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**RESEARCH ARTICLE**

# THE USE OF DATA MINING AND AUTOMATED SOCIAL NETWORKING TOOLS IN VIRTUAL LEARNING ENVIRONMENTS TO IMPROVE STUDENT ENGAGEMENT IN HIGHER EDUCATION

**Ilakiya G[1] Vennila S[2] and Sathya R[3]**

[1]*PG and Research, Department of Computer Science, St.Ann's College of Arts and Science Tindivanam.* Email: jeevailak18@gmail.com
[2]*Assistant Professor & Head, Department of Computer Science, St.Ann's College of Arts and Science Tindivanam.* Email: moulikrishna19@gmail.com
[3]*Principal & Head of the Department, PG & Research Department of Computer Science, St.Ann's College of Arts and Science Tindivanam*
Email: sathiyaat@gmail.com

## Abstract

Virtual learning environments (VLEs) are a component of current educational pedagogy; they contain student usage data that has the ability to inform and improve pedagogical practices. This article investigates how the creation of data mining and log analysis technologies for the Moodle virtual learning environment can boosts tudents' course engagement. The research claims that students will finish missed tasks faster if their use of the VLE is automatically recorded and electronic prompts are issued when VLE activities are missed. To investigate and test the notion, Moo Twit, a software program, was created to notify students who fell behind in their VLE studies. To see whether student timely participation improved, the study used Moo Twit with two groups of students over a period. Over the course of 15 weeks, I only messaged one group when they fell behind. Statistical analyses and comparisons were conducted to determine how quickly each group interacted with the missing pieces.The use of Moo Twittotrack and contact students had an impact on the timeliness with which they engaged in VLE activities. Specifically, the findings indicate that by directly messaging a student to interact with missing content, they finished missed activities closer to the man dated completion date. The thesis's findings suggest that educational data mining has the potential to improve pedagogy in VLE-linked education by increasing timely participation and raising course designers' acceptance of data mining to improve the validity and quality of course evaluation.

**Keywords:** Virtual learning environments, student engagement, higher education, social networks

## Introduction

A large majority of assessed educational institutions in the UK employ virtual learning environments (VLEs) to complement learning opportunities through online courses, supplemental activities, and resources for learners [1], [2]. The introduction of such technology has resulted in a broader choice of methods for engaging students with is relevant to their areas of study. This increased reliance on resources used independently by students has generated new hurdles for the learner; in order to succeed in their studies a learner must engage with VLE systems and make efficient use of the time they spend on learning materials. The desired goals align with the memorable remark "Good habits."

Many research have been conducted on VLE data mining [3]-[7], learning analytics [8]-[11], and data- informed design [12] to determine the amount of utilization of activities and resources within them. The common thread running through these investigations is the success in generating information from data; the conclusions drawn from the studies consistently avoid determining whether there was any positive impact from providing the information to either the course designer/deliverer or the students themselves. Conclusions of ten indicate that data-mining algorithms can exceed expert teacher knowledge for learning analytics [5]. Additionally, educators without skills in data mining can also utilize their knowledge in these sectors. [3] Although Kaur evaluates the success of despite the accuracy of the information in identifying slow learners, there is little evidence that the research has had an impact on student performance.

This study investigates the development and impact of data mining an open-source Modular Object-Oriented Dynamic Learning Environment (Moodle)-based virtual learning environment and automatically prompting learners who missed the deadline to access materials and activities via social networking. It was hypothesized that students receiving automated prompting would engage with missed VLE course materials in a timelier manner than unprompted students. The investigation was conducted at Lincoln College, a Further Education College in Lincolnshire, UK, which offers further education and higher education courses to post-secondary and adult learners in the area.

## Literature Review

Virtual learning environments are the most prevalent technologies used to offer learning materials and activities in UK further education institutes, and they are considered Higher education institutions increasingly rely on technology.[13]. The educational foundation for the use of VLEs is designed to facilitate the transition from teacher-led delivery to a more student-centred learning environment. The UK government and the education- funded Joint Information Systems Committee (JISC) have supported their adoption, noting digital technologies such as VLEs as exciting opportunities to revaluate how we educate, connect with, and involve learners in new ways [14]. The application of VLEs present opportunities at the institutional, teacher, and student levels to improveand enhance learning, resulting in a major investment in learning technology. Teachers that lack experience with VLE technology sometimes fail to educate students how to utilize it successfully. As a result, students may struggle with technology-based work. [15].

More importantly, students who do not participate in the learning process may not be detected until they have fallen so far behind that they are unable to advance with their studies. This is a concern for the participants in this study, Lincoln College's Computer Studies section, which supports students' learning by using Moodle VLE courses to provide all learning materials and activities for the section.

A Moodle course is divided into a structured series of exercises. Figure 1 depicts a typical Moodle course structure, which consists of a sequence of topics (Moodle sections) containing a number of activities (Moodle modules); some of the activities are required for a student to complete the course at a minimum level and must be completed on time.

The course is presented to students via a web interface, which allows them to traverse sections and interact with modules. Themes can be used to change the interface's appearance and feel, as shown in Figure 2. A sample chunk of a Moodle course taught to a computing student at Lincoln College is displayed. There are four modules within the section that the student should engage with.

- Introduction to XNA presentation (pop-up URL module).
- Exercise 01: Create an XNA project video (Page module).
- λ Adding text to an XNA screen presentation (Pop-up

Exercise 02: XNA. Writing to the Screen' is an example of a Moodle lesson module that would appear to the student as a navigable lesson with quiz components. Within Lincoln College's computing division, all teachers want students to be completely engaged with their courses on the VLE, and it has been found that many students have struggled to keep track of online exercises and activities assigned. This issue has been confirmed. Another study about VLE engagement that concluded. Some students participated in online activities, but many did not or did not interact as much as the course staff and lecturers expected. [16]. In this case, Morgan detected a lack of involvement with the VLE, which can have an impact on a student's level of success [17]. Kuh et al. identified two critical components for a student's success: time and effort invested in academics.

The way the institution allocates resources and organizes learning opportunities and services to encourage student participation. [18]. The University of Wolver hampton conducted a study to encourage student participation in VLE learning activities using the Wolver hampton Online Learning Environment (WOLF). The study's analysis suggested monitoring regular habits in using WOLF, including activities, to Fig. 3. A sample Moodle lesson module.

There have already been attempts to improve the quality of reporting offered to tutors. Previous research and system developments focused on the use of log


analysis to produce a ―learning analytics dashboard‖ [21], charts and graphs alongside materials in Moodle [19], or ‚provides aggregated and useful statistical reports.‖ [10]. These all require the direct engagement of the designer and deliverer to interpret and action the results. Typically, non-engagement of a student is URL module). resolved and identified by the deliverer, and it is expected that they will be able Previous research reporting systems have a diverse amount of efficacy in terms of their ease of use and the expected technical level. The previous research found that reporting systems had varying degrees of success interm so fease of use, expected technical level of users, and capacity to analyze the information supplied.

In essence, the purpose of this study is to determine whether it is possible to improve the timeliness of student interaction with VLE activities and materials. This is achieved through the development of a soft ware arte fact Moo Twit - a Moodle plug-in enabling checking student engagement with the VLE and automating the process of prompting the students regarding their lack of timely engagement and examining the change in the study participants' behaviors and attitudes because of the use of the software.

- Use log analysis to assess student engagement.

Ensure adequate engagement [11].AccordingtoMazza and Milani, monitoring student learning is crucial for high-quality education [19]. However, tutors must manually navigate an HTML forms-based query system to assess a student's engagement with a Moodle course [20].
The approach is labor-intensive; applying to a full student cohort on a regular basis would put a tutor under a tremendous workload. This scenario can be avoided via software automation. Moodle gathers extensive data about student interactions, like as content, assessments, and conversation [6], which can be mined.

- Use Twitter and email to refer late

students to VLE materials and congratulate those who complete assignments on time.
- Provided course instructors with feedback on low student engagement.

## Methods

When developing the study methodology, it was necessary to consider data collection in order to evaluate the system's success.The research employs a quantitative approach, using data from Moodle database logs of students' VLE accesses. This aligns with Neall's quantitative criteria, which include looking for specific changes in engagement and knowing what the researcher is looking for [27].

The research technique attempted to avoid bias, recognizing that it cannot be totally avoided [28].

1. Automating virtual learning access logging reduces participant bias by making data gathering activities invisible.
2. Automated social media message generated by the engagement system reduces bias due to experimenter behavior. This ensures all participants receive consistent feedback at the same time and format.

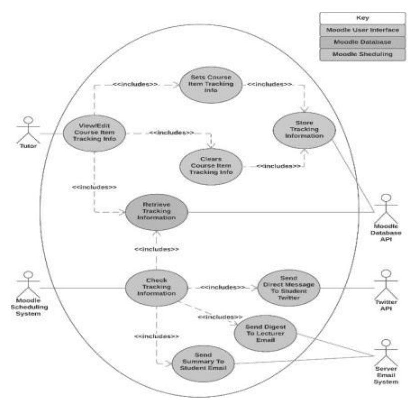
The use of log analysis removes the learner's ability to be aware of what they are being tracked on; obscuring the tracking stops them from modifying their behavior until the system alerts them that they have missed the milestone for finishing the job. The tutor's withdrawal from the tracking and prompting process lowers their power over the students when they miss work, reducing the impact on how quickly the student may complete the missing work.

The system was created as a proof-of-concept to demonstrate how a Moodle and Twitter plug-in may be used to track and improve timely engagement with critical VLE course resources. As a proof of concept, the plug-in is scal ablein accordance with the database and server technologies that power the VLE; its limitation is that social media restricts the usage of automated direct messaging.

## Over view of Plug-In Development

Development was limited to the Moodle VLE due to the skill set of the users participated in the study and the system's operational use at Lincoln College. The engagement system's main development language was PHP: Hypertext Preprocessor (PHP), an HTML-embedded scripting language.The justification for this was predicated on allowing web developers to swiftly produce dynamically generated pages and its interoperability with the Moodle VLE, both written in PHP[29]. This facilitated development by allowing us to call the existing Moodle log API [20]. To communicate the amount of engagement to a student required a link to an existing social net working

**Fig.4.Use case diagram student engagement system.**



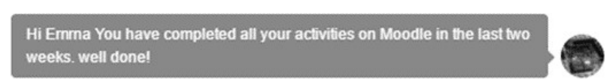
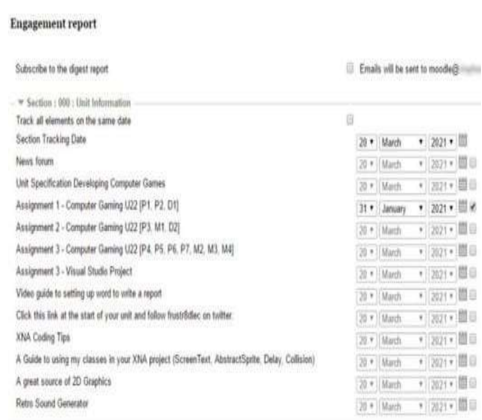




**Fig.5. MooTwit engagementplug-in.**

If the student had completed all of the tasks, a message of congratulations was delivered instead (Fig. 8 Twitter direct message).Fig. 8. Twitter direct message (Completed all work) Messaging infrastructure for direct messaging.

Twitter was chosen as the optimal system for the trial. Direct messaging. Lincoln College chose Twitter due to its regular use with students and open API for developers. However, the product's scalability was limited by a daily limit of 250 direct messages peruser during evaluation [30]. The hosting service chosen for this study has a built – in PHP mail function that enables sending e-mails straight from a PHP script [31] that is to be used for giving a summary of course items missing each week to both the student and the course coordinator.

To integrate the desired functionality into the Moodle VLE, a Moodle plug-in was chosen as the objective for development rather than creating a separate web site to a ccomplish the task. The MoodleVLEcanbeextended via a plug-in-based framework, which is the simplest way to add new functionality to Moodle (MoodleDocs 2016b). This solution ensured student data had the same level of security as the VLE, meeting the Technical element of the DELICATE checklist for learning analytics [32].




The study used two independent classes of students, both in their second year of a level 3 BTEC Extended Diplomain IT course, who had enter edwith equalentry standards and studied the same courses with the same instructors prior to the intervention. One class served as the control group, and the other as the experimental group; both were notified of the intervention and agreed to participate, but were unaware of whether they were in the controlor experimental groups; neither group was aware of the other's involvement. To avoid the likelihood of one group influencing the other, communication about the research between the two groups was limited by scheduling their classes on different days of the week.

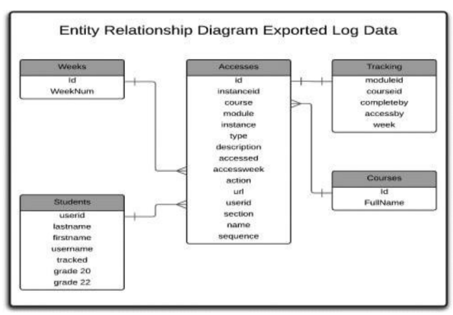
The study lasted 15 weeks, with 14 students in the control group and 15 in the experimental group. The control group originally had 15 participants, but one became unwell during the first week of the study and was unable to contribute. During the first week of the study, both groups were asked to enter their Twitter names.

The control group was opted out of the study's engagement mechanism and did not receive any messages via Twitter or email. Over the course of 15 weeks, 57 monitoring deadlines were established.

The premise that the experimental group will access missed content sooner than the control group because the system prompted them to do so established the system's success evaluation. Then ull hypothesis stated that the experimental group would not access the learning activities any earlier than the control group when asked. The engagement system was evaluate by comparing log data from the control and experimental groups. To finish this procedure, the data from Moodle' slog table was exported to a single table, which was then divided into relational tables, as illustrated in Fig.9 Entity relationship diagram exported log data.

To ensure consistent tracking of student conduct, tracking dates were divided into weeks from the start of the course; access measurements were then based on the week of access to facilitate the classification of timely access to learning activities. Access results were based on the initial access a student made to a learning activity and were classified as:

Positive accesses occurred by the deadline or within a 2-week prompting window, indicating the student is on track.




Late access occurred beyond the2-week period of Prompting (the pupil has slipped behind).

The student did not complete the activity within the course timeframe, resulting in missed access.

The accesses for each group were tallied as indicated in Table I, with the total number of weekly accesses recorded after the expected week of access.

The evaluation examined changes in student access to the VLE on both a group and individual level, assessing changes before and after the system; and further inspection at regular intervals through out there search to acquire additional insights into differences in involvement over time. The evaluation's conclusions will identify the system's accomplishments and/or

| Tracked | Yes | No |
|---|---|---|
| N | 900 | 840 |
| Mean(X) | 0.54 | 0.33 |
| Std. Deviation (□) | 0.5 | 0.47 |
| S.E.Mean | 0.02 | 0.02 |

Short comings in improving involvement and serve as a model for others to emulate with other student groups.

**Analysis**

Student engagement was measured by the timeliness with which they accessed the resources on the VLE; a student was considered appropriately engaged with the material if they accessed it either before the expected access date or within a two-week window after the date; if a student failed to access the material after that date, they were considered not to be appropriately engaged. Before evaluating the quantitative data from the log files, statistical tests were performed to confirm that the findings were statistically significant. IBMSPSS software was used to extract pertinent results, and an additional

calculation was performed to determine the effect size. Performing the statistical tests necessitated some pre- processing of the collected data using the criteria listed below.

Positive access within 2 weeks of projected

- Negative access within 2 weeks of expected date or no access made.
- The groupings were divided into categories.

## A. Independent SamplesT-Test.

- An independent-samples t-test was used to examine the timeliness of VLE access in tracked (electronically urged to engage in missed activities) and untracked situations. There was a significant difference in scores between prompted ($M = 0.54$, $SD = 0.50$) and unprompted ($M = 0.33$, $SD = 0.47$) circumstances;$t(1738)=9.24, p=0.0002$.

Table II has full details on the t-test results.

- These findings indicate that electronic tracking and
- The findings were analyzed using Cohen's d computation [35] (1).
- Cohen'sd=0.43(1).
- The experiment's hypothesis stated that students who were tracked would engage more than non- tracked students; however, because the T value is bigger than the crucial value 1.96 found from table B2 [36], the null hypothesis that both groups would engage equally cannot be accepted.
- The findings were analyzed using Cohen's d computation [35] (1).
- Cohen'sd = 0.43(1).
- Prodding of students who miss events influences the timeliness of their engagement with VLE activities. The findings indicate that when students receive a Twitter direct message to engage with missing material, they finish missed activities closer to the mandatory

## B. Comparison between Accessed

From the results of the t-test and Cohensd it was identified that the hypothesis for students Being prompted accessing the materials earlier was most likely and that the effect size was close to being classifieds medium. From Fig.10 Graph of student access profile it can be seen that the positive accesses for the experimental group was 22% higher and they completed 19% more activities than the control group. The high numbers of late and missing events by the untracked group provides a compelling rationale for the requirement for tracking of student engagement, given that the tracked activities were designated as mandatory aspects of the courses.

### C. Positive Access Trend Comparison.

Throughout the trial, the urging was repeated on the experimental group to determine whether the process would have a good or negative cumulative effect on them in compared to the control group. Miltenberger's research revealed that using several prompts should boost engagement [23].

Engagement trends during the study, the experimental group demonstrated a 16% increase in mean timeliness of access from the beginning of the trial, demonstrating that frequent prompting had a positive cumulative effect over time. In comparison, the control group's improvement over time has not grown and is 34% lower than the experimental group by the end of the trial when evaluating the results, it was noted that then untracked group had alower initial level of performance than the tracked group and remained so throughout the study; however, this does not relate to how prompting altered student behavior because the study compares the improvement from each group's starting point. In Fig. 11, the trend of the prompted participants showed continuing improvement from the participants' starting point when compared to the static result so fun prompted students, indicating that there was an increase in engagement in the experimental group as are sult of the messages sent to them. The data points in weeks 6 and 7 on the graph show a higher level of completions by both groups.

This can be explained by the fact that delivery in those weeks is lighter around the half-term break within the 15 weeks of study, giving students more time in class and during the week break to finish some work.

### D. Analysis Summary

The study's data analysis revealed that the experimental group performed better overall. The study's findings indicate that using a software solution to generate an electronic message as a stimulus to produce a change in operant behaviour was successful within the experiment's parameters, effectively rejecting the null hypothesis that the experimental group would not access the learning activities any earlier than the control group after being prompted.

When reflecting on the research's success, it is necessary to consider the study's limitations, such as the use of a small sample of computing students from one institution, which may not represent the spectrum of learners in the greater academic community. The study's 15-week duration may not have provided enough time to determine if the experimental group's performance increases might be increased further by continuing to use the system, or whether the learners would get disillusioned with the system and stop responding to prompts.

The utilization of extracted quantitative data from the Moodle database provided unambiguous empirical evidence to demonstrate student activity and identify behavioral changes, making it an effective research tool in this setting that simplified data collecting and processing.

The experiment successfully extracted data from the Moodle database using a plug-in, validating previous research by Mazza et al. [9] and Zhang & Almeroth [10]. documentation. Despite the development challenges and the fact that Moodle is an open source project, the plug-in system proved to be entirely stable and work edreliably through out there search, implying

It is crucial to highlight that the plug-in development process was hampered by a lack of documentation regarding then at ure of the data stored within the system, as well as omissions in the open source Moodle that it should be considered a suitable system for conducting research on student use of the Moodle virtual learning environment.

Early in the research, the literature review revealed that, while Mohammad and Tasir [7] proposed the use of social networking as a possible communication mechanism, only Twitter provided an API for direct messaging, which had limitations on the number of messages that could be sent in 24 hours.

Although Twitter automatically provided a direct messaging system on a variety of target platforms, including all mobile phones, tablets, and PCs, it was discovered that a tiny number of learners did not use Twitter and had to create accounts.

Given the limited messaging API provision by social networking providers and the variety of providers that learners may or may not use, social networking may not be the best solution; messaging applications, such as Facebook's Whats App messenger, may provide a better system of communication.

While this study may not have a significant impact on the motivation of students to learn independently, it does show that automated prompting is effective. It is hoped that the findings will spark debate and additional research into various automated processes that aid in learner engagement through prompting mechanisms.

The inquiry tool can be used as is in Moodle installations and serves as a plat form for future Moodle plug-in developers to conduct research as well as develop plug-ins for general use. For course designers and tutors, the plug-in provides a consistent way for addressing small groups of students who do not participate in critical learning activities; it also gives a methodology for determining whether there is measurable increase in engagement for the students. If the plug-in is used in other academic institutions, the system should at least provide helpful prompts for students so that they may readily recognize missed work before falling behind in their studies.

**C.PositiveAccessTrendComparison.**

Throughout the trial, the urging was repeated on the experimental group to determine whether the process would have a good or negative cumulative effect on them in compared to the control group. Miltenberger's research revealed that using several prompts should boost engagement [23]. According to Fig. 11 Engagement trends during the study, the experimental group demonstrated a 16% increase in mean timeliness of access from the beginning of the trial, demonstrating that frequent prompting had a positive cumulative effect over time.In comparison, the control group's improvement over time has not grown and is 34% lower than the experimental group by the end of the trial When evaluating the results, it was noted that the untracked group had a lower initial level of performance than the tracked group and remained so throughout the study; however, this does not relate to how prompting altered student behavior because the study compares the improvement from each group's starting point. In Fig. 11, the trend of the prompted participants showed continuing improvement from the participants' starting point when compared to thes tatic results of unprompted students, indicating that there was an increase in engagement in the experimental group as a result of the messages sent to them. The data points in weeks 6 and 7 on the graphs how a higher level of completions by both groups.

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When reflecting on the research's success, it is necessary to consider the study's limitations, such as the use of a small sample of computing students from one institution, which may not represent the spectrum of learners in the greater academic community. Thestudy's 15-week duration may not have provided enough time to determine if the experimental group's performance increases might be increased further by continuing to use the system, or whether the learners would get disillusioned with the system and stop responding to prompts.

The utilization of extracted quantitative data from the Moodle data base provided un ambiguous empirical the plug-in system proved to be entirely stable and worked reliably throughout the research, implying that it should be considered a suitable system for conducting research on student use of the Moodle virtual learning environment.

Early in the research, the literature review revealed that, while Mohamad and Tasir [7] proposed the use of social networking as a possible communication mechanism, only Twitter provided an API for direct messaging, which had limitations on the number of messages that could be sent in 24 hours.

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**Conclusion**

All previous research have focused on techniques of analyzing and displaying information, but none have looked at whether this could have a positive impact on students. The primary goal of the Moo Twit development was to extend the data mining process in to a system that improved student engagement with VLE courses by analysing their accesses and automatically prompting them via social networking, backed up by email, when they were falling behind on VLE activities.

The hypothesis was that the experimental group (students who received automated prompting) would get access to missed VLE course materials sooner than the control group. The study's findings corroborate this hypothesis, indicating that electronic tracking and urging of students who skip activities has a small to medium effect on the timelines with which they engage in VLE tasks. Specifically, the findings indicate that when students receive a Twitter direct message to engage with missed content, they finish missed tasks closer to the mandated completion date than un prompted students. In the context of the initial goal of the research of boosting students involvement with the activities, clearly there has been a verifiable shift in behavior by students in the experimental group.

There is strong evidence that implementing the system would be beneficial, increasing student use of course resources at the right stage in their studies and improving the quality of their educational experience. The extent of this success is limited by the fact that these results may not be reflected in the context of the larger learner community; this experiment concentrated on a specific group of pupils; and the success exhibited here may not provide the same outcome with a different learner demographic.

This limitation allows for the investigation to be expanded into a larger domain to determine whether the findings can be completely generalised by varying parameters such as technological ability, students' initial engagement level with the VLE, participant age, or course subject studied.

During the initial examination of the research results, there was concern that prompting could demotivate pupils or reduce its effectiveness over time. The initial statistical data analysis addressed demotivation by examining the statistical outcome of prompting having a positive effect; however, it did not take into account the use of prompting over time.

The students may have been open to the system at the beginning of the experiment, but they were less so toward the end. Thet-test and Cohen's Deffect level did not give a temporal metric that enabled this level of before falling behind in their studies

**References**


1. UCISA, ―Survey of technology enhanced learning for higher educationin the UK,‖ 2018.
2. Of sted & The Office for Standards in Education, Virtual learning environments: An evaluation of their development in a sample of educational settings,‖ *Alexandra House*, 2009, pp. 1–28.
3. P.Kaur,M.Singh,andG.Josan,―Classification and prediction baseddata mining algorithms to predict slow learners in education sector,‖ *Procedia Computer Science*, vol. 57, 2015, pp. 500–508.
4. S. K. Mohamad and Z. Tasir, ―Educational data mining: A review,‖ in *Proc. Social and Behavioral Sciences*, vol. 97, 2013, pp. 320–324.
5. C. Romero, C. Castro, and S. Ventura, ―A Moodle block for selecting,visualizing and mining students usage data,‖ presented at 6th International Conference on Educational Data Mining, Memphis, TN,USA, 2013.
6. R.Mazza*etal*.,―MOCLog—Monitoringonline courses with logdata,‖ in *Proc. 1st Moodle Research Conference*, 2012, pp. 132–139.
7. A. Ortigosa and R. M. Carro, ―The continuous mpirical evaluation approach: evaluatingadaptive web-based courses,‖ in *Proc. 9th International Conference on User Modelling*, Berlin, Heidelberg:Springer-Verlag, 2003, pp. 163–167.
8. D. Y. T. Liu *et al*., ―Knowledge acquisition for learning analytics: comparing teacher-derived, algorithm-derived, and hybrid models in the moodle engagement analytic splugin,‖*PacificRimKnowledgeAcquisitionWorkshop*, 2016,pp. 183–197.
9. D. Yen *et al*., ―An enhanced learning analytics plugin for Moodle: student engagement and personalised intervention,‖ *GloballyConnected, Digitally Enabled. Proceedings of Ascilite 2015*,pp.180–189.
10. H.ZhangandK.Almeroth,―Moodog:Tracking student activity inonline course management systems,‖ *Journal of Interactive Learning Research*, vol. 21, no. 3, 2010, pp. 407–429.
11. C. Dale, ―A wolf in sheeps' clothing? An analysis or student engagement with virtual learning environments,‖ *The Journal of HospitalityLeisureSportandTourism*,vol.6,no


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