies that employed student achievement, perceived learning and student satisfaction independently to measure success in e-learning (e.g. (Alshare, Freeze, Lane, & Wen, 2011); (Eom, Wen, J., & Ashill, 2006); (Lim, Morris, & Yoon, 2006). However, few studies have employed the combined measures of perceived learning and student satisfaction as course outcomes in evaluating successful e-learning. Thus, the major goal of this study is to investigate the factors contributing to the perceived course outcomes in e-learning, as measured by perceived learning and student satisfaction, in an LMS environment.

II. Review of Related Literature

Background of LMS

LMS can be broadly defined as an IT platform used by educators to administer, document, track, report and deliver curriculum to students (Naveh, Tubin, & Pliskin, 2010). While LMS varies in specific functionalities, (Coates, James, & Baldwin, 2005) described the LMS as an institutional-wide and internet-based systems that typically provides an array of pedagogical and course administrative tools of differing complexities and potentials. A variety of e-tools is typically found in LMS including discussion boards, forum, chat, online grading, online assessment, file sharing, management of assignments, syllabi, schedules, announcements and course plans (Findik Coskuncay & Ozkan, 2013). LMS can be implemented to strengthen e-learning programs that blend in-class teaching and online teaching within the learning process (Cigdem & Topcu, 2015).

E-learning success research

There is a corpus of literature that focuses on the range of factors that influence the use and satisfaction of e-learning systems, and most of these studies were conducted in the context of online collaborative learning (e.g. (Arbaugh & Benbunan-Fich, 2007); (Kang & Im, 2013); (Liaw & Huang, 2007); (Marks, Sibley, & Arbaugh, 2005). (Swan K., 2001) examined the factors that affect student satisfaction and perceived learning in an asynchronous online learning and found that clarity of design, interaction with instructors, and active discussion among participants significantly influenced student satisfaction and perceived learning. Sun et al. (2008) found that learner computer anxiety, instructor attitude toward e-learning, e-learning course flexibility, e-learning course quality, perceived usefulness, perceived ease of use, and diversity in assessment are critical factors that affect learners’ satisfaction. (Arbaugh & Benbunan-Fich, 2007) investigated the role of interactions in e-learning, and found that while collaborative environments were associated with higher levels of learner-learner and learner-system interaction, only learner-instructor and learner-system interactions were significantly associated with higher perceived learning. Based on two studies conducted for a sample involving 2196 students using LMSs from 29 Austrian universities, it was found that course content that facilitated self-regulated learning led to higher student satisfaction (Paechter & Maier, 2010) and students’ assessment of the instructors’ e-learning expertise and their counselling and
support to the students were the best predictors for student learning achievement and course satisfaction (Paechter, Maier, & Macher, 2010).

The Moodle Engagement Analytics Plug-in

The Moodle Engagement Analytics Plugin (MEAP) originally developed by Phillip Dawson, Adam Oley, and Ashley Holman and released under the GNU General Public License, provides staff such as unit conveners (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 analyses 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, Dawson, & Priem, 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.

In this study, perceived course outcomes consisting of perceived learning and satisfaction will be employed as the dependent variable, while perceived usefulness, perceived ease of use, lecturer support, and interaction with peers are considered as independent variables. For the purpose of this study, e-learning contents and online learning activities were delivered using the LMS. Hence, the research questions are as follow:

1. What are the factors that significantly influence perceived course outcomes among polytechnic students?
2. To what extent do the factors predict the perceived course outcomes among polytechnic students?
3. What additional information would be meaningful to include in MEAP?
4. How might information be better represented?
5. How can affordances for action be implemented to allow staff to enact necessary interventions?

III. Research Model and Hypotheses

Perceived Ease of Use

Perceived ease of use is “the degree to which a person believes that using a system would be free of effort” (Davis, 1989). In the case of e-learning system, perceived ease of use was found to directly influence perceived usefulness (e.g. Sánchez & Hueros, 2010); Šumak, Heričko, Pušnik, & Polančič, 2011); (De Smet, Bourgonjon, De Wever, Schellens, & Valcke, 2012); (Lee, Hsieh, & Chen, 2013) When learners perceived the e-learning to be easy to use, it is likely that they will be satisfied with the system (Sun, et al., 2008); (Teo & Wong, 2013). In another study, it was found that when learners perceived an e-learning system is easy to use, they tend to devote more time to learning the contents, thus leading to higher satisfaction (Lee, 2010). The following hypotheses were formulated:

H1: Students’ perceived ease of use will significantly influence their perceived usefulness of e-learning.
H2: Students’ perceived ease of use will significantly influence their perceived course outcomes in e-learning.

Perceived Usefulness
Perceived usefulness is defined by (Davis, 1989) as “The degree to which a person believes that using a particular system will enhance job performance” (p.320). An e-learning system is perceived to be useful if the learners believe that the system will help them acquire the desired knowledge and skills to perform well in their studies (Teo & Wong, 2013). Studies have found that perceived usefulness has a positive relationship with learners’ satisfaction with the e-learning system (Sun, et al., 2008); (Teo & Wong, 2013) Therefore, it is hypothesized:

H3: Students’ perceived usefulness will significantly influence their perceived course outcomes in e-learning.

Lecturer Support
In e-learning, the lecturer plays a critical role as a facilitator in providing support to troubleshoot and resolve both hardware and software issues (Yuksel, 2009) When learners face problems with e-learning, timely assistance to resolve the problems would encourage the learners to continue with the learning, which include interacting with the peer students and lecturers. Past research had shown that lecturer’s timely response to learners’ needs and problems had significantly influence learners’ satisfaction ((Arbaugh, 2002); (Thurmond, Wambach, Connors, & Frey, 2002). Hence, the following hypotheses were proposed:

H4: Students’ perceived lecturer support will significantly influence their perceived ease of use of e-learning.
H5: Students’ perceived lecturer support will significantly influence their perceived interaction with peer students in e-learning.
H6: Students’ perceived lecturer support will significantly influence their perceived course outcomes in e-learning.

Interaction with Peers
In e-learning, interaction with peers allows learners to share information, receive feedback and evaluate their own learning progress (Piccoli, Ahmad, & Ives, 2001). For instance, when using asynchronous learning tool such as discussion forum, students could post comments, review other students’ comments, and respond to these comments. Over a period of time, such student to student interactions should lead to deeper and broader information processing, more knowledge transfer and deeper learning than if learning is done in isolation (Johnson, Hornik, & Salas, 2008). (Marks, Sibley, & Arbaugh, 2005) found that online student-to-student activities had a positive influence on perceived learning, suggesting that learning is facilitated by communications among the students themselves. Other studies indicated that students’ role in interaction most significantly predict student learning and/or satisfaction (Arbaugh, 2002); (Borthick & Jones, 2000);(Poole, 2000); (Arbaugh & Benbunan-Fich, 2007). Hence, the following hypotheses were proposed:

H7: Students’ interaction with peers will significantly influence their perceived ease of use with e-learning.
H8: Students’ interaction with peers will significantly influence their perceived course outcomes with e-learning.
H9: Students’ interaction with peers will significantly influence their perceived usefulness with e-learning.

IV. Methodology

Participants
Participants were 255 third-year students of a university taking a blended learning module on Laboratory Management. Among the participants, 160 (62.7%) were females and 95 (37.3%) males. A majority of 230 (90.1%) students were Indian, 12 (04.7%) Arabian and 13 (05.1%) Other races. The mean age of the participants was 19.88 years (SD = 1.68). All of the participants owned and used laptops in school, and they have access to the LMS to support their e-learning or face-to-face lessons. The e-learning portion of the module included participants taking part in the lecturer-led online forum discussion and completing online quizzes. An LMS was employed to these e-learning activities in this study.

Measures
A questionnaire employed in this study comprised of items adapted from several empirical studies using the e-learning systems or LMS (e.g. (Naveh, Tubin, & Pliskin, 2010); (Paechter, Maier, & Macher, 2010); (Sun, et al., 2008); (Teo & Wong, 2013). The questionnaire was pilot tested with a group of students and reviewed by a panel of lecturers for face and content validity. It comprises 15 statements on perceived ease of use (3 items), perceived usefulness (3 items), interaction with peers (3 items), lecturer support (3 items) and perceived course outcomes (3 items). Participants were asked to give their responses to each of the statement on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). When answering the questions in the questionnaire, the respondents were asked to relate their experience using the LMS for the e-learning lessons which they had completed. Demographic data such as gender and age were also collected in the questionnaire.

Statistical Analysis
The analysis of the study was carried out in two stages using a measurement model and structural model (Anderson & Gerbing, 1988). The first stage involved building a measurement model based on a confirmatory factor analysis (CFA), and examining the descriptive statistics, and assessing the validity and reliability. The second stage involved building a structural equation model of the latent constructs, and testing the hypothesised relationships among the constructs.

Context (MEAP)
We worked together with unit convenors and student support staff of Christ University with just under 20,000 students and 1,000 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).
V. Results

Descriptive Statistics
The mean ratings of all the five constructs were between 3.54 and 4.16, and above the mid-point of 3.00 of the scale (see Table 1). This indicated an overall favourable response to the constructs measured in the study. The standard deviations ranged from .09 to 1.17, which revealed a wide spread around the mean. The skewness ranged from - .69 to -.05 and kurtosis ranged from -.40 to .65 were all within Kline’s (2005) suggested cut-offs of absolute values greater than 3 and 10 respectively, indicating univariate normality. The Mardia’s coefficient in this study was found to be 91.95, below the recommended value of $255(p(p+2) = 15(17) = 255$ where $p$ is the number of observed variables in the study) by Raykov and Marcoulides (2012). Hence, multivariate normality is met. Therefore, the data is suitable for the purpose of structural equation modelling.

Table 1: Descriptive statistics of the constructs

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Ease of Use (PE)</td>
<td>3</td>
<td>4.16</td>
<td>1.07</td>
<td>-.45</td>
<td>-.27</td>
</tr>
<tr>
<td>Perceived Usefulness (PU)</td>
<td>3</td>
<td>3.81</td>
<td>1.14</td>
<td>-.50</td>
<td>-.08</td>
</tr>
<tr>
<td>Lecturer Support (LS)</td>
<td>3</td>
<td>4.61</td>
<td>.97</td>
<td>-.69</td>
<td>.65</td>
</tr>
<tr>
<td>Interaction with Peers (IP)</td>
<td>3</td>
<td>3.54</td>
<td>1.17</td>
<td>-.05</td>
<td>-.40</td>
</tr>
<tr>
<td>Perceived Course Outcomes (CO)</td>
<td>3</td>
<td>4.04</td>
<td>1.06</td>
<td>-.69</td>
<td>.32</td>
</tr>
</tbody>
</table>
Convergent and Discriminate Validities

Convergent validity examines whether the respective items are measuring the construct that they purported to measure. The item reliability assessed by its factor loadings of the individual items into the underlying construct was between .78 and .90 (see Table 2). This exceeded the threshold of .70 set by Hair et al. (2006), indicating convergent validity at the item level. The average variance extracted (AVE) is the amount of variance captured by the construct in relation to the variance attributable to measurement error.

Discriminant validity is the extent to which a construct is absolutely distinct from other constructs (Hair, Black, Babin, Anderson, & Tatham, 2006) Discriminant validity was assessed by comparing the square root of the AVE for the given construct with the correlations between that construct and all other constructs. As shown in Table 3, the square root of the AVEs were greater than the off-diagonal numbers in the rows and columns in the matrix, and suggested that the construct is more strongly correlated with its items than with other constructs in the model.

Table 2: Results of the measurement model

<table>
<thead>
<tr>
<th>Latent Variable</th>
<th>Item</th>
<th>SFL</th>
<th>SE</th>
<th>t-value</th>
<th>R²</th>
<th>AVE</th>
<th>Cronbach’s alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Ease of Use</td>
<td>PE1</td>
<td>.789</td>
<td>.054</td>
<td>15.857**</td>
<td>.789</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>PE2</td>
<td>.889</td>
<td>.050</td>
<td>15.857**</td>
<td>.889</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>PE3</td>
<td>.902</td>
<td>.063</td>
<td>19.632**</td>
<td>.902</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lecturer Support</td>
<td>LS1</td>
<td>.868</td>
<td>.044</td>
<td>21.091**</td>
<td>.868</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lecturer Support</td>
<td>LS2</td>
<td>.949</td>
<td>.039</td>
<td>21.091**</td>
<td>.949</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lecturer Support</td>
<td>LS3</td>
<td>.835</td>
<td>.048</td>
<td>18.834**</td>
<td>.835</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction with Peers</td>
<td>IP1</td>
<td>.775</td>
<td>.063</td>
<td>15.345**</td>
<td>.775</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction with Peers</td>
<td>IP2</td>
<td>.894</td>
<td>.043</td>
<td>15.345**</td>
<td>.894</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction with Peers</td>
<td>IP3</td>
<td>.796</td>
<td>.063</td>
<td>13.887**</td>
<td>.796</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Course Outcomes</td>
<td>CO1</td>
<td>.825</td>
<td>.049</td>
<td>16.435**</td>
<td>.825</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Course Outcomes</td>
<td>CO2</td>
<td>.802</td>
<td>.048</td>
<td>15.264**</td>
<td>.802</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Course Outcomes</td>
<td>CO3</td>
<td>.903</td>
<td>.048</td>
<td>15.264**</td>
<td>.903</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Discriminant validity for the measurement model

<table>
<thead>
<tr>
<th>Construct</th>
<th>PE</th>
<th>PU</th>
<th>LS</th>
<th>IP</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE</td>
<td>(.84)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>.66**</td>
<td>(.85)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LS</td>
<td>.44**</td>
<td>.42**</td>
<td>(.91)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IP</td>
<td>.57**</td>
<td>.66**</td>
<td>.36**</td>
<td>(.80)</td>
<td></td>
</tr>
<tr>
<td>CO</td>
<td>.61**</td>
<td>.74**</td>
<td>.45**</td>
<td>.65**</td>
<td>(.85)</td>
</tr>
</tbody>
</table>

* p < .01; diagonal numbers in parenthesis indicate the square root of the average extracted variance.
Assessment of Direct, Indirect and Total Effects

There are multiple interactions that exist among the four factors that have an influence on perceived course outcomes directly or indirectly. Table 6 shows the direct, indirect and total effects of the exogenous and endogenous variables associated with each of the 5 variables in the study. Interaction with peers is the determinant of perceived course outcomes with a large total effect of .749, followed by lecturer support, perceived usefulness, and perceived ease of use with total effect sizes of .485, .460 and .151 respectively. As for perceived usefulness, a large total effect of .736 was contributed by interaction with peers, whereas lecturer support and perceived ease of use contributed moderate total effects of .401 and .312 respectively. For perceived ease of use, interaction with peers was a strong determinant with total effect of .639 followed by lecturer support with total effect of .495. Among the four exogenous variables, perceived course outcomes had the largest amount of variance attributed to the four determinants at approximately 77%. This is largely attributed to the total effects contributed by interaction with peers, lecturer support and perceived usefulness.
Discussions

The aims of this study were to investigate the factors that influence students’ perceived course outcomes, and to determine the extent to which the factors significantly predict perceived course outcomes. LMS was employed as a platform to deliver the e-learning in this study. It was hypothesised that perceived course outcomes (CO) as a dependent variable, is predicted by four independent variables on perceived ease of use (PE), perceived usefulness (PU), lecturer support (LS) and interaction with peers (IP). Using structural equation modelling, the research model was tested and the results showed a good model fit with the data. Among the 9 hypotheses tested in the research model, 7 were supported and 2 not supported. The four independent variables accounted for 77% of the total variance in the students’ perceived course outcomes. It is noteworthy that 13% of the variance was not explained and accounted for by the model which suggested a limitation of this study and potential for future research. Except for PE and LS, PU and IP were significant predictors of perceived course outcomes. Except for PU, all the 3 other variables (i.e. LS, PE and IP) had indirect effects on CO.

In this study, perceived usefulness had a positive and significant influence on perceived course outcomes. On closer examination, perceived usefulness items had higher and significant correlations with satisfaction item (.63 ≤ r ≤ 0.71, p < .01) than with perceived learning achievements (.57 ≤ r ≤ .63, p < .01) in the perceived course outcomes. One possible explanation for this is that when students perceived the e-learning contents and online activities to be useful in helping them to perform well in their studies, their levels of satisfaction with e-learning would increase and perceived learning achievements higher. The positive and significant influence of students’ perceived usefulness on the satisfaction can be found in a few studies related to the use and adoption of e-learning(Sun, et al., 2008);(Yuen & W., 2008);(Teo & Wong, 2013).

Interaction with peers had a significant influence on perceived course outcomes. Interaction with peers also had the largest total effect on perceived course outcomes (β = .749, p < .01), compared with 3 other variables. Due to the limited literature on perceived course outcomes, this result is somewhat consistent with previous studies which found that active discussion among students significantly influenced students’ satisfaction and perceived learning (Swan K., 2001); learner-learner interactions positively predicted perceived learning(Arbaugh & Rau, 2007), and significantly affect students’ satisfaction(Eom, Wen, J., & Ashill, 2006). In this study, the results showed that the students perceived that participating in the online discussion forum is critical to learning, and they derived satisfaction through participating in the online collaborative learning activities.
Although perceived ease of use did not have a significant influence on perceived course outcomes, the result suggested that it has an indirect effect on perceived course outcomes through perceived usefulness. Employing the steps used in the mediation analysis recommended by Sobel (1982), the result showed that perceived usefulness is a significant mediator between perceived ease of use and perceived course outcomes ($z = 8.64, p < .01$), reducing the effect of PE $\rightarrow$ CO by 94.7%. Hence, the finding indicated that perceived course outcomes are not affected by perceived ease of use alone, however when students perceived e-learning to be useful, the perceived ease of use becomes an important consideration in influencing perceived course outcomes. The results showed that lecturer support is not a significant predictor of perceived course outcomes.

Applying the mediation analysis (Sobel, 1982) again, interaction with peers is found to be a significant mediator between lecturer support and perceived course outcomes ($z = 5.45, p < .01$), reducing the effect of LS $\rightarrow$ CO by 77.3%. Therefore, lecturer support alone may not exert a significant influence on perceived course outcomes. The instructional roles of the lecturers in supporting students’ learning by providing feedback to the students’ work could be extended through encouraging more students to interact with each other in the online activities, as these could have significant influence on the perceived course outcomes.

Conclusion

Based on a theoretical framework, this study proposed and tested a research model that examined the impact of the four factors (i.e. perceived ease of use, perceived usefulness, instructor support, interaction with peers) on perceived course outcomes in e-learning using the LMS among polytechnic students. The study showed that perceived usefulness and interaction with peers were significant predictors of perceived course outcomes, whereas perceived ease of use and lecturer support were not significant. The findings of this study have important implications for educators and researchers to be cognisant of the four key factors, and how these interact with each other, in the instructional design of e-learning courses using the LMS to ensure success in students’ e-learning. 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, Drachsler, Stoyanov, & Specht, 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.

Appendix

Items Used in the Study

Lecturer Support

- LS1 My lecturer gave me adequate feedback about my comments.
- LS2 My lecturer supported my learning when the lesson was conducted on LMS.
- LS3 My lecturer conducted the lesson smoothly using LMS.

Interaction with Peers
IP1 I used the LMS to communicate with my team members.
IP2 LMS helped me to work well with my team members.
IP3 I could share information with my team members easily through LMS.

Perceived Ease of Use

PE1 LMS was easy to use.
PE2 LMS was easy to navigate.
PE3 I found it easy to get LMS to do what I wanted it to do.

Perceived Usefulness

PU1 Using LMS would improve my learning in this module.
PU2 Using LMS made my learning more productive.
PU3 I find LMS useful in my learning.

Course Outcomes

CO1 I gain new knowledge from the e-learning lessons using LMS.
CO2 I have increased my knowledge of the subject using LMS.
CO3 Overall, I am satisfied with the e-learning lessons using LMS.

References


